

Ship detection and characterization from SAR imagery linked with cooperative vessel tracking data Ramona-Maria Pelich

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Tention : Sciences et Technologies de l'Information et de la Communication

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Ship detection and characterization from SAR imagery linked with cooperative vessel tracking data

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Ship detection and characterization from SAR imagery linked with cooperative vessel tracking data

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Abstract

SAR imagery presents an increased interest in maritime surveillance applications. The research work completed in this thesis is dedicated to vessels detection and signature characterization from data acquired by different spaceborne SAR sensors. Firstly, we assess the performances of different ship detectors based on adaptive threshold algorithms. The detection algorithms are based on various clutter distributions and assessed automatically with a systematic methodology. Evaluation using large datasets of medium resolution SAR images and AIS (automatic identification system) data as ground truths allows to evaluate the efficiency of each detector. Depending on the datasets used for testing, the detection algorithms offer different advantages and disadvantages. The systematic method used in discriminating real detected targets and false alarms in order to determine the detection rate, allows us to perform an appropriate and consistent comparison of the detectors. The impact of SAR sensors characteristics (incidence angle, polarization, frequency and spatial resolution) is fully assessed, the vessels length being also considered. Experiments are conducted on Radarsat-2 and CosmoSkymed ScanSAR datasets and AIS data acquired by coastal stations.

Secondly, the effects of stationary-based processing of moving ship signatures in SAR imagery are assessed and a methodology that makes it possible to estimate and compensate them is introduced. SAR imaging of moving targets usually results in residual chirps in the azimuthal SLC processed signal. The Fractional Fourier Transform (FrFT) allows to represent the SAR signal in a rotated joint time–frequency plane and performs an optimal processing and analyse of chirp signals. Employing the FrFT reduces the effects of residual chirps achieving compensation of the along-track defocus of a moving target and estimation of the target's azimuthal speed itself. Experiments are conducted on Radarsat-2 Multilook Fine and Ultrafine SAR images. Evaluation using a large number of ship signatures allows to assess the efficiency of the proposed method. Comparisons with AIS data as ground truth and with a method based on the assessment of the temporal correlation between a sequence of sublook images are carried out for a complete performance analysis.

Finally, the use of complex dual-polarization data for SAR vessel detection is assessed. As a first step, an intercomparison between the individual use of each polarimetric channel is considered, as well as the fusion of the detection results corresponding to the two polarimetric channels. In a second phase, the fusion of both polarization channels before the detection step is assessed. When dealing with amplitude data only, we propose to employ a method based on the generalized temporal moments (Hölder means), in order to fuse the information of both polarization channels. When dealing with complex data, the coherence coefficient or target dual-polarimetric decompositions, which may provide additional information in comparison with single channel imagery, are employed.

Keywords: Automatic identification system (AIS), azimuth speed, Constant False Alarm Rate (CFAR), dual-polarization, Fractional Fourier Transform (FrFT), non-parametric, refocusing, ship detection, statistic distribution, Synthetic Aperture Radar (SAR).

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Résumé

L'imagerie Radar à Synthèse d'Ouverture (RSO) est fréquemment utilisée dans les applications de surveillance maritime, notamment en raison de son indépendance à la lumière du jour, aux nuages ou aux conditions météorologiques. Le travail de recherche mené dans cette thèse est consacré à la détection de navires et à la caractérisation de leurs signatures à partir de données acquises par différents capteurs RSO. Premièrement, nous avons évalué les performances des différents algorithmes de détection de navires basés sur un seuillage adaptatif. Ces algorithmes de détection sont basés sur diverses distributions statistiques de "fouillis de mer" et sont automatiquement évalués. Une analyse prenant en entrée de nombreux jeux de données d'images RSO et de données AIS utilisées comme "vérité terrain", a permis d'évaluer l'efficacité de chaque algorithme. En fonction des jeux de données utilisés, les algorithmes de détection présentent différents avantages et inconvénients. Une méthode de couplage RSO-AIS a été utilisée pour discriminer les cibles réelles détectées des fausses alarmes et ce, afin de déterminer le taux de détection et d'effectuer une comparaison cohérente des différents algorithmes de détection. L'influence des caractéristiques des capteurs RSO (angle d'incidence, polarisation, fréquence et résolution spatiale) a été évaluée, ainsi que l'influence de la longueur des navires. Des expériences ont été menées sur des jeux de données Radarsat-2 et CosmoSkymed ScanSAR ainsi que sur des données AIS acquises depuis les stations côtières.

Ensuite, les effets de l'hypothèse de la stationnarité lors du traitement de l'image RSO ont été évalués sur la signature des navires mobiles. Une méthodologie qui permet d'estimer et de compenser ces effets a alors été introduite. L'imagerie RSO des cibles mobiles se traduit généralement par des signaux résiduels de type "chirp" dans le signal complexe et dans la direction azimutale. La Transformée de Fourier Fractionnaire (FrFT) permet de représenter le signal RSO dans un domaine de rotation temps-fréquence, ce qui permet d'effectuer un traitement optimal des signaux de type "chirp". L'emploi de la FrFT réduit les effets de ces signaux résiduels de type chirp et permet de compenser la défocalisation azimutale d'une cible mobile ainsi que d'estimer la vitesse azimutale de la cible visée. Des expériences sur des données Radarsat-2 ont été menées et l'utilisation d'un grand nombre de signatures de navires a permis d'évaluer l'efficacité de la méthode proposée. Des comparaisons avec les données AIS ainsi qu'avec une méthode basée sur l'évaluation de la corrélation temporelle dans une séquence de sous-images ont été effectuées pour obtenir une analyse complète des performances.

Enfin, l'utilisation de données à double polarisation dans la détection des navires RSO a été évaluée. Dans un premier temps, une comparaison des résultats de détection propres à chaque canal polarimétrique a été considérée, pour ensuite évaluer la fusion des résultats. Dans une deuxième phase, la fusion de ces deux canaux de polarisation avant l'étape de détection a été étudiée. Concernant la fusion des données en amplitude, nous avons proposé d'utiliser une méthode basée sur les moments temporels généralisés (moyenne Hölder). Pour les données complexes, le coefficient de cohérence ou les décompositions polarimétriques ont été utilisés et ont pu fournir des informations supplémentaires par rapport à l'imagerie à un seul canal.

Mots clés : Automatic Identification System (AIS), polarisation duale, Fractional Fourier Transform (FrFT), non-paramétrique, Radar à Synthèse d'Ouverture (RSO), refocalisation, détection de navires, distribution statistique, vitesse azimutale.

Résumé étendu

La foi vient de l'intuition, et la foi, c'est l'ancre de la raison humaine. La raison flotte, vogue, navigue, explore, découvre, va, et c'est là le voyage sublime. Elle dresse la carte de l'idée, elle éclaire toute la périphérie de ce problème éternel qui est pour notre pensée la mer; mais c'est avec l'ancre seulement, avec la foi, avec l'intuition qu'elle peut en trouver le fond et s'y rattacher. Jamais de repos, jamais de mouillage, jamais de port pour ce navire, s'il n'a cette ancre.

Victor Hugo

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Note : Theses completed in a French institution but written in another language are required to provide a French abstract.

Note : Les thèses accomplies dans un établissement français mais écrits dans une autre langue doivent fournir un résumé français.

Introduction

La surveillance maritime est définie comme étant le contrôle de toutes les activités au sein du domaine maritime et la possibilité, si nécessaire, d'assurer un processus de décision dans des délais impartis [2,3]. Elle est impliquée dans différents secteurs d'activités tels que le contrôle de la pêche, la surveillance des frontières, la sécurité du transport maritime, la piraterie maritime et les vols armés en mer. Elle est généralement réalisable en combinant des informations provenant de différentes sources de données. Ces sources sont habituellement réparties en deux catégories : les systèmes de notification ou de messagerie et les systèmes de capteurs. Les premiers systèmes s'appuient sur les navires de fournir les informations et sont donc des systèmes dits de coopération. De nombreux systèmes coopératifs sont actuellement utilisés tels que [2,47,93] : Vessel Monitoring System (VMS), Automatic Identification system (AIS), Satellite AIS (Sat-AIS) or Long Range Identification and Tracking (LRIT). Les systèmes coopératifs sont une technique efficace pour surveiller les navires. Il existe cependant un nombre important de navires actifs ne possédant aucun transpondeur AIS, VMS ou LRIT. La deuxième catégorie de systèmes, dits non coopératifs, collectent quant à eux des informations sur les navires sans leur coopération. Ils sont généralement représentés par des systèmes de capteurs tels que les radars, les caméras ou les bateaux de patrouille. Parmi le grand nombre de sources de données actuellement disponibles pour les systèmes non coopératifs, les plus fréquemment utilisés sont : l'imagerie Radar a Synthèse d'Ouverture (RSO), les images satellitaires optiques et les données radar côtières.

L'imagerie RSO n'étant pas dépendante de la couverture nuageuse ni de l'éclairage et possédant une grande zone de couverture, elle présente un fort intérêt pour différentes applications de surveillance maritime. L'imagerie satellitaire RSO offre en effet aujourd'hui un potentiel considérable dans le domaine de l'observation et de la surveillance de l'environnement marin. Ce potentiel existe tant à travers la diversité des informations qu'il est possible d'extraire (détection de pollutions par hydrocarbures des navires, mesures d'états de mers, mesures des champs de vents) qu'à l'opportunité unique d'obtenir de telles informations dans le domaine du proche côtier grâce à des images de résolutions spatiales inégalées. De plus l'amplitude et la phase du signal RSO peuvent être utilisées pour détecter et même quantifier le mouvement des navires. Dans cette thèse, nous nous focalisons sur la détection de navires ainsi qu'à la caractérisation de leur signature en utilisant des données acquises par différents capteurs spatiaux RSO.

Dans les images RSO, les signatures de navires sont représentées par des pixels qui sont nettement plus brillants que ceux aux alentours. Cela vient du fait que la plupart des navires sont constitués de superstructures métalliques et ont des configurations de ponts spécifiques qui agissent comme des réflecteurs en coin. Ces éléments correspondent donc à une forte rétrodiffusion radar. Le fouillis de mer se comporte quant à lui comme une surface rugueuse avec un signal de rétrodiffusion correspondant généralement inférieur à celui des navires. Par conséquent, la détection des navires à partir d'images RSO peut être simplement définie comme l'identification des pixels brillants dans un fond plus sombre. Les chaînes classiques de détection de navires sont conçues pour détecter statistiquement un contraste significatif entre le navire et le fouillis local de mer. La littérature et les applications développées dans ce domaine sont vastes [22]. Cependant, le fouillis de mer n'a pas toujours la même énergie, et peut donc compliquer le processus de détection. En effet, l'imagerie RSO du fouillis de mer est fortement dépendante de l'état de la mer, des conditions météorologiques et également des caractéristiques du système RSO. Dans des conditions défavorables telles qu'un état de mer agité, le signal RSO représentant le fouillis de mer est caractérisé par un bruit de chatoiement (speckle) de haut niveau d'énergie. Dans de tels cas, les algorithmes de détection classiques doivent être adaptés avec des techniques de traitement de signal ou d'image appropriées.

Cette thèse a été menée à Collecte Localisation Satellites (CLS), en collaboration avec l'Institut Mines Télécom, Télécom Bretagne de Novembre 2012 à Novembre 2015. CLS est une filiale du Centre National d'Etudes Spatiales (CNES), l'Institut Français de Recherche pour l'Exploitation de la Mer (IFREMER) et la société d'investissement ARDIAN. Les principaux objectifs du CLS sont d'exploiter des systèmes satellitaires et de fournir des produits et services à haute valeur ajoutée. CLS fournit des services opérationnels pour la surveillance de l'environnement, la gestion durable des ressources marines, et la sécurité maritime. Comme mentionné précédemment, les images RSO représentent un élément clé pour la sécurité maritime. La détection de navires à partir de l'imagerie RSO représente l'un des principaux produits proposés par CLS. L'objectif de cette thèse est de recommander et d'élaborer des méthodologies nouvelles et innovantes qui permettent d'améliorer les performances et de surmonter simultanément les limitations des chaînes de détection de navires actuellement employées. Pour cela, nous proposons plusieurs solutions qui répondent aux problématiques de recherche introduites dans la section suivante. L'évaluation expérimentale de ces méthodes est réalisée sur des images RSO conjointement avec des données AIS fournies par CLS. Par conséquent, les ensembles de données employées dans cette thèse sont limitées par le type de données disponibles à CLS. Nous avons principalement employé des images RSO acquises par les capteurs radar satellitaires RADARSAT-2 et Cosmo SkyMed. D'ailleurs, au cours de la dernière année de la thèse, nous avons eu l'opportunité d'utiliser des images RSO acquises par le capteur Européen Sentinel-1,

qui a été lancé en Avril 2014 et qui fournit des images calibrées depuis la fin de l'année 2014. La dernière partie de cette étude est donc focalisée sur l'utilisation des images Sentinel-1, qui ont l'avantage d'être disponibles dans des modes à double polarisation.

Problématique de recherche

Le principal élément de recherche de cette thèse est d'examiner des méthodes nouvelles et innovantes dans le domaine de détection des navires par imagerie RSO. Même si la littérature et les applications développées dans ce domaine de recherche sont vastes, l'évolution des capacités des capteurs RSO ainsi que la disponibilité des données engendrent de nouveaux axes de recherche. L'objectif de cette thèse est de proposer des solutions aux problématiques suivantes :

- Amélioration des algorithmes de détection classiques : Les méthodologies usuelles de détection des navires RSO sont basées sur la modélisation statistique du fouillis de mer et sur la détection des échantillons individuels de pixels dont les valeurs de brillance sont statistiquement inhabituelles. L'imagerie RSO de zones de fouillis de mer dépend de plusieurs facteurs tels que l'état de mer, les conditions météorologiques et les caractéristiques du système RSO. Dans des conditions défavorables, les mécanismes de rétrodiffusion de l'océan peuvent être hétérogènes, compliquant ainsi la modélisation statistique du fouillis de mer dans l'imagerie RSO. Afin de remédier à ce problème, une analyse étendue de la distribution statistique des signaux RSO est nécessaire pour développer proprement les algorithmes de détection.
- Évaluation des performances en fonction des différentes paramètres clés qui influencent le processus de détection : Généralement, les performances de détection varient en fonction de divers facteurs : l'état de mer (vagues, vent, ...), les caractéristiques instrumentales des capteurs (bande de fréquence, polarisation), les conditions d'acquisition (angle d'incidence) et les conditions météorologiques. Afin de traiter cette problématique, on peut estimer statistiquement ces performances a posteriori sur une base de données d'images analysées. Cela permettra de définir un modèle prédictif d'évaluation de ces performances.
- Couplage avec des données de positionnement coopératives : Plusieurs types de données de positionnement coopératives sont disponibles. Ces données peuvent être utilisées pour fournir une vérité terrain sur la position des navires présents dans les scènes radar utilisées. Dans cette étude, nous évaluons les problèmes de poursuite de navires à partir de différentes sources d'information (données coopératives et détection RSO) considérées séparément ou conjointement.
- Exploitation de la multi-polarisation : Les missions RSO relativement nouvelles donnent accès aux données de la même scène imagée selon plusieurs canaux polarimétriques. Il s'agira ici d'étudier la détection conjointe sur ces différentes images afin de dépasser les limitations d'une détection successive sur chaque polarisation.
- Meilleure caractérisation des navires détectées : Cette partie se réfère au développement des méthodes robustes qui sont en mesure d'estimer les caractéristiques des navires à partir de l'imagerie RSO. Dans le cas des données à très haute résolution, des techniques de refocalisation de cibles seront considérées.

Contributions

Afin de répondre aux problématiques de recherche mentionnées précédemment, plusieurs méthodologies s'appuyant sur des outils de traitement du signal et d'image, sont proposées dans cette thèse. La contribution du travail menée pendant la durée de cette thèse se divise en trois parties principales :

- Détection de navires grâce à l'imagerie RSO en amplitude et polarisation singulière.
- Refocalisation des navires détectés à partir de données RSO complexes (SLC).
- Exploitation des données complexes à polarisation duale dans les chaînes RSO de détection de navires.

Détection de navires grâce à l'imagerie RSO en amplitude et polarisation singulière

L'objectif principal de cette partie (chapitre 2) est de comparer et d'analyser les résultats issues des différents algorithmes de détection appliquées à des jeux de données de grandes dimensions, contenant des images RSO (en intensité). Pour cela nous utilisons le détecteur classique nommé Taux de Fausse Alarme Constant (TFAC) basé sur la distribution Gaussienne ou la distribution Gamma. Pour les images d'intensité en multi-vues, le fouillis est généralement distribué selon une loi statistique Gamma, convergeant vers la distribution Gaussienne pour un grand nombre de vues indépendantes. Nous utilisons également un algorithme de détecter un signal avec une distribution inconnue dans la présence d'un bruit blanc Gaussien. Cette méthode non-paramétrique (section 2.1.3) a été appliquée pour la première fois dans la détection des navires RSO. Un atout de cette approche est que les modèles non paramétriques permettent de s'adapter plus précisément aux données réelles que les méthodes basées sur les distributions statistiques classiques.

Afin d'évaluer les performances de détection des navires avec des jeux de données exhaustives, une méthodologie systématique est proposée (section 2.2). Cela permet d'intégrer automatiquement les fluxs de données AIS comme une vérité terrain fiable. Cette méthode systématique est utilisée pour compter les bonnes détections et les fausses alarmes afin de déterminer le taux de détection, ce qui permet d'effectuer une comparaison appropriée et cohérente des différents détecteurs RSO.

Nos jeux de données contiennent une grande quantité d'images RSO (voir Annexe B). Cela nous permet d'estimer la probabilité de détection en fonction de différents paramètres clés, tels que les caractéristiques d'imagerie RSO ou les conditions météorologiques. L'influence de l'angle d'incidence, la vitesse du vent (conditions météorologiques) et de la longueur du navire, qui sont des paramètres clés pour la détection des navires, est évaluée dans cette partie (section 2.4.3).

La méthode non-paramétrique donne des résultats très satisfaisants sur les jeux de données de faible résolution (RS-2 ScanSAR Wide and CSK ScanSAR Huge Region). Les algorithmes TFAC Gaussien et Gamma donnent des résultats similaires sur tous les jeux de données, avec une performance légèrement meilleure du détecteur Gamma sur les RS-2 ScanSAR Narrow. Cela est conforme avec le fait que les images RS-2 ScanSAR Narrow s'adaptent plus précisément à une distribution Gamma qu'à une distribution Gaussienne, sachant que dans ce cas le nombre de vues utilisées pour le traitement des images RSO est plus faible en comparaison avec les autres jeux de données. Lorsque le nombre de vues est plus élevé, la distribution Gaussienne est adaptée à la détection TFAC, comme observé avec les jeux des données RS-2 ScanSAR Wide and CSK.

Les comparaisons des caractéristiques de la scène et des capteurs RSO indiquent que le jeu des données RS-2 ScanSAR Narrow donne les meilleures capacités de détection. Le taux globale de détection sur ce jeu de données (voir Fig. 2.11, page 39) est impacté par les plages de valeurs d'angles d'incidence et de vitesse du vent. De bonnes capacités de détection ont été obtenues avec le jeu de données CSK ScanSAR Huge Region. Même si les caractéristiques du capteur et les conditions météorologiques sont relativement similaires à celles de RS-2 ScanSAR Wide, il induit des performances de détection moins performantes, ce qui permet de conclure que CSK ScanSAR Huge Region est mieux adapté pour la détection des navires à cette résolution. Analyser les capacités de détection par rapport aux jeux de données utilisés est important pour les applications opérationnelles afin de choisir le type de données le plus approprié pour les différentes applications.

Refocalisation des navires détectées à partir de données RSO complexes (SLC)

Cette partie (chapitre 3) comporte une étude sur les effets causés par la représentation des cibles dynamiques dans l'imagerie RSO, sachant qu'ils sont traités avec des techniques de traitement du signal basées sur des hypothèses de stationnarité. Une nouvelle méthodologie basée sur la Transformée de Fourier Fractionnaire (FrFT), qui permet d'estimer et de compenser ces effets, est ainsi proposée [83]. L'imagerie SAR des cibles mobiles se traduit généralement par des signaux de type chirp, qui sont des signaux résiduels dans le signal RSO complexe traité dans la direction azimutale. La FrFT permet de représenter le signal RSO dans une rotation du plan (conjoint) temps-fréquence et permet d'effectuer un traitement et une analyse optimale de ces signaux chirp résiduels. La défocalisation azimutale de la cible peut donc être compensée et la vitesse azimutale de la cible estimée. L'opérateur FrFT est habituellement appliqué aux données brutes tandis que notre étude démontre qu'il peut être appliqué aux données complexes traitées. Pour une évaluation complète des performances, une intercomparaison avec une méthode basée sur une décomposition en sous-vues Doppler, est employée. Dans cette approche, les paramètres de mouvement sont estimés en évaluant la différence du spectre Doppler entre les représentations successives temporelles de la cible mobile.

Les méthodologies présentées en cette partie on pour but de répondre à deux objectifs majeurs. Premièrement, refocaliser des signatures de navires extraites à partir de données RSO complexes, en utilisant la FrFT et la méthode de décomposition en sous-vues Doppler. En second lieu, estimer la vitesse azimutale en s'appuyant sur les mêmes outils de traitement du signal.

L'applicabilité à la fois de la méthodologie FrFT et de la méthode de décomposition en sous-vues est vérifiée en utilisant des données RSO spatiales (section 3.4.1). Les signatures de navires sont extraites de deux jeux de données RADARSAT-2, contenant des images à haute résolution dans les modes Multilook Fine (MLF) et Ultrafine (UF). Les caractéristiques des navires ainsi que leur paramètres de déplacement sont extraites à partir des informations AIS considérées comme données de vérité terrain. Nous considérons que notre approche est applicable aux signatures de navires qui ont un niveau de rétrodiffusion beaucoup plus élevé que celui du fouillis de mer. Ainsi, la dynamique de la mer n'est pas intégrée dans notre approche d'estimation de la vitesse azimutale. Cependant, si les niveaux de rétrodiffusion de la mer et des navires sont comparables, le fait que la mer n'est pas stationnaire doit être pris en compte.

Une évaluation basée sur des critères quantitatifs démontre l'efficacité des méthodes présentées (section 3.4.4). Les indicateurs des critères de refocalisation, le contraste et l'entropie, sont calculés pour chaque signature de navires avant et après l'application du traitement de refocalisation. A partir des résultats expérimentaux, on peut conclure que la méthode FrFT donne les meilleures capacités de refocalisation. De plus, en analysant les études de cas présentées dans le chapitre 3, nous remarquons que l'énergie de points des cibles est mieux concentrée et les détails sont mieux préservées avec l'approche FrFT.

Les Look-up-Tables (LUT) employées pour le traitement de données Radarsat-2 représentent un élément important dans l'évaluation des effets de défocalisation des cibles mobiles imagées par les capteurs RSO (par exemple, navires). Le choix d'un LUT pour le traitement d'une image RSO dépend de chaque application spécifique (section 3.4.5). Pour une caractérisation précise des signatures de navires et pour l'estimation des paramètres de mouvements correspondants, il est recommandé d'utiliser les LUTs qui permettent de conserver les valeurs de rétrodiffusion d'origine.

La vitesse azimutale de cibles mobiles peut être estimée en trouvant les paramètres optimaux de la FrFT et une nouvelle approche Short Time FrFT (STFrFT) est proposée dans cette étude (section 3.4.6). Plusieurs estimations de la vitesse azimutale RSO correspondant à différentes cibles sont comparées avec les résultats de la méthode de décomposition en sous-vues. Basée sur la validation avec de données AIS, la méthode de décomposition sous-vues donne une performance légèrement meilleure, probablement due au nombre plus élevé d'échantillons utilisés par cette approche. Toutefois, les estimations des deux méthodes présentent une forte variance. Dans une certaine mesure, les erreurs d'estimation de la vitesse azimutale peuvent être partiellement expliquées par l'influence des valeurs d'accélération dans la direction radiale, comme le montre cette étude. Une méthode paramétrique avec un modèle explicite de phase qui incorpore tous les termes cinématiques, pourrait permettre d'obtenir une estimation de la vitesse azimutale plus précise.

Exploitation des données complexes à polarisation duale pour la détection RSO de navires

L'objectif de cette partie (chapitre 4) est de démontrer l'applicabilité des données Sentinel-1 complexes et à polarisation duale pour les applications de surveillance maritime. Le satellite Européen Sentinel-1, lancé en Avril 2014, acquiert systématiquement des données à double polarisation pour les deux modes StripMap et ScanSAR. Les modes ScanSAR correspondants ont l'avantage de fournir de grandes largeurs de fauchée, présentant un intérêt important pour les applications de surveillance maritime. De plus, des données complexes sont disponibles grâce au mode ScanSAR, ce qui représente une nouveauté par rapport aux missions RSO civiles précédentes. Il est donc important d'analyser l'utilisation de ce type de données pour les algorithmes de détection de navires et de déterminer si cela apporte un avantage par rapport à des algorithmes de détection de navires classiques conçus pour des données en amplitude et à polarisation singulière.

Tout d'abord, l'évaluation des détecteurs classiques appliquée à des données Sentinel-1 à double polarisation est présentée (section 4.2). L'algorithme TFAC classique avec la méthodologie systématique intégrant des données AIS en tant que vérité terrain, introduites dans le chapitre 2, sont utilisées pour évaluer les résultats de détection [85]. Selon les résultats obtenus, nous pouvons remarquer que le canal de polarisation croisée (VH) donne de meilleures performances de détection que le canal de co-polarisation, pour les modes IW et EW de Sentinel-1. La fusion des résultats de détection obtenus indépendamment sur chaque canal de polarisation, est également envisagée. Néanmoins, ses avantages restent limités, les résultats de détection VV et VH n'étant pas complémentaires. Les performances de détection du mode de polarisation VV ont été comparés avec les résultats obtenus avec les jeux de données RS-2 et CSK, présentées dans le chapitre 2. Cette analyse permet d'observer que le jeu de données S-1 IW donne de meilleurs capacités globales de détection, probablement en raison de sa haute résolution spatiale correspondante. Pour les jeux de données de résolution inférieure à IW, mais de même polarisation VV, le mode EW donne des performances légèrement meilleures que RS-2 et CSK.

Plusieurs méthodologies qui permettent de fusionner les informations contenues dans les images à double polarisation ont été évalués également dans cette partie (section 4.3). Leurs avantages et inconvénients correspondants ont été expérimentalement démontrés avec différentes études de cas d'imagettes extraites à partir d'une image Sentinel-1 IW, disponibles en amplitude ainsi qu'en donnée complexe. Pour la fusion des données d'amplitude, nous avons utilisé les moyennes généralisées, connues comme les moyennes d'Hölder. La fonction de densité de probabilité jointe entre les moyennes géométrique et quadratique des deux canaux de polarisation permet de définir un seuil pour différencier les échantillons de navires du fouillis de mer. Cette méthodologie présente un avantage majeur par rapport aux algorithmes classiques de détection : une fenêtre glissante, qui implique généralement des temps de calcul longues, n'est pas nécessaire. Les paramètres polarimétriques présentés dans ce chapitre ont montré une représentation intéressante, qui pourrait être utile pour définir une hypothèse de détection des navires. Le coefficient de cohérence et l'angle de diffusion alpha ont montré des comportements similaires avec un niveau de contraste élevé entre les navires et le fouillis de mer. Une opération de seuillage pourrait être définie en utilisant ces deux paramètres polarimétriques. Une comparaison avec des algorithmes classiques de détection est nécessaire, pour la validation d'un tel procédé. En ce qui concerne le temps de calcul, les méthodologies pourraient présenter des similitudes car ils exigent tous les deux une fenêtre glissante. L'utilisation du degré de polarisation (DOP) a montré un intérêt particulier, car sa représentation permet de conserver les cibles de petites tailles qui sont visibles uniquement dans un canal de polarisation. Une analyse plus approfondie du ce paramètre est nécessaire pour déterminer s'il permettra de détecter des cibles avec une signature moins importante, en maintenant un taux de fausse alarme faible.

Conclusion

Cette étude propose plusieurs méthodologies nouvelles qui permettent d'améliorer les performances actuelles de chaînes RSO de détection de navires. Ces améliorations présentent un grand intérêt dans le cadre d'un système complèt de surveillance des navires par satellite, qui représente un élément clé pour les systèmes de surveillance maritime. L'apport des travaux présentés dans cette thèse se divise en plusieurs parties principales énumérées ci-dessous :

Une nouvelle méthode de **détection non-paramétrique**, qui a été appliquée pour la première fois dans le domaine RSO de surveillance des navires, est tout d'abord présentée. Ce modèle permet de s'adapter plus précisément aux données réelles que les méthodes basées sur les distributions statistiques traditionnelles. Pour effectuer une évaluation rigoureuse de cette approche, une comparaison avec deux versions du détecteur TFAC classique, est présentée. Des résultats expérimentaux avec des jeux de données RSO de volume important permettent d'effectuer une évaluation complète. Les jeux de données utilisés dans cette étude contiennent un grand nombre d'images RSO avec des milliers de positions AIS de navires correspondantes.

Pour une utilisation efficace et conjointe des données RSO et AIS, une méthodologie systématique qui permet d'**intégrer automatiquement les fluxes de données AIS** comme une vérité terrain fiable, est employée. Par conséquent, les données AIS collectées à partir des bases de données contenant des messages acquises par les stations côtières AIS sont modélisées par rapport aux capacités d'accueil de ces stations. Cette méthode systématique est utilisée pour différencier les vraies détections des fausses alarmes et ainsi de déterminer le taux de détection. Cela permet d'effectuer une comparaison appropriée et cohérente des différents détecteurs SAR.

Le taux de détection, qui dépendent de différents paramètres clé tels que les caractéristiques d'imagerie RSO ou les conditions météorologiques, ont été ainsi évalués dans cette étude. Ce type d'analyse permet de définir un modèle prévisionnel des performances de détection. Ce modèle est utile pour les applications opérationnelles, afin de choisir le type le plus approprié de données pour chaque application.

Une nouvelle méthodologie, présentée dans cette étude, emploie la Transformée de Fourier Fractionnaire (FrFT) et permet d'effectuer la **refocalisation des navires à partir de l'imagerie RSO complexe**. Une étude sur les effets de la représentation des cibles dynamiques dans l'imagerie SAR, lorsqu'ils sont traités avec des techniques développées en considérant des hypothèses de stationnarité, a d'abord été effectuée. L'outil FrFT permet de compenser les effets de cibles mobiles résultant de la vitesse des cibles se déplaçant dans la direction azimutale. Une comparaison avec la méthode de décomposition en sous-vues Doppler est également utilisée. L'applicabilité à la fois du FrFT et de la méthode de décomposition en sous-vues est vérifiée à l'aide données RSO spatiales. Une évaluation avec des critères quantitatifs montre l'efficacité de ces méthodes.

La vitesse azimutale de cibles mobiles peut être déterminée en déterminant les paramètres optimaux de la FrFT. Une **nouvelle approche STFrFT d'estimation de vitesse** est proposée dans cette thèse. Plusieurs estimations de la vitesse RSO STFrFT correspondant à différentes cibles sont comparées avec les résultats de la méthode de décomposition en sous-vues et des données de validation AIS, afin d'analyser les performances de cette méthode.

L'utilisation de données à **polarisation duale** pour les algorithmes de détection des navires a également été évaluée. Plusieurs méthodes qui permettent de fusionner, avant l'étape de détection, l'information contenue dans les canaux polarimétriques ont été proposées. Lorsque seulement les données d'amplitude sont disponibles, l'approche est basée sur les moyennes généralisées (moyennes d'Hölder). La fonction de densité de probabilité jointe entre les moyennes géométrique et quadratique des deux canaux de polarisation permet définir un seuil qui différencie les échantillons de navire du fouillis de mer. Pour les données complexes, la possible utilisation des paramètres polarimétriques pour le processus de détection a été évaluée : coefficient de cohérence, decomposition $(H, \overline{\alpha})$ et degré de polarisation. Les avantages et les inconvénients de chaque approche permettant de mélanger deux images de polarisation différentes, ont été expérimentalement évaluées avec différentes études de cas. Certaines de ces approches ont montré des représentations particulières du rapport du signal navire-fouillis de mer, qui pourraient être utiles pour définir des nouvelles hypothèses de détection des navires.

Perspectives

Des futures études de recherche pourraient suivre le travail présenté dans cette thèse et sont indiquées ci-dessous :

1. L'étape de classification est d'une grande importance dans une chaîne complète RSO de détection de navires. Toutefois, notre décision était de se concentrer seulement sur les problématiques de détection et de caractérisation des signatures. Ainsi, l'étape de classification n'est pas abordée dans cette thèse. En raison du niveau réduit des détails, des classificateurs simples sont recommandées pour les signatures de navires détectés à partir d'images RSO de résolution moyenne. Un classificateur avec deux classes qualifiant les cibles comme fiables et non-fiables peut être suffisant. À une résolution plus élevée et avec des signatures de navires plus détaillées, un classificateur plus complexe avec plusieurs classes pour le type de signature d'un navire, peut être utilisé. Par exemple, un classificateur à base des machines à vecteurs de support (Support Vector Machine, SVM) intégrant l'information sur le navire en soi (longueur, direction, etc.) ainsi que différentes paramètres clés (angle d'incidence, vitesse du vent ou type de polarisation), peuvent présenter un intérêt pour ce sujet.

- 2. Pour élargir l'évaluation de l'impact de tous les paramètres clés qui influencent les capacités de détection RSO, une analyse conjointe de tous ces paramètres est nécessaire. Pour cela, la méthodologie de détection RSO-AIS devrait être appliquée à des jeux de données de très grandes dimensions et être ensuite suivie d'une analyse croisée des résultats obtenus. Une telle analyse est importante pour les services opérationnels, car elle permet de sélectionner le type de données le plus approprié pour différentes applications dans les systèmes de surveillance maritime.
- 3. Les estimations de vitesse avec l'approche STFrFT présentées dans cette étude ont montré une forte variance. Dans une certaine mesure, les erreurs d'estimation de vitesse azimutale peuvent être partiellement expliquées par l'influence du terme d'accélération dans la direction radiale. Une méthode paramétrique avec un modèle explicite de phase, qui reprend tous les termes cinématiques, pourrait permettre d'obtenir une estimation de la vitesse azimutale plus précise.
- 4. Pour mieux évaluer les effets de déplacement des navires dans l'imagerie RSO, une plus haute résolution du radar serait nécessaire et peut représenter une possible future ligne de recherche. Les signatures de navires acquises dans le mode Spotlight avec une résolution nominale d'environ 1m devraient fournir suffisamment de détails pour les petits navires. L'algorithme de traitement pour les images Spotlight est différent de celui des images StripMap. La présence d'éventuels signaux résiduels liés à la vitesse des cibles devrait être analysée pour déterminer si la FrFT pourrait être appliquée à ce type de données.
- 5. Des futures recherches concernant la méthode de refocalisation FrFT appliquée aux données multi-polarimétriques pourrait être d'intérêt. Les navires imagés par des capteurs RSO multi-polarisation pourraient avoir des signatures de polarisation distinctes, qui reflètent avec différentes niveaux d'intensité en fonction du mode de polarisation. Ces informations peuvent fournir des détails complémentaires pour une meilleure caractérisation de la signature d'un navire. Par conséquent, une méthode qui permet d'analyser ou de fusionner les différentes représentations polarimétriques d'une cible dans le domaine FrFT mérite attention.
- 6. La disponibilité des données RSO à très haute résolution impose de nouvelles contraintes et défis pour les algorithmes de traitement du signal et d'image actuels. En général, les grandes dimensions de données RSO nécessitent un traitement de données itératif sur une succession d'imagettes conduisant à un temps de calcul important. Cet aspect est encore plus important pour une très haute résolution des images RSO. Afin de surmonter ce problème, l'utilisation de méthodes particulières telles que des décompositions multi-échelles peut être envisagé. Il pourrait être utile d'effectuer la détection des navires de grandes tailles à un niveau de résolution réduit. Une fois détectées, ces cibles pourraient être éliminées. Ensuite, un algorithme de seuil adaptatif correctement configuré pour les cibles de petite taille pourrait être employé.

Introduction and State of the Art

A ship in port is safe, but that is not what ships are built for. Sail out to sea and do new things.

Grace Murray Hopper

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1.1 Introduction

1.1.1 Maritime Surveillance

Maritime surveillance is defined as the ability to monitor all the activities within the maritime domain and to be able to ensure, when required, a timely decision process [2,3]. The maritime domain is defined as "all areas and things of, on, under, relating to, adjacent to, or bordering on a sea, ocean, or other navigable waterway, including all maritime related activities, infrastructure, people, cargo, and vessels and other conveyances" [1]. In addition to these factors, which render the maritime domain as a significant element for ensuring the safety of human life at sea, we remind here that 90% of the world's commerce is carried by sea and 95% of international communications are made possible by undersea cables.

Maritime surveillance is involved in diverse fields such as: fisheries control, border surveillance, maritime transport safety or maritime piracy and armed robberies at sea. Figure 1.1 gives a synthesis of general maritime surveillance applications based on the three main domains composing it: Security, Safety and Defence. The European Maritime Safety Agency (EMSA) is the European Union (EU) agency in charge of the development and implementation of the EU legislation with respect to maritime safety and security. EMSA is furthermore also able to ensure operational services in the fields of: oil pollution detection, vessel monitoring and tracking. Its primary objective is to reduce the risks of maritime accidents, marine pollution and loss of human lives at sea.



Figure 1.1 – European Maritime Surveillance Missions and Tasks ¹.

Maritime surveillance is usually made possible by combining information from a range of different data sources. These sources are generally divided in two categories:

- reporting or messaging systems
- sensor systems

The first systems rely on the ships to provide information and belong to the so called cooperative systems. Many cooperative systems are currently employed such as: Vessel Monitoring System (VMS), Automatic Identification system (AIS), Satellite AIS (Sat-AIS) or Long Range Identification and Tracking (LRIT). The second systems, which are termed as non-cooperative systems because they collect vessels information without their cooperation, are usually represented by sensor systems like radars and cameras or patrol boats.

The cooperative systems are supposed to be an effective monitoring ship technique. Nevertheless, there are an important number of active vessels without carrying AIS, VMS or LRIT transponders. Additionally, it is possible for vessels aiming to deliberately hide their identity to switch off their transponders. Therefore, the non-cooperative sensors represent a good alternative way to close these loopholes.

A large number of data sources are currently available for these non-cooperative systems. Among these, the most frequently used are:

• Synthetic Aperture Radar (SAR) satellite images: The most important benefit of SAR systems is its independence on daylight and cloud cover. This makes it possible to assure a guaranteed acquisition over areas of interest for monitoring the maritime domain.

 $^{^{1}}$ The presented diagram is designed based on a presentation of the European Defence Agency(EDA) on the topic of Maritime Surveillance, available online at http://www.yorkhapweek.org/DOCS/DOCS/HAS-WA-5.pdf.

- Optical satellite images: Earth observation imagery from optical satellite sensors are able to provide high resolution images of vessels in deep sea or coastal areas. However, the usage of optical images for ship detection remains limited due to their sensibility to cloud coverage, haze or fog, and their dependence on daylight.
- **Coastal radar data:** Vessels moving along coastline areas are usually tracked by local radar systems. Their aim is to ensure the safety of vessels traffic through different risky areas, such as Traffic Separating Scheme (TSS), marine protected areas or wind farms.

Due to its cloud cover and lighting independence and its large coverage areas, SAR imagery presents an increased interest in maritime surveillance applications. SAR signal's amplitude and phase can be employed to detect and even quantify the motion of vessels. In this thesis report, we focus our interest on vessels detection as well as their signature characterization by employing data acquired by different spaceborne SAR sensors.



Figure 1.2 – Illustration of a maritime surveillance system integrating different sources of information.

1.1.2 Synthetic Aperture Radar

Synthetic Aperture Radar (SAR) sensors have been increasingly employed for many different applications such as: environmental monitoring of agriculture/geology/forestry, mapping of natural disasters (flooding/earthquake/tsunami) or surveillance of the maritime environment. In comparison with the optical imagery, the interpretation of SAR images is directly related to its specific signal processing and image formation techniques. This section briefly describes fundamental SAR concepts. Specific and detailed information are available in the vast literature on the topic [17,21,66,71].

The imaging SAR sensors employ an active radar system operating in the microwave region of the electromagnetic spectrum. Such systems are usually embarked on a moving air- or spaceborne platforms and operate in a side-looking geometry with an illumination perpendicular to the flight line direction. To generate a SAR image, two main operations are required:

- transmission of successive microwave pulses over the illuminated scene,
- reception and recording of the echo of each pulse, representing the electromagnetic signal backscattered from the illuminated terrain.

Signal processing techniques are employed to synthesize a 2-D spatial image of the earth's surface reflectivity from all the received signals. In order to obtain SAR images of high spatial resolution, large bandwidth pulses are necessary and a synthetic aperture antenna is employed. The distance the SAR device has to travel over a scene in the time taken for the radar pulses to return to the antenna permits to create the large synthetic antenna aperture.

Radar resolution: The spatial resolution represents one of the most important characteristics in defining the quality of SAR imaging systems. The radar resolution is defined in two dimensions: the azimuth direction (or along-track) parallel to the radar's line of flight and the range direction (or across-track) which is perpendicular to the line of flight.

The **range resolution** is dependent on the range pulse duration, high resolution requiring very short pulses. Actually, due to physical implementation limitations, long pulse signals with distributed energy over their duration are transmitted. Pulse compression techniques are thus required to obtain a fine resolution in the range direction. With this purpose, chirp signals and matched filtering techniques are the most frequently employed in SAR systems.

The **azimuth resolution**: of real aperture radar systems is proportional to antenna beamwidth. Therefore, large size antennas are required to create a narrow beam allowing to achieve high azimuth resolution. For SAR systems, the achievement of high resolution is based on the concept of synthetic aperture. For this, on one hand a longer effective antenna is employed by moving the real sensor antenna along the flight direction. On the other hand an electronic squint with phased arrays antennas may be employed. A wide beam collects the returns from multiple pulses, and synthesizes a narrow beam by filtering the array of pulses after data collection. Depending only on the physical size of the real antenna, the azimuth resolution is independent from range resolution.

SAR acquisition modes: The effective resolution of SAR images is directly linked to the type of acquisition mode. Some of the most frequently employed operation modes include:

- **Spotlight:** The Spotlight mode is designed for images of very high spatial resolution. The radar beam is electronically steered to dwell on the area of interest over a longer aperture time. Therefore, the beam is able to continuously illuminate one terrain patch while the radar platform moves along its flight direction. In this mode, it is possible to acquire data with up to 1-meter ground resolution². Nevertheless, the swath coverage is limited due to the high sampling rate necessary to keep data rate within the recorder limits. This limitation is also due to the fact that the antenna beam coverage on ground is not moving forward with the SAR platform and thus a reduced size-area on the ground can be imaged.
- Stripmap: For the Stripmap mode the pointing of the antenna beam is maintained constant with fixed azimuth and elevation angles, while the ground swath is illuminated by a continuous sequence of pulses. This makes it possible to generate an image strip with constant image quality in the azimuth direction. The Stripmap mode is commonly employed due to its reasonable compromise between the size of the area covered and the spatial resolution.
- ScanSAR: In the ScanSAR mode several beams covering adjoining swaths are combined. The beams are operated sequentially for a series of pulse transmissions and receptions. Therefore, data is collected from a wider swath than is possible with a single beam. Since

 $^{^2{\}rm The}$ given resolution is based on the current capabilities of civilian space-borne systems. For instance, the Spotlight modes of the Cosmo SkyMed and TerraSAR-x sensors.

this mode provides images of very wide swaths in a single satellite pass, it is employed for applications requiring large-scale area coverage such as maritime monitoring.

SAR processing algorithms: Depending on the SAR acquisition modes, several processing algorithms adapted to SAR sensors were developed [21]. The objective of SAR processing is to transform the raw data into an image representation of the original 2-D reflectivity function. Various processing techniques have been developed to effectively process SAR data from its raw signals into well focused images. Some of the most commonly used processing algorithms include:

- Range-Doppler Algorithm (RDA)
- Chirp Scaling Algorithm (CSA)
- Omega-k method
- Spectral Analysis method (SPECAN)

The RDA and CSA are one the most frequently employed algorithms achieving image formation by employing matched filtering techniques. However, it must be noted that these two algorithms are approximation methods which discard higher order phase terms. The Omega-k algorithm is implemented in the 2-D frequency domain which allows to process very high azimuth aperture data. The SPECAN algorithm employs single and short FFTs during the compression operation. Therefore, it represents a good choice for medium and low resolution data processing, as well as quicklook imagery.

Data Processing Level: SAR image formation depends on different factors such as: type of transmitted/received signal, imaging geometry, and its evolution through time. All these factors are taken into account by the processing algorithms. Processed SAR signals are able to provide information on both the amplitude and phase of the received signal. Amplitude data is directly linked to the radar cross section (RCS) of the imaged scene while the phase represents the range history of the target. Depending on the processing level, different types are available:

- Single Look Complex (SLC) data: SLC images are delivered in a complex data format, containing both the amplitude and phase terms. Within this representation, pixels are physically related to the sensor dimensions and geometry. The amplitude information is however representative of the imaged area. The phase term represents the major benefit of this data type, as it is useful for different applications such as SAR interferometry or moving target analysis.
- **Ground range data:** For this kind of data, the range pixel spacing and range resolution are measured in ground range coordinates. For this, the data is projected onto the Earth's surface, that follows the shape of the ellipsoid. Ground range products contain magnitude detected pixels.

SAR Polarization: Besides the types of SAR data defined based on the processing level (briefly introduced previously), different image types may be defined in terms of polarization of the SAR sensor.

Traditionally, SAR systems transmit waves polarized with a specific design polarization and receive waves at the same polarization. Currently, complex radar systems are designed to transmit and receive waves at more than one polarization. The two most common basis polarizations employed in SAR imagery are horizontal linear (or H), and vertical linear (or V). A radar system using H and V linear polarizations is able to have four different channels: HH, HV, VH and VV. On this basis, classical SAR sensor cover the following polarization modes:

- single polarization: HH or VV or HV or VH
- dual polarization: HH and HV, VV and VH, or HH and VV
- quad polarization: HH, VV, HV, and VH

The largest amount of information is contained in quad-pol data, since it preserves the relative phase between the four channels. Dual-pol SAR provides amplitude data and phase data between the two polarization channels, while single-pol SAR offers only one complex data. Even though SAR sensors are traditionally single polarization systems, the conventional singlepolarization mode is often replaced with the dual or quad polarization modes for the newly launched SAR missions.



Figure 1.3 – SAR space borne sensors and their corresponding characteristics.

SAR Missions: During the past 30-40 years, numerous civil spaceborne and airborne SAR sensors have been launched and further missions are being planned to provide high-resolution Earth observation data [78]. There are many airborne SARs developed by various organizations, such as: the AIRSAR system designed and built by the USA Jet Propulsion Laboratory (JPL), the Canadian C/X-SAR sensor aboard a Convair 580 aircraft or the French ONERA SETHI system, mainly employed as a test bench for new technologies. A large number of SAR sensors carried by satellites are referred to in the scientific literature and have served to an exhaustive number of applications. The first spaceborne SAR was the NASA SEASAT satellite, launched in 1978, which, despite its relatively short lifetime, collected a great deal of SAR imagery employed in pioneer scientific research. Following SEASAT, a series of spaceborne SAR sensors have been launched: the European mission ERS-1/2 followed by Envisat, NASA's SIR-C/X-SAR sensor or the the Canadian Radarsat-1 mission. Several recently launched SAR spaceborne missions are currently providing a great amount of SAR images, such as: the Canadian Radarsat-2 (RS-2) satellite, the Italian CosmoSkyMed (CSK) satellites constellation, the German satellite constellation TerraSAR-X and TanDEM-X or the Japanese Earth-observation

satellite ALOS-2. Figure 1.3 provides a synthesis of some of these spaceborne sensors and their specific characteristics. The newly launched European Sentinel-1A satellite is equipped with a medium resolution SAR sensor which will be used for systematic monitoring of European Waters [116].

1.1.3 SAR vessel detection

As mentioned in section 1.1.1, non-cooperative systems, such as SAR or optical sensor, constitute an essential tool for a complete and effective maritime surveillance. Ship detection represents a major element in maritime monitoring. Satellite optical and radar imagery is predominantly used in order to achieve ship detection from space. Optical sensors such as Pleiades or QuickBird, are able to provide very detailed images with a resolution that reaches 0.5 meters. Optical images present also a particular interest for the classification and identification of ships within a particular area of interest. Nevertheless, their usage for ship detection remains limited due to some of their characteristics like their reduced swath sizes, their sensibility to cloud cover, haze or fog, and their dependence on daylight.



Figure 1.4 – SAR images acquired with a difference of 30 minutes by the Radarsat-2 (ScanSAR Wide Mode) and Sentinel-1 (Interferometric Wide Swath mode) sensors. The images illustrate that ship signatures are generally represented by pixels that are significantly brighter than the ones of the sea clutter.

In comparison with optical sensors, imagery acquisition by SAR sensors is not restricted by daylight or cloud coverage conditions. Therefore, such sensors are able to overcome the optical imagery limitations. Moreover, SAR sensors provide images covering large geographic areas. All these advantages render SAR data very useful in maritime surveillance applications. Within SAR images, ship signatures are represented by pixels that are significantly brighter than the ones in the surrounding area. This originates from the fact that most of the ships are made of metallic superstructures and have specific deck configurations that act as direct or corner reflectors. Such elements result in a strong radar backscattering. On the contrary, the sea clutter behaves as rough surface with a corresponding backscattering signal generally lower than those of ships. Therefore, the ship detection from SAR imagery can simply be defined as



Figure 1.5 – CosmoSkyMed Spotlight image acquired over the city of Brest.

the identification of bright pixels within a darker background. Classical ship detection chains are designed to statistically detect a significant contrast between the ship and the local sea clutter background. The literature and the applications developed in this area are vast [22].

Figure 1.4 gives an example of two SAR images acquired over the English channel, which is one of the world's busiest shipping lane. We notice that ship signatures are represented by bright pixels within the sea surface generally presenting a lower energy level. Nevertheless, as we can observe from the Radarsat-2 image (Figure 1.4), the sea clutter is not always of low energy, and it can thus hinder the detection process. SAR imaging of sea clutter is highly dependent of the sea state, meteorological conditions and even the characteristics of the SAR system. Under unfavourable conditions such as heavy sea states, the SAR signal representing the sea clutter is characterized by a high level of speckle noise. In such circumstances, simple detection algorithms must be adapted with appropriate signal/image processing techniques.

The two images given in Figure 1.4 have different spatial resolution: approximately 100 $m \times 100 m$ (range \times azimuth) for the Radarsat-2 image and approximately 20 $m \times 20 m$ (range \times azimuth) for the Sentinel-1 image. If we compare them, we observe that the higher the spatial resolution is, the higher is the contrast between the ships and the sea clutter background. Figure 1.5 presents a CosmoSkyMed image acquired in the Spotlight mode, with a corresponding spatial resolution of about 1m. We notice that, at a very high resolution, details of the ship superstructure are distinguishable.

1.1.4 Cooperative vessel tracking systems

As mentioned in section 1.1.1, maritime surveillance tools may include cooperative vessel reporting systems, such as terrestrial and satellite Automatic Identification System (AIS), Long Range Identification and Tracking (LRIT) or Vessel Monitoring System (VMS).

Automatic Identification System (AIS): AIS is a communication system in the maritime navigation domain which is standardized by the International Telecommunication Union (ITU) and adopted by the International Maritime Organization (IMO) [99]. The main purpose of the AIS system is to provide information about vessels such as Maritime Mobile Service Identity (MMSI), type, position, course, speed, navigational status and other safety-related information. AIS carriage regulations require mandatory AIS for [2, 47]: system vessels over 300 tonnage on

international voyages, passenger ships of any size, tankers on international voyages, and cargo ships of over 300 tonnage not sailing in international waters. Warships, state-operated vessels in public service and vessels shorter than 45 m (fishing vessels, traditional ships and recreational crafts) are not obliged to carry AIS transponders.

The AIS transfers data packets over the VHF (Very High Frequency) channel 16 (156.8 MHz). Ships employing the AIS system are equipped with a transponder unit including GPS, VHF transmitter/receiver and display/terminal. The transponder unit broadcasts AIS messages every 2, 4, 6 or 10 seconds depending on the speed or course of vessels. The AIS systems employ the Time Domain Multiple Access (TDMA) technique which implies sending short messages during specific time slots. The limited number of time slots and their re-assignation at every 60 seconds causes message loss within very high shipping density areas. The range coverage of AIS receivers is limited by the VHF propagation loss. Additionally, the AIS equipment is user configurable and can thus be maliciously used, for instance by ships deliberately hiding their identity. The lack of supervision by local authorities on the proper use of the equipment or on the accuracy of the data entered represents another limitation in the use of AIS for maritime security matters [47].

As an anti-collision based system, the AIS is designed to exchange messages from vessel-tovessel. However, AIS messages from vessels can be captured by shore-based or satellite receivers in order to track the marine traffic. The terrestrial-based AIS system is limited to identify vessels at a distance of up to 40 nautical miles of the coasts. AIS reception from satellite overcomes this limitation. Satellite-based AIS data makes it possible to monitor a vessel's location and status well beyond coastal regions. Satellite receivers are usually embarked on Low Earth Orbit (LEO) satellites. Therefore, the AIS coverage is global at the expense of persistence, due to the orbiting platform revisit time. Due to the limitations of the AIS system several other cooperative and non-cooperative systems are necessary in order to ensure an effective maritime monitoring.

Vessel Monitoring System (VMS): VMS is a satellite-based fishing vessel monitoring system that provides ship information such as location, course and speed to fisheries authorities and at regular intervals [93]. VMS systems employ satellite-based communications from onboard transceiver units and ground based transponder stations. VMS transceiver units transmit position reports including vessel identification, time, date, location, heading and speed. Those information are mapped and can be displayed on the end user's computer screen. VMS generally transmit data at least every 60 minutes depending on law regulations specifications.

Long Range Identification and Tracking (LRIT): LRIT is an automated and satellitebased vessel tracking system designed to collect and diffuse vessel position information received from vessels [93]. The LRIT equipments embarked on vessels must be able to automatically send the following data: vessel's identity, its position (longitude and latitude) and the corresponding date and time information. The use of LRIT systems is mandatory for vessels on international voyages including: passenger ships carrying more than 12 passengers, high speed ships, offshore drilling and cargo ships over 300 tonnes. LRIT system are designed to ensure that ships provide daily position reports, at a basic frequency of once every 6 hours (i.e. 4 times a day).

1.2 Research Motivation

1.2.1 Challenges in maritime vessel detection and tracking

The principal research motivation of this thesis is to examine new and innovative methods in the domain of SAR vessel detection. Even though the literature and the applications developed in this research area are vast, the evolution of SAR sensors capabilities and the availability of data produces new research issues. This thesis aim is to propose solutions to the following issues:

- Improvement of classical detection algorithms: Classical SAR vessel detection methodologies are based on statistically modelling of the sea clutter and detection of individual pixels samples whose brightness values are statistically unusual. The SAR imaging of sea clutter areas depends of several factors such as sea state, meteorological conditions and even the characteristics of the SAR system. Under unfavourable conditions, the ocean scattering mechanisms may be heterogeneous, hindering thus the statistical modelling of sea clutter from SAR imagery. In order to overcome this issue, an extended analysis of SAR signals statistical distribution is required to properly design detection algorithms.
- Performance assessment based on key parameters influencing the detection process: Usually, the detection performances vary depending on several factors: sea state (waves, wind), SAR sensors characteristics (frequency-band, polarization, spatial resolution), acquisition conditions (incidence angle) or meteorological conditions. Solving this issue may involve an *a posteriori* statistical assessment of SAR image database. This will allow to define a predictive model of the detection performances.
- Integration of cooperative positioning data within SAR vessel detection chains: As mentioned in section 1.1.4, several types of positioning cooperative data are available. Such data may be used to provide a ground truth about the position of vessels present within SAR scenes. Within this research study, we assess ship tracking problems from different information sources (Cooperative data and SAR detection) considerated separately or jointly.
- Survey on employing multi-polarization data: Relatively new SAR missions provide access to data of the same scene imaged within several polarimetric channels. The aim here is to study the joint detection on these images in order to overcome the limitations of a successive detection on each polarization channel.
- Better characterization of detected vessels: This part refers to the development of robust methods that are able to estimate vessels characteristics from SAR imagery. When employing very high resolution data, target refocusing techniques will be considered.

1.2.2 Thesis Background

This thesis was conducted at Collecte Localisation Satellites (CLS) in collaboration with Institut Mines Telecom, Télécom Bretagne from November 2012 to November 2015. CLS is a subsidiary of Centre National d'Etudes Spatiales (CNES), Institut Français de Recherche pour l'Exploitation de la Mer (IFREMER) and the investment company ARDIAN. The main objectives of CLS are to operate satellite systems and provide high value-added products and services. CLS provides operational services for environmental monitoring, sustainable management of marine resources, and maritime security. As previously mentioned, SAR images represent a key element for maritime security. Vessel detection from SAR imagery represents one of the main products proposed by CLS. This thesis aims to recommend and develop new and innovative methodologies that make it possible to simultaneously improve the performances and overcome the limitations of the current employed ship detection chains. For this, we propose several solutions that respond to the research challenges introduced in section 1.2. The experimental assessment of these methodologies is carried out on SAR images together with AIS data, provided by CLS. Therefore, the datasets employed in this thesis are constrained by the type of data available at CLS. We mainly employed SAR images acquired by the Radarsat-2 and Cosmo SkyMed sensors. Moreover, during the last year of the PhD, we had the benefit to use SAR images acquired by Sentinel-1 sensor, which was launched in April 2014 and provides calibrated SAR images available since the end of 2014. The latter part of this study is thus focused on the use of Sentinel-1 images, presenting the advantage of being available in the dual polarization.

1.2.3 Thesis Outline

In order to answer the challenging issues mentioned previously, several novel methodologies are proposed in this thesis. The work contribution is divided into three main parts that correspond to the following chapters:

Chapter 2 examines classical adaptive threshold algorithms which are predominantly employed in SAR vessel detection. The use of typical statistical distribution if firstly assessed followed by the introduction of a novel non-parametric approach. To evaluate and compare their performances, the different detection algorithms are applied to large SAR datasets consisting of intensity images. AIS dataflows modeled with respect to reception capabilities of shore-based stations are employed as ground truth data. The SAR-AIS systematic method is used to discriminate real detected targets and false alarms, which makes it possible to determine the detection rate. Thus, it allows to perform an appropriate and consistent analysis of the impact of different key parameters influencing the detection. The impact of SAR sensors characteristics (incidence angle, polarization, frequency and spatial resolution) and weather conditions (e.g. wind speed) is fully assessed, the vessels'length being also considered.

Chapter 3 is dedicated to the characterization of vessel signatures from SAR Single Look Complex (SLC) imagery. Firstly, the effects of stationary-based processing of moving ships signatures in SAR imagery are assessed. Then a novel methodology which allows to estimate and compensate such effects is proposed. SAR imaging of moving targets generally results in residual chirp signals in the azimuthal SLC processed signal. The Fractional Fourier Transform (FrFT) makes it possible to represent the SAR signal in a rotated joint time-frequency plane and performs optimal processing and analysis of these residual chirp signals. The along-track defocus can thus be compensated for and the target's azimuthal speed estimated. The impact of higher order motion terms (e.g. acceleration) is also considered. An intercomparison with a standard Doppler Sub-look Decomposition Method (SDM) is carried out, as well as a complete performance analysis with AIS data as ground truth.

Chapter 4 introduces the use of complex dual-polarization data for SAR vessel detection. First of all, an intercomparison between the individual use of each polarimetric channel is considered, as well as the fusion of the detection results corresponding to the two polarimetric channels. Then, the fusion of both polarization channels before the detection step is assessed. When dealing with amplitude data only, we propose to employ a method based on the generalized temporal moments (Hölder means), in order to fuse the information of both polarization channels. When dealing with complex data, the coherence coefficient or target dual-polarimetric decompositions, which may provide additional information in comparison to single channel imagery, are employed. General conclusions and perspectives for future work are presented in the closing **Chapter 5**.



Vessel detection for single-polarization amplitude SAR imagery

Adde parvum parvo magnus acervus erit. Add a little to a little and there will be a great heap.

Publius Ovidius Naso

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2.1 Detection Methodologies

2.1.1 State of the art

The literature on the topic of SAR vessel detection is vast and numerous algorithms were developed for the corresponding applications [22, 58]. Typical ship detection systems usually involve the following steps: land masking, pre-processing, detection algorithm, classification and human supervision. For land masking, a dedicated coast line database is used with a buffer zone of variable size depending on operational services. The pre-processing step consists in applying different operations to the input data, such as RCS calibration or speckle filtering, that allow to ease the detection algorithm. The detection phase, also known as pre-screening, involves searching the potential ship pixels. Following the detection step, detected pixels within



Figure 2.1 – Adaptive threshold algorithms - classical sliding window design.

the same neighbouring area, are clustered into a single target. The classification step is of high importance to reduce the false alarm rate. Human supervision aims to assess and discriminate the detection results in view of the final detection report.

In this chapter, we focus on the detection phase. Generally, vessels are made of reflecting materials and their corresponding RCS is much higher compared to the backscatter originating from the sea clutter. Thus, ships appear in SAR as bright points within the sea clutter. Aiming at detecting ship pixels (e.g. bright points) within the sea clutter, various detection methodologies have been developed. Depending on the employed data, these methodologies can be separated into two main categories: single and multi channel detectors. Since the experimental data used for this chapter is single channel SAR imagery, we consider here a brief review on the literature referring to single channel pre-screening methods. The major types of single channel algorithms according to detection criteria are classified into global threshold algorithms and local adaptive threshold methods.

Global threshold algorithms are usually designed to detect all pixel with values above the same threshold within the entire image [37,55]. However, considering that the vessels reflectivity may vary widely in a SAR scene with the vessel size or its construction materials, it is hard to differentiate all targets within as SAR image in the same manner. Also, the various SAR acquisition characteristics such as incidence angle or meteorological conditions, may result differently in the SAR images, creating a heterogeneous background that hamper the efficiency of global detection methods. For such detection algorithms, other post processing steps like morphological operations are required to properly detect ship pixels only. For all these reasons and the need of applying further processing to eliminate false alarms, this kind of algorithms are rarely used in ship detection chains.

When ship pixels are brighter compared to the surrounding area, but not necessarily to the entire SAR image scene, local detection criteria are required. Adaptive threshold algorithms are very often used in SAR target detection and a multitude of variants exist in classical ship detection chains. Such methods involve the search of pixel values brighter than their surrounding area, based on a local thresholding operation. Within a sliding window central pixels are compared to statistics computed in the neighbour area. A very common setup of the sliding window is shown in Figure 2.1, including a target cell which regroups the pixels under test, surrounded by a guard area and the background cell. The guard or buffer cell is used for ensuring that no pixel of an extended target is included in the background cell. The size and the geometry of each cell are defined with respect to SAR spatial resolution and the size of vessels to be detected.

The most widely used adaptive threshold algorithm is the well-known constant False Alarm Rate (CFAR) detector. For implementing this technique, numerous strategies are available, the cell averaging (CA-CFAR) and two-parameter CFAR being the most frequently used in SAR ship detection. For the CA-CFAR algorithm, the threshold depends only on the first order
moment of the background area (mean), while for the two-parameter CFAR it depends on both the mean and the variance. In designing the CFAR detector, the probability of false alarm (PFA) is supposed to be constant within the sliding window that sweeps the entire image. To ensure this, the background area (sea clutter) is modelled with its probability density function (PDF). The detection threshold is estimated from the PDF parameters and thus allows to maintain a specified PFA. The choice of the statistical model for the speckle noise depends on the SAR image type. The speckle distribution depends on whether the data is complex, or if amplitude or intensity data is used [35]. For instance, the Gamma distribution usually characterizing multi-look intensity images, is frequently used in deriving the CFAR detection threshold [17, 39]. Also the K-distribution which is widely used to characterize heterogenous surfaces and fits SAR oceanic surface reflectivity is employed in designing CFAR detectors [81].

Another manner to compute the threshold for adaptive algorithms is to estimate the background statistics considering non-parametric models, which allow to fit more precisely real SAR data. The Parzen window often used for nonparametric PDF estimation in the pattern recognition domain, was demonstrated to be suitable for estimating the PDF of SAR images with applicability to the CFAR detector [36]. In this thesis, we propose to employ a non-parametric method based on the so-called soft-thresholding, commonly used for sparse signals [10,25]. We suppose that in SAR imagery the signal containing vessel information is much lower than the sea clutter, thus fulfilling the hypothesis of sparse signals.

In addition to global and adaptive threshold methods, other approaches are employed for the detection step. For instance, the discrete wavelet transform (DWT) shows a different statistical behavior of ships and sea clutter through the wavelet coefficients, thus providing a reliable detection [34, 108]. Another interesting approach is based on the coherence between sub-look images processed with different sub-apertures of the SAR image [12, 77].

In this chapter our objective is to compare and analyze the results of different detection algorithms applied to large datasets of SAR intensity images. With this purpose we use the classical CFAR detector based on the Gaussian or the Gamma distribution. For multilook intensity images, the clutter is known to be Gamma distributed, converging to Gaussian distribution for large number of independent looks. We also use a non-parametric adaptive detection algorithm that we proposed in [82] and allows to detect a signal with unknown distribution in the presence of white Gaussian noise.

2.1.2 Adaptive threshold algorithms

The following section briefly describes the detection algorithms that will be assessed in this chapter. We remind that designing an adaptive threshold algorithm (CFAR in our case, see Figure 2.1) implies to compare pixels from the target cell within a sliding window (pixels under test x_{test}) to a threshold depending on the statistics of the surrounding area (background cell x_B). A guard cell area is used for ensuring that no pixel of an extended target is included in the background cell. In order to compute the threshold τ , statistics in the background cell and the corresponding probability density function (PDF) for a desired probability of false alarm (PFA), should be estimated by:

$$PFA = \int_{\tau}^{\infty} f(x/x_B) \,\mathrm{d}x. \tag{2.1}$$

2.1.2.1 Gaussian CFAR detection

The Gaussian distribution is frequently employed in defining the CFAR detector. For SAR intensity images, obtained by averaging a large number of looks (multi-looking process), the

corresponding statistical law converges towards a Gaussian distribution. If we consider as statistical model the Gaussian distribution, defining the detection threshold leads to employ the two-parameter CFAR:

$$\mu_{test} \gtrless \mu_B + \sigma_B \tau, \tag{2.2}$$

where μ_{test} is the mean value over the target window, μ_B and σ_B represent the statistical parameters of the background area, mean and respectively standard deviation. Under this approach, the threshold test implies to search for groups of pixels within the target window (e.g. their mean, μ_{test}) that are unusually bright. This is possible since the average of several Gaussian samples produces another Gaussian distribution.

Two classical methods for estimating parameters of statistical distributions are the Method of Moments (MoM) and the Maximum Likelihood Estimation (MLE) [60]. In this study, the MoM has been used to estimate μ_{test} , μ_B and σ_B from target, respectively background samples.

Finding τ involves only the PFA as a parameter for solving the following equation:

$$PFA = \frac{1}{2} - \frac{1}{2} \operatorname{erf}\left(\frac{\tau}{\sqrt{2}}\right).$$
(2.3)

Thus for a desired PFA value the threshold is adaptively estimated within the sliding window.

2.1.2.2 Gamma CFAR detection

Another very common statistical model employed with the CFAR detection is the Gamma distribution, being a more realistic model for SAR intensity imagery. In this case, the detector is defined by the classical CA-CFAR:

$$\mu_{test} \gtrless \mu_B \tau. \tag{2.4}$$

The detection threshold τ is retrieved by relation [17,27]:

$$PFA = \frac{\Gamma(L,\tau)}{\Gamma(L)},$$
(2.5)

where $\Gamma()$ represents the gamma function and L is the order parameter of the gamma distribution and the effective number of looks used for multi-look processing. We can use for L's value, either the number of looks given in the sensors documentation, or its estimation from the background statistics. Depending if the background cell is considered as homogeneous or heterogeneous, other versions of the Gamma CFAR algorithm are available [27]. However, their implementation complexity requires a high computation time. For this reason and due to the experimental similarities with the so-called "ideal" Gamma CFAR detector, these methods have not been considered in our study.

To estimate the equivalent number of looks (ENL), which is an important parameter to statistically model multilook SAR images, several methods are available in the reference literature. For instance, a method based on a nonparametric estimation and the use of orthogonal Laguerre functions was proposed in [33]. In this study we will employ a classical approach that proposes to estimate the ENL in small sliding windows over the whole image [65]:

$$\text{ENL} = \left(\frac{\mu_B}{\sigma_B}\right)^2. \tag{2.6}$$

In order to be consistent with the CFAR detector the same window size as for the CFAR background, is used. To estimate the σ_B , the Median Absolute Deviation (MAD) estimator is proposed. It is supposed to be more robust than the standard estimator. The only disadvantage is that it requires median computations, which becomes a very expensive computation for a large window size.

2.1.3 Non-parametric Detection

Besides defining the CFAR detector by modelling the background area with a PDF function, a non-parametric model that allows to fit more accurately real data, is introduced in this section. The non-parametric detector [10] aims at detecting a signal of unknown distribution in presence of white Gaussian noise, using a simple approach that requires only the estimation of the noise variance. We consider the following hypothesis :

$$\begin{cases} H_0: Y \sim N(0, \sigma^2) \\ H_1: Y = S + X, \quad \lambda_u \le |S|, X \sim N(0, \sigma^2). \end{cases}$$
(2.7)

In our approach S represents the target information, a signal of unknown distribution and X is the background which is considered as white Gaussian noise. X and S are considered independent. We assume that S is of very small dimensions compared to X, which makes the signal Y similar to wavelets sparse representation. According to wavelets literature [23,28], the maximum of X has a strong probability of being close to λ_u , the so-called universal threshold:

$$\lambda_u = \sigma \sqrt{2 \ln N},\tag{2.8}$$

where N is the number of pixels employed to estimate the standard deviation of the noise, σ . Within this approach the maximum of any N independent and identically distributed (i.i.d.) white Gaussian variables is smaller than the universal threshold with a probability approaching to one for large N values.

We assume that the probability of occurrence of H_1 is less than a certain p - the probability of presence of signal in noise (≤ 0.5). Under all these assumptions, a non-parametric threshold [10], representing a lower-bound for |S|, is defined by the following Equation:

$$\lambda_n = \sigma \xi \left(\frac{\lambda_u}{\sigma}, p\right),\tag{2.9}$$

with $\xi(\cdot, \cdot)$ given by:

$$\xi(a,p) = \frac{a}{2} + \frac{1}{a} \left[\ln \frac{1-p}{p} + \ln \left(1 + \sqrt{1 - \frac{p^2}{(1-p)^2} e^{-a^2}} \right) \right].$$
 (2.10)

Finding λ_u or λ_n implies the estimation of σ , which is the standard deviation of the background, in our case. Since we use intensity images, the assumption $X \sim N(0, \sigma^2)$ is not valid. However, multi-looked SAR intensity images are the sum of L terms $(I_L^2 + Q_L^2)$, where I_L and Q_L represent the real and imaginary components of radar scatter for each look. Because I_L and Q_L are independently Gaussian distributed of zero mean and identical variance $\sigma_{I/Q}^2$, we can easily find a relationship between $\sigma_{I/Q}$ and the standard deviation of the intensity image, $\sigma_{intensity}$. Thus this relation can be employed for finding λ_u or λ_n . For multilook intensity images, $\sigma_{I/Q}$ is given by:

$$\sigma_{\rm I/Q} = \frac{\sigma_{\rm intensity}\sqrt{L}}{2}.$$
(2.11)

When dealing with an amplitude SAR image, the relation between its standard deviation $\sigma_{\text{amplitude}}$, and the one of the corresponding I_L and Q_L is the following:

$$\sigma_{\rm I/Q} = \sigma_{\rm amplitude} \sqrt{\frac{2L}{4-\pi}}.$$
(2.12)

 $\sigma_{\text{intensity}}$ or $\sigma_{\text{amplitude}}$ are estimated from background samples within a sliding window as for the Gaussian/Gamma CFAR method. Finding λ_n involves only the parameter p, the probability



Figure 2.2 – Accumulation of AIS messages received by Enez Eusa, Alderney and Hastings AIS stations during July 2011 (cell resolution for counting vessels - $0^{\circ}0.25'$).

of presence of |S|, as a parameter for solving equation (2.9). Thus for a desired p value, the non-parametric threshold is adaptively estimated within the sliding window.

2.2 Modelling of Vessel tracking data

To assess the ship detection performance with a comprehensive dataset, a systematic methodology is proposed, allowing to automatically integrate AIS data flows as a reliable ground truth. AIS data is collected from databases containing messages acquired by three coastal AIS base stations, located in the British Channel and nearby the Ushant island. Details about the characteristics of each station are given in Table 2.1 and their location is indicated in Figure 2.2.

Being a collision avoidance system for vessels, AIS requires only line of sight communications systems and the Very High Frequency (VHF) band is suited for this. However, the range

AIS Station	ID	Lat / Lon:	Covered Area [km ²]	Elevation [m]
Alderney	290	$49.714^{\circ}/-2.201^{\circ}$	9471	107
Enez Eusa	314	$48.45979^{\circ}/-5.09585^{\circ}$	8733	40
Hastings	246	$50.87768^{\circ}/0.53937^{\circ}$	1476	75

Table 2.1 - SAR Datasets characteristics



Figure 2.3 - (a),(b) - Accumulation of AIS messages received by the Alderney, respectively Hastings stations during July 2011. (c),(d) - Normalized accumulation of AIS messages within the nearest traffic channel. (e),(f) - Distance to the AIS station within the nearest traffic channel.

coverage of AIS receivers is limited by the VHF propagation loss. In the maritime environment, several factors may influence the propagation of VHF signals [43]. For instance, messages from vessels at a distance of 20 Nautical Miles to the AIS stations, are hardly received. The transmission range of AIS signals is notably influenced by the refraction/diffraction phenomena over the earth's curvature or the antennas height. The system configuration (link budget) or multipath effects cause also inaccuracies in receiving AIS messages.

2.2.1 AIS coverage area - VHF reception and distance to TSS

In order to properly integrate AIS messages in our SAR-AIS vessel detection scheme, we have modeled [73, 82] the reception capabilities of the three coastal AIS receivers. For each AIS station, an accumulation of all the AIS messages received during a long period (e.g. one month) is first extracted. The impact of the propagation range loss can be observed in Figure 2.2. We notice that vessel density within the traffic lanes is thicker in areas located nearby to AIS stations. To determine and model the VHF propagation loss, we rely on the accumulated ship density within the Traffic Separating Scheme (TSS).

Our methodology is based on characterizing the accumulation of AIS messages received within the TSS and their distance to the AIS reception. From Figure 2.2 we observe that the highest density of AIS messages received by an AIS station is located within the nearest TSS lanes. Therefore we assume a constant flow of vessels in the TSS between the ascending and descending routes, and also within the scheme itself. The area of interest for modelling the AIS reception capabilities, is delineated using the geographical limits of the closest TSS lane to the AIS station and its corresponding accumulation of AIS messages within a long period of time (one month, in our case). For the Alderney and Hastings stations, the delineated TSS areas are shown in Figure 2.3. We notice that for the Alderney station with AIS messages received within a larger area, the selected TSS area is larger than for the Hastings station.

The number of received positions per range distance is computed and the probability of receiving AIS messages is then fitted by a polynomial function ψ , depending on the distance from the AIS receivers:

$$\psi(d, acc_{AIS}) = \begin{cases} 1 & \text{if } d < d_{\min\text{-AIS}} \\ P(d, acc_{AIS}) & \text{if } d_{\min\text{-AIS}} \le d < d_{\max\text{-AIS}} \\ 0 & \text{if } d \ge d_{\max\text{-AIS}}, \end{cases}$$
(2.13)

where $d_{\min-AIS}$ and $d_{\max-AIS}$ represents the minimum, respectively maximum distance from the AIS station to the nearest TSS lanes. P() is polynomial function of order 6 that serves to fit a regression between the accumulation of AIS messages acc_{AIS} and a set of distance values d in the $[d_{\min-AIS}, d_{\max-AIS}]$ range. In defining ψ we suppose that the reception probability is maximum within the area defined by the distance from the AIS receiver to the nearest TSS lane. Knowing that the AIS stations modelled in this study are situated in proximity to TSS lanes, we consider that the errors that may be induced by this supposition remain negligible. Figure 2.4 presents the polynomial fitting obtained for the three AIS stations. We notice that for the AIS receiver. Instead, for the Hastings station ψ exhibits a decreasing trend as a function of the distance parameter, but does not rigorously constitute a decreasing function. This is probably due to the lower coverage area of the TSS lanes for the latter AIS station, which implicitly impacts the estimation of the distance parameter. A systematic sampling (transects) of distance parameter coupled with a mean estimation of its corresponding values, could improve this issue.



Figure 2.4 – The probability of receiving AIS messages fitted by a polynomial function ψ , depending on the distance from the AIS receivers and the accumulation of AIS messages within the TSS area.

2.2.2 SAR detection assessment within the AIS area

Considering the modeling of AIS stations, SAR ship detection reports are compared to AIS data in order to evaluate the detection algorithms. The comparison is performed in the AIS area determined by the modeling of AIS stations. Only SAR targets whose correspondent ψ is above 0 are used to assess the detector's performances. Figure 2.5 gives the modeled confidence indicator of receiving AIS messages.

Vessels positions given by SAR reports and AIS data are used to perform the comparison. For each SAR image, the corresponding AIS data is first extracted with a time range of \pm 3h with respect to the SAR image acquisition time. The AIS data flow is interpolated at the time of SAR acquisition, using either a bi-linear interpolation when 2 or more positions are available ($\pm x$ minutes), or the route/speed when one position is available [73]. For a better coupling, AIS points are correctly positioned on the SAR image taking into account the exact acquisition time in the azimuth direction and the possible azimuthal offset related to their radial speed. Simple iterative process based on distance criteria between SAR echoes and interpolated/extrapolated AIS vessels is then applied. A minimal distance between the AIS and SAR locations has to be attained in order to consider a match. Targets not attaining the minimal distance criteria are considered as false alarms if SAR targets, or missed detections if AIS targets.

All detected SAR targets with a corresponding AIS position are considered as valid SAR detections. Otherwise, detected SAR targets without a corresponding AIS position are classified as false alarms. Finally, AIS positions without matching detected SAR targets are considered as missed detections.

This classification allows us to estimate the effective detection probability, P_{d-eff}^{AIS} , and the effective probability of false alarm, PFA_{eff}^{AIS} . In this context P_{d-eff}^{AIS} is estimated as follows:

$$\mathbf{P}_{\text{d-eff}}^{\text{AIS}} = \frac{\sum\limits_{i=1}^{N_m} \psi_i}{\sum\limits_{j=1}^{N_{\text{AIS}}} \psi_j},\tag{2.14}$$



Figure 2.5 – Area covered by modeling the receiving capabilities of the three AIS stations.

where N_m is the total number of detected SAR targets matched with AIS data and N_{AIS} is the number of all existent AIS targets. ψ represents the probability of receiving AIS messages in their corresponding targets locations (see Figure 2.5).

The effective value of P_{d-eff}^{AIS} is estimated by the following ratio:

$$PFA_{eff}^{AIS} = \frac{\left(\sum_{i=1}^{N_{FA}} \psi_i\right) \times N_{PPT}}{\sum_{k=1}^{N_{PA}} \psi_k - \left(\sum_{j=1}^{N_{AIS}} \psi_j\right) \times N_{PPT}},$$
(2.15)

where $N_{\rm FA}$ is the total number of SAR targets classified as false alarms. $N_{\rm PA}$ represents the number of pixels in the area covered by the AIS stations, delimited by the land masking process. $N_{\rm PPT}$ is defined as the maximum number of pixels per target with respect to image resolution and represents the area of a circle having the diameter equal to the length of the longest desired target. This definition of $N_{\rm PPT}$ is used in order to be able to compare the PFA^{AIS}_{eff} for the various detectors. $N_{\rm PPT}$ cannot be defined as the number of pixels detected by the SAR based detector for each particular target due to the fact that for the CFAR detector the threshold comparison is pixel based and thus the number of pixels per target will not be comparable between detectors.

AIS carriage regulations require sending AIS messages for all ships exceeding 300 tons engaged on international voyages, cargo ships exceeding 500 tons not engaged on international voyages and all passenger ships, whatever their size. Since the AIS dataset may not contain all existent ships in the area, the estimations of P_{d-eff}^{AIS} and PFA_{eff}^{AIS} are influenced by this. For instance, a real ship detected on the SAR image, but with no correspondent AIS position, will be classified as false alarms, causing a decrease of P_{d-eff}^{AIS} and increase of PFA_{eff}^{AIS} . Given the large number of targets used in our study (See Appendix B) this kind of cases are minor and will slightly change detection rates.

2.3 SAR experimental validation

To evaluate the detection algorithms we used three different datasets of SAR intensity images. The data is acquired by the Radarsat-2 and CosmoSkyMed sensors in the Scan SAR mode. Such images are of medium spatial resolution and have the advantage of a wide coverage capability. Furthermore, the processing time of ship detection chains is much lower than for high resolution data, making the Scan SAR mode suitable for almost real time operational services. However, at this resolution, the detection of small size vessels or the characterization of the detected targets remains limited. Table 2.2 provides a summary of sensors characteristics corresponding to each dataset [67], [52]. A detailed description of the datasets is given in Appendix B.

Dataset	Resolution	Polarization	Number	Frequency
(number of images)	$(rng \times az) [m]$		of looks	band
Radarsat-2 ScanSAR Wide (200)	$72.1 - 160 \times 100$	VV	8	С
Radarsat-2 ScanSAR Narrow (40)	$37.7 - 79.9 \times 60$	HH	4	С
CosmoSkymed ScanSAR Huge Region (35)	100×100	VV	15	X

2.3.1 Statistical distribution of SAR signals

As depicted in section 1.1.2, SAR signals are characterized by different statistical distributions, depending on the number of looks employed for the SAR image processing and whether complex, amplitude or intensity data is available. The choice of the best suited distribution is usually based on estimating the parameters of statistical models from real data samples. The datasets employed for the experimental results of this chapter contain multi-look SAR intensity images. For this type of data the Gamma distribution is usually used in characterizing homogeneous regions while the K distribution is one of the most widely used to characterize heterogenous surfaces. According the central limit theorem, when the number of looks is sufficiently large the SAR intensity observed values are considered as Gaussian distributed.

The CFAR detectors employed in this study are based on the Gaussian and Gamma distributions. The K distribution is not considered since the CFAR is applied to small regions, which are statistically shown to be homogeneous (i.e. to obey Gaussian or Gamma distributions). Additionally, heterogeneity characteristics are relatively small in medium resolution and multi-look SAR images [17].

In order to determine whether the Gaussian and Gamma distributions fit the real data, the PDF of images samples is compared to theoretical PDF. As showcased in figure 2.6 the Gamma distribution fits better the real data. To quantitatively assess the validity of a statistical model, different testing methods are available. In this section we apply the Kolmogorov–Smirnov test to several images patches. Figure 2.7 gives the P-values obtained by testing whether two array of samples are drawn from the same Gamma distribution. The first array sample contains SAR real data, extracted from clutter-image patches of a size equal to the CFAR background. The other array contains Gamma random variables generated with parameters estimated from the SAR image patches. For each dataset 2000 patches are extracted randomly from several SAR



Figure 2.6 – PDF of intensity samples extracted from a RS-2 ScanSAR Wide image, compared to theoretical Gamma and Gaussian PDFs.



Figure 2.7 – Distribution of P-values obtained with the Kolmogorov–Smirnov test applied to several image patches extracted SAR real data and their corresponding estimated Gamma random variables.

intensity images. The P-values lower than 0.1 (highlighted in red in Figure 2.7) correspond to reject the hypothesis of Gamma distribution. According to this we notice that approximately 10% of the image patches do not follow the Gamma distribution for the RS-2 ScanSAR Wide and CSK datasets. For the RS-2 ScanSAR Wide 20% of the image patches are rejected. The non validated samples probably correspond to heterogeneous areas and a suited distribution should be considered in such cases. However this would have increased the complexity of the detection algorithm and is not considered in this study.

The results of testing the Gaussian distribution as a statistical model are not illustrated here since a limited number of image patches were validated. For instance, for the CSK dataset approximately 50% of image patches were validated as Gaussian samples. This is in concordance with the large number of looks employed for processing the SAR intensity images contained in this dataset (15).



Figure 2.8 – PDF of Real and Imaginary part samples extracted from a SLC RS-2 Wide image, compared to theoretical Gaussian PDF.

The non-parametric detection method that we propose, is based on the use of white Gaussian noise. The complex components of the radar scatter are supposed to be white noise signals and obey a Gaussian distribution. Since for the RS-2 and CSK Scan SAR mode, the complex data before the multi-looking process is not available, we employ a SLC RS-2 image in the Wide mode in order to analyse distribution of the real and imaginary parts. Figure 2.8 illustrates the distribution of I_L and Q_L for an sea clutter image patch. We notice that for both I_L and Q_L the sample PDF fits a Gaussian PDF of zero mean. This makes the SAR data suited for the non-parametric detector, introduced in section 2.1.3.

According to the statistical distribution tests and comparisons performed illustrated above, we conclude that the Gamma distribution fits the majority of the RS-2 and CSK ScanSAR intensity images and is suited to be employed for the CFAR detection. Even if validated on a fewer number of intensity patches, the Gaussian distribution is also considered for the CFAR detection, due to its reduced complexity. As for the non-parametric detection, it was illustrated that the complex components of the radar scatter fit a Gaussian distribution.

2.3.2 General Parameters Settings

2.3.2.1 SAR image patch and CFAR window design

The application of the ship-detection process on the entire SAR image at full resolution has a high computational requirement, due to their large size. To this goal, before applying any processing to SAR images at full resolution, a division into several patches is required. Then each operation of the ship detection chain is applied sequentially to image patches. A parallel processing of several patches will allow to speed up the detection algorithm process. The size of image patches is chosen with respect to the global size of the entire image. An overlap region between successive patches is necessary to ensure the detection on edge areas.

For the CFAR sliding window, the size of the different cells (target, buffer and background) is chosen depending on the image resolution and the minimal/maximal sizes of targets under consideration. In our experiments, the buffer area is related to the dimensions of the biggest

desired target (for instance 400 m – world longest ship in service), and thus is defined by a circle with a proportional radius. The square-shaped background area is then constrained by this dimension, enlarged by a factor of $\sqrt{2}$. As for the non-parametric detector, estimating the variance of the background uses the same circle-box architecture with same size, for the sake of a coherent assessment between methods.

2.3.2.2 Equivalent Number of Looks Estimation

Concerning the number of statistically independent SAR looks (L), as a parameter for the Gamma CFAR and the non-parametric detectors, several possibilities were tested to set its value. We consider either the value determined by the SAR sensor processor, or the ENL value estimated globally for each image or locally at pixel level.

In order to estimate the ENL we employ the classical definition given by relation (2.6). As mentioned above the detection algorithm is applied to SAR image patches. If the ENL value is estimated for each patch we consider it as a global estimation. For a local estimation the statistical moments are determined with a sliding window within the patch framework. To estimate the standard deviation two methods were tested: the classical definition given by :

$$\sigma = \sqrt{E[X]^2 - E[X^2]}$$
(2.16)

for a finite dataset of random values X, and the Median Absolute Deviation (MAD) - based estimation, which is supposed to be a robust measure [121]. For the latter, the standard deviation is approximated by:

$$\sigma_{MAD} = 1.4826 \times \operatorname{median}\left(|X - \operatorname{median}(X)|\right). \tag{2.17}$$

Figure 2.9 gives the ENL estimates for an image patch over a sea clutter region with no targets. When targets are present within the sea clutter, it is advised that they be removed and replaced with the mean sea clutter value of the neighbourhood. A coarse detection of these points is performed, allowing to eliminate targets and any other outliers, that might impact the ENL estimation.



Figure 2.9 – (a) Image patch (sea clutter) extracted from a Radarsat-2 ScanSAR Wide image and (b) its corresponding ENL estimation: classical approach and (c) MAD. Number of looks extracted from the SAR product annotation files: L=8.

Then, ENL values are estimated locally with both standard deviation-definition methods. We notice that texture patterns are very similar for both the classical and MAD methods, but the numerical values vary between the two methods. Knowing that the MAD is much less sensitive to outliers, its corresponding standard deviation estimation will be lower than for the classical method. Varying inversely proportional to the standard deviation, the ENL values obtained with the MAD method will be higher than for the classical one, as shown in Figure 2.9 (b),(c). MAD ENL values are closer to the value extracted from the SAR processing information. However the MAD estimation requires a high computational time and several tests have shown that the detection thresholding itself, is very slightly impacted by the standard deviation method. For this reason, the classical standard deviation definition is employed in developing our detection methodology.

For the Gamma detector, the ENL estimated locally is employed. Background statistics of the image (μ_B and σ_B) are estimated using the sliding CFAR window in order to remain consistent with the detection scheme. However, for the non-parametric detector, the *L* value given in sensors documentations was used, giving better results.

2.3.3 Illustration of the SAR-AIS detection scheme

To illustrate the SAR detection process and the fusion with the AIS methodology, a case study analysis is presented in the following. A SAR image extracted from the RS-2 ScanSAR Wide dataset is used for explaining each step of our proposed SAR-AIS detection procedure.

Firstly the SAR detection is performed employing the CFAR Gaussian detector ($PFA=10^{-7}$). Then AIS data flows are extracted considering the SAR scene coverage area and acquisition time. Each SAR detection is compared to the AIS positions taking into consideration their projection onto the SAR image. Using a minimal distance criteria between SAR and AIS positions, targets are classified into threes classes as shown in Figure 2.15 (a). SAR targets matched with AIS positions are considered as valid detections within our methodology, while those with no corresponding AIS information are classified as false alarms. AIS positions unmatched with SAR detection are considered as missed targets.

It is very important to point out that this classification is reliable only if the modelled AIS coverage area (Figure 2.15 (b)) is taken into consideration. The probability of receiving AIS messages ψ , plays a very important role in this approach. Each target, no matter the class it belongs to, is weighted by ψ .

For example, we notice a large number of SAR targets with no matching AIS positions, within the ship lanes between the traffic channels. According to our classification, these targets will be considered as false alarms, whereas they are probably real ships. Due to the lack of AIS coverage in the area, no ground truth is available. If we consider the AIS coverage, we observe that the probability of receiving AIS messages is very low in this area. Thus if these targets are accounted to determine PFA_{eff}^{AIS} , the false alarms are weighted by a zero or very small value of ψ . In this way the real false alarm targets are considered only within the covered AIS area and weighted by the probability of receiving VHF signal. However, some of these targets, even if weighted by a high ψ value, may still represent real vessels without a matched position. This kind of situations may be due to high density traffic areas, where the matching operation may be erroneous if a simple interpolation/extrapolation of AIS points is considered.

The SAR-AIS matched targets considered as valid detections within our methodology, belong to areas with a high probability of receiving AIS messages. Thus, when these targets are accounted to determine P_{d-eff}^{AIS} , the detections are weighted by one or close to one values of ψ . The missed targets are part of the same area and probably represent small size ships that are not visible at the resolution of RS-2 ScanSAR Wide images.

This illustration demonstrates the utility of modelling the AIS covered area depending on the reception of VHF signals, in the analysis of the SAR-AIS targets fusion. The probability of receiving AIS messages is shown to be essential in determining the detection rate by counting



Figure 2.10 – Influence of the AIS coverage area for validating the SAR detection capabilities: (a) SAR-AIS detection scheme for a Radarsat-2 ScanSAR Wide image and (b) its corresponding AIS coverage.

valid detections and false alarms. This approach is applied to the datasets described in Table 2.2 and overall detection performances are discussed in the following.

2.4 Performance evaluation

2.4.1 First level analysis

2.4.1.1 The use of ROC curves for detection performance assessment

In order to analyze the overall performances of the different detection algorithms we use the Receiver Operating Characteristic (ROC) curves as a tool which allows to measure the effectiveness of a system controlled by a variable input parametrization [32]. Each ROC curve is generated by plotting the effective detection probability versus the false alarm rate (P_{d-eff}^{AIS} versus PFA_{eff}^{AIS} in our case), for a set of detection threshold values.

We remind that the parameter which controls the CFAR detectors is the desired PFA and for the non-parametric detector, is p (the probability of presence of signal in noise). By giving different values for these parameters we plot the ROC curves and analyze the detectors behavior. For the desired PFA we give values from 10^{-2} to 10^{-16} , adding that for lower values the number of detections remains constant. For p, values between 10^{-5} and 0.5 are given. For low p values, the non-parametric threshold λ_n tends to the universal threshold λ_u .

Figure 2.11 shows the results obtained by the detection algorithms applied on our three datasets. Depending on the prior PFA and p, the estimated PFA_{eff}^{AIS} and P_{d-eff}^{AIS} range from 10^{-4} to 10^{-2} , and from 40% to 80%, respectively.

We notice that the Gaussian and Gamma CFAR detectors give similar results, but one given PFA value would result in different $(PFA_{eff}^{AIS}, P_{d-eff}^{AIS})$ values with the Gaussian or the Gamma



(c) 35 CSK ScanSAR Huge Region images



assumptions. The results over the RS-2 ScansSAR Narrow dataset show that for PFA equal to 10^{-5} the Gaussian detector gives (PFA_{eff}^{AIS} = $10^{-3.1}$, P_{d-eff}^{AIS} = 0.68) while the Gamma detector gives (PFA_{eff}^{AIS} = $10^{-3.4}$, P_{d-eff}^{AIS} = 0.6).

We can observe that the Non-parametric detector gives slightly better performances than the CFAR detectors for CSK and RS-2 ScanSAR Wide but lower performances for RS-2 ScanSAR Narrow.

Regarding the polarization type of our datasets, CSK and RS-2 ScanSAR Wide contain both VV polarization data, while RS-2 ScanSAR Narrow contains HH polarization data. According to [22], [88], HH polarization is better for ship detection than VV polarization due to a higher ship-sea contrast. The detection results obtained with the RS-2 ScanSAR Narrow dataset are significantly better than with the RS-2 ScanSAR Wide dataset ($P_{d-eff}^{AIS} \in [0.5, 0.8]$ vs $P_{d-eff}^{AIS} \in [0.4, 0.65]$). Beside the higher resolution of the RS-2 ScanSAR Narrow dataset, the HH polarization plays an important role for the ship detection.

If we compare the performances by image type, we notice that the best results are achieved on CSK data, and the lower ones for RS-2 ScanSAR Wide, even though both have almost the same resolution and same VV polarization. For CSK, X-band could be a potential benefit compared to C-band for ship detection: sea surface backscattering at X- and C-bands are in the same order for standard wind speed (~ 7m/s), but backscattering from targets could be higher at X-band (even if relatively badly known). We may expect to get the best results from the dataset having the best SAR characteristics known for ship detectability (higher resolution, HH polarization, ...), but the first level analysis with ROC curves may lead to contradictory conclusion with global results better for the CSK Huge Region data than RS-2 ScanAR Narrow data. An in-depth analysis of the datasets characteristics explaining the obtained results is given in the subsequent sections. The differences may be caused by the higher number of looks for Huge Region CSK (L=15) compared to ScanSAR RS-2 (L=8 for Wide and L=4 for Narrow). Out of the sensors/modes characteristics, the corresponding ranges of incidence angle, weather conditions (e.g. wind speed) and vessels length over our datasets may impact the detection performances. The influence of all this parameters is discussed in Section 2.4.3.

2.4.1.2 Optimal threshold point of ROC curves

As pointed out in section 2.4.1.1, based on the ROC analysis the Gaussian and Gamma CFAR detectors give similar results. However, for the same PFA entry value the detectors result in different (PFA_{eff}^{AIS} , P_{d-eff}^{AIS}) values. Thus, finding a optimal detection value within a set of threshold values, represents an important step in assessing ROC curves.

To this purpose we introduce two criteria indicators for ROC curves that allow to determine an optimum overall detection value. ROC curves are often used to evaluate the accuracy of medical diagnostic systems, for examining the effectiveness of continuous diagnostic markers in order to distinguish diseased and healthy individuals. If the diagnostic marker is greater than a given threshold, the individuals are considered as diseased (positive) and healthy (negative) if otherwise. The threshold accuracy is measured by plotting the corresponding ROC curve as the probability of a true positive (sensitivity) versus the probability of a true negative (specificity).

In the medical domain several methods that determine the optimal cut off value of ROC curves, are proposed [8, 46]. Two methods frequently used are based on computing a specific distance to the ROC curve. The first one implies searching the minimum distance from the curve to upper-left corner and the second method is based on finding the maximum vertical distance of the ROC curve points to the diagonal line. The latter one is called the Youden index. Usually the sensitivity and specificity take value in the [0, 1] range. In defining the minimal distance or the Youden index the [0, 1] plot limits are employed.

In this section we aim at determining the optimal cut off values for the ROC curves presented in 2.11. The range limits of these curves vary with each dataset and each detection methodology. For instance, PFA_{eff}^{AIS} values usually vary between $[10^{-4}, 10^{-2}]$. For such values the ROC curve pattern is hardly comparable to the upper-left corner [0, 1] or the first angle bisector, that is the line of equation y = x. Thus, for a proper use of the minimal distance or the Youden index methods, we propose to adapt these methods to our specific ROC curves. This supposes to either normalize the plot limits to the [0, 1] range or define mathematical formula of each method, considering the specific limits of the ROC curves. For coherency considerations, we define the minimal distance and the Youden index by taking into account the effective value ranges of each ROC curve. The distance from the curve to upper-left corner is defined as follows:

$$d_{\rm ROC}(\tau_i) = \sqrt{\left(\min\{{\rm PFA}_{\rm eff}^{\rm AIS}\} - {\rm PFA}_{\rm eff}^{\rm AIS}(\tau_i)\right)^2 + \left(\max\{{\rm P}_{\rm d-eff}^{\rm AIS}\} - {\rm P}_{\rm d-eff}^{\rm AIS}(\tau_i)\right)^2},\tag{2.18}$$

where τ_i represents the set of detection threshold values employed to generate the ROC curve. The optimal threshold is therefore given by $\min_{\tau_i} \{ d_{\text{ROC}}(\tau_i) \}$. The Youden index (J) is defined by:



Figure 2.12 – Youden index and minimal distance criteria for the ROC curves with the RS-2 ScansSAR Narrow dataset and the SAR detection algorithms: (a) CFAR Gaussian, (b) CFAR Gamma and (c) Non-parametric.

$$J_{\text{ROC}}(\tau_i) = P_{\text{d-eff}}^{\text{AIS}}(\tau_i) - \frac{\max\{P_{\text{d-eff}}^{\text{AIS}}\} - \min\{P_{\text{d-eff}}^{\text{AIS}}\}}{\max\{\text{PFA}_{\text{eff}}^{\text{AIS}}\} - \min\{\text{PFA}_{\text{eff}}^{\text{AIS}}\}} \times \text{PFA}_{\text{eff}}^{\text{AIS}}(\tau_i).$$
(2.19)

The optimal threshold is therefore given by $\max_{\tau_i} \{J_{\text{ROC}}(\tau_i)\}$. In this approach the line of equation y = x is replaced with the line defined by the points: $\left(\min\{\text{PFA}_{\text{eff}}^{\text{AIS}}\},\min\{\text{P}_{\text{d-eff}}^{\text{AIS}}\}\right), \left(\max\{\text{PFA}_{\text{eff}}^{\text{AIS}}\},\max\{\text{P}_{\text{d-eff}}^{\text{AIS}}\}\right)$.

In Figure 2.12 the minimal distance and the Youden index are plotted within their corresponding specific ROC curves. For the CFAR detectors the set of threshold values is defined for PFA entry values from 10^{-4} to 10^{-16} , while for the non-parametric detector values between 10^{-5} and 0.5 are given for p. We notice that for the CFAR Gaussian detector both ROC indices find the same cut off position. Within the set of threshold values, PFA= 10^{-7} gives the optimal detection rates. For the CFAR Gamma detector the cut off values obtained with the two ROC criteria are different, PFA= 10^{-7} for the Youden index and PFA= 10^{-6} for the minimal distance. Even if the Youden index determines the same threshold (PFA= 10^{-7}) as a cut off value for both CFAR detectors, the (PFA_{eff}^{AIS}, P_{d-eff}^{AIS}) differ. This demonstrates that this kind of measure is not appropriate to compare the optimal threshold value for ROC curves with different behaviours. The two criteria defined in this section are suited to analyse each ROC curve individually, in determining the optimal threshold within a set of input values. The determined cut off values vary depending on the range and sampling step of the set containing the input values that controls each detector.



2.4.2 Fusion of Detectors

Figure 2.13 - (a) ROC curves - CFAR Gaussian and Gamma algorithms, detectors fusion with logical operators. (b) Effective Probability of detection - AND operator (c) Effective Probability of detection - OR operator.

As each detector considers different statistical models, parametric or not, the detectors fusion may be considered. Several methods of combining the three detectors employed in this chapter could be considered. One would be to fusion the detection results of two algorithms with logical operators. Employing a logical AND operator allows to retain common targets and eliminate false alarms, while an OR operator will retain all targets from both detectors but increase the number of false alarms. This kind of merging permits to verify if the results given by the different detectors are complementary.

Other method could involve to join the statistical parameters of the detectors before the thresholding operation, by employing combinations based on T-norm and T-conorm fuzzy op-

erators. For example, multiplying the CFAR statistic and detection threshold for the Gaussian and Gamma models:

$$CFAR_{Gauss} \times CFAR_{Gamma} \geq \tau_{Gauss} \times \tau_{Gamma}$$
 (2.20)

In this section we assess the merging result of detectors with the logical operators: AND/OR. The fusion is performed for a set of detection threshold values given to each detector. Figure 2.13 gives the detection rates for merging the CFAR Gaussian and Gamma detectors. We notice that global detection rates are similar to the individual performances of each detector. The CFAR Gaussian detection values have a smooth variability and influence the joint detection rates only for the first half set of threshold values corresponding the CFAR Gamma detector. For the latter one the variability of detection values is sharper, saturating the joint detection rates threshold values defined for a desired PFA lower than 10^{-8} .



Figure 2.14 - (a) ROC curves - CFAR Gaussian and non-parametric algorithms, detectors fusion with logical operators. (b) Effective Probability of detection - AND operator (c) Effective Probability of detection - OR operator.

Concerning the fusion of the CFAR Gaussian and the non-parametric detectors we notice from Figure 2.14 that the joint detection rates give better performances than the individual detectors, especially. We notice that by mixing the detectors with a logical AND, the number of false alarms is more reduced than for individual detectors at the same probability of detection. The CFAR method and the non-parametric are thus complementary detectors. Several combinations based on T-norm and T-conorm fuzzy operators were tested. Nevertheless, their benefits remain limited, so that they will not be further documented. The reason may be related to the fact that the three detectors are highly dependent from one to another so that their fusion does not bring in a significant increase in their fusion.

2.4.3 Influence of Different Key Parameters

Our datasets contain a large amount of SAR images (See Appendix B). This allows us to estimate the probability of detection depending on different key parameters, such as SAR imaging characteristics or meteorological conditions. The influence of the incidence angle, wind speed (weather condition) and vessel length, which are key parameters for ship detection, has been assessed in this study. At this stage, it should be mentioned that we do not perform a multi-parameter analysis but instead a one-by-one assessment of the detection rate. The first approach would have required a much larger dataset. Knowing that for similar (PFA_{eff}^{AIS}, P_{d-eff}^{AIS}) values the detected SAR targets are almost the same no matter the employed detector, the analysis of the influence of different key parameters on the detection rate will be realized using results of the Gaussian detector. The PFA value employed for the CFAR threshold is chosen according to the optimal ROC cut off value, as showcased in Figure 2.12 (a) (PFA= 10^{-7}).

2.4.3.1 Incidence angle



Figure 2.15 – Effects of the incidence angle on the detection process: (a) SAR-AIS detection scheme for a Radarsat-2 ScanSAR Narrow image and (b) its corresponding incidence angle values.

The incidence angle is a relevant parameter for ship detection algorithms, knowing that low incidence angles are favorable to ocean backscattering, while larger values reduce it and increase the ship Radar Cross Section (RCS) [88], [91]. Figure 2.15 (b) gives the incidence angle distribution for a RS-2 ScanSAR Narrow image and its corresponding ship detection results. We notice that the number of missed targets (AIS without SAR matching) is higher in



Figure 2.16 – Incidence angles distribution for all the pixels of our dataset with $\psi > 0$ (Histogram binsize = 1 degree, Histogram smoothed with a mean filter of size 5). The horizontal lines indicate the nominal range of the incidence angles corresponding to each dataset.

the area of low incidence angle values. In such areas we also distinguish a grouped number of missed targets. Whereas in areas of high incidence angle values, the missed detections are more dispersed and probably due to other parameters, such as SAR spatial resolution and vessels size.

Therefore the ship detection performances over our datasets will necessarily be correlated with incidence angles values. For this reason it is important to consider the incidence angle distribution when assessing the detections performances. The distribution of the incidence angles over each dataset is given in Figure 2.16.

Regarding the incidence angle range of the RS-2 ScanSAR Narrow dataset we observe that almost 50% are lower than 30° which rends a substantial part of SAR data less appropriate for the detection. Instead, the ScanSAR Wide images show a wider range of the incidence angle than ScanSAR Narrow images and a considerable part (70%) of the corresponding incidence angles are greater than 30° . In terms of incidence angle we state that a high percentage of the RS-2 ScanSAR Wide dataset is adequate for ship detection. We notice that for the CSK dataset, a small amount of data has low corresponding incidence angles (20% of data with incidence angles between 20° and 30°) and the range for higher values extends comparing to the RS-2 datasets (up to 50°). This makes the CSK dataset better suited for the detection with respect to the incidence angle.

Figure 2.17 gives the detection performances depending on the incidence angle for both the CFAR Gaussian and non-parametric detectors. We notice the similar behaviour of the detection rates with respect to the incidence angle, no matter the employed detector. This demonstrates that SAR targets given by the different detectors for similar values of $(P_{d-eff}^{AIS}, PFA_{eff}^{AIS})$ are almost the same, no matter the key parameters which influence the global detection. In order to estimate P_{d-eff}^{AIS} and PFA_{eff}^{AIS} (given in Eqs. (2.14) and (2.15)) as a function of the incidence angle, N_m , N_{FA} , N_{PA} and N_{AIS} were determined taking into account incremental steps of the incidence angle.

We can observe that P_{d-eff}^{AIS} increases with the incidence angle, over all datasets, which is in accordance with the fact that ships signature are enhanced at higher incidence angles. The



Figure 2.17 – Detection rates depending on the incidence angle.

same assumption is confirmed by the low number of detections at low incidence angles, P_{d-eff}^{AIS} increasing with the incidence angle (for instance for RS-2 ScanSAR Wide and CSK datasets the P_{d-eff}^{AIS} varies from 0.2 to 0.4 for incidence angles from 20 ° to 30 °).

For 70% of the RS-2 ScanSAR Wide dataset with corresponding incidence angles greater than 30°, P_{d-eff}^{AIS} values vary from 0.4 to 0.8 (sub-figure 2.17-(*a*)) while for the rest of data are lower than 0.4. The reduced detection rate for higher incidence angles may be caused by the other key parameters with impact on detectors performances. For 50% of the RS-2 ScanSAR Narrow dataset with corresponding incidence angles lower than 30°, P_{d-eff}^{AIS} values vary from 0.2 to 0.7 (sub-figure 2.17-(*b*)) while for the rest of data, the values are between 0.8 and 0.9. Therefore we can state that for RS-2 ScanSAR Narrow dataset the ship detection is best suited for incidence angles greater than 30°. In case of the CSK images for incidence angles between 30° to 40° P_{d-eff}^{AIS} values vary from 0.5 to 0.8 (sub-figure 2.17-(*c*)) while for higher incidence angles (40°), P_{d-eff}^{AIS} remains constant around 0.8 achieving the best performances for this dataset.

Intrinsically, the ScanSAR Narrow dataset, our only dataset with HH-polarization, which is known to have the lowest sensitivity to sea-clutter and thus better suited for ship detection, provides the best detection capabilities whatever the incidence angle. In the previous part, the global detection rates over this dataset were clearly impacted by the incidence angle distribution, being diminished by the large percentage of SAR data at low incidence angles.

As shown in Figure 2.17 the values of PFA_{eff}^{AIS} increase with the incidence angle. The corresponding Signal-to-Noise Ratio (SNR) depends upon the incidence angle, as large incidence angles imply a higher likelihood of low SNR [42].



2.4.3.2 Sea Surface Roughness

Figure 2.18 – Effects of the sea surface roughness on the detection process: (a) SAR-AIS detection scheme for a Radarsat-2 ScanSAR Wide image and (b) its corresponding wind speed values.

As the wind blows over the sea surface, it generates capillary-gravity ocean surface waves. These waves increase the surface roughness with respect to wind speed and direction and respond immediately to the ocean surface wind. In the microwave domain, the backscattered signal from the ocean surface directly depends upon the size of these waves. At a given time, the roughness observed on a SAR image is thus directly related to the local and instantaneous wind [42]. Therefore the wind speed being correlated with the sea surface roughness will impact the detection capabilities, the increase of wind speed values implying a decrease of the detection rate [5]. The wind direction and the stability of the atmospheric surface layer are also contributing to the surface roughness. Adding this parameters for detector's analysis would have required a much larger dataset and increase the complexity for results analysis. Also the potential information extracted from ancillary data demands an elaborate work in order to be integrated automatically in our assessment.

Rain cells or other atmospheric effects may also impact locally the sea roughness. We have not considered this aspect as the information potentially extracted from ancillary data would be complex to integrate automatically. Also the automatic flagging of "erroneous" areas corresponding to atmospheric fronts, rain cells is not really mature, and as far our knowledge goes, no robust algorithm exists nowadays. The stability of the atmospheric surface layer cannot be estimated precisely before data acquisition. Thus, for operational applications choosing datasets considering the prior influence of the stability of the atmospheric surface layer on detection capabilities may not be accurate.

In this study we will only analyze the wind speed impact on detection performances using the wind field information provided by National Centers for Environmental Prediction (NCEP) with 3-hour temporal and 0.2° spatial resolution. All this ancillary information was co-located and interpolated to the SAR image grid, taking the closest temporal available data.

Figure 2.18 (b) gives the wind speed distribution for a RS-2 ScanSAR Wide image and its corresponding ship detection results. For this example we observe a large number of missed targets (AIS without SAR matching), that are due to high wind speed values. Within the AIS covered areas the wind speed values vary between 12 and 20 m/s. It can be noticed that the missed detections are denser with the increase of the wind speed values.

The ship detection performances over our datasets are clearly impacted by the wind field information. For this reason it is important to consider the wind speed values when assessing the detections performances. Figure 2.19 gives the wind speed distribution over our datasets for the corresponding SAR images.



Figure 2.19 – Wind speed distribution for all the pixels of our dataset with $\psi > 0$ (Histogram binsize = 1 m/s, Histogram smoothed with a mean filter of size 4).

The RS-2 ScanSAR Wide dataset contains for almost 50% of the SAR data, corresponding wind speeds lower than 6 m/s, which are favorable for the detection, P_{d-eff}^{AIS} being constant around 0.6 as shown in Figure 2.20 (the best global detection rate obtained on this dataset - see Figure 2.11-(a)). For the other half of the dataset detection rates decrease. This confirm us that for RS-2 ScanSAR Wide the detection rate varies with the wind speed, decreasing for wind speeds values from 6 m/s to 20 m/s. For the RS-2 ScanSAR Narrow dataset we observe that for low wind speed values, P_{d-eff}^{AIS} varies between 0.7 and 0.8, which are close to the best global performances over this dataset. As we expected for higher incidence values, P_{d-eff}^{AIS} decreases. The wide range around 8 - 10 m/s corresponding to a decrease for P_{d-eff}^{AIS} makes the dataset less favorable for ship detection. Concerning the wind speed values corresponding to CSK dataset, the majority of data is distributed around 5 m/s and detection reports have demonstrated that in this case P_{d-eff}^{AIS} values vary between 0.6 and 0.7. Though, for higher wind speed values, according to Figure 2.20, P_{d-eff}^{AIS} is increasing contradicting the hypothesis of lower detection performances at higher wind speed values. The small amount of data for corresponding high wind speed values could explain it, further analysis of this contradiction being implied in our future work.



Figure 2.20 – Detection rate (Gaussian detector - $PFA = 10^{-7}$) depending on the wind speed.

As shown in Figure 2.20, the values of PFA_{eff}^{AIS} decrease with the wind speed. For low wind speed values, SAR scenes are affected by the sensor's noise, which explains the high number of false alarms.

2.4.3.3 SAR Resolution and Vessel Length

Spatial resolution of SAR images plays a very important role in evaluating the detection algorithms. In view of Section 2.4.1 the detection rate depends strongly on ships size existing in our datasets. Certain ships with a prominent signature can be detected in SAR images and others not, depending on their size with respect to images spatial resolution. In medium resolution SAR imagery, ships signatures do not contain a large amount of pixels, especially for medium and small vessels. The retrieval of ship length from medium resolution SAR imagery, is hardly feasible and may result in erroneous estimates. The AIS data flows provide for the majority of vessels information about their size.

Figure 2.21 illustrates the SAR signature of different size vessel extracted from a CSK ScanSAR Huge Region image. A priori the AIS information for each vessel is extracted and then projected onto the SAR image. The first vessel represents a fishing vessel which was not detected in the SAR image, being of smaller size than the spatial resolution of the SAR image. Such vessels are not visible at a spatial resolution of $(100 \times 100 m)$, as shown in Figure 2.21 (a). The other two image patches showcase vessels that were detected within the SAR image. The container ship of almost same length as the SAR spatial resolution, is detectable within its surrounding area. Even if the cargo ship, shown in Figure 2.21 (b), is of higher size and occupies more pixels, it is difficult to characterize its signature at this SAR spatial resolution.

The histograms shown in Figure 2.22 give the distribution of the number of ships, depending on their length (given by AIS information), over our datasets.

For the RS-2 ScanSAR Wide images, with resolution of $72.1 - 160 \times 100 m$, we expect that ships of length lower than 100 m can be difficult, even impossible to detect. Figure 2.23 gives





(a) Horizon Fishing Ship, Length \times Breadth: 24m \times 8m



(b) Alma (Cimbria) Container Ship, Length \times Breadth: 101m \times 18m





(c) MSC Maureen Cargo Ship, Length \times Breadth: 299.99m \times 40m







the detection rate depending on ships length, showing that for low ship lengths the detection probability is low. For ship lengths under 50 m, P_{d-eff}^{AIS} is almost 0, which is consistent with the resolution of the dataset. We also notice that for ship lengths between 50 m to 150 m, P_{d-eff}^{AIS} grows from 0.1 to 0.7, and for higher ship lengths (> 150 m) P_{d-eff}^{AIS} varies from 0.7 to 1. For example, about 20% of the ships existing in the dataset, have lengths lower than 50 m with a detection rate tending to 0, while ships with lengths greater than 300 m with a detection rate tending to 1, represent less than 5%.

For the CSK dataset, the spatial resolution of SAR images $(100 \times 100 m)$ is similar with the one of the RS-2 ScanSAR Wide dataset. Still, an overall comparison of the variation of



Figure 2.23 – Detection rate (Gaussian detector - $PFA = 10^{-7}$) depending on the ship length. The vertical lines indicate the minimal resolution values corresponding to the SAR datasets.

 P_{d-eff}^{AIS} with ship length, shows that the CSK dataset is more advantageous for detection. For small ships (length < 50 m), the detection rate varies ascending from 0.1 to 0.5, for ships of low-medium lengths (50 m to 150 m) P_{d-eff}^{AIS} varies ascending from 0.5 to 0.9. Since the range of wind speed and incidence angle over the RS-2 ScanSAR Wide and CSK ScanSAR Huge Region datasets are relatively similar, we can state that the CSK dataset is intrinsically better than RS-2 ScanSAR Wide for ship detection.

The RS-2 ScanSAR Narrow dataset, with greater spatial resolution $(37.7 - 79.9 \times 60 m)$ than ScanSAR Wide dataset, should provide a better detection. For instance, for ships of lowmedium length (50 m to 150 m), Figure 2.23 shows that P_{d-eff}^{AIS} values increase from 0.4 to 0.9, being greater than for the ScanSAR Wide dataset. Regarding small ships (length < 50 m), the detection rate varies ascending from 0.1 to 0.4, while for large length ships (length > 150 m) P_{d-eff}^{AIS} is around 0.9. As mentioned in the previous sections, detections on RS-2 ScanSAR Narrow images is affected by the range of the incidence angle values (to a lesser extend of the wind speed range), explaining the relatively low performances.

At this stage, it should be mentioned that the best achieved P_{d-eff}^{AIS} are about 0.9-0.95 for ships longer than 150 m. Even with the worst conditions (low incidence angle and large wind speed), we would expect to achieve 100% detection for large vessels over 250 m. The proposed methodology which automatically integrates AIS data flows to assess the detection performances could be further improved. For instance, the determined area covered by AIS stations could be affected by errors in our modelling (weather condition, temporary unavailability of AIS receivers, temporary very high density traffic). Also, matching SAR targets with AIS positions in high traffic areas could be erroneous and may require advanced interpolation/extrapolation functionalities.

2.5 Conclusion

In this chapter we have evaluated the performances of different ship detection algorithms. We have proposed a non-parametric approach, which has been applied for the first time in SAR ship detection. An advantage of this approach is that non-parametric models allow to fit more accurately the real data than methods based on statistical distributions. Besides this, two variants of the classical CFAR detector, based on the Gaussian and the Gamma distribution, were employed.

The datasets used in this study contain a large number of SAR images with thousands of corresponding AIS vessels positions (See Appendix B). Depending on the datasets, the detection algorithms offer different performances. A systematic methodology that permits to automatically integrate AIS data flows as a reliable ground truth is proposed in this chapter. This systematic method is used for counting good detections and false alarms in order to determine the detection rate, allowing to perform an appropriate and consistent comparison of the SAR detectors.

The non-parametric method gives quite satisfactory results on the lower resolution datasets (RS-2 ScanSAR Wide and CSK ScanSAR Huge Region). The Gaussian and Gamma CFAR algorithms give similar results over all the datasets, with a slightly better performance of the Gamma detector on the RS-2 ScanSAR Narrow data. This is in accordance with the fact the the RS-2 ScanSAR Narrow images rather fit more accurately a Gamma distribution than a Gaussian distribution, knowing that in this case the number of looks used for the SAR multilook processing is lower in comparison with the other datasets. When the number of looks is higher, the Gaussian distribution is suitable for the CFAR detection, as observed with the RS-2 ScanSAR Wide and CSK datasets.

The one-by-one scene and sensors characteristics comparisons show that the RS-2 ScanSAR Narrow dataset yields the best detection capabilities, the global detection rates over this dataset (see Fig. 2.11) being impacted by the incidence angle and wind speed ranges. Good detections capabilities were obtained with the CSK ScanSAR Huge Region dataset. Even though the sensor characteristics and meteorological conditions are relatively similar to the ones of the RS-2 ScanSAR Wide dataset, it induces lower detection performances, allowing to conclude that CSK ScanSAR Huge Region is better suited for ship detection at this resolution. Analyzing the detection capabilities with respect to the used dataset is valuable for operational applications, in order to chose the most appropriate type of data for different applications.

The newly launched European Sentinel-1 satellite provides similar data being equipped with a medium resolution SAR sensor which will be used for systematic monitoring of European Waters. Two requisites for an efficient maritime surveillance with Sentinel-1 are the automatic validation of SAR-based ship detection products and an advanced methodology for vessel characterization and classification.

The integration of worldwide Satellite AIS data flows should complete the ground truth data with much wider *metocean* conditions and then should facilitate the automatic validation. Our proposed method that determines the area covered by AIS stations is susceptible of improvement by considering different parameters that may influence the VHF propagation such as earth's curvature or the antennas height. Future work also involves verifying each AIS target information with a database containing accurate ship details.

The use of the classification step reduces the false alarm rate and should provide a better ship characterization in a complete ship detection system for maritime surveillance. The SAR vessels signatures in medium resolution images do not contain much details and applying a classifier in such cases may cause inaccuracies. Simple classifiers are recommended at this resolution, for instance two classes that qualify the targets as reliable and non-reliable may be sufficient. At a higher resolution where vessels signatures are more detailed, a more complex classifier with several classes for the ship signature type, may be used. In defining such classes, accurate SAR ship signatures are required, which is not always the case with real data. Because our choice was to focus on the detection challenge only, the classification step is not addressed in this thesis. Often SAR ship signatures are badly focused, due to their dynamical properties and SAR processing based on stationarity hypothesis. To this end in the following chapter we introduce a methodology that allows to estimate and compensate the effects of SAR defocused targets.

Towards moving target refocusing from SAR SLC data

Život je i će zauvijek ostati neka jednadžba nesposobni rješenje, ali sadrži određene poznate faktore. Life is and will ever remain an equation incapable of solution, but it contains certain known factors.

Nikola Tesla

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3.1 Theoretical issues

3.1.1 State of the art

The analysis and understanding of ship signatures from SAR imagery is of great importance for an accurate vessel classification step, as a post-detection operation, in a complete ship detection chain. Nowadays, the availability of large amounts of high resolution (HR) SAR data provides detailed ship signatures. Such ship signatures allow to perform an accurate target characterization that may lead to develop an advanced ship classification process.

The digital processing of common HR SAR imagery involves signal processing techniques which are developed and implemented assuming stationary scenes. However, for SAR scenes over sea areas, the hypothesis of stationarity is no longer valid, being affected by different phenomena such as ocean wave dynamics or moving targets (e.g. vessels). For instance, the orbital motions of ocean waves generate velocity bunching phenomena. The velocity bunching effect is a modulation process that generates non-linear SAR imaging artefacts. It results in a periodical translation of the wave pattern in the image plane, caused by the orbital motion of long gravity waves in the range direction. Another effect is the tilt modulation that refers to changes in the local incidence angle, caused by surface wave slopes. These and other effects caused by wave motion have been investigated in many early SAR studies [7,48] and remain a research subject in current studies [123].

The effects of stationary based processing of moving targets in SAR imagery, were firstly introduced in [92]. Many other research publications have treated this subject both in theoretical and experimental terms [50, 63, 69, 100, 103, 115]. SAR signatures of moving targets suffer from azimuthal displacement, smearing and defocusing caused by motions in the range direction as well as a loss of focus due to the azimuthal velocity. Figure 3.1 gives an example of two vessel signatures extracted from a RS-2 Ultrafine image: we notice that for the stationary target the SAR signature is well focused, while for the moving target the signature appears refocused in the azimuth direction.



Figure 3.1 – SAR ship signature extracted from a RS-2 Ultrafine image: (a) tanker Maran Taurus - stationary target, (b)container Tian Qing He - moving target (6m/s).

In this study we focus on the analysis of moving targets defocused in the azimuth direction. The objective of our work is two-fold: to improve (refocus) the target signatures and to estimate their associated azimuthal velocities. However, note that for SAR processing involving complex scenes with multiple dynamic targets, refocusing each individual target signature is not possible by applying the same correction to the whole image in real-time processing. Adjusting the loss of focus within a SAR sea scene implies the analysis of each phenomenon/target in particular. Usually the refocusing corrections are applied locally and aposteriori to SAR images and each moving target case is considered separately.

Several techniques are studied and developed with the purpose of compensating the imaging loss due to moving targets. Many of these techniques use multichannel SAR systems which are nowadays available with different spaceborne sensors, such as the dual-receive antenna mode of RS-2 (Moving Object Detection EXperiment - MODEX) or the dual-platform Ground Moving Target Indication (GMTI) of TSX/TDX. Thus, when using two or more channels, various signal processing methods may be used for an accurate imaging procedure of SAR moving targets. For instance Along-Track Interferometry (ATI) and Displaced Phase Center Antenna (DPCA) approaches are used for detecting moving objects and estimating their corresponding motion parameters [57, 69, 95]. Another technique extensively used in focusing SAR moving targets is the Space Time Adaptive Processing (STAP) which performs efficient clutter suppression in multichannel SAR imagery [29, 109]. Matched filter banks have also been employed for this issue [41, 100]. Nevertheless, the availability of the aforementioned imaging modes of RS-2 and TSX/TDX is limited due to the reduced number of multichannel SAR sensors in comparison with traditional single channel sensors. Therefore, in this chapter we focus on single channel data.

Various methods have been investigated to analyze, estimate and correct the effects of moving targets imaged by single channel SAR sensors as well.

- Ship wakes: The study of ship wakes dynamics may provide useful information in characterizing the effects of moving targets within single-channel SAR imagery [102]. In order to estimate the target motion, several techniques rely on extracting information from SAR ship wakes. For instance estimating the radial velocity by considering the azimuth displacement of the ship from its wake has been proposed in [113]. Another approach is based on the connection between the ship velocity and the kinematic features of the Kelvin wakes and on the assumption that a ship moves along a straight path with constant speed [125].
- **ISAR imagery:** Inverse SAR (ISAR) processing is a technique commonly used in focusing moving targets [11,68]. This SAR mode employs the following hypothesis: the target is moving and the radar system is stationary. The role reversal leads to the term of Inverse SAR.
- Matched Filter Banks: Matched filters based on non-stationary assumptions are also used to refocus moving targets. For instance the analysis of an Ambiguity Function based on the principle of matched filtering for identifying moving targets has been proposed in [104].
- Spectral sub-look Decomposition: The assessment of the temporal correlation between a sequence of sub-look images (generated from the Doppler spectral decomposition of a Single Look Complex (SLC) SAR image) [61] makes it possible to track the motion of vessels. For this method no consideration of the *a priori* artefacts of moving targets in the processed SAR signature is presumed, as for the FrFT method.
- **Time-Frequency techniques:** Other approaches are based on time-frequency processing methods like the Wigner-Ville distribution [54,94] or the Fractional Fourier Transform (FrFT) [50], both aiming at optimum processing of chirp signals which are mainly used in the digital process of synthetic aperture image formation.

The FrFT with application to SAR moving targets has been studied intensively in the past few years. Some research studies propose using the FrFT as a tool in new SAR processing algorithms [16,86]. However, the main purpose of FrFT applied either to single or multichannel channel SAR data is to estimate and then compensate for the moving target effects arising from the across-track or along-track speed [50, 56, 106, 119, 124]. In the former case, the processing is based on raw data while in the latter case SAR raw data processed in the range direction only are generally employed. Classical SAR processing algorithms imply pulse compression operations in both the range and azimuth directions. In few studies the FrFT is applied to SAR SLC processed images, for instance [64] employs it for analysing a moving target extracted from airborne processed SAR data. In [53] the FrFT is applied to processed SLC SAR images for computing log cumulants parameters in the FrFT domain, with the purpose of generating a feature descriptor for SAR image categorization.

In this chapter the FrFT is applied to spaceborne processed SAR SLC data. When dealing with a target moving in the azimuth direction, a residual chirp remains from the erroneous matched filtering in this direction [21]. The FrFT allows performing an optimal processing and analysis of these residual chirps. First, the azimuth defocus caused by targets motions in the azimuth direction can be compensated for. This approach makes it possible to refocus the SAR signal without considering any specific model for the residual Doppler phase. An important contribution of this methodology is that all the moving effects contributing to target defocusing are corrected with the estimated FrFT FM rate. This method makes it possible to obtain the refocused image and implicitly corrects all kinematic terms (acceleration and higher order terms).

On the other hand, the azimuthal speed itself can be estimated by finding the optimal parameters of the FrFT. For estimating the azimuthal speed we propose a new approach based on the Short Time Fractional Fourier Transform (STFrFT) [107]. The STFrFT makes it possible to separate the contribution of different scatters, originating from the ship signature. In this specific context (of kinematic estimation), we can not inverse one estimated STFrFT phase and obtain both velocity and acceleration terms. Hence, for velocity estimation, higher order kinematic terms are neglected.

The purpose of the methods treated in this chapter is two fold. First, it allows to refocus ship signatures extracted from processed SAR SLC data by using the FrFT transform and the sub-look decomposition method. Second, the azimuthal speed itself may be estimated relying on the same signal processing tools. A refocusing assessment based on quantitative criteria (contrast and entropy) and the comparison of speed estimates to ground truth data, allow to assess and evaluate the employed methods.

3.1.2 SAR signal analysis for non-stationary targets

This purpose of this section is to describe the influence of moving target kinematic parameters on the azimuthal SAR signal. A simplified model of the SAR signal for unfocused targets, is illustrated. Such a model allows to select appropriate signal processing tools for obtaining a properly focused image.

The processing of SAR raw data implies that the energy of each point target received by the SAR sensor to be compressed in the processed image. Different signal processing operations both in the range and azimuth directions are required. Several choices of SAR processing algorithms are available depending upon the SAR geometry and parameters and also upon the accuracy and efficiency required by each particular application [21]. The most frequently employed algorithms are the Range Doppler Algorithm (RDA), the Chirp Scaling Algorithm (CSA) and the ω -K algorithm, which are usually employed to process Stripmap SAR images. Even though their implementation has evolved greatly over time, the signal processing steps are principally the same. A typical RDA processing algorithm includes the following steps: range compression, RCMC and azimuth compression. For instance, for the CSA algorithm, the RCMC interpolator is replaced by a more accurate DSP operator. The SAR signal received from a point target which is a delayed and scaled version of the transmitted signal, can be written as [21]:

$$s_{\rm rec}(t_{rg}, t_{az}) = A_0 w_{rg} \left(t_{rg} - \frac{2R(t_{az})}{c} \right) w_{az} \left(t_{az} - t_c \right) \\ \times \cos \left(2\pi f_0 \left(t_{rg} - \frac{2R(t_{az})}{c} \right) + \pi K_r \left(t_{rg} - \frac{2R(t_{az})}{c} \right)^2 \right),$$

$$(3.1)$$

where t_{rg} represents the time scale in the range direction (e.g. fast imaging time) and t_{az} denotes the azimuthal time also known as slow imaging time. $w_{rg}(\cdot)$ and $w_{az}(\cdot)$ are the range and azimuth pulse envelopes, usually approximated by a rectangular function, respectively sinc-squared function. The received signal is multiplied by a complex constant A_0 , which models the backscatter coefficient σ_0 and the elevation and azimuth angles. $R(t_{az})$ represents the range from the radar to the target (e.g. instantaneous slant range). The other variables that occur in the SAR received signal equation are: f_0 - the the radar carrier frequency, t_c - the beam center offset time, K_r - the range chirp FM rate and c is the speed of light.

The received signal is shifted in the baseband by employing a quadrature demodulation operation that allows to remove the high frequency carrier. The demodulated baseband signal is given by the following relation:

$$s_{\rm rec}^{\rm baseband}(t_{rg}, t_{az}) = A_0 w_{rg} \left(t_{rg} - \frac{2R(t_{az})}{c} \right) w_{az} \left(t_{az} - t_c \right) \\ \times \exp\left(-j4\pi f_0 \frac{R(t_{az})}{c} \right) \exp\left(j\pi K_r \left(t_{rg} - \frac{2R(t_{az})}{c} \right)^2 \right).$$
(3.2)

Then, in classical SAR processing chains, the signal is processed in the range direction. Usually a range compression consisting of a matched filter, followed by a correction of the range migration is applied. After range processing the signal has the following mathematical form:

$$s_{\rm rg}^{\rm proc}(t_{rg}, t_{az}) = A_0 p_{rg} \left(t_{rg} - \frac{2R_0}{c} \right) w_{az} \left(t_{az} - t_c \right) \exp\left(-j4\pi \frac{R(t_{az})}{\lambda} \right), \tag{3.3}$$

where $p_{rg}(\cdot)$ is the compressed pulse envelope (e.g. sinc function) and $\frac{f_0}{c}$ has been replaced with the radar wavelength *lambda*.

The range from the radar platform to the target varies with the azimuth time, t_{az} and is given by:

$$R^{2}(t_{az}) = R_{0}^{2} + v_{\text{SAR}}^{2} t_{az}^{2}, \qquad (3.4)$$

where R_0 represents the slant range at $t_{az} = 0$, and v_{SAR} is the velocity of the SAR sensor platform. For a stationary target located at $(0, y_0, 0)$ and the SAR platform with the coordinates $(0, 0, H), R(\cdot)$ takes the following form:

$$R^{2}(t_{az}) = H^{2} + y_{0}^{2} + v_{\text{SAR}}^{2} t_{az}^{2}.$$
(3.5)

On the other hand, for a point target located at the same position $(0, y_0, 0)$, but moving with the velocity components v_{rg} and v_{az} and acceleration components a_{rg} and a_{az} in the range and azimuth direction, $R(\cdot)$ becomes:

$$R^{2}(t_{az}) = H^{2} + \left(v_{\text{SAR}} - v_{az} - \frac{a_{az}t_{az}}{2}\right)^{2} t_{az}^{2} + \left(y_{0} + v_{rg}t_{az} + \frac{a_{rg}t_{az}^{2}}{2}\right)^{2}.$$
 (3.6)

A simpler formulation for $R(\cdot)$ is obtained with a Taylor series expansion of (3.6). The approximation for a second-order expansion is given by [92, 100]:

$$R(t_{az}) = R_0 + \frac{y_0 v_{rg}}{R_0} t_{az} + \frac{1}{2R_0} \left[\left(v_{\text{SAR}} - v_{az} \right)^2 + v_{rg}^2 \left(1 - \frac{y_0^2}{R_0^2} \right) + y_0 a_{rg} \right] t_{az}^2.$$
(3.7)

From the above relation we notice that the linear term is impacted by the range velocity component. Within the phase of (3.3), this term results in a Doppler frequency shift, respectively an azimuthal shift in the image plane. As for the quadratic term, which generates a variation of the Doppler rate, we notice that it is affected by both the range and azimuth velocity components and the range acceleration.

In the following we shall concentrate on the Doppler rate variation effects on the azimuth compression step. For reasons of simplicity we consider the following simplified form for the range processed signal, depending only of t_{az} :

$$s_{\rm rg}^{\rm proc}(t_{az}) = w_{az}(t_{az})e^{j\pi K_A t_{az}^2},\tag{3.8}$$

where K_A is the azimuth frequency modulation (FM) rate.

The azimuth compression generally involves a matched filter for each given range gate. The matched filtering function is represented by the complex conjugate of the range process signal given in (3.8):

$$h_{\rm MF}^{\rm az}(t_{az}) = w_{az}(t_{az})e^{-j\pi K_{\rm SAR}t_{az}^2}.$$
(3.9)

In classical SAR processing the matched filter is designed for a stationary target and its corresponding Azimuth FM rate depends on (3.5) and has the following form:

$$K_{\rm SAR} = \frac{2v_{\rm SAR}^2}{\lambda R_0}.$$
(3.10)

When dealing with a moving target in the azimuth direction, the radar to target range is defined by (3.5). Thus, the azimuth FM rate of the range compressed signal is given by:

$$K_{\rm SAR}^{\rm motion} = \frac{2}{\lambda R_0} \left[\left(v_{\rm SAR} - v_{az} \right)^2 + v_{rg}^2 \left(1 - \frac{y_0^2}{R_0^2} \right) + y_0 a_{rg} \right].$$
(3.11)

Considering the FM rate variation with the velocity components of a target, the azimuth matched filtering will be affected by a mismatching of the quadratic phase term. Under these circumstances, the azimuth matched filtering becomes:

$$s_{\rm az}^{\rm MF}(t_{az}) = \int_{-\infty}^{\infty} h_{\rm MF}^{\rm az}(\tau) s_{\rm rg}^{\rm proc}(\tau - t_{az}) \,\mathrm{d}\tau$$

=
$$\int_{-\infty}^{\infty} w_{az}(\tau) e^{-j\pi K_{\rm SAR}\tau^2} w_{az}(\tau - t_{az}) e^{j\pi K_{\rm A}(\tau - t_{az})^2} \,\mathrm{d}\tau.$$
 (3.12)

The mismatching causes a spread in azimuth of the target energy and the resulting effects are azimuth defocusing and decrease of the signal magnitude. The additional FM rate term is denoted by ΔK and is equal to:

$$\Delta K = K_{\rm A} - K_{\rm SAR} = \frac{2}{\lambda R_0} \left[-2v_{\rm SAR}v_{az} + v_{az}^2 + v_{rg}^2 \left(1 - \frac{y_0^2}{R_0^2} \right) + y_0 a_{rg} \right], \qquad (3.13)$$

with ΔK the additional term of the azimuth FM rate.

The expression (3.12) represents a definite integral of e^{τ^2} , with no analytic solution [49,100]. In this study we employ an approximation that is derived as follows. We factorize by ΔK the phase term in (3.12), with the requirement that $\Delta K \neq 0$, which implies non-null velocity components. The match filtering takes the following form:

$$s_{\rm az}^{\rm MF}(t_{az}) = e^{-j\pi \left(\frac{K_{\rm SAR}^2}{\Delta K} + K_{\rm SAR}\right) t_{az}^2} \int_{-\infty}^{\infty} w_{az}(\tau) w_{az}(\tau - t_{az}) e^{-j\pi \Delta K \left(\tau - \frac{K_{\rm SAR} + \Delta K}{\Delta K} t_{az}\right)^2} d\tau.$$
(3.14)

In the above integral the quadratic phase term in τ^2 is substituted by u and equation (3.14) may be approximated with:

$$s_{\rm az}^{\rm MF}(t_{az}) \approx e^{-j\pi \left(\frac{K_{\rm SAR}^2}{\Delta K} + K_{\rm SAR}\right) t_{az}^2} \int_0^\infty \widetilde{w}_{az}(u) \frac{e^{-j\pi\Delta K u}}{2\sqrt{u}} \,\mathrm{d}u.$$
(3.15)

For the integral in (3.15) we observe that $\tilde{w}_{az}(\cdot)$ only changes the integration limits, and for the other part a solution from the table of integrals is possible.

Then, the processed SAR signal after azimuth matched filtering can be approximated by:

$$s_{\rm az}^{\rm proc}(t_{az}) \approx s_{\rm az}(t_{az})e^{-j\pi \left(\frac{K_{SAR}^2}{\Delta K} + K_{SAR}\right)t_{az}^2}.$$
(3.16)

In the derivation of the above equation, $s_{az}(\cdot)$ represents the azimuth compressed signal under the stationary assumption.

We consider the complex exponent in Eq. (3.16) as an azimuthal residual phase which remains after applying classical processing SAR algorithms to a moving scene. The residual phase term results in a chirp with the modulation rate depending on both the range and azimuth velocity components and the range acceleration. Such chirp signals may be assessed using the FrFT tool, described in Section 3.2.

3.2 On the use of the Fractional Fourier Transform

3.2.1 Theory Introduction

The Fractional Fourier Transform (FrFT) was firstly introduced in quantum mechanics as version of fractional powers of the classical Fourier Transform (FT) [74]. Then it was mainly used in optics applications [80] but also as a signal processing tool [6]. The FrFT represents a generalized form FT, introducing a rotation operation in the time-frequency domain. The FT function is based on the development of sine and cosine signals, while the FrFT can be considered as a development of chirp signals. This makes the FrFT useful in SAR applications systems, knowing that the radar signal processing tools usually involve chirp signals. SAR signals in the time domain lack of a frequency description and signals in the FT cannot represent the spectral change with time. Thus the FrFT may be employed for a better representation of such signals.

The FrFT of order α is a linear integral operator that maps a given function x(t) onto:

$$X_{\alpha}(u) = \int_{-\infty}^{\infty} x(t) K_{\alpha}(t, u) \,\mathrm{d}t, \qquad (3.17)$$

where $K_{\alpha}(t, u)$ is the kernel function defined as [80]:

$$K_a(t,u) = \begin{cases} \sqrt{\frac{1-j\cot\alpha}{2\pi}} e^{j(\frac{u^2+t^2}{2}\cot\alpha - ut\csc\alpha)} & \text{if } \alpha \neq n\pi \\ \delta(t-u) & \text{if } \alpha = 2n\pi \\ \delta(t+u) & \text{if } \alpha = (2n+1)\pi. \end{cases}$$
(3.18)



Figure 3.2 – The Fractional Fourier representation as a rotation of the timefrequency domain. Illustration of a chirp signal in the time domain ($\alpha = 0$), frequency domain (e.g. Fourier transform, $\alpha = \frac{\pi}{2}$) and Fractional Fourier domain (α_{opt}).

A slightly different form of the above definition is obtained by rewriting the complex amplitude term, $A_{\alpha} = \sqrt{\frac{1-j\cot\alpha}{2\pi}}$, as:

$$A_{\alpha} = \frac{e^{-j\left(\frac{\pi \operatorname{sgn}(\alpha)}{4} - \frac{\alpha}{2}\right)}}{\sqrt{\sin\alpha}},\tag{3.19}$$

where $sgn(\cdot)$ is the sign function.

Applied to chirp signals, the FrFT makes it possible to determine an appropriate domain, where the energy is concentrated in a compact representation. For instance the classical FT of a chirp signal spreads its energy in the spectral domain, whereas the FrFT concentrates the energy. The order α of the FrFT makes it possible to find the rotation optimizing the representation in the time-frequency domain and the FM rate of the input chirp signal. Figure 3.2 illustrates the Fractional Fourier representation as a rotation of the time-frequency domain.

FrFT-based energy distribution maps can be used to suppress the defocusing effects of moving targets by finding an optimal representation of the SAR processed data. In [100, 104] matched filter banks are used to estimate the moving target parameters and SAR Ambiguity Functions are assessed. Their results are similar to FrFT time-frequency representation.

Different implementation algorithms of the FrFT are presented in the literature [15,79]. The algorithms are based either on approximations of the continuous FrFT or on a discrete definition of the FrFT. For a fast and direct implementation the approximation algorithm described in [79] is employed in this study. The algorithm is designed for one-dimensional (1D) signals.

3.2.2 Optimal order of the FrFT

The optimal order of the FrFT is usually determined by computing the FrFT for a set of α values. These values are defined considering α as modulo 4 number and by using its additivity properties with an additional inverse FFT. Thus, the definition domain of the α argument is usually reduced to the interval $\left(-\frac{\pi}{2}, \frac{\pi}{2}\right]$, in order to avoid unnecessary transformations. Outside


Figure 3.3 – FrFT applied to a simulated SAR chirp signal in the azimuth direction. For the simulation, the parameters of the RS-2 sensor in the MLF are considered. The FrFT optimal order is determined with two methods: classical maximization of the FrFT energy (solid line in green) and the Spectral Kurtosis method (dashed line in magenta).

this interval, the FrFT is a cyclic operator. Therefore, the search of the optimal α order lies between $-\frac{\pi}{2}$ and $\frac{\pi}{2}$. When applied to one dimensional signals, finding the optimal order implies a two dimensional search for the energy distribution peak over the time frequency domain. The optimum transformation angle of the FrFT is defined by locating the peak value of $|X_{\alpha}(u)|^2$ [50]:

$$\alpha_{opt}, u_{opt} = \underset{\alpha, u}{\arg \max} |X_{\alpha}(u)|^2.$$
(3.20)

In order to illustrate the use of the FrFT with chirp signals, we employ a simulated SAR chirp signal in the azimuth direction. The simulation is realized considering the parameters of the RS-2 sensor in the MLF mode. Figure 3.3 gives its corresponding FrFT distribution map. The FrFT energy distribution map is obtained by applying the FrFT to the chirp signal for a set of α values ranging from -90° to 90° . $\alpha = 0^{\circ}$ corresponds to the time domain of the chirp signal while $\alpha = 90^{\circ}$ is equivalent with the frequency domain. We can observe that the amplitude distribution is highly concentrated for a specific α value. This value is usually determined by locating the maximum of the energy distribution. In the ideal case of a pure chirp signal, as presented in Figure 3.3, the optimal α can be found by maximizing the amplitude value of the FrFT distribution.

Figure 3.4 illustrates the result of the FrFT applied to a simulated chirp signal compressed in the slow-time domain, considering the azimuthal parameters of the RS-2 sensor of a stationary scene. The chirp signal in Figure 3.4 being compressed with an ideal matched filter, its distribution is maximal in the time domain. The same can be noticed with its FrFT representation, the optimal order being $\alpha = 0^{\circ}$ which corresponds to the time domain. As shown in Section 3.1.2, if the hypothesis of stationarity is not valid, the result of the azimuthal matched filter will contain a residual chirp. Such residual signals will result in a FrFT maximal energy concentration at non-zero α values, which allows to determine their corresponding chirp rate. If the SAR signal contains single scatterers originating from the moving target, the FrFT joint time-frequency representation is similar to the one given in Figure 3.4. In such cases the simple location of the peak in the FrFT domain with a classical maximum search, allows to determine the FrFT optimal order and thus chirp rate. Nevertheless if several scatters are present within the SAR signal, the FrFT joint time-frequency representation are more difficult to assess.



Figure 3.4 – FrFT applied to a compressed SAR chirp signal in the azimuth directions, with parameters of the RS-2 sensor considering a stationary scene. The FrFT optimal order is determined with two methods: classical maximization of the FrFT energy (solid line in green) and the Spectral Kurtosis method (dashed line in magenta).

Thus, when dealing with the presence of clutter and multiple scatterers in SAR data, locating the optimal order by a peak amplitude search may be inaccurate or biased. For this purpose the normalized Spectral Kurtosis (SK), which gives a measure of peaks in the presence of strong additive noise, may also be employed. An iterative search method was proposed by [45], for the cases when high precision of the FrFT order is required. Several comparisons between the SK method and the intensity peak location were tested. Nevertheless, the benefits of the SK remain limited, so only the intensity peak location is mainly employed in this study.

As mentioned above the accuracy of the alpha estimates depends on the target-to-clutter ratio (SCR). We have simulated the azimuth filter matching process considering non-stationary signals and several SCR values and then estimated a mean error as shown in Table 3.1.

We notice that in order to ensure a negligible error for estimating α_{opt} , a certain target-toclutter ratio is required. A SCR of 5 dB is equivalent to a mean residual error of 6 %, while a SCR of 10 dB ensures a mean error of 2 %. In our approach only ship signatures with a backscattering level much higher than the sea clutter, are considered. Thus the SCR will not impact the FrFT parameter estimation.

In addition, the number of pixels containing ship signature certainly impacts the quality of the alpha retrieval. It depends on the radar resolution, SAR image sampling and the size

SCR [dB]	0	5	8	10	12
Optimal FrFT order,	33.5	6.2	35	2.1	15
Mean Absolute Error $[\%]$	JJ.J	0.2	5.5	2.1	1.0

Table 3.1 – Mean Absolute Error for estimating the optimal FrFT order forsimulated SAR signals of several SCR values.

of the vessel. The two modes (MLF and UF) of RS-2, employed in this study contain high resolution images which provide detailed ship signatures as illustrated in Figures 4(a) and 7(a). The higher the spatial resolution, the better noticeable the defocusing effects. The resolution of SAR image sampling (e.g. pixel spacing) which has lower values than the spatial resolution in order to avoid aliasing, will certainly affect the backscattering information represented in the SAR signal and therefore induce inaccuracies in estimating the moving parameters. Modeling a system that considers all these parameters would have required a much larger dataset and is not considered in this study.

3.2.3 Azimuth velocity estimation

Once the optimal order of the FrFT applied to a chirp signal is determined, its corresponding chirp rate may be estimated as follows [16]:

$$K_{\alpha} = \frac{F_S^2}{2N} \cot \alpha_{\text{opt}} \tag{3.21}$$

where N represents the number of samples and F_S the sampling frequency, which is equivalent to the receiver pulse repetition frequency (PRF) for SAR azimuthal signal expressions.

As explained in Section 3.1.2, a residual chirp signal remains after the azimuth matched filtering of a moving target. The additional Doppler rate generated by target motions may be determined with the FM rate estimated by the FrFT tool. As we notice from Equation (3.11) the residual chirp expression contains both the range and azimuth velocity components and the range acceleration.

Usually for space-borne SAR sensors the ratio $\frac{y_0}{R_0}$, which occurs in the term multiplying the range velocity component, has low values (<10). Therefore the range velocity associated term is quite low in comparison with the term containing v_{SAR} and may be neglected. However, the range acceleration term being multiplied by y_0 (which may go up to 1000 km) may have an impact on the Doppler rate, for high acceleration values.

Thus the terms that impact the residual chirp rate are the azimuthal velocity and the range acceleration. Trying to estimate the motion parameters from the FrFT residual Doppler rate results in one equation with two unknown variables. Hence, given only the estimated residual Doppler rate, we are unable to inverse the Doppler model and obtain estimates for each kinematic term. In this study, we propose to estimate the azimuthal target velocity by neglecting acceleration terms, and then quantify the impact of such acceleration terms on the estimated speed. A study of the acceleration impact on the azimuthal speed estimation is given in Section 3.2.5.

Under the assumption that the acceleration values are negligible, the azimuthal speed is given by:

$$v_{az} = v_{\text{SAR}} \left(1 - \sqrt{1 + \frac{2v_{\text{SAR}}^2}{\lambda R_0 \frac{PRF^2}{N} \cot \alpha_{\text{opt}} - 2v_{\text{SAR}}^2}} \right)$$
(3.22)



Figure 3.5 – FrFT applied to a signal containing several compressed chirp signals simulated with parameters corresponding to a RS-2 MLF moving target scene. Its corresponding optimal FrFT order gives a speed estimation of 9.5 m/s.

When imaging targets such as vessels, the SAR ship signature in the azimuth direction can be complex with many scatterers. The azimuthal SAR signal contains several point scatterers originating from the target which are represented with different energy levels in the SAR image. If the FrFT is applied to such data, its optimal order is estimated with a combination of multiple point scatterers. Figure 3.5 gives an example of applying the FrFT to a simulated signal considering several point scatterers of a moving target with 10 m/s, with a corresponding optimal FrFT order $\alpha \approx 0.61^{\circ}$. We notice in its FrFT distribution map that the time-frequency representations of the different point scatterers cross and are added together, which hinder the localization of a global maximum in the FrFT joint time-frequency domain, giving the optimal FrFT order.

3.2.4 Short Time Fractional Fourier approach

To determine the optimal order α_{cot} corresponding to the global motion of a target, a Short Time Fractional Fourier (STFrFT) method is proposed. This method is supposed to dissociate the influence of different point scatterers. The STFrFT was introduced as a time-frequency transform in [107] making it possible to display the time and the FrFT frequency jointly in the STFrFT domain. The STFrFT employed in this study relies partially on the definition given in the [107]. Usually the STFrFT is applied within a short-time window moving along the time axis. Thus the STFrFT is obtained at every instant and a 2-D representation is available. In



Figure 3.6 – Flowchart of the STFrFT method employed in azimuthal speed estimation for signals contains multiple moving point scatters. For the simulation presented in Figure 3.5 the estimated speed with this method is 9.8 m/s.

our case the FrFT is applied locally to segments extracted around maximum values from the input signal and STFrFT 2-D representation is not employed.

The STFrFT is obtained by multiplying the input signal $x(\cdot)$ with a window $g(\cdot)$, before applying the FrFT:

$$\mathrm{STFRT}_{\alpha}(t,u) = \int_{-\infty}^{\infty} x(\tau) g(\tau - t) K_{\alpha}(\tau, u) \,\mathrm{d}\tau.$$
(3.23)

For $g(\cdot)$ we employ a rectangular window with a short time support.

The flowchart given in Figure 3.6 summarizes the main steps for determining the global FrFT order for a signal containing several point scatterers. Firstly local maxima values are determined and segments around each local maximum are extracted from the original signal. Then segments containing ship scatterers are selected with a thresholding operation based on the mean value of ship backscattering. The STFrFT is applied to each selected segment, after performing a zero-padding operation. All resulting STFrFT energy distribution maps are summed, giving a global FrFT map employed for finding the optimal order, relative to the vessel's motion.

3.2.5 Estimation the azimuthal velocity in presence of the range acceleration

In order to study the acceleration impact on the azimuthal speed estimation, we assess the azimuth compression of a simulated SAR signal. For the simulation procedure we employ the theoretical parameters of the RS-2 sensor in the MLF Stripmap mode, given in the following table:

Two chirp signals are simulated considering the following phase definition:

$$s_1 = e^{j\pi \frac{2v_{\text{SAR}}^2 \cos^2(\theta_{\text{beam}})t_{az}^2}{\lambda R_0}},\tag{3.24}$$

SAR sensor velocity: v_{SAR}	$7545 \mathrm{~m/s}$
Sensor Altitude: H_0	798 km
Slant Range: R_0	1000 km
Antenna beamwidth: θ_{beam}	0.19°
SAR wavelength: λ	$0.0566 {\rm m}$

Table 3.2 – Radarsat-2 SAR parameters for azimuthal compression simulation.

corresponding to a SAR stationary scene, and

$$s_2 = e^{j\pi \frac{2((v_{\text{SAR}} - v_{az})^2 + y_0 a_{rg})}{\lambda R_0} \cos^2(\theta_{\text{beam}}) t_{az}^2},$$
(3.25)

for a moving target, with v_{az} the azimuth velocity and a_{rg} the range acceleration. For the latter two parameters we set different values in order the assess their impact in estimating FM rate using the FrFT. After performing the filter matching operation employing the chirp signals defined above, we apply the FrFT and the azimuthal velocity considering the approach given by relation (3.22). Then we compute the velocity estimation error for several acceleration values, that were set in the simulation process, but we did not considered in the estimation approach.



Figure 3.7 – Range acceleration impact on FrFT azimuthal velocity estimation.

As we can observe from Figure 3.7, the azimuthal velocity estimates are sensitive to the range acceleration values. The higher the acceleration values, the more biased the estimated velocity values. From references [4,31], we can infer that the maximal acceleration values for large size ships, given in limiting operability conditions, are comprised between 0.5 and 1 m/s². Most of the literature on the subject focuses on vessels design, and are thus based on extreme admissible acceleration values. In the following we illustrate the computation of an acceleration component by taking into account the extreme values of parameters that intervene in its definition. If for instance, we consider the rolling motion of a vessel, the tangential roll acceleration is given by [4]:

$$a_{\rm roll} = \phi_{\rm roll} \left(\frac{2\pi}{T_{\rm roll}}\right)^2 R_R,\tag{3.26}$$

where $\phi_{\rm roll}$ and $T_{\rm roll}$ represent the roll angle and period, and R_R is the distance in m from the center of mass to the axis of rotation. Then, for a ship container with a roll period of 20 s and a roll angle of 10°, the acceleration value is about 0.15 m/s², for a point located at 10 m from the center of mass to the axis of rotation. Projecting the acceleration in the range direction leads to a value of a_{rg} that may impact the estimation of the azimuthal speed, depending on v_{az} itself. On the first hand, for the dataset used in this study, the mean wind speed values are about 5-6 m/s, which correspond to the Beaufort sea states no. 2 or 3 [31]. On the other hand, the type of vessels contained in the dataset (i.e. cargo, tanker) does not show a roll angle as high as 10°. Hence, we consider that acceleration values above 0.1 m/s² are unrealistic for large size vessels.

However, the velocity estimation error bias introduced by accelerations below 0.1 m/s^2 may range between 3% and 100 % depending on the speed values. As we can observe from Figure 3.7, the relative error is greater for small velocity values than for high velocity values. This error value is not negligible, since for very high velocity values of about 15 m/, the error rate is equivalent to approximately 20% for a range acceleration of 0.1 m/s^2 . Therefore in assessing the FrFT velocity estimation, the variation caused by the possible range acceleration values must be taken in consideration. It remains difficult to extract and dissociate the impact of the motion components (azimuthal speed and range acceleration) from the estimated SAR Doppler rate, and this issue may be addressed in a study. Additionaly, acceleration measurements are not available, thus hindering the assessment of this parameter in our methodology.

3.3 Doppler sub-look Decomposition Method (SDM)

The azimuthal motion effects can be estimated by assessing the Doppler spectrum of a moving target at different time instances [61, 64]. Such information is extracted by splitting its entire Doppler spectrum in several bands. Then, the sub-look images are processed from each Doppler band and we obtain a sequence of successive images, in which the position of the moving target will change from one to another. The center Doppler frequency of a subimage k at the azimuthal instant t_k is given by:

$$f_{c}^{i} = \frac{2(v_{\text{SAR}} - v_{az})^{2}}{\lambda R_{0}} t_{i}, \qquad (3.27)$$

for $i = 0...N_l$, with N_l the number of sub-look images.

The azimuthal motion parameters are obtained by estimating the displacement vector between pairs of sub-look images from the generated sequence. To determine the target displacement between two sub-look images, a block matching criteria, based on the maximization of the cross correlation function, is considered. The maximization of the cross correlation between two images is defined by the following relation:

$$\underset{(\Delta_{\rm rg}, \Delta_{\rm az})}{\arg\max} \{ \operatorname{Corr} \{ S_i(x - \Delta_{\rm rg}, y - \Delta_{\rm az}), S_{\rm ref}(x, y) \} \},$$
(3.28)

where $(\Delta_{rg}, \Delta_{az})$ are the translated positions between the two sub-images.

For the refocusing operation, each azimuthal line in the original image can thus be corrected by a shifting operation with the azimuthal displacement, Δ_{az} . In the frequency domain this consists in multiplying the signal by a correction function of phase exp $\{-j2\pi\Delta_{az}\}$.

The azimuthal speed of a moving target can also be obtained employing the estimated displacement between sub-look images, as follows [61]:

$$v_{az}^{sub-look} = v_{\text{SAR}} \left(1 - \frac{1}{\sqrt{1 - \frac{2v_{\text{SAR}}\Delta_{az}}{\lambda R_0 \Delta_{f_D}}}} \right).$$
(3.29)

 Δ_{az} represents the estimated spatial displacement between two sub-look images and is equal to the difference shift in pixels multiplied by the pixel spacing in the azimuth direction (in meters). Δ_{f_D} is the difference between the center frequencies of the sub-look images. The above speed estimation formula is equivalent to the one given in relation (3.22), since the term $\frac{\Delta_{az}}{\Delta_f}$ equals $\frac{Nv_{\text{SAR}}}{PRF^2 \cot \alpha_{\text{out}}}$.

Equation (3.29) represents an enhanced form of relation [61, 77]:

$$v_{az}^{sub-look} \approx \frac{\Delta_{az} v_{\rm SAR}^2}{\Delta_{f_D} \lambda R_0}.$$
 (3.30)

This relation is valid only for the assumption $v_{az}^{sub-look} \ll v_{SAR}$. The assumption may be not fulfilled for slow carrier platforms and fast moving targets. When dealing with space-borne platforms and slow moving targets (e.g. vessels), as in our case, relation (3.30) may be employed.

For the spectrum splitting several possibilities can be used. For instance, we can extract from the entire spectrum, either disjoint or overlapping bands. When a disjoint split is employed, a compromise between the number of sub-look images and their azimuthal spatial resolution is necessary. For example, within SAR scenes with a spatial resolution of 3 meters, a signature of a large size vessel is represented with about 100 samples in the azimuth direction. In such cases, generating a large number of subimages will degrade the image resolution and make difficult to measure the target displacement.



Figure 3.8 – Flowchart of the sub-look Decomposition Method.

To generate a larger sequence of successive sub-images, an overlapping split may be used, as illustrated in Flowchart 3.8. To this end an overlapping window, that slides the image spectrum

in the azimuthal direction, extracts different frequency bands. These bands are then employed to generate the sub-look images, by an inversion in the spatial domain. In each sub-look, the moving target will have a different location due to the corresponding different integration time. When handling a sequence of several sub-look images, the estimated displacement values between the reference image and the successive images is vectorized and linearly interpolated with the difference between their corresponding center frequencies. Thus the term $\frac{\Delta_{az}}{\Delta_{f_D}}$ in (3.29), can be replaced with the line slope of the displacement-frequency interpolation.

3.4 Experimental results

3.4.1 Dataset description

To evaluate the compensation of moving target effects we use a database composed of different ship signatures extracted from RS-2 SLC images. Table 3.3 provides a summary of the data employed in this study. Ship targets are detected in SAR imagery and identified by Automatic Identification System (AIS) data flows, using the systematic methodology proposed in [82,84]. The signatures of ships exclusively moving in the range direction have been discarded. The selection is based on AIS ship heading projected onto SAR geometry.

Processing algorithms of RS-2 images imply a step for scaling pixel values into a dynamic range of 16-bit at the end of image formation, employing Look-up Tables (LUTs) [105]. Several LUTs are available depending on the specific applications that the SAR images are used for. LUTs must be selected before processing SAR products. For certain LUTs, values above a defined level are saturated, while for others a coarser quantization over areas of very low backscatter is applied. For this study three LUTs are considered: Constant Beta, Mixed and Point Target.

The Mixed LUT is recommended in part for a wider swath imaging of water scenes containing low backscatter features. High value pixels from bright points are saturated. Constant Beta is the recommended default LUT suited to general applications, with values above 25 dB being saturated. The Point Target LUT is of choice when bright points are present in the imaged scene, presents a coarser quantization over very low backscatter areas, preserving high value pixels.

3.4.2 Refocusing via FrFT - Case study analysis

This section presents the effectiveness of using the FrFT to remove the defocusing effects of moving targets imaged by classical SAR sensors. To demonstrate the FrFT's applicability to moving ship signatures, a case study analysis is presented in this section A ship signature extracted from a RS-2 MLF image, given in Figure 3.9(a), is used for explaining each step of our proposed refocusing procedure.

The FrFT is applied to the SAR image patch containing the ship signature as a 1D operator by extracting 1D signals in the azimuth direction for each given range. The FrFT is then

Image Type	No. of	Mean inc.	Resolution SLC	No. of
(Polarization)	images	angle [deg]	$(rng \times az) [m]$	targets
RS-2 Multilook Fine (HH)	10	45	3.1×4.6	40
RS-2 Ultra Fine (HH)	14	38	1.6×2.8	20

Table 3.3 – SAR Datasets characteristics



Figure 3.9 – (a) Ship signature extracted from the amplitude SAR image (RS-2 MLF). (b) Picture of Mineral Nippon Bulk Carrier (source: http://worldmaritimenews.com/). (c) Refocused SAR ship signature - FrFT Method. (d) Refocused SAR ship signature - sub-look Method.

computed for a set of α values ranging from -90° to 90° . Figure 3.10 gives the result of the FrFT applied to samples of the SLC patch containing the moving target, showing different behaviours depending on the extracted information.

We can observe that, when the azimuth lines contain strong bright points and low clutter reflectivity, the FrFT distribution map illustrates well the energy concentration of the ship energy, as shown in Figure 3.10(a). Even though structures corresponding to the clutter are visible in the energy distribution maps, the FrFT of the reflecting points of the moving target is predominant and consistent with the FrFT of a simulated chirp signal. After azimuth compression, the result of the matched filtering usually concentrates the energy of each point target received by the SAR sensor into focused signals, sinc-like functions. The azimuthal speed of the moving target causes the optimal transform angle of the FrFT distribution energy to be located at non-zero α values. For the example shown in Figure 3.10(a) we can notice that the energy distribution map is maximal at approximately 2°, corresponding to the most compact representation of the azimuthal residual chirp. As showcased in Figure 3.10(b), when several bright points from the target are present within the same line, their path contributions cross in



Figure 3.10 – FrFT energy distribution map of lines in the azimuth direction extracted from the ship signature given in Figure 3.9: (a) range 69, the line contains a dominant ship scatterer, (b) range 77, the line contains several strong ship scatterers, (c) range 7, the line contains only sea clutter which results in a noisy FrFT map and (d) range 39, the line contains target and azimuthal ambiguities which result in several paths that cross within the FrFT domain.

the FrFT domain. In such cases the optimal FrFT order corresponds to a mixture of the several target bright points and manages to correct the moving effect of their global contribution in the FrFT domain.

Having determined the optimal FrFT representation, the line in the FrFT domain with the corresponding optimal α is then replaced in the SLC image. This operation is repeated for all the lines in the azimuth direction, in order to compensate the residual chirps originating from the azimuthal motion of the target. The results of this procedure are given in Figure 3.9(c), showing the refocused ship signature. Visual analysis of images before and after refocusing, shows that ship point targets are better focused, providing a clearer ship signature.

Figures 3.10 (c), (d) showcase the FrFT distribution maps obtained for azimuthal signals containing sea clutter or target ambiguities. For clutter lines, noise scatters result in a multitude of paths that cross in the FrFT domain as shown in Figure 3.10(c). When dealing with azimuthal lines containing either strong clutter reflectivity or possible effects of secondary lobes, the residual chirps associated with the ship signature are mixed as shown in Figure 3.10(d). For



Figure 3.11 – (a) Ship signature extracted from the amplitude SAR image (RS-2 UF). (b) Picture of Tian Qing He container (source: http://www.shipspotting.com/). (c) Refocused SAR ship signature - FrFT Method. (d) Refocused SAR ship signature - sub-look Method.

such cases, both the intensity peak location and SK approaches have been tested for finding the optimal α order, but their accuracies remain limited.

3.4.3 Refocusing via SDM - Case study analysis

This section illustrates the applicability of the SDM approach to our experimental data. For this, we employ the ship signature extracted for a RS-2 UF images, given in Figure 3.11 (a). The sublook images are extracted by splitting in the azimuth direction the spectrum of the image patch. As mentioned in section 3.3 several possibilities may be employed for splitting the spectrum in several bands. In this study we have first considered a disjoint split by dividing the spectrum in two equal parts. Since the sub-looks are processed with different frequency bands, the scene is seen at different look angles and its corresponding SAR azimuthal integration time changes between the sub-looks. Furthermore, the fact of having a shorter integration time with respect to full resolution image, induces the defocusing effect to be attenuated in the sub-look images. The sub-look images generated from the two spectrum bands are given in Figure 3.12 (a), (b).



Figure 3.12 – Sub-look decomposition methodology: (a), (b) - images generated by splitting the Doppler spectrum into two disjoint bands; (c) - refocused image: mean of the two sub-looks after their registration.

We notice that the target appears at different positions in each sub-look and the defocusing effect is less pronounced. The displacement vector between the two images is then computed and after a shift operation the moving object is relocated at the same reference position in both sub-looks. In order to obtain a refocused image, the sub-look images are averaged and thus the moving target appears better focused at a reference position. Still as it can be noticed from Figure 3.12 (c), in the refocused image, obtained from the two disjoint sub-looks, the defocusing effects are not completely removed. For a better refocusing a solution would be to use a larger number of sub-look images with a shorter azimuthal integration. However, for a disjoint spectrum splitting, the number of sub-looks is constrained by their spatial resolution. An overlapping split which allows to maintain a reasonable resolution for a large number of sub-look images is employed thereafter.



Figure 3.13 – Azimuthal displacement for a sequence of successive sub-looks with respect to center sub-look image. The sub-look image are extracted from the SAR image patch given in Figure 3.11

To generate a large sequence of sub-look images, for the Doppler splitting we employ a sliding window of size equal to the half size of the entire spectrum. This window slides the entire image spectrum and extracts sub-look images with the central frequency corresponding to each line of the image in the azimuth direction. The sub-look image in the center of the sequence is chosen as reference and the target displacement vector of each sub-look image is determined with respect to this one. Figure 3.13 gives the azimuthal displacement, for the entire sequence of the sub-look images. We notice that the displacement values are low for the subimages in the middle of the sequence and increase as we move away from the central reference image. Knowing that the sub-look images are no longer independent, the refocused image cannot be obtained by averaging referenced sub-looks. Therefore, each azimuthal line in the original image is corrected by a shifting operation with displacement vector of the sub-look image corresponding to the respective azimuth line. The refocused image obtained under this approach is given in Figure 3.11 (d). We notice that defocusing effects are better corrected than when using two disjoint sub-looks. In the following we use only the SDM approach based on the overlapping split of the Doppler spectrum.

3.4.4 Refocusing - Quantitative assessment

In the previous sections we have demonstrated the applicability of the SDM and FrFT methods for refocusing two particular SAR ship signatures. From Figure 3.9(d), which gives the refocused ship signature with the sub-look decomposition method (SDM), we observe that the energy of point targets is better concentrated than for the original SAR signature (Figure 3.9(a)). However this occurs with some loss in the signature details. The signature refocused via the FrFT method, given Figure 3.9(c) seems to better concentrate the signature energy and simultaneously preserve details. Figure 3.11 gives the results of similar study case for a ship signature extracted from a RS-2 UF image. As the spatial resolution is higher for the RS-2 UF mode, the refocusing correction is more noticeable for this example. We can observe that the azimuthal smearing is compensated with both refocusing methods. Still, we can notice that with the FrFT method, several point targets are better focused and the signature's details are preserved.

However, the two experimental results presented in Figures 3.9 and 3.11 are not sufficiently concluding on the methods performances. To this end, in the following, a statistical comparison of these refocusing methods is assessed. Both refocusing methods are applied to all the ship signatures in the dataset described in Table 3.3. Then, focusing criteria are applied to each ship signature before and after the refocusing operation. Such criteria allow to analyse the overall performances of both refocusing methods. Several focusing criteria indicators, such as contrast, entropy, Renyi entropy or spectral indicators, are available in the literature references [24, 72, 122]. In this study we employ two basic focusing indicators: contrast and entropy. The contrast of an image I is defined as:

$$C = \frac{\operatorname{std}\left(I^2\right)}{\operatorname{mean}\left(I^2\right)}.$$
(3.31)

When an image is refocused the contrast increases as point targets get sharper. Image entropy is defined by:

$$E = -\sum_{i} \sum_{j} \bar{I}_{i,j} \ln\left(\bar{I}_{i,j}\right)$$
(3.32)

where $\bar{I}_{i,j}$ denotes the pixel value at location (i, j), normalized by the total sum of elements. The entropy varies inversely to image contrast, decreasing for unfocused images. $\bar{I}_{i,j}$ denotes pixel value at location (i, j).

The focusing criteria indicators being measured are presented in Figures 3.14 and 3.15. Results are obtained with the RS-2 MLF and UF datasets. We notice that image contrast generally increases with both refocusing methods. Entropy values decrease, varying inversely to image contrast. This demonstrates the efficiency of these techniques for almost all ship signatures. We observe from Figures 3.14 and 3.15 that the refocused contrast/entropy for the FrFT is higher/lower than for the sub-look decomposition method. In conclusion, the FrFT method yields the best refocusing capabilities.



Figure 3.14 – Image contrast (a) and entropy (b) of ship signatures before/after refocusing techniques, extracted from the RS-2 MLF dataset (see an example in Figure 3.9), processed with the Mixed LUT.



Figure 3.15 – Image contrast (a) and entropy (b) of ship signatures before/after refocusing techniques, extracted from the RS-2 UF dataset (see an example in Figure 3.11), processed with the Mixed LUT.

The choice of the LUT employed for SAR processing algorithms affects the refocusing capabilities. The Mixed LUT is employed for the experiments presented in Figures 3.14 and 3.15. Results obtained with Constant Beta and Point Target LUT are presented in Section 3.4.5.

When using the Mixed LUT, the ship signature pixels are thresholded, which induces saturation of the ship signatures and causes them to be represented with the same energy level in the SAR image. The scatterers of maximal values are represented by several bright points originating from the target. Having the same energy level, their contribution results in the same manner in the FrFT domain and will be therefore taken into consideration for the refocusing algorithms. When using the Mixed LUT, the improvement of the refocusing process is visible on various pixels of the ship signature, which is demonstrated with the quality indicators after refocusing (higher constrast/lower entropy).

3.4.5 Comparative analysis of SAR LUT impact



Figure 3.16 – SLC sample distribution corresponding to different LUTs, for the SAR ship signature given in Figure 3.11 (a).

The influence of using different Look-up-Tables (LUT) employed for processing Radarsat-2 images, has been outlined in Section 3.4.1 and is further discussed in this section. To better understand the influence of the LUTs on the SAR ship signatures representation, in Figure 3.16 we illustrate the SLC sample distribution for different LUTs. The same ship signature is represented with different energy levels depending on the employed LUT. We notice that for the Mixed LUT, a high percentage of the pixels are thresholded inducing a saturation of the ship signature, while for the Constant Beta LUT only some pixels are saturated. For the Point Target LUT, the high value pixels are preserved and in this case, for scaling the dynamic range of the image, a coarser quantization over areas of low backscatter is applied.

Compared to the Mixed LUT, the use of the Constant Beta LUT or Point Target LUT presents similarities. For example, the maximal Radar Cross Section (RCS) value for the RS-2 MLF dataset processed with Point Target LUT (respective Constant Beta) is about 30 dB (respective 25 dB) while it saturates with the Mixed LUT at 5 dB. As the Mixed LUT is extensively studied in the manuscript, only the Point Target LUT is considered in the following.

Figures 3.11 (a) and 3.17 (a) give the same SAR ship signature processed with the LUTs Mixed and Point Target, respectively. From their simple visualization it may be deduced that the target is better focused when employing the Point Target LUT. Actually, their pixels different varying dynamic makes the defocusing effect less noticeable for the Point Target LUT. This is due to the high value pixels, corresponding to the signature strong scatters, which represent a reduced percentage of the entire signature. For the Mixed LUT, these pixels are thresholded, and the signature is therefore represented with an almost uniform energy level, which renders the defocusing effect more noticeable. Figure 3.17 (b) presents the refocused ship signature processed with the Point Target LUT. The target signature appears better focused even if the refocusing methodology is influenced only by strong ship scatterers, which are more noticeable than with the Mixed LUT.

Figures 3.18 gives the focusing criteria indicators for the RS-2 UF dataset processed with the Point Target LUT. Similarly with Figure 3.15 corresponding to the Mixed LUT, the image



Figure 3.17 – Example given in Figure 3.11, processed with the Point Target LUT: (a) Ship signature extracted from the amplitude SAR image (RS-2 UF). (b) Refocused SAR ship signature - FrFT Method.

contrast generally increases and entropy values decrease for the refocused image, demonstrating the efficiency of the refocusing methods. However the contrast/entropy gain is lower than the one given in Figure 3.15 using the RS-2 UF Mixed dataset. A first level analysis may conclude that the refocusing operation gives the best results when employing the Mixed LUT, and the refocusing process yields a poorer result with the Point Target LUT.



Figure 3.18 – Image contrast (a) and entropy (b) of ship signatures extracted from the RS-2 UF dataset processed with the Point Target LUT.

The varying dynamic range of SAR images processed with different LUTs explains the obtained results. When employing the Point Target LUT, high value pixels are preserved, resulting in a precise representation of strong scatterers. The refocusing algorithms mainly impact these pixels, which usually represent few ship signature points. Therefore, the contrast and entropy values will be certainly affected by these high value pixels. It is therefore not

appropriate to compare them with the quality indicators obtained for the dataset processed with the Mixed LUT.

The LUTs are an important factor in assessing the defocusing effects within SAR imagery. Choosing the LUTs for processing a SAR image, depends on each specific application. In order to estimate accurate moving target parameters from the SAR signature, the LUTs maintaining the original scattering of bright points, should be employed. We may consider the Constant Beta LUT which is usually employed for general applications, typically saturating only very bright targets. For a higher accuracy, the Point Target LUT, which preserves the original backscattering energy values, is required. Therefore, in the following section, which gives the experimental results for estimating the azimuthal velocity, we employ the Point Target LUT for our SAR dataset.

3.4.6 Azimuthal velocity estimation - results assessment

This section evaluates the experimental results obtained for the azimuthal speed estimation using the FrFT and SDM approaches described in Section 3.2.3 and 3.3 respectively. To perform an appropriate and consistent evaluation of the these methods, we employ AIS data as ground truth. The speed information is extracted from AIS data flows and projected onto the azimuthal SAR direction. In this section only datasets processed with Point Target LUT, which preserves the original range dynamic of ship signatures, are assessed. The impact of using the Mixed or Constant Beta LUTs has been also tested. Nevertheless, their benefits remain limited and no further assessment will be presented in this section. Only the estimated values lower than 12m/s for the result assessment have been retained, considering that higher values are not realistic for large vessels, which our dataset is composed of.

Firstly the STFrFT-based method described in Section 3.2.4 is illustrated by a real data case study. To estimate the azimuthal speed using the FrFT approach, an optimal order α_{cot} is required. Since the FrFT is applied to the ship signature for each range line in the azimuth direction, one option would be to fuse the α values determined for each range. Several combinations were tested (maximum, average, weighted average, median) with limited accuracy. Another alternative would involve, adding all the FrFT energy distribution maps for each given range, and finding a global α value within the resulting FrFT map, but tests show erroneous speed values. Assuming the ship signature is not completely oriented in the azimuth direction, as for the examples given in Figures 3.9 and 3.11, the azimuthal position of ship scatterers changes from one given range to another. Thus the FrFT range maps are moved in the joint time-frequency domain and do not properly combine, if summed.

For the above mentioned solutions, several point scatterers are combined with an incoherent method. Thus, we propose to employ the method outlined in the flowchart illustrated in Figure 3.19, which extends the methodology presented in Section 3.2.3 rendering it applicable to image patches containing moving targets. The flowchart in Figure 3.19 shows how image patches are processed, in order to determine an optimal FrFT order corresponding to the global motion of the ship. From each given range, segments around local maxima are extracted. Then the segments containing ship scatterers are selected with a thresholding operation based on the mean value of ship backscattering. The STFrFT is applied to each selected segment, after performing a zero-padding operation. All resulting STFrFT energy distribution maps are summed, giving a global FrFT map that is used for finding the optimal order.

Figure 3.20 gives a comparison of FrFT energy distribution maps obtained with a entire azimuthal line and with separate segments. The line extracted for this example contains several strong scatterers whose energies cross one another in the FrFT domain, as shown in Figure 3.20 (a). Thus, the estimated FrFT order obtained as the global maximum of the superposition of individual scatterers responses, represents a biased measure for the target azimuthal speed.



 $Figure \ 3.19$ – Flowchart of the STFrFT method employed for azimuthal speed estimation with ship signatures extracted from SAR imagery.



Figure 3.20 - (a) - FrFT energy distribution map of line 40 parallel to the azimuth direction extracted from the ship signature given in Figure 3.9, (b) Sum of FrFT energy distribution maps of segments extracted from the same azimuthal line.

Dividing the azimuthal lines into segments makes it possible to dissociate the information originating from different point scatterers, and the sum of their corresponding STFrFT maps can be used to find a compact and coherent representation. In order to perform a global performance assessment we employed the same segment size for all ships. Thus we have tested several values and selected the one giving the smallest error rate. Starting from a certain segment size the estimated velocity corresponds to the value estimated from the entire line (which may contain mixed terms). In order to perform a global performance assessment we employed the same segment size for all the ships. A more precise approach would have required a compromise between the segment size and the target size. However this would have required a much larger dataset. Our actual dataset is limited by the number of available SAR images and the corresponding AIS information. As it can be noticed from the FrFT representation of the simulated and real data given in Figure 3.4 and 3.10 respectively, the displacement introduced by the residual chirps in the FrFT domain corresponds to low α_{opt} values. Therefore in order to reduce the computational cost, the range of α values for computing the FrFT is reduced to $\pm 9^{\circ}$. For instance a ship with an azimuthal speed of 5m/s corresponds to an optimal order of about 0.25°. For speed estimation accuracy, a small quantization step of α values is required, and has been chosen equal to 0.01° in this study.



Figure 3.21 – SAR speed estimates vs AIS speed, for both estimation methods: (a) FrFT and (b) SDM. The ship signatures are extracted from the RS-2 MLF dataset, processed with the Point Target LUT.



Figure 3.22 – SAR speed estimation vs AIS speed, ship signatures extracted from the RS-2 MLF and RS-2 UF datasets, processed with the Point Target LUT. Corresponding Mean Absolute Error: 2.75 m/s - STFrFT, 2.3 m/s - sub-look decomposition.

Figure 3.21 gives the FrFT and SDM speed estimates with respect to ground truth values, extracted from AIS data. We notice that for both methods, the results are biased with respect to the AIS values. The results obtained for both the MLF and UF datasets give average performance as shown in Figure 3.22. The measured error between the estimated values and AIS data, show inconsequential differences for the two methods, being slightly lower for the sub-look decomposition method. This differences might be caused by the following situations:

- Method resolution: The higher number of samples employed for the SDM renders this method more effective. Compared to the STFrFT method, for which segments of few pixels are employed, for the SDM the speed estimation is based on splitting the Doppler spectrum into several overlapping windows of a size equal to a third of the original image.
- Method parametrization: The choice of input parameters, for both azimuthal speed estimation methods, is the same no matter the target size or spatial resolution. For instance, in the sub-look decomposition the size of the sliding window for band-pass filtering the image spectrum equals half the azimuthal size of the input image and when applying the STFrFT, segments of 10 pixels are extracted. Varying this type of parameters result in more accurate speed estimates for certain targets, depending on their size and spatial resolution. A method determining the best suited and robust parameters requires a much larger dataset.
- **SAR-AIS time-acquisition differences:** To some extent the SAR-AIS measured error can be explained by the differences between SAR acquisition time and time stamps of received AIS messages, leading to the need for AIS data interpolation/extrapolation.
- Space-borne sensor vs. vessel velocity: Considering the SAR geometry, target motions are extremely low compared to the sensor's velocity and are difficult to be evaluated in space-borne SAR imagery, having a weak impact in SAR signals.
- **Higher order motion components:** Only the azimuthal velocity has been considered in this study, even though vessels on the sea may have 3-dimensional motion (i.e. velocity and acceleration in x-y-z directions). As mentioned in section 3.2.5, the estimates of the azimuthal velocities are clearly influenced by the target's range acceleration. From the residual SAR Doppler rate present in SAR SLC data, it remains difficult to dissociate the contribution of these two terms. The use of azimuthal raw data (e.g. before azimuth compression) could probably provide more accuracy in assessing the SAR Doppler and therefore find a way to determine and dissociate the different motions components.
- Mixture of scatterers having different velocities within the same resolution cell: Scatterers with different motion parameters can be contained within the same resolution cell as well. For example, vertical structures with roll or pitch effects have different velocities from bottom to top.

All these phenomena make it difficult or nearly impossible to estimate the vessel speed in a precise way. There is no simple solution for the issue caused by all the above mentioned factors. However, some particular aspects may be considered in order to ameliorate the estimation of vessels motion parameters. For instance, employing higher resolution data, which are supposed to give a more extensive representation of vessels signatures, could be considered. As well, the use of data acquired by airborne sensors, with a different SAR geometry (lower distances to the ground scenes, and lower platform velocity), could provide a more accurate estimation of the azimuthal velocity by employing the FrFT and SDM methods.

3.5 Conclusion

This chapter contains a study about the effects of representing dynamical targets on SAR imagery, when processed with stationary based techniques. A new methodology based on the Fractional Fourier Transform (FrFT) tool, that allows to estimate and compensate these effects, is proposed. SAR imaging of moving targets usually results in residual chirps in the azimuthal SLC processed signal. The FrFT makes it possible to represent the SAR signal in a rotated joint time–frequency plane and performs an optimal processing and analysis of these residual chirp signals. The along-track defocus can be then compensated, and the target's azimuthal speed, estimated. The FrFT operator is usually employed with raw data while our study demonstrates that it can be suited to SLC processed data.

For a complete performance assessment, an intercomparison with a standard Doppler sublook Decomposition Method (SDM) is employed. In this approach, motion parameters are estimated by evaluating the Doppler spectrum difference between temporal successive representations of the moving target. The applicability of both the FrFT and sub-look Decomposition methods is verified using space-borne SAR data. SAR vessel signatures are extracted from two Radarsat-2 datasets, containing high resolution images in the MLF and UF modes. Vessels characteristics and motion parameters are extracted from AIS information considered as ground truth data. We consider that our approach is applicable to ship signatures which have a backscattering level much higher than the one of the sea clutter. Thus, the sea-clutter dynamics are not integrated in our azimuthal speed estimation approach. However, note that if the backscattering level of the sea-clutter and targets are comparable, the fact that the sea is not stationary should be taken into account.

An assessment based on quantitative criteria shows the effectiveness of the presented methods. The focusing criteria indicators, contrast and entropy, are computed for each vessel signature before and after applying the refocusing processing. From the experimental results, one may conclude that the FrFT method yields the best refocusing capabilities. Furthermore, from the case studies presented in this chapter we notice that the point target energy is better concentrated and details are better preserved with the FrFT approach.

The Look-up-Tables (LUT) employed for processing Radarsat-2 data represents an important factor in assessing the defocusing effects of SAR-imaged bright moving targets (e.g. vessels). The choice of a LUT for processing a SAR image depends on each specific application. For an accurate vessel signature characterization and to estimate its corresponding motion parameters, it is recommended to employ the LUTs maintaining the original backscattering values.

The azimuthal speed of moving targets can be estimated by finding the optimal parameters of the FrFT and a novel STFrFT approach is proposed in this study. Several SAR azimuth speed estimates corresponding to different targets are compared with results from the sub-look decomposition method. Based on AIS validation data, the sub-look decomposition approach gives slightly better performances, probably due to the higher number of samples employed in this approach. However, the estimates of both methods present high variance. To some extent, the errors of the azimuthal velocity estimates can be partially explained by the influence of the range acceleration term, as shown in this study. A parametrical method with an explicit phase model that incorporates all the kinematic terms, could allow to obtain a more accurate azimuthal velocity estimation. This issue shall be addressed in a future study.

In the SAR Stripmap images employed in this study, small vessels are represented with a limited number of pixels. To better estimate the motion effects of vessels, higher radar resolution would be required and represents possible future line of research. Ship signatures acquired in the Spotlight mode with a nominal resolution of about 1m should provide sufficient details for small vessels. The processing algorithm for Spotlight images is different from Stripmap images. The

presence of eventual residual signals linked to target velocities should be analysed to determine whether the FrFT can be applied to this type of data.

In this chapter it was demonstrated that the moving effects of vessel signatures, imaged with SAR single channel systems, can be estimated with appropriate signal/image processing tools. As mentioned in the state of the art Section (3.1.1), a multitude of algorithms dealing with moving targets, are designed for multichannel SAR data, acquired by multi-receive antenna or multi-platform systems. A different kind of multichannel images are also available from polarimetric SAR sensors. SAR polarimetric images may provide valuable extra information in the representation of ship signatures, that reflect differently depending on the polarization mode. To this end, in the following chapter we exploit the use of polarimetric data in ship detection chains, particularly focusing on SAR dual-polarization images.



On the use of complex dual polarization data for SAR ship detection chains

Spre deosebire de vin, știința nu trebuie lăsată să se învechească. Unlike wine, science should not be left aging.

Grigore Moisil

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4.1 State of the art

The use of images acquired by SAR space-borne sensors, in maritime surveillance applications has been always increasing with the launch of new sensors. SAR ship detection has been intensively studied using data acquired by the earliest C-band civilian satellite missions Canadian Radarsat-1 (RS-1) satellite, the European satellites: European Remote Sensing (ERS-1/2) or the Environmental Satellite (ENVISAT) [22, 59, 62, 88]. Nowadays, it is still a current research issue studied with the Canadian Radarsat-2 (RS-2) satellite the Italian CosmoSkyMed (CSK) satellites constellation or the German satellite constellation TerraSAR-X/TanDEM-X (TSX/TDX) [13,70,75,82,112,114]. These sensors yield a diversity of polarization modes, new emitting X-band frequency along with the capability of Left/Right looking with higher spatial resolutions which may provide additional assets for maritime surveillance. Furthermore, newly launched SAR sensors such as the European Sentinel-1A satellite or the Japanese satellite Advanced Land Observing Satellite (ALOS)-2 (band L), provide large amounts of SAR images that serve to a diversity of applications, including vessel detection. In order to ensure data continuity over the next decades new satellite launches are planned. For instance, the Canadian RADARSAT Constellation Mission (RCM) that includes three identical Earth observation satellites, is planned for 2018.

In this study we shall focus on data acquired by Sentinel-1, which is used for systematic monitoring of European Waters [116]. Sentinel-1 is a constellation of two satellites carrying Cband SAR sensors that can acquire day-night and all weather conditions imagery for different user services [40, 87]. One of the great benefits of this satellite mission is the full and open access data policy. Sentinel-1A has been successfully launched in April 2014 and calibrated SAR images are available since the end of 2014. Sentinel-1B is scheduled for launch in 2016, and will share the same orbit plane with Sentinel-1A, with a 180° orbital phasing difference, providing a 6 days repeat cycle. Several acquisition modes with different resolution and coverage are available: Stripmap Mode (SM), Interferometric Wide Swath Mode (IW), Extra-Wide Swath Mode (EW) and Wave Mode (WV). The IW and EW modes use the Terrain Observation with Progressive ScanSAR (TOPSAR) imaging technique which provides large swath widths (250 km for IW and 400 km for EW) and enhanced radiometric performances by reducing the scalloping effect. Both modes can be acquired in dual polarization (co and cross polarization). For these ScanSAR modes, Slant-Range Single-Look Complex products (SLC) and Ground Range Detected products (GRD) are available. For the GRD images two resolution classes are possible: High Resolution (HR) and Medium Resolution (MR).

Sentinel-1 SAR images with appropriate characteristics are suitable for ship detection [116]. A first study on the use of early Sentinel-1 data for ship detection, was presented in [44]. Other research studies treating this subject were recently published. Sentinel-1 data is exploited in [96] for demonstrating the capabilities of an algorithm that can be used to discriminate and remove SAR target ambiguities. A comparison and synergetic use of Sentinel-1 and TerraSAR-X SAR imagery for ship detection applications are given in [118]. Other studies presenting new ship detection algorithms, based on localized wavelets or the H-dome transform (a method employed for finding local maxima), and testing their performances with Sentinel-1 data, were presented in [97,98].

The use of Sentinel-1 TOPSAR images for vessel detection, presents an interest due to a good compromise between its corresponding spatial resolution and swath width (i.e. coverage). All relevant coastal zones and North Atlantic shipping routes are covered by IW mode while EW mode acquires data over open ocean assuring in this way a complete global coverage for ship detection applications [30]. As mentioned above the Sentinel-1 IW and EW modes provide large swath widths, that are currently suited for maritime surveillance applications. For an efficient maritime surveillance system with Sentinel-1, the automatic validation of different SAR products in ship detectability is required. In this chapter we evaluate the performances of large Sentinel-1 TOPSAR datasets by using the automatic ship detectors chains proposed in Chapter 2. Compared to the classical ScanSAR mode the TOPSAR mode is supposed to achieve the same resolution, but with a nearly uniform Signal-to-Noise Ratio (SNR). In order to assess impact of this aspect on ship detectability, a comparison with detection performances from Radarsat-2 and CosmoSkymed ScanSAR datasets is also considered [85].

Sentinel-1 is a dual polarization radar, which is suited for diverse polarimetric applications including ship detection and classification. The dual polarized antenna allows to transmit one single but selectable polarization (H or V) and receive simultaneously both H and V polarization. Compared to single-channel systems, the multi-channel radar polarimetry is one of the advances in SAR imagery, that has demonstrated its usefulness through its numerous decomposition techniques, in various applications, such as agriculture, oceanography or maritime surveillance. Traditional multi-polarization data includes two main SAR imaging modes: linear quad-polarization (i.e. fully polarimetric data) and dual-polarization. Even though the quad-polarization data provides a larger amount of information on SAR targets than singleor dual-polarization modes for current SAR sensors, induces a lower availability of such data. Classical quad-polarization modes imply high resolutions systems but reduced swath widths. This makes such data less suited for maritime surveillance applications, that usually imply wide area surveillance. The Sentinel-1 sensor can acquire systematically data in dual-polarization modes with large swath widths. Thus, it can compensate the quad-polarization mode disadvantages, with the compromise of providing a lower amount of information (in terms of resolution). Vessels imaged by such sensors, may have distinctive polarisation signatures, which reflect with different intensities depending on the polarization mode. Thus, the use of more than one type of polarisation channel may provide additional information in a complete SAR vessel detection chain. Several polarimetric decompositions, originally developed for quad-polarization data, were adapted for the dual polarization case [18, 51]. In this study, we assess the use of different polarimetric decompositions for a more accurate target representation, in comparison to single channel SAR images. Usually, single channel detectors rely on the amplitude or intensity images. The Sentinel-1 sensor provides both amplitude and phase data for its both polarization channels in the Stripmap and TOPSAR modes. Compared to previous SAR sensors with similar characteristics (Envisat, ERS-1 or RS-1/2), the availability of complex data for the Sentinel-1 ScanSAR modes (TOPSAR) represents an advance in SAR imagery from which diverse applications may benefit. As demonstrated in 3, the use of complex data for target refocusing, presents a benefit for characterizing ship signatures.

In this chapter, we aim at demonstrating the benefits of using Sentinel-1 complex and dual-polarimetric data for maritime surveillance applications. Firstly, the individual use of each polarimetric channel is demonstrated by using the automatic SAR-AIS detection chain, proposed in Chapter 2. Additionally, the fusion of detection results between the two polarimetric channels is considered. Then, the fusion of both polarization channels before the detection step is considered. For this, several signal/image processing techniques are employed, depending on whether the data are complex or not. When handling amplitude data, we propose to employ a method based on the generalized temporal moments [90], in order to fuse the information of both polarization channels. If dealing with complex data, the coherence coefficient or target dual-polarimetric decompositions, which may provide additional information in comparison to single channel imagery, are employed. Several experimental case studies, make it possible to demonstrate the effectiveness of each technique and compare their utility in SAR ship detection processing chains.

4.2 Evaluation of Sentinel-1 dual-pol data with classical single channel detection algorithms

Before assessing the contribution of using dual polarization data for SAR vessel detection, we evaluate individually the detection performances obtained on each polarization channel. To this end, we employ the SAR-AIS systematic detection methodology presented in Section 2.2.2. Experiments are conducted with two datasets containing Sentinel-1 TOPSAR images acquired in both the IW and EW modes. The datasets are available in the VV/VH dual polarization mode, which is used by default for Sentinel-1 maritime surveillance applications. Table 4.1 provides a summary of characteristics corresponding to each dataset.

A point of interest is the comparison of the Sentinel-1 results with detection performances obtained over datasets acquired by different SAR sensors. Therefore experiments conducted on Radarsat-2 (RS2) and CosmoSkymed (CSK) datasets and presented in Section 2.4.1 of Chapter 2, are recalled in this Section. Given that for these datasets only single polarization images were available, we firstly evaluate the detection performances of the co-pol(VV) Sentinel-1 datasets, in order to be consistent with the other datasets.

Dataset	Resolution	Polarization	Number	Frequency
(number of images)	$(rng \times az) [m]$		of looks	band
S1-A Extra Wide Swath (35)	50×50	VV/VH	3	С
S1-A Interferometric Wide Swath (20)	20×22	VV/VH	5	С

Table 4.1 – Sentinel-1 SAR Datasets characteristics



Figure 4.1 – Receiver operating characteristic–ROC curves, performance comparison by datasets containing images from several sensors with different modes of acquisition.

4.2.1 Global detection performances for co-polarization SAR images

For analyzing the overall detection performances, we use the Receiver Operating Characteristic (ROC) curves, generated with a set of different detection thresholds. For the desired PFA we give values from 10^{-3} to 10^{-16} and the plot the ROC curves. Figure 4.1 shows the detection results obtained on our different datasets. We can observe that Sentinel-1 datasets provide better global results than RS2 and CSK. For Sentinel-1 IW giving the best detection rates, the higher resolution is clearly a benefit allowing to detect small size ships which are not visible at a coarser resolution. However we notice the false alarm probability for the IW mode is greater than for the other modes, probably originating from image artefacts, as azimuthal ambiguities or open water ambiguities (e.g. rain cells), which are also more prominent at high resolution.

Comparing datasets having almost the same resolution, we notice the Sentinel-1 EW mode gives slightly better performances than RS-2 ScanSAR Narrow dataset, even if the latter contains HH polarization data which is supposed to be better suited for ship detection due to a higher ship–sea contrast. As seen in Section 2.4.3, the RS-2 ScanSAR Narrow dataset, is affected by its proper characteristics (high percentage of low incidence angles values), that explain its relatively low performances. Compared to RS-2 ScanSAR Wide and CSK with same VV polarization, but lower resolution, the Sentinel-1 EW performances remain superior probably due to its higher resolution.

The very overall conclusions that can be drawn from this short analysis are as follows. The IW datasets yields the best overall detection capabilities. For the datasets of lower resolution than IW but same VV polarization the EW gives slightly better performances than the RS-2





Figure 4.2 – (a) ROC curves for the Sentinel-1 IW dataset. VV and VH detectors fusion with logical operators. (b) Effective Probability of detection - AND operator (c) Effective Probability of detection - OR operator.

and CSK datasets. This kind of analysis represents an important requisite in validating the use of data for systematic monitoring of the maritime environment.

4.2.2 Fusion of dual-polarization ship detection results

Since the Sentinel-1 datasets contain dual polarization images (VV/VH), detection performance analysis between the channels themselves and of their fusion is also considered. Generally, within co-polarization SAR images, the sea clutter backscattering is represented with high energy values. For the cross-polarization channel the ocean clutter is of very low energy values, being comparable to instrument noise floor. Thus, the signal to clutter ratio is lower for the cross-polarization channel, making this type of data better suited for ship detection. The VV polarization channel allows a better observation of the sea surface. The availability of dual VH and VV polarization products over ocean will thus allow to carry out a more efficient integrated maritime security service. For instance, performing the monitoring of oil spills and illegal discharges with mixing sea surface analysis and vessel detection.



Figure 4.3 – (a) ROC curves for the Sentinel-1 EW dataset. VV and VH detectors fusion with logical operators. (b) Effective Probability of detection - AND operator (c) Effective Probability of detection - OR operator.

Results illustrating the polarization influence on the detection for the IW and EW datasets are showcased in Figures 4.2 and 4.3, respectively. We notice that cross-pol polarization (VH) achieves the best detection capabilities, confirming that target-clutter ratio is higher for the cross polarization. For the IW dataset, if we compare the VV/VH performances at the same detection rate we observe that false alarm rate remains higher for the VV channel, no matter the value of P_{d-eff}^{AIS} . On the contrary, for the EW dataset, the range of the effective false alarm is lower for the VH channel, and its corresponding values are lower for then VV channel. Nevertheless, the detection rate remains superior for VH, no matter the value of P_{d-eff}^{AIS} .

As the SAR-AIS detector behaves differently depending on the polarization channel, the fusion of their results may be considered. In this section the detection results of the two polarization channels, are mixed with logical operators. A logical AND operator makes it possible to retain common targets and eliminate false alarms, while for the OR operator, all targets are retained with compromise of joining also all false alarms. This kind of merging can be used to verify if the results obtained on different polarization channels are complementary.

Figures 4.2 and 4.3 give the merging results with logical AND/OR operators. The fusion is performed for a set of detection threshold values, corresponding to a desired PFA that ranges

from 10^{-3} to 10^{-16} . We notice that for both IW and EW datasets, the fusion of VV and VH detection reports with a logical OR, results in almost same detection rates as for the VH channel. In addition, the number false alarms is higher than for the individual detector, for the same values of P_{d-eff}^{AIS} . Therefore, the corresponding detection performances of this fusion type, remain limited, being comparable with those of the cross-polarization channel. If we consider the logical AND fusion of VV and VH results, we notice that the detection rates are almost the same as for the co-polarization channel. The false alarm rates are slightly lower than the ones obtained separately on each polarization channel. Thereby, in order to use the channel fusion, a compromise between the detection rates, obtained for several threshold values of the individual channel detections, are given. This kind of representation may be useful in choosing the input parameters for either the individual channel detector or their fusion. As mentioned above, we notice that the AND logical operator presents similar results with the VV channel, while the logical OR operator is similar with the VH detection. From this we conclude that the detections obtained separately on the two polarization channels are not complementary.

4.2.3 Influence of Key Parameters on the Detection Rate

As explained in Section 2.4.3, the statistical analysis of detection performances depends on different key parameters, such as SAR imaging and processing characteristics or meteorological conditions. The influence of the incidence angle, wind speed and vessel length is assessed in the following. For all these key parameters, we determine the detection rates for the co- and cross-polarization channels.

The **incidence angle** is a relevant parameter for ship detection algorithms, knowing that low incidence angles are favorable to ocean backscattering, while larger values reduce it and increases therefore the ship Radar Cross Section (RCS). As shown in Figure 4.4(a), for the IW data the incidence angle usually takes values in the domain: $[30^{\circ}, 45^{\circ}]$. Though for medium to high values, the incidence angle has an insignificant impact on ship detectability. This is confirmed by the very small variation of the detection rate with the incidence angle showcased in Figure 4.4(b). For the EW dataset, the incidence angle values range in a wider domain $([20^{\circ}, 45^{\circ}])$, as showcased in Figure 4.5 (a). For the VV channel, we notice that the detection rates are influenced by the incidence angle values. Usually, for co-polarization, the ocean clutter decreases with the increase of the incidence angle. This is in accordance with the increase of the detection rates with increasing incidence angles, as shown in Figure 4.5 (b). Instead, the crosspolarization clutter level is lower in comparison to co-polarization. Therefore, the detection rates, are slightly dependent to the incidence angle variability as we can notice Figure 4.5 (b).

The wind speed also impacts the detection capabilities, the increase of wind speed values implying a decrease of the detection rate. Ancillary wind speed information, colocated and interpolated to the SAR image grid, is employed in this study. Figures 4.4(c) and 4.5(c) give the wind speed distribution over IW and EW datasets. For the IW dataset, we observe from Figure 4.4(d) that for low wind speed values, P_{d-eff}^{AIS} varies between 0.8 and 1, which are close to the best global performances over this dataset. As expected, P_{d-eff}^{AIS} decreases with higher wind speed values. Similar conclusions may be drawn from Figure 4.5(d), for the EW dataset. For both datasets the detection rates are lower for the VV polarization channel, no matter the wind speed values.

The detection rate depends strongly on **ships size**, certain ships with a prominent signature can be detected in SAR images and others not, depending on their size with respect to images spatial resolution. We assume that for the IW images with a resolution of 20m, only small size vessels can be difficultly detected. Figure 4.4(f) gives the detection rate depending on ships length, showing that for ship lengths under 50m the detection probability decreases. We notice



Figure 4.4 – Distribution of incidence angle (a,b), wind speed (c,d), ship length (e,f) over the IW dataset, and their corresponding detection rates, Gaussian detector ($PFA = 10^{-7}$).

that the VH polarization achieves better performances than VV, for the detection rate of small vessels. For the latter polarization mode, small ships are less visible due to its low target-clutter ratio characteristics. We remark that for larger length ships (over 100m) detection capabilities are not impacted by the polarization, being identical for both channels. For the EW images, with a resolution of 50m, the detection rates are decreasing for ship lengths under 50m, as shown in Figure 4.5(f). The detection rates are lower for the VV polarization, for almost the ship lengths. Only for very high ship lengths (above 300m), the detection rates of the VV channel are comparable to the VH channel.

Validating the detection performances depending on different characteristics, such as SAR imaging and processing characteristics or meteorological conditions, is an important issue to be considered for ship monitoring. Analyzing the detection capabilities with respect to the used dataset is valuable for operational applications, in order to chose the most appropriate type of data for different applications.



Figure 4.5 – Distribution of incidence angle (a,b), wind speed (c,d), ship length (e,f) over the EW dataset, and their corresponding detection rates, Gaussian detector ($PFA = 10^{-7}$).

4.3 Fusion of the two-polarization channels before the detection step

While in the previous section the detection step was performed independently on each polarization channel, we introduce in the current section several methodologies, that make it possible to first merge the two images and then perform the detection. Several studies have considered the use of dual polarimetric data in ship detection techniques, either for complex or only amplitude images [9, 18, 20, 38, 117].

4.3.1 Amplitude/Intensity data

When only amplitude (or intensity) data is available, one possibility would be to use the SPAN technique, that implies to sum the two polarization channels and then apply the detection [38, 120]. Another technique supposes to fuse the two channels by multiplying them [20]. In this study, we propose to employ the generalized temporal moments for characterizing the joint information between the two polarization images. This approach was proposed in [90] for performing an automatic change detection with SAR time series.

Generalized means (Hölder) - theoretical approach: The generalized means also known as Hölders mean, represent a generalization of classical Pythagorean means. The Hölder mean, of two random variables x and y, taking values in \mathbb{R}^+ , is given by:

$$M_p(x,y) = \begin{cases} \left(\frac{x^p + y^p}{2}\right)^{\frac{1}{p}}, & p \in \mathbb{R}^*\\ \sqrt{xy}, & p = 0 \end{cases},$$
(4.1)

where the exponent p represents the mean order. Depending on its value, $M_p(\cdot, \cdot)$ will correspond to elementary mean values such as the harmonic, geometric, arithmetic and the quadratic (or root mean square) means for p = -1, 0, 1, 2. Several studies have treated the generalized means [14,26,110], allowing to conclude that $M_p(\cdot, \cdot)$ is a monotonically non-decreasing function with respect to p:

$$M_{-\infty}(x,y) = \min(x,y) \le \cdots M_{-p}(x,y) \cdots \le M_{-1}(x,y) \le M_0(x,y) \le M_1(x,y) \le \cdots$$

$$\cdots M_p(x,y) \cdots \le M_\infty(x,y) = \max(x,y).$$
(4.2)

Herein we refer to the (x, y) pair as the amplitude of the dual polarization channels. For datasets available in VV/VH polarization mode, for instance, we shall have the (A_{VV}, A_{VH}) pair. We consider their geometric and quadratic mean, which are given by

$$\begin{cases} M_0 = \sqrt{xy} \\ M_2 = \sqrt{\frac{x^2 + y^2}{2}} \end{cases} .$$
 (4.3)

In [90], the (M_0, M_2) scatter plot representation is interpreted as the joint distribution between M_0 and M_2 . The joint probability density function (PDF) of (M_0, M_2) is determined considering the joint distribution of (x, y). In our approach, the parameters corresponding to the distribution of (x, y) are estimated considering only clutter samples. This procedure will lead to a $p(M_0, M_2)$ that only predicts the sea clutter, without the ship targets. Then, the theoretical PDF of (M_0, M_2) is compared to the (M_0, M_2) scatter plot in order to detect the ship samples.

We consider that x and y are statistically independent. Therefore, their joint PDF is given by the product of the PDF of x and y:

$$p_{XY}(x,y) = p_X(x)p_Y(y).$$
 (4.4)

The clutter samples employed to estimate the parameters $p_X(x)$ and $p_Y(y)$, are extracted from the amplitude data of the dual polarization channels. For this, a coarse detection of ship samples is firstly required. When dealing with amplitude data from SAR single-look images, the Rayleigh distribution is usually employed to characterize the clutter distribution and therefore $p_X(x)$ and $p_Y(y)$. For SAR multi-look images, the intensity images are supposed to be Gamma distributed. Once determined the joint PDF of the (x, y) pair, the PDF of (M_0, M_2) is defined by using the inverse function theorem [89]:

$$p(M_0, M_2) = 2 \frac{p_{XY}(x_1, y_1)}{|J_F(x_1, y_1)|}.$$
(4.5)

 x_1 and y_1 represent the solutions obtained by the inversion of the system given in (4.3):

$$\begin{cases} x_1 = \frac{M_0^2}{\sqrt{M_2^2 + \sqrt{M_2^4 - M_0^4}}} \\ x_2 = \sqrt{M_2^2 + \sqrt{M_2^4 - M_0^4}} \end{cases} .$$
(4.6)

For the system inversion, the Jacobian determinant $J_F(\cdot, \cdot)$, computed in (x_1, y_1) is also required:

$$J_F(x_1, y_1) = \begin{vmatrix} \frac{\partial M_0(x,y)}{\partial x} & \frac{\partial M_0(x,y)}{\partial y} \\ \frac{\partial M_2(x,y)}{\partial x} & \frac{\partial M_2(x,y)}{\partial y} \end{vmatrix}_{x=x_1,y=y_1} = \begin{vmatrix} \frac{y}{2\sqrt{xy}} & \frac{x}{2\sqrt{xy}} \\ \frac{x}{2\frac{x^2+y^2}{2}} & \frac{y}{2\frac{x^2+y^2}{2}} \end{vmatrix}_{x=x_1,y=y_1}$$
(4.7)

If we consider the particular case when x and y are Rayleigh distributed, the joint PDF of (M_0, M_2) becomes:

$$p(M_0, M_2) = 2 \frac{F_{\mu_x, \sigma_x}(x_1) F_{\mu_y, \sigma_y}(y_1) + F_{\mu_x, \sigma_x}(y_1) F_{\mu_y, \sigma_y}(x_1)}{|J_F(x_1, y_1)|}.$$
(4.8)

The parameters of F_{μ_x,σ_x} and F_{μ_y,σ_y} are determined from clutter samples extracted for the SAR amplitude images. As mentioned above, the joint PDF of (M_0, M_2) will only represent the sea clutter distribution. Very low values of $p(M_0, M_2)$ will therefore correspond to samples that are not distributed according to the clutter distribution (i.e. target pixels). An iso-curve of the joint probability density $p(M_0, M_2)$ can thus be employed for delimiting the clutter samples of targets in this kind of representation. We can therefore assume the following test of hypothesis:

$$\begin{cases} \mathcal{H}_0 : p(M_0, M_2) \ge \tau_{Holder} \\ \mathcal{H}_1 : p(M_0, M_2) < \tau_{Holder} \end{cases}, \tag{4.9}$$

where τ_{Holder} represents the value defining the clutter-target delimiting iso-curve. Within this detection hypothesis, the false alarm probability can be defined as the area of $p(M_0, M_2)$ lower than τ_{Holder} :

$$PFA_{Holder} = \iint_{p(M_0, M_2) < \tau_{Holder}} p(M_0, M_2) dM_0 dM_2.$$
(4.10)

Generalized means (Hölder) - experimental assessment: In the following paragraph, we evaluate the generalized means detection methodology on SAR real data acquired by the Sentinel-1 sensor. Several patches are therefore extracted from an amplitude single-look S-1 IW image, in the VV/VH dual polarization mode. Such type of data is supposed to be Rayleigh distributed. The two polarization amplitude images usually present different energy levels. In order to properly mix two image patches by using the generalized means, the data should be normalized for bringing all variables into proportion with one another. To this end, we normalize each image patch by its corresponding standard deviation value.

Firstly, we consider an image patch containing only sea clutter information. The corresponding sample distribution of both polarization channels are given in Figure 4.6. We notice that the real data distributions fit properly the theoretical Rayleigh distributions of parameters estimated from the clutter samples. The maximum-likelihood estimation (MLE) is used to determine the statistical's model parameters. The same parameters are employed to determine the (M_0, M_2) joint probability defined by (4.8). Figure 4.7 gives the joint distribution function corresponding to this first example. For the M_0 and M_2 variables which were employed to compute $p(M_0, M_2)$, two 1-d arrays ranging from 0 to $\max(M_0^{xy}, M_2^{xy})$ were generated. We denote by M_0^{xy} and M_2^{xy} the geometric and quadratic means, directly computed from the SAR image patches. From Figure 4.7(a) which illustrates the shape of the joint PDF $p(M_0, M_2)$, we notice that all values of $p(M_0, M_2)$ are situated above the first angle bisector (i.e. line of equation $M_0 = M_2$), accordingly to relation (4.2). As mentioned in the above section, an iso-curve drawn in the $p(M_0, M_2)$ domain makes it possible to fix a threshold between clutter and target samples. In Figure 4.7(a) we illustrate an iso-curve that ensures a PFA_{Holder} of approximately 10^{-4} .



Figure 4.6 – Clutter distribution of two clutter patches extracted from an amplitude Sentinel-1 IW image in the VV and VH mode. Both image patches are supposed to follow Rayleigh distribution.



Figure 4.7 – (a) - (M_0, M_2) joint density function, generated from the parameters estimated from SAR image samples, presented in Figure 4.6. The iso-curve (in magenta) corresponds to a threshold value that ensures a PFA_{Holder} value of approximately 10^{-4} . (b) - (M_0, M_2) scatter plot of the clutter samples. The $p(M_0, M_2)$ predicted from clutters samples corresponds to the area under a threshold value that ensures a PFA_{Holder} value of approximately 10^{-4} .

Figure 4.7(b) gives the scatter plot corresponding to the clutter samples. We notice that the majority of points are situated under the curve that ensures a false alarm probability of 10^{-4} . However, knowing that all (M_0^{xy}, M_2^{xy}) points represent target clutter samples, an iso-curve that allows to label them in the \mathcal{H}_0 hypothesis is required. For this, a threshold value that ensures a false alarm probability of 10^{-8} is required. The corresponding (M_0, M_2) representation can be observed from Figure 4.7(b). The dynamical range of the theoretical $p(M_0, M_2)$ (generated from the parameters estimated from SAR image samples) has been changed in order to highlight the area defined by the clutter samples.

Figure 4.8 presents a second case study of an image patch containing a cargo ship of medium size (length × width = 89m × 12m). From the corresponding VV and VH image patch, we notice that the ship signature is represented with a backscattering level superior to the sea clutter for both polarization channels. In order to determine the parameters corresponding to the F_{μ_x,σ_x} and F_{μ_y,σ_y} that are employed in the estimation of $p(M_0, M_2)$, only clutter samples are required. Therefore, a coarse detection of ship samples is firstly effectuated. For this, we employ


Figure 4.8 – Image patches extracted from a S1 IW image in the VV (a) and VH (b) polarization mode. The target visible in the image patch represents a cargo vessel with following characteristics (extracted from AIS data): length = 89m, width = 12m. (c) (M_0, M_2) joint density function, generated from the parameters estimated from SAR image samples, presented in (a) and (b). The points (red circles), that correspond to a $p(M_0, M_2)$ lower than a certain threshold value ensuring a PFA_{Holder} value of approximately 10^{-8} , represent the ship samples, highlighted in (d).

the universal threshold defined by relation (2.8). From the estimated Rayleigh distribution parameters we obtain the joint PDF $p(M_0, M_2)$ which is illustrated in Figure 4.8(c). The scatter plot of the geometrical and quadratic means corresponding to SAR image patches, is also drawn in this figure. We notice that the predicted $p(M_0, M_2)$ allows to distinguish between clutter (labelled with dark cross symbols) and ship samples (labelled with red circle symbols). The dynamical ranging of $p(M_0, M_2)$ was chosen in order to highlight the area under the \mathcal{H}_1 hypothesis, that ensures a PFA_{Holder} value of approximately 10^{-8} . This region contains the points corresponding to ship samples, which are also highlighted in the M_2 image illustrated in Figure 4.8(d).

Figure 4.9 presents another case study, which contains two fishing vessels. Their small size coupled with the resolution of the S1 IW mode makes their signatures to be hardly distinguishable with respect to the sea clutter. The purpose of this example is to examine whether the (M_0, M_2) representation allows to detect or not very small size targets. The corresponding representation of the predicted $p(M_0, M_2)$ together with the scatter plot of the geometrical and quadratic means computed from SAR image patches, is given in Figure 4.9(c). As for the previ-



Figure 4.9 – Image patches extracted from a S1 IW image in the VV (a) and VH (b) polarization mode. Two targets are visible in the image patch, representing fishing vessel of same size: length × width = 17×6 m (extracted from AIS data). (c) (M_0, M_2) joint density function, generated from the parameters estimated from SAR image samples, presented in (a) and (b). The points (red circles), which correspond to a $p(M_0, M_2)$ lower than a certain threshold value ensuring a PFA_{Holder} value of approximately 10^{-8} , represent the ship samples highlighted in (d).

ous example, the dynamical ranging of $p(M_0, M_2)$ highlights the area under the \mathcal{H}_1 hypothesis, ensuring a PFA_{Holder} of approximately 10^{-8} . While only one false alarm was identified among the same patch, we notice that the points belonging to this areas mainly correspond to the ship samples.

The study cases presented in Figures 4.8 and 4.9 showcased the Hölder detection within two particular image patches containing medium and small size vessels. The purpose of the following example is to assess the behavior of the proposed Hölder detector applied to an image patch containing different types of targets. The image patch given in Figure 4.10 includes three large size vessels, that are noticeable in both VV and VH polarization channels, and two vessels of medium and small size, that are less visible within the VV image. Figure 4.11(a) gives the corresponding (M_0, M_2) scatter plot representation. Due to the large number of ship samples with different energy levels, the shape of the $p(M_0, M_2)$ distribution is hardly interpretable from a first analysis. However, a detailed analysis of the area separation between the clutter and ship points permits to conclude that (M_0, M_2) joint distribution preserves its behavior. The points detected within the (M_0, M_2) area corresponding to false alarm rate of approximately



Figure 4.10 – Patch extracted from a Sentinel-1 IW image available in the VV/VH dual polarization. The image patch contains several bright targets representing vessels of different size. Their corresponding details are extracted from AIS data.



Figure 4.11 – (a) (M_0, M_2) joint density function, generated from the parameters estimated from SAR image samples, presented in Figure 4.10. The points (red circles), which correspond to a $p(M_0, M_2)$ lower than a certain threshold value ensuring a PFA_{Holder} value of approximately 10⁻⁸, represent the ship samples highlighted in (b).

 10^{-8} , are mainly target samples. All targets were detected, no matter their size. Nevertheless, some false alarms were also detected. The false alarms are represented by a very low number of pixels in comparison with the large size vessels, but comparable with the number of pixels detected for small size ships. This makes it difficult to automatically distinguish between false alarm and small size vessels, within the result obtained by the amplitude Hölder detection. In the following section, we assess the use of different polarimetric parameters that employ both the amplitude and phase information of the polarization channels and could possibly improve the small vessel size and false alarm issue.

4.3.2 Complex data

As mentioned in section 4.1, an important characteristic of the Sentinel-1 TOPSAR mode is the availability of complex images (i.e. amplitude and phase). The complex SAR images can lead to different polarimetric parameters. In this section, several polarimetric parameters (the coherence coefficient or the $(H, \overline{\alpha})$ incoherent decomposition) are employed to transpose the information contained in the two polarization channel into a singular domain. An intercomparison between the polarimetric parameters permits to analyse whether, in the polarimetric decomposition domain, the detection procedure is facilitated or not.

Dual-polarization complex coherence coefficient: The complex coherence, also known as the correlation coefficient, is one of the simplest modes to fuse the two polarization channels and may be an important source of information in representing the targets with a an improved signal to clutter ratio. The complex coherence between two complex signals S_a and S_a is defined as follows: [66, 111]:

$$\rho_{\rm coh} = \frac{E\left[S_a S_b^*\right]}{\sqrt{E\left[|S_a|^2\right]}\sqrt{E\left[|S_b|^2\right]}},\tag{4.11}$$

where $E[\cdot]$ represents the statistical expectation. S_a and S_a represent the components of the corresponding dual-polarization SAR scattering vector. For the data acquired by the Sentinel-1 sensor, two linear polarization cases are considered: vertical emission with vertical and horizontal reception (VV,VH) and horizontal emission with horizontal and vertical reception (HH, HV). Their corresponding scattering vectors are expressed as:

$$k_{VV/VH} = [S_{VV} S_{VH}]^{\mathsf{T}}$$

$$k_{HH/HV} = [S_{HH} S_{HV}]^{\mathsf{T}}.$$
(4.12)

Numerically, the estimation of the coherence is given by the following relation:

$$\hat{\rho}_{\rm coh} = \frac{\langle S_a S_b^* \rangle}{\sqrt{\langle |S_a|^2 \rangle} \sqrt{\langle |S_b|^2 \rangle}},\tag{4.13}$$

where $\langle \cdot \rangle$ represents the ensemble averaging. Usually, a boxcar filter is employed for this operation. Pixels within a sliding of a given size $w \times w$, are therefore employed for the sample coherence estimation. In this study we take interest in the magnitude of the coherence, as an indicator of the correlation effects between the two polarization channels. In [76], it has been demonstrated that correlation between the two co-polarization and cross-polarization represents a interesting measure for assessing the presence of man-made metallic targets within the sea clutter background. Supposing that the sea clutter is a natural distributed target (extended target) and under the hypothesis of reflection symmetry, the correlation between co-and cross-polarized channels is assumed to be zero. Therefore, in the case of sea clutter, the expected values of the coherence magnitude are close to zero. Nevertheless, when dealing with

the presence of man-made targets (i.e. ships), the reflection symmetry is no longer valid, implying expected values of the coherence significantly larger than for the sea clutter. We therefore assume, that within the coherence representation, the target to clutter ratio will be higher than for each polarization channel independently considered.



Figure 4.12 – Coherence between the VV and VH channels for the image patch given in Figure 4.8. Several window sizes $(k \times k)$ were employed for the averaging operation (i.e. boxcar filter).

For computing the coherence parameter we employ the VV/VH image patches showcased in Figure 4.8 (a), (b). Their corresponding complex data is used for computing the polarimetric parameters. Figure 4.12 gives the coherence coefficient between the two complex SAR image patches, for several window sizes employed for the boxcar filter. We notice that, for small window sizes, the coherence is overestimated over the clutter area due to the an insufficient number of samples associated to the window size. In such cases, it is difficult to distinguish between targets and sea clutter within the coherence representation. For higher window sizes, the coherence values corresponding to the target are highly superior to the ones of sea clutter. However, the target to clutter coherence ratio decreases with the increase of the window size. This is due to the fact, that the larger the window size is, the more influenced is the target coherence by a larger number clutter samples. Considering the high target-clutter observed within the coherence domain, a simple thresholding operation, directly related to the coherence coefficient may permit to detect ship samples. The threshold values must be defined with respect to boxcar filter window size.

Dual-Polarimetric $(H, \overline{\alpha})$ **Decomposition:** Polarimetric decompositions are mainly developed to interpret the polarimetric radar measurements and relate it to basic scattering measurements. Such techniques are generally classified into coherent and incoherent decompositions. While the incoherent decompositions are based on the incoherently based covariance or coherency matrices, the coherent decomposition is based on the scattering matrix. In this study, we focus on an incoherent decomposition based on eigenvalues and eigenvectors, known as the $(H, \overline{\alpha})$ decomposition or the Cloude and Pottier decomposition, which was firstly introduced by [19]. A dual polarization version of this decomposition was introduced by [18].

The $(H, \overline{\alpha})$ decomposition consists in eigenvalue decomposition of the coherence matrix defined as follows for the dual polarization case:

$$C_{COH} = \begin{bmatrix} < |k_1|^2 > < k_1 k_2^* > \\ < k_2 k_1^* > < |k_2|^2 > \end{bmatrix},$$
(4.14)

where, $k_1 = S_a + S_b$ and $k_2 = S_a - S_b$. Since the coherence matrix is Hermitian, it can be diagonalized by using a transition matrix $[\overline{U}]$:

$$C_{COH} = [\bar{U}] \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} [\bar{U}]^{*T} = \begin{bmatrix} \cos\alpha & \sin\alpha e^{j\delta} \\ \sin\alpha e^{j\delta} & \cos\alpha \end{bmatrix} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \begin{bmatrix} \cos\alpha & \sin\alpha e^{j\delta} \\ \sin\alpha e^{j\delta} & \cos\alpha \end{bmatrix}^{*T}.$$
 (4.15)

Based on this decomposition, Cloude and Pottier [19] define three parameters: entropy, scattering angle and anisotropy. For the dual-polarization case, we take interest in the first two parameters.

The entropy defines the degree of statistical disorder of each reflected wave and is given by:

$$H = -P_1 \log_2 P_1 - P_2 \log_2 P_2 \tag{4.16}$$

where, $P_i = \frac{\lambda_i}{\lambda_1 + \lambda_2}$ corresponds to the pseudo-probabilities obtained from the eigenvalues λ_i . The entropy H values vary between 0 and 1. If H is of low value it means that the backscattering measurements are fully polarized, containing a pure target. However, when the H values increase, the backscattering measurements become unpolarized and a mixture of different point scatterers occurs. When the backscattering measurements are fully unpolarized, it is impossible to extract a dominant point scatterer and the measurements represent a random noise process (H=1). Therefore, for our particular application, we expect to have high entropy values over the sea clutter areas and low entropy for ship samples .

The scattering angle is defined by:

$$\overline{\alpha} = P_1 \alpha + P_2 (\frac{\pi}{2} - \alpha). \tag{4.17}$$

The range of the $\overline{\alpha}$ parameter varies between 0 and $\pi/2$. $\overline{\alpha}$ angles of 0° correspond to surface scattering under physical optics to the Bragg surface model. For angles of 45°, dipole scattering or single scattering by a cloud of anisotropic particles, are commonly associated. Finally, angles of 90° correspond to double bounce scattering mechanisms between two dielectric surfaces or dihedral scatter from metallic surfaces. All these theoretical aspects were usually demonstrated with quad-polarization data. The purpose of this study is to examine whether the dual-polarization parameters H and $\overline{\alpha}$ behave in the same manner.

The entropy H and scattering angle $\overline{\alpha}$ are also dependent of averaging operation employed for computing the coherence matrix (4.14). Therefore, these $H/\overline{\alpha}$ also vary with respect to boxcar filter window size, as the coherence coefficient. As mentioned in theoretical part describing the entropy parameter, low values of entropy should correspond to pure point scatterers. Figure 4.13, illustrating the experimental for entropy parameter, showcases that low entropy values partially correspond to the target samples. However, some clutter samples have a similar low entropy, no matter the window size. Other point scatterers originating from the vessel, result in high entropy values, which are theoretically supposed to characterize a noise process. We therefore conclude that VV/VH polarimetric entropy parameter does not represent a relevant measure in distinguishing ship from clutter samples.

The results corresponding to the scattering angle $\overline{\alpha}$ are given in Figure 4.14. It can be noticed, that for small sizes of the boxcar filter window, the values of $\overline{\alpha}$ corresponding to ship sample are hardly discernible from the ones of some clutter areas. Instead, for larger window



Figure 4.13 – Entropy (eigenvalue analysis) between the VV and VH channels for the image patch given in Figure 4.8. Several window sizes $(k \times k)$ were employed for the averaging operation.



Figure 4.14 – Alpha (eigenvalue analysis) between the VV and VH channels for the image patch given in Figure 4.8. Several window sizes $(k \times k)$ were employed for the averaging operation.

sizes, the ship signatures have a significant energy level with respect to sea clutter, within the the $\overline{\alpha}$ domain. The behaviour of this parameter is similar to the one of the coherence coefficient and may also represent a prospective future direction for performing a simple thresholding operation. However, $\overline{\alpha}$ is more computationally involved than the coherence coefficient.

Degree of polarization: The degree of polarization is a parameter that allows to quantify the weights of the polarized and unpolarized components in the composition of a wave. In [101] a generalized definition of Degree of Polarization (DoP) is given. The Stokes vector for a generic transmit polarization i (either V or H for the linear polarization case) and a linear receive polarization is defined as follows:

$$g_{0} = \langle |E_{iV}|^{2} + |E_{iH}|^{2} \rangle$$

$$g_{1} = \langle |E_{iV}|^{2} - |E_{iH}|^{2} \rangle$$

$$g_{2} = 2\Re \langle E_{iV} E_{iH}^{*} \rangle$$

$$g_{3} = 2\Im \langle E_{iV} E_{iH}^{*} \rangle.$$

$$(4.18)$$

The corresponding generalized degree of polarization takes the following form:

$$DoP = \frac{\sqrt{g_1^2 + g_2^2 + g_3^2}}{g_0}.$$
(4.19)



Figure 4.15 – Degree of polarization between the VV and VH channels for the image patch given in Figure 4.10. Targets with a pronounced signature for both polarization channels are represented with a high DoP value, while targets only visible for one polarization channel (VH, for this example) correspond to low DoP values.

The range of DoP varies between 0 and 1, 0 corresponding to totally depolarized waves and 1 to fully polarized waves. In this study, we assess the use of DoP for linear dual polarized data for discriminating ship targets from sea clutter.

In order to demonstrate the usefulness of the DoP parameter, we apply it to image patch presented in Figure 4.10. We have purposely chosen this case study since it contains different size targets which have different representations according to the polarization channel. Compared to the coherence and $H/\overline{\alpha}$ decomposition, that do not preserve targets visible only within one of the polarization channel (usually small size vessels), the DoP presents an interesting advantage of maintaining these targets in its representation. As showcased in Figure 4.15, on one hand we notice that high and medium size vessels are represented by high values of the DoP which usually correspond to fully polarized waves. On the other hand, it may be observed that small size vessels, that are usually not noticeable in the VV channel, are equivalent to low values of the DoP. Based on this consideration, a detector employing two thresholds may be defined: one threshold for finding large DoP values, that correspond to ship visible in both polarization channels and a threshold that delimits low DoP values for discriminating vessels present only within one polarization channel.

In this section, several different polarimetric parameters were applied to study cases, in order to test their possible usage for ship detection algorithms. Several tests on lower size vessels (e.g. Figure 4.9) were tested. Nevertheless, their benefits remain limited due to the fact that small size ships are hardly visible within the VV channel. Therefore, their contribution to the coherence and $H/\overline{\alpha}$ parameters is insignificant. Because of this, these tests are not further documented. While the coherence coefficient and alpha scattering angle showed similar behaviors with an elevated target to clutter contrast, the entropy parameter did not result in a representation that allows to simply distinguish targets from sea clutter. The DoP allows to preserve small size targets that are visible only within one polarization channel. However, all these conclusions are the result of some case studies. A complete validation on several SAR images presenting different characteristics and environmental conditions is required. This would make it possible to establish whether these polarimetric parameters are suited for SAR ship detection chains.

4.4 Conclusion

In this chapter, we have assessed the use of dual polarization data for ship detection algorithms. The newly launched European satellite Sentinel-1 systemically acquires data in the dual polarization for both Stripmap and ScanSAR modes. Its corresponding ScanSAR modes have the advantage of providing large swath widths, presenting an increased interest for maritime surveillance applications. Furthermore, the data complex are available, which represents a novelty compared to previous civil SAR missions, acquiring data in the ScanSAR mode. It is therefore important to analyse the use of such kind of data for ship detection algorithms and determine if it brings a benefit with respect to classical ship detection algorithms designed for single polarization amplitude data.

Firstly, the evaluation of classical single channel detector applied to Sentinel-1 dual-pol data is presented. The classical CFAR algorithm together with the systematic methodology incorporating AIS data as ground truth, introduced in chapter 2, are employed to assess the detection results. From the obtained results we may remark that cross-polarization channel (VH) yields better detection performances than the co-polarization channel, for both the IW and EW modes of S-1. The fusion of detection results, obtained independently on each polarization channel, has also been considered. Nevertheless, its benefits remain limited, the VV and VH detection results not being complementary. The detection performances of the VV polarization mode were compared with the results obtained with the RS-2 and CSK datasets,

presented in chapter 2. This analysis permits to conclude that the S-1 IW dataset yields the best overall detection capabilities, probably due to its corresponding higher spatial resolution. For the datasets of lower resolution than IW but same VV polarization, the EW gives slightly better performances than the RS-2 and CSK datasets.

Several methodologies that make it possible to fusion the information contained in the dualpolarization channels were assessed in this chapter. Their corresponding pros and cons, were experimentally demonstrated with different case studies of image patches extracted from an S-1 IW image, available in amplitude and complex data. To fusion the amplitude data, we employed the generalized mean, known as Hölder means. The joint PDF between the geometric and quadratic means between the two polarization channels permits to simply threshold the vessel samples from the ones of the sea clutter. This methodology constitutes one major advantage with respect the basic adaptive detection algorithms: a sliding window, which is usually computationally involved, is not required. The polarimetric parameters introduced in this chapter showed an interesting representation, that could be useful for defining a ship detection hypothesis. The coherence coefficient and alpha scattering angle showed similar behaviors with an elevated target to clutter contrast. A threshold operation could be defined by employing these two polarimetric parameters. A comparison with classical adaptive detection algorithms is required, for validating such a method. From a computational point of view, the methodologies could present similarities since they both require a sliding window. The use of the degree of polarization (DoP) showed a particular interest, because its representation allows to preserve small size targets that are visible only within one polarization channel. A further investigation of the parameter is required to determine if it allows to detect targets with a less prominent signature, maintaining a reduced false alarm rate.

One major limitation of the assessment of the several methodologies fusing the two polarization channels, is their experimental validation with some case studies. A complete validation on several SAR images presenting different characteristics and environmental conditions is required in order to establish whether these methods are suited or not for SAR ship detection chains. The Sentinel-1 SLC data present a large number of false alarms due to inaccuracies of the product calibration or mosaicking, hindering thus the procedure of an automatic validation procedure, for the moment.



General Conclusions and Perspectives

Do not say a little in many words but a great deal in a few!

Pythagoras of Samos

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5.1 Conclusion

This research study has examined several novel methodologies that make it possible to improve the current performances of SAR ship detection chains. Such improvements are of great interest in a complete satellite vessel monitoring framework, which represents a key element for maritime surveillance systems. The work contribution presented in this thesis is divided into the following main parts:

A novel **non-parametric detection approach**, which has been applied for the first time in SAR vessel monitoring domain, is firstly presented. This model allows to fit more accurately the real data than methods based on traditional statistical distributions. To perform a rigorous evaluation of this approach, a comparison with two variants of the classical CFAR detector, based on the Gaussian and the Gamma distribution, is presented. Experimental results with large SAR datasets allow to perform a complete assessment. The datasets used in this study contain a large number of SAR images with thousands of corresponding AIS vessels positions.

For an effective and joint usage of both SAR and AIS data, a systematic methodology that permits to automatically **integrate AIS data flows** as a reliable ground truth is employed. Therefore, AIS data, collected from databases containing messages acquired by AIS shore-based stations, is modeled with respect to reception capabilities of such stations. This systematic method is used for counting correct detections and false alarms in order to determine the detection rate. Thus, this allows to perform an appropriate and consistent comparison of the SAR detectors.

The detection rates, which depend on different key parameters such as SAR imaging characteristics or meteorological conditions, were as well assessed in this study. This type of analysis makes it possible to define a predictive model of the detection performances. This model is valuable for operational applications, in order to chose the most appropriate type of data for different applications.

A new methodology, presented in this study, relies on the Fractional Fourier Transform (FrFT) tool and allows to perform **vessel refocusing from SAR SLC imagery**. A study about the effects of representing dynamical targets on SAR imagery, when processed with stationary based techniques, was initially carried out. The FrFT tool permits to compensate for

the moving target effects arising from along-track speed of moving targets. An intercomparison with a standard Doppler sublook Decomposition Method (SDM) is also employed. The applicability of both the FrFT and sub-look Decomposition method is verified using space-borne SAR data. A quantitative criteria assessment shows the effectiveness of these methods.

The azimuthal speed of moving targets can be determined by finding the optimal parameters of the FrFT and a **novel Short Time FrFT speed estimation approach** is proposed in this thesis. Several SAR STFrFT speed estimates corresponding to different targets are compared with results from the sub-look decomposition method and AIS validation data, in order to analyze the method's performances.

The use of **dual polarization** data for ship detection algorithms was also assessed in this thesis. Several methodologies that make fusion possible, before the detection step, between the information contained in the dual-polarization channels were proposed. When only amplitude data is available, the approach is based on the generalized mean (Hölder means). The joint PDF between the geometric and quadratic means between the two polarization channels permits to simply threshold the vessel samples from the ones of the sea clutter. For complex data, the possible usage of the following polarimetric parameters for the detection process was evaluated: coherence coefficient, $(H, \overline{\alpha})$ decomposition, and degree of polarization. The pros and cons of each approach permitting to mix two polarization images were experimentally assessed with different case studies. Some of these approaches showed particular representations of the vessel to clutter signal ratio, that could be useful for defining a ship detection hypothesis.

5.2 Future work

Potential future research studies that may follow up the work presented in this thesis are given next:

- 1. The classification step is of high importance in a complete SAR ship detection chain. However, our decision was to focus on the detection and signature characterization challenges only, thus the classification step is not addressed in this thesis. Due to the reduced level of details, simple classifiers are recommended for SAR vessels signatures from medium resolution images. A classifier with two classes qualifying the targets as reliable and non-reliable may be sufficient. At a higher resolution and with better detailed vessels signatures, a more complex classifier with several classes for the ship signature type may be used. For instance, a Support Vector Machines (SVM)-based classifier integrating information about the vessel itself (length, direction) as well as key parameters (incidence angle, wind speed or polarization type), may present interest for this issue.
- 2. To extend the one-by-one assessment impact of all the key parameters influencing the SAR detection capabilities, a joint analysis of all these parameters is required. For this, the SAR-AIS detection methodology should be applied to very large datasets and followed by a cross analysis of the obtained results should be performed. Such an analysis is valuable for operational services, allowing to select the most appropriate type of data for different applications in maritime surveillance systems.
- 3. The STFrFT speed estimates presented in this study showed high variance. To some extent, the errors of the azimuthal velocity estimates can be partially explained by the influence of the range acceleration term. A parametrical method with an explicit phase model, which incorporates all the kinematic terms, could allow to obtain a more accurate azimuthal velocity estimation.

- 4. To better estimate the motion effects of vessels, higher radar resolution would be required and represents possible future line of research. Ship signatures acquired in the Spotlight mode with a nominal resolution of about 1m should provide sufficient details for small vessels. The processing algorithm for Spotlight images is different from Stripmap images. The presence of eventual residual signals linked to target velocities should be analysed to determine whether the FrFT could be applied to this type of data.
- 5. Future investigation concerning the FrFT refocusing method applied to multi-polarization data could be of interest. Vessels imaged by multi-polarization SAR sensors could have distinctive polarisation signatures, which reflect with different intensities depending on the polarization mode. Such information may provide complementary details for a better characterization of the ship signature. Therefore, a method that allows to analyse or fusion the different polarimetric representations of a target within the FrFT domain deserves attention.
- 6. The availability of very high resolution SAR data imposes new constraints and challenges for current processing algorithms. In general, the high dimensions of SAR data requires iterative data processing on a succession of image patches leading to an increased computational effort. This aspect is even more important for very high resolution SAR images. In order to overcome this problem, the use of particular methods such as multiscale decompositions could be employed. It could be useful to perform the detection of high sized vessels at a reduced resolution level. Once detected, these targets could be eliminated and then an adaptive threshold algorithm, appropriately configured for small sized target, could be employed.

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SAR datasets

As mentioned in the introduction chapter 1, the experimental data employed in this thesis, is constrained by the type of data available at CLS. We mainly employed SAR images acquired by the Radarsat-2 and Cosmo SkyMed sensors. Moreover, during the last year of the PhD, we had the benefit to use SAR images acquired by Sentinel-1 sensor, which was launched in April 2014 and provides calibrated SAR images available since the end of 2014. The latter part of this study is thus focused on the use of Sentinel-1 images, presenting the advantage of being available in the dual polarization mode. Figures A.1 and A.2 give the geographical area coverage



(a) 200 RS-2 ScanSAR Wide images

(b) 40 RS-2 ScanSAR Narrow images



(c) 35 CSK ScanSAR Huge Region images

Figure A.1 – RS-2 and CSK: product area coverage.

of the SAR images employed for the experimental validation of the methodologies presented in Chapters 2 and 4. Table A.1 provides details of the sensor characteristics corresponding to each dataset.



(a) 20 S1-A Interferometric Wide Swath images

(b) 35 S1-A Extra Wide Swath images

Figure A.2 – Sentinel-1 datasets: product area coverage.

	Radarsat-2	Radarsat-2	Cosmo Skymed	Sentinel-1	Sentinel-1
	ScanSAR Wide	ScanSAR Narrow	ScanSAR HR	TOPS IW	TOPS EW
Resolution					
$(rng \times az) [m]$	$72.1-160 \times 100$	$37.7-79.9 \times 60$	100×100	20×22	50×50
Pixel spacing					
$(rng \times az) [m]$	50×50	25×250	50×50	10×10	25×25
Nominal scene size					
$(rng \times az) [km]$	500×500	300×300	400×400	250×250	410×410
Incidence Angle	20-49 (SCWA)	20-39 (SCNA)			
range [deg]	20-46 (SCWB)	31-47 (SCNB)	20-59	29-46	19-47
Polarization	VV	HH	VV	VV/VH	VV/VH
Number of looks	8	4	15	5	3
Acq. Start Date	2011/11	2011/04	2011/04	2014/10	2014/10
Acq. End Date	2013/04	2012/08	2011/11	2015/04	2015/04
Number of images	200 (90% SCWB)	40 (90% SCNA)	35	20	35
AIS targets	5900	1200	1300	300	800

Table	A.1 -	SAR	Datasets	characteristics
Table	A.1 –	SAR	Datasets	characteristics



Author Publications

- [A-1] Ramona Pelich, Nicolas Longépé, Grégoire Mercier, Guillaume Hajduch, and René Garello. "AIS-Based Evaluation of Target Detectors and SAR Sensors Characteristics for Maritime Surveillance". In: IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 8.8 (2014), pp. 3892 – 3901. DOI: 10.1109/JSTARS.2014.2319195.
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- [C-1] Ramona Pelich, Nicolas Longépé, Grégoire Mercier, Guillaume Hajduch, and René Garello. "Ship detection in SAR Medium Resolution Imagery for maritime surveillance: algorithm validation using AIS data". In: Proceedings of the IEEE International Geoscience and Remote Sensing Symposium. Quebec City, Canada, 2014, pp. 3690 –3693. DOI: 10.1109/IGARSS.2014.6947284.
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Résumé

L'imagerie Radar à Synthèse d'Ouverture (RSO) est fréquemment utilisée dans les applications de surveillance maritime, notamment en raison de son indépendance à la lumière du jour, aux nuages ou aux conditions météorologiques. Le travail de recherche mené dans cette thèse est consacré à la détection de navires et à la caractérisation de leurs signatures à partir de données acquises par différents capteurs RSO. Premièrement, nous avons évalué les performances des différents algorithmes de détection de navires basés sur un seuillage adaptatif. Ces algorithmes de détection sont basés sur diverses distributions statistiques de «fouillis de mer» et sont automatiquement évalués. Une analyse prenant en entrée de nombreux jeux de données d'images RSO et de données AIS utilisées comme «vérité terrain», a permis d'évaluer l'efficacité de chaque algorithme. En fonction des jeux de données utilisés, les algorithmes de détection présentent différents avantages et inconvénients. Une méthode de couplage RSO-AIS a été utilisée pour discriminer les cibles réelles détectées des fausses alarmes et ce, afin de déterminer le taux de détection et d'effectuer une comparaison cohérente des différents algorithmes de détection. L'influence des caractéristiques des capteurs R50 (angle d'incidence, polarisation, fréquence et résolution spatiale) a été évaluée, ainsi que l'influence de la lonqueur des navires. Des expériences ont été menées sur des jeux de données Radarsat-2 et CosmoSkymed ScanSAR ainsi que sur des données AIS acquises depuis les stations côtières.

Ensuite, les effets de l'hypothèse de la stationnarité lors du traitement de l'image RSO ont été évalués sur la signature des navires mobiles. Une méthodologie qui permet d'estimer et de compenser ces effets a alors été introduite. L'imagerie RSO des cibles mobiles se traduit généralement par des signaux résiduels de type «chirp» dans le signal complexe et dans la direction azimutale. La Transformée de Fourier Fractionnaire (FrFT) permet de représenter le signal RSD dans un domaine de rotation tempsfréquence, ce qui permet d'effectuer un traitement optimal des signaux de type «chirp». L'emploi de la FrFT réduit les effets de ces signaux résiduels de type chirp et permet de compenser la défocalisation azimutale d'une cible mobile ainsi que d'estimer la vitesse azimutale de la cible visée. Des expériences sur des données Radarsat-2 ont été menées et l'utilisation d'un grand nombre de signatures de navires a permis d'évaluer l'efficacité de la méthode proposée. Des comparaisons avec les données AIS ainsi qu'avec une méthode basée sur l'évaluation de la corrélation temporelle dans une séquence de sous-images ont été effectuées pour obtenir une analyse complète des performances.

Enfin, l'utilisation de données à double polarisation dans la détection des navires R50 a été évaluée. Dans un premier temps, une comparaison des résultats de détection propres à chaque canal polarimétrique a été considérée, pour ensuite évaluer la fusion des résultats. Dans une deuxième phase, la fusion de ces deux canaux de polarisation avant l'étape de détection a été étudiée. Concernant la fusion des données en amplitude, nous avons proposé d'utiliser une méthode basée sur les moments temporels généralisés Hölder. Pour les données complexes, le coefficient de cohérence ou les décompositions polarimétriques ont été utilisés et ont pu fournir des informations supplémentaires par rapport à l'imagerie à un seul canal.

Mots-clés : Automatic Identification System (AIS), Polarisation duale, Fractional Fourier Transform (FrFT), Non-paramétrique, Radar à Synthèse d'Ouverture (RSO), refocalisation, Détection de navires, Distribution statistique, Vitesse azimutale

Abstract

SAR imagery presents an increased interest in maritime surveillance applications. The research work completed in this thesis is dedicated to vessels detection and signature characterization from data acquired by different spaceborne SAR sensors. Firstly, we assess the performances of different ship detectors based on adaptive threshold algorithms. The detection algorithms are based on various clutter distributions and assessed automatically with a systematic methodology. Evaluation using large datasets of medium resolution SAR images and AIS (automatic identification system) data as ground truths allows to evaluate the efficiency of each detector. Depending on the datasets used for testing, the detection algorithms offer different advantages and disadvantages. The systematic method used in discriminating real detected targets and false alarms in order to determine the detection rate, allows us to perform an appropriate and consistent comparison of the detectors. The impact of SAR sensors characteristics (incidence angle, polarization, frequency and spatial resolution) is fully assessed, the vessels length being also considered. Experiments are conducted on Radarsat-2 and CosmoSkymed ScanSAR datasets and AIS data acquired by coastal stations.

Secondly, the effects of stationary-based processing of moving ship signatures in SAR imagery are assessed and a methodology that makes it possible to estimate and compensate them is introduced. SAR imaging of moving targets usually results in residual chirps in the azimuthal SLC processed signal. The Fractional Fourier Transform (FrFT) allows to represent the SAR signal in a rotated joint time-frequency plane and performs an optimal processing and analyse of chirp signals. Employing the FrFT reduces the effects of residual chirps achieving compensation of the along-track defocus of a moving target and estimation of the target's azimuthal speed itself. Experiments are conducted on Radarsat-2 Multilook Fine and Ultrafine SAR images. Evaluation using a large number of ship signatures allows to assess the efficiency of the proposed method. Comparisons with AIS data as ground truth and with a method based on the assessment of the temporal correlation between a sequence of sublook images are carried out for a complete performance analysis.

Finally, the use of complex dual-polarization data for SAR vessel detection is assessed. As a first step, an intercomparison between the individual use of each polarimetric channel is considered, as well as the fusion of the detection results corresponding to the two polarimetric channels. In a second phase, the fusion of both polarization channels before the detection step is assessed. When dealing with amplitude data only, we propose to employ a method based on the generalized temporal moments (Hölder means), in order to fuse the information of both polarization channels. When dealing with complex data, the coherence coefficient or target dualpolarimetric decompositions, which may provide additional information in comparison with single channel imagery, are employed.

Keywords : Automatic identification system (AIS), Azimuth speed, Constant False Alarm Rate (CFAR), dual-polarization, Fractional Fourier Transform (FrFT), Non-parametric, Refo-cusing, Ship detection, Statistic distribution, Synthetic Aperture Radar (SAR)



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