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Shadow classification performances evaluation of Mine Hunting Sonar

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Abstract
Modern mines have become very stealthy. Sonar systems, designed to detect them, will now also hand over to the classification process many more small non-mine bottom objects, with mine-like target strength. Hence, the classification process is now called upon much more often than it was in the past, hereby increasing its share in the overall mine hunting effort.
In order to evaluate the global performance of the mine hunting operation, the performance of the classification process and especially the shadow classification process has to be evaluated.
This performance is described by COC (Classification Operational Characteristics) curves which give the probability of classification (Pc) and the probability of false classification (Pfc) as functions of sonar characteristics and operational conditions. The paper describes the operational incidence of this new approach for shadow classification performance evaluation.

1. OPERATIONAL EVALUATION OF MINE HUNTING SONAR

1.1 MINE HUNTING SONAR FUNCTIONALITIES

Mine hunting is a general capability that can include many operational aspects and missions: mine sweeping, exploration, reconnaissance, general survey, etc.

For these applications, sonar systems aim at finding mines within a given operation time. On a predefined operation theatre, operational performances then depend on two points: the probability to find the mines and the time required to cover the zone. Normally, those two criteria are concurrent, that is, increasing the probability to find the mine leads to increasing also the mission time.
Those criteria depend also on several parameters related to the environmental conditions, the threat, the sonar characteristics and the way of using it in an operational context.

Classically, mine hunting is a three steps process: (1) detection, (2) classification and (3) identification (possibly followed by mine disposal). This way of dividing the operation process in three steps could appear somehow arbitrary. In some systems, some of those operations can be merged, as detection and classification for a side scan sonar for instance. This does not change the proposed theoretical approach, which can be adapted for the different kinds of situations.

The first stage is detection. It aims at deciding whether there is a MILEC (Mine Like Echo) within the sonar field. This stage can be a one shot or a multi-ping detection process.

The second stage is the classification process. Measurements of each MILEC are analysed to decide if the MILEC corresponds or not to a MILCO (Mine Like Contact). Classification is performed from an acoustic image or echo of the object, including shadow shape or echo, given by a classification sonar that has a fine resolution.

The third decision stage is related to the identification of the MINE or the NOMBO (Non Mine Like Bottom Object). Identification aims at deciding what sort of mine has been detected (MANTA, ROCKAN, MP80, …) whereas classification aims only at deciding if the detected echo is potentially a mine.

Possibly optical means or human intervention can be added to sonar in order to perform the identification step. As this last step can be time consuming (especially if it is followed by mine disposal) and risky when human intervention is required, the performances of the mine hunting sonar for both detection and classification shall be high.

Formerly, as classification was a rather episodic process of the mine hunting operation, it was not necessary to compute the efficiency of this step to determine the global performance of the mine hunting sonar operation. However, as the classification process has become a more time consuming exercise and is today the most critical step of both detection and classification, the precise evaluation of its performance becomes mandatory.

1.2 NOTION OF RISK AND CLEARING PERCENTAGE

The system performance at the output of the classification step can be evaluated by the residual risk (which is the probability that a mine within the field of operation has not been classified as MILCO, compared to an initial risk of mine presence) within a given operation time on a predefined operation theatre. The performance can be evaluated, dually, by the residual risk within an operation time, or by the operation time required to obtain a given residual risk R.

Considering a number of detected objects set to several hundreds per square nautical mile, it becomes necessary to classify the objects as rapidly and as securely as possible in order to limit the global time to fulfil the mine hunting mission. Obviously, the overall performance of the mine hunting operation depends not only on the classification process performance but also on the overall optimisation and operational combination of the detection and classification sonar systems.

From an operational point of view, the performance can be evaluated by two measures:
- the probability P to find a mine of a given type,
- the sonar operation time Top, that is the time required to find the mines within the zone for a fixed value of P.

The first measure is related to residual risk R estimated from the detection probability P1 and the classification probability P2.
After the two first steps (detection and classification steps), the residual risk is the probability that any existing mine would not have been classified as such during the sonar operation.

A mine can be missed in two cases:
- the mine is not detected: probability 1-P1
- the mine is detected but not classified: probability P1*(1-P2)

So, the residual risk and the probability to find a mine are derived:

$$R = 1\text{-}P_1 + P_1(1\text{-}P_2) = 1\text{-}P_1 P_2 \quad \textbf{(1)}$$

$$P = P_1 P_2 \quad \textbf{(2)}$$

Remark: P1 (P2 respectively) depends not only on the intrinsic detection Pd (classification Pc respectively) probability of the sonar on a single ping but also on its trajectory, manoeuvre and use.

The quantity R represents the operational risk, that is the proportion of mines which are not going to be classified as such and which therefore, at the conclusion of the operation, are going to represent a risk for navigation.

1.3 WHY ARE RISK AND SONAR OPERATION TIME INSUFFICIENT TO DESCRIBE THE PERFORMANCE OF THE SONAR SYSTEM ?

Detecting and classifying the mines as such are not the only purpose of the military operation. These steps are always followed by other operation phases. In a clearance perspective, they are followed by identification and mine disposal. In some other situations, as when using an autonomous underwater vehicle (AUV) for reconnaissance or exploration, the sonar detection and classification steps could be followed by a wide avoidance manoeuvre for the whole following fleet, in order to keep it away from the detected/classified mine field.

In this global perspective, considering the residual risk and the sonar operation time as the only criteria of sonar performance evaluation could lead in fact to very optimistic and false conclusions.

As new available sonar systems are now able to detect very stealthy mines, they also detect more and more small objects that can be assumed, in a first time, as being mines. A sonar system that rapidly detects and

classifies any encountered object as a mine, would be given a very good performance evaluation when considering only residual risk and time of operation : in fact it is true that such a system detects and classifies any encountered mine with high probability. The only problem, which is in fact a huge limitation, is that, it will also declare as "mine" a large number of NOMBO (Non Mine Bottom Objects as rocks, empty bottles, wash machines or soda cans). The high false classification rate will not penalise the sonar operation but will induce failure and defeat of following operation phases: the identification phase or the manoeuvre of the fleet. The ROV used for identification will have too many objects to identify that will slow down its operation. The mine field estimated dimensions will be to high and that will induce a pointless and unnecessary avoidance manoeuvre for the fleet. So, the aim of the classification step shall be not only to classify mines as such, but also to reduce the number of pointless false detection alarms, in classifying NOMBO as NON MINE objects.

In fact, considering the global operation of the marine forces leads to the introduction of an additional criterion for the sonar evaluation: the probability for a NOMBO to be detected and classified as a mine.
This quantity P2' represents the operational inefficiency (we could say as well that 1-P2' represents the operational efficiency), that is the proportion of NOMBOs which are going to be declared pointlessly "mine" and therefore will slow down the operation.

The evaluation of this inefficiency factor could be considered as a difficult task, as it mainly depends on what type of knowledge is introduced in the classification decision step. So, despite some rare attempts to unify the standards of shadow classification performance evaluation, the fact is that, practically, the usual requirements of classification sonar are summarised in a specified number of beams on the object (e.g. more than 3 or 4) and a given reverberation to shadow contrast (e.g. more than 5 dB). In the following sections a more precise definition of the performances of the classification step is given.

2. PRINCIPLES OF SONAR IMAGE BASED CLASSIFICATION

2.1 DESCRIPTION OF THE CLASSIFICATION OPERATION

To realise the classification step two solutions can be used. The first method is long range echo classification, which can be performed with a long range detection sonar analysing the echo signal structure. The second method is image based classification, which uses a more detailed acoustic image of the object, including both echo structure and shadow shape, given by a classification sonar that has a better resolution. The second one is considered here.

Classification process inputs are the measures associated to previous detected MILEC. A MILEC is the detection phase output. The classification phase aims to decide whether or not a mine is present.
The classification operation is described in Figure 1 as a two hypothesis decision process. Considering this approach, the classification theory can be derived by today classical statistical mathematics for hypotheses testing (see Borovkov [2] or Kendhal & al [3] for instance). This is very similar to the two hypothesis decision process of the detection theory.

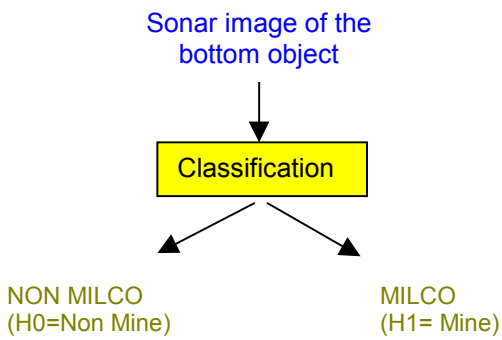


Figure 1 - Classification decision process

The differences with the detection stage lie in the input that is now a sonar image of the object and the two decisions that are MILCO (H1= Mine) or NON MILCO (H0=Non Mine).

Classification is based on a sonar image analysis that can include both echo and shadow contributions of the object.

2.2 DEFINITION OF THE COC CURVES

Assuming that parametric statistical models are defined to describe the measured image under the respective hypotheses H0 and H1, the performance of the classification can be described by the COC curves (Classification Operational Characteristic curves) of the sonar. These curves draw the dependence between probability of classification (Pc is the probability to decide that the image corresponds to MILCO knowing that the object is a mine) and probability of false classification (Pfc is the probability to decide that the image corresponds to MILCO knowing that the detected object -in a wide sense that is including detection false alarms- is not a mine). COC curves are defined for a given sonar in well defined environmental conditions (grazing angle, range, reverberation level, shadowing, characteristics of NOMBO and false detection- see below) and for a specific mine. In fact, it is obvious that the probability of classification depends on the mine type as the probability of detection does too.

Pc and Pfc evaluation requires the definition of not only the parameters of the sonar (wavelength, bandwidth, array size,…) but also of the implemented classification algorithm. This algorithm is not easily accessible, not only because sonar designers keep it secret, but also because its statistical model is not easily analytically derived. The algorithm performance depends on the mine and non mine on board data base knowledge, and on the operator ability, knowing that, classification is most often an "operator in the loop" process. So, only the case where the classification algorithm is a near-optimal test derived from the Neyman-Pearson optimal decision test is considered. In that case, considering the sonar ability to classify mines, sonar design parameters can be compared in an unbiased perspective, assuming that the decision algorithms and software are designed for reaching more or less a kind of optimal strategy, based on a referenced database.

These COC curves can be interpreted in an operational way. Pfc represents the proportion of NOMBO objects that will be classified as MINE and is a direct evaluation of the operational efficiency of the classification. Each such false classification will bring about an ineffective identification. This identification will slow down the global mine hunting operation. In fact Pfc has to be chosen in relation with the MILEC density (i.e. number of detected NOMBO per square mile) and with the global time period allocated to the mine hunting operation. 1-Pc represents the proportion of MINES that will be classified as NOMBO and is a direct evaluation of the operational risk of the classification. This risk is of course critical as it represents the number of missed mines.

2.3 SONAR IMAGE AND MASK MODEL

The evaluation of the classification process requires the possession of a model and a database of measurements from mine and non mine objects. A model and an associated technique of classification performance evaluation called DMC (Delta-Mask Classification) have been introduced in a previous paper and are briefly recalled below (see Florin and al. [1]).

A sonar image contains namely three kinds of pixels: reverberation, echoes, and shadow.
Each pixel category can be given a statistical distribution function or equivalently a probability density function. This function describes the statistical behaviour of the pixel, that is, roughly, the probability that the pixel takes its numerical values within a given interval. It is assumed that the distribution functions of the pixels are chi-squared distributions.
In the following, it is considered that the image is a "raw image", that is an image sampled with a rate corresponding to sonar resolution in range and bearing. Then, it can be assumed that the pixel statistics are independent. This is of high importance for the following.
Assuming that one knows the object and sonar characteristics, the associated theoretical statistics of the pixels can be determined. Each pixel can belong to one of the following statistical laws:

- Bottom reverberation p1(x)
- Shadow p2(x)
- Echo p3(x)
- Undetermined p_(x)

The statistical behaviour of an image can be represented with a 2D mask (or grid). Each square of the grid corresponds to a pixel of the image and includes the index number of the statistical law associated to this pixel (see Figure 2).

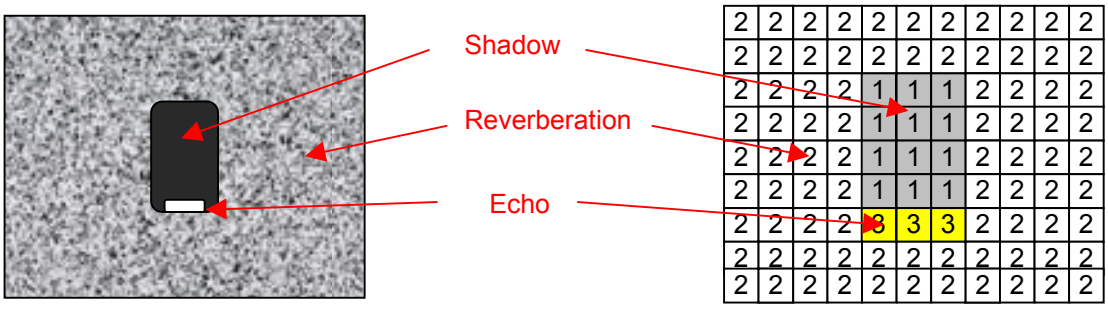


Figure 2 – Sonar image and the corresponding 2D mask

2.4 OBJETS (MINE AND NOMBO) MODELISATION

During a mine hunting operation the sonar can face a wide variety of situations including various NOMBO and MINE masks.

Even for a single mine, the variations of the position of the mine on the sea bed, and so the variations of relative positions to the sonar and the bottom, lead to variations of the mine masks for a same operational hypothesis. As a consequence, a large set of masks was simulated to model the mine shadow for a nominal use of the sonar (altitude and distance to the object) and several points of view.

Considering the natural variability of natural or man made bottom objects, the same sonar can meet a large number of NOMBO types of various size, shapes and asymmetric forms, that induces a large number of NOMBO hypothesis.
In the previous paper [1], we extracted rocks shadows from real sonar images. The images were used to elaborate a NOMBO database. The database can be adapted to other operational conditions described by a given resolution and a given position of the sonar. Moreover, some undetermined pixels have to be introduced in the model in order to simulate the uncertainty at the frontier. This can be performed by first characterising each mask by three features, i.e. the shadow width and length and the shape principal axis orientation in the image. Secondly, a clustering is performed in the 3D characteristic space and 200 cluster centroids are found. Finally, a mask per centroid is computed by adding its closest neighbours and by determining whose pixels are undetermined, thanks to a threshold on added pixels values.

2.5 STATISTICAL DECISION TEST AND DELTA-MASK

Using the theoretical mask of a known object in hypothesis H1 (if the object is the mine) or H0 (if it corresponds to a NOMBO or a detection false alarm) and assuming that the pixels are independent, the probability density function of the image can be written as the product of the probability density functions of its pixels. So the Neyman-Pearson hypothesis test comes down to:

$$\prod_{i,j} \frac{p(x_{ij} / H_1)}{p(x_{ij} / H_0)} \underset{0}{\overset{1}{\gtrless}} Threshold \qquad \textbf{(3)}$$

were x_{ij} is the pixel value of row i and column j.

Due to the pixels statistical independence hypothesis, this test has the interesting property that the product can be limited to the set of pixels (i j) corresponding to different statistical behaviours for H0 and H1. Hence, when the statistical density of a given pixel is the same under the hypothesis H1 and under the hypothesis H0, the contribution of this pixel to the product in equation (1) is a factor equal to 1 (that is, there is no information coming from this pixel for testing).

So, the previous test can be limited to what can be named the delta-mask, that is the mask of pixels corresponding to different statistical laws under H1 and H0. The delta-mask determination sets the problem of centring the shadows under H0 and H1, for determining the correct delta-mask. Centring is in fact a

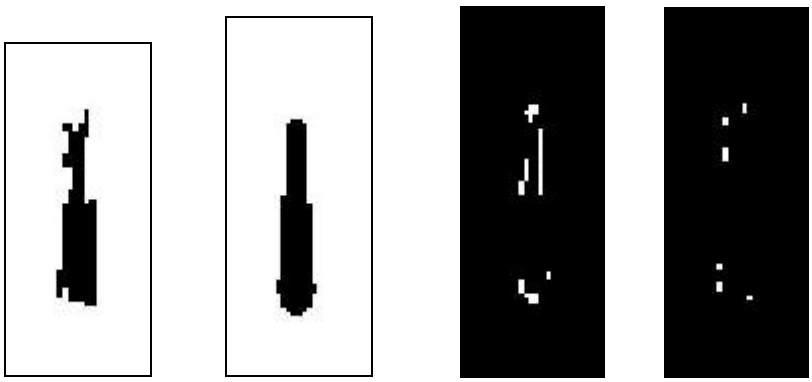
common operation in sonar image classification, which is implicitly, or explicitly realised (See for example Quidu and al [4] or Fawcett [5]). For the determination of the delta-mask, it is preferred here to centre the two masks by choosing the delta-mask, which minimises the number of its pixels.

So the effective optimal test for a given delta-mask Δ is expressed by the following equation (2).

$$\prod_{i,j\in\Delta} \frac{p(x_{ij} / H_1)}{p(x_{ij} / H_0)} \underset{0}{\overset{1}{\gtrless}} Threshold \qquad \textbf{(4)}$$

A given delta mask Δ is divided in six sub-masks Δ^{12}, Δ^{13}, Δ^{21}, Δ^{23}, Δ^{31}, Δ^{32} . For a sub-delta mask Δ^{kl} , k and l represent the statistical category of the pixel for the NOMBO and for the MINE respectively. This category can be 1=shadow, 2=reverberation, 3=echo. The sub-masks Δ^{11}, Δ^{22}, Δ^{33} and the undetermined pixels are of no interest, because they don't contribute to the statistical decision.

For example, the masks of a NOMBO (rock), a MANTA MINE, and the corresponding sub-masks Δ^{21} and Δ^{12} are given on Figure 3. The echo effects are not taken into account in this example; focus is made here on pure shadow classification.



a b c d

Figure 3 - Examples of NOMBO (a), MINE (b), Δ21 (c) and Δ12 (d) masks

Assuming that the basic pixels statistical distributions are chi-squared distributions, it can be shown that equation (4) is equivalent to the following test:

$$\sum_{\substack{k,l \\ k\neq l}}^{3\,3} \left(\alpha_h^{kl} \cdot \chi_{2N^{kl}}\right) \underset{0}{\overset{1}{\gtrless}} Threshold_{bis} \qquad \textbf{(5)}$$

where N^{kl} is the number of pixels of the sub-mask Δ^{kl}, $\chi_{2N^{kl}}$ is a chi-square variable with a $2N^{kl}$ degrees of freedom, and α_h^{kl} is a set of real coefficients depending on the measured mean powers of noise (shadow), reverberation and echoes.
A shadowing effect, as produced by sand ridges, can be taken into account by suppressing some pixels of the delta-mask in equation (5).

2.6 COC CURVES COMPUTING

Using common statistical inferences on chi-square variables the COC-curves corresponding to equation (5) can be easily computed, either with Monte-Carlo techniques or with numerical derivation of analytical equations.

So, for given SONAR characteristics (range and beam resolutions, grazing angle, noise, reverberation, and echoes measured powers), a given MINE and a given NOMBO, the related COC curve can be computed, which gives the maximal performance of the classification capability of the sonar.

This COC curve is defined in a one shot situation ([1]), that is for one image of the object. In real operation condition the sonar operator (or the autonomous classification process) can take his decision after getting several images of the same object. It is obvious that this multiple shots situation, where a high number of images of the same object can be obtained, tends to improve the classification performance. For M images of the same object, and assuming that the object is declared as a mine when it is declared as such at least P times on the M individual images, the probability of classification and the probability of false classification become :

$$\overline{P}_c = \sum_{p=P}^{M} C_M^p \, P_c^{\,p} \left(1 - P_c\right)^{M-p} \tag{6}$$

$$\overline{P}_{fc} = \sum_{p=P}^{M} C_M^p \, P_{fc}^{\,p} \left(1 - P_{fc}\right)^{M-p} \tag{7}$$

Those equations are defined for a fixed aspect of the object.

For a fixed aspect of the mine and a fixed value of the resulting probability of false classification $\overline{P}_{fc}$, the mean value of the probability of classification $\overline{\overline{P}}_c$ in the mono-aspect situation is given by :

$$\overline{\overline{P}}_c = \sum_{\theta \in \Theta 0} q(\theta) \overline{P}_c(\theta) \tag{8}$$

where q defines a prior given statistical distribution on the NOMBO set (named here Θ_0).
The probability of false classification is in that case fixed and is unchanged :

$$\overline{\overline{P}}_{fc} = \sum_{\theta \in \Theta 0} q(\theta) \overline{P}_{fc}(\theta) = \overline{P}_{fc} \sum_{\theta \in \Theta 0} q(\theta) = \overline{P}_{fc} \tag{9}$$

In the multiple aspects situation, when several aspects of the mine are imaged, the equations are sensibly modified. The values of Pc and Pfc vary with the time and the number of imaged aspects. If it is supposed that K different aspects of the object have been imaged, and that the object is declared as a mine when it is declared as such in at least one amongst the K configurations, the values of the probability of classification and the probability of false classification become :

$$\breve{P}_c = 1 - \prod_{k=1}^{K} \left(1 - \overline{\overline{P}}_c(k)\right) \tag{10}$$

$$\breve{P}_{fc} = 1 - \prod_{k=1}^{K} \left(1 - \overline{P}_{fc}(k)\right) \tag{11}$$

3. PRACTICAL APPLICATION EXEMPLE

3.1 CONDITIONS OF THE EVALUATION

To study the performances of sonars a very simple scenario is determined, for which the performances of navigation and detection are idealised and for which the performances of the detector and classification sonars are supposed constant in the sonar field and equal to those measured at the nominal range.
The sonar operation aims to realise detection and classification but neither identification nor neutralisation.

Duration and performances of the detection phase are supposed to be the same for all the sonars. The detection performances are idealised for simplification: sonar detection durations are supposed identical on the zone (they are compatible with typical speeds of use), the probability of detection P1=1, the probability of false alarms P1'=0. Therefore, investigation will focus only on classification performances.

Several theoretical sonar system are tested whose characteristics are described bellow:

Sonars characteristics	SONAR A	SONAR B	SONAR C	SONAR C'
Beam-width at nominal range	10 cm	25 cm	50 cm	50 cm
Resolution in range (c/2B)	3 cm			6 cm
grazing angle	11 degrees			
Reverberation to shadow contrast	7 dB			3 dB
Number N of sonar pings on a single aspect	1	61	164	

It is supposed that the sonar A makes a single passage on the object and must classify a single image. The other systems can benefit of several pings on the objects in a mono-aspect situation. The three systems are assumed to have the same range resolution, excepted SONAR C' that has a range resolution twice larger. It also has a worst reverberation to shadow contrast. They also differ in their beam width. SONAR A (in red) has the best resolution in bearing on the mine when the SONAR C has the worst one.
The COC curves are computed to compare the different sonar systems using the previous database and equations.

3.2 RESULTS

COC curves are presented bellow and are plotted for a single point of view of the Manta mine. Multi-ping process is applied except for sonar A. The COC curves consist in plotting the operational inefficiency Pfc versus the operational risk 1-Pc. The reference database of NOMBO masks has been obtained as described in section 2.4 with real sonar images. It contains about 550 NOMBO masks that are clustered into 200 centroids. The COC curves are computed with the thresholded centroids. The masks of the mine are simulated for a reference grazing angle. It includes a 5 cm zone of unknown pixels around the shadow in order to take into account uncertainties on the true position of the mine on the bottom floor and on its true detailed shape.

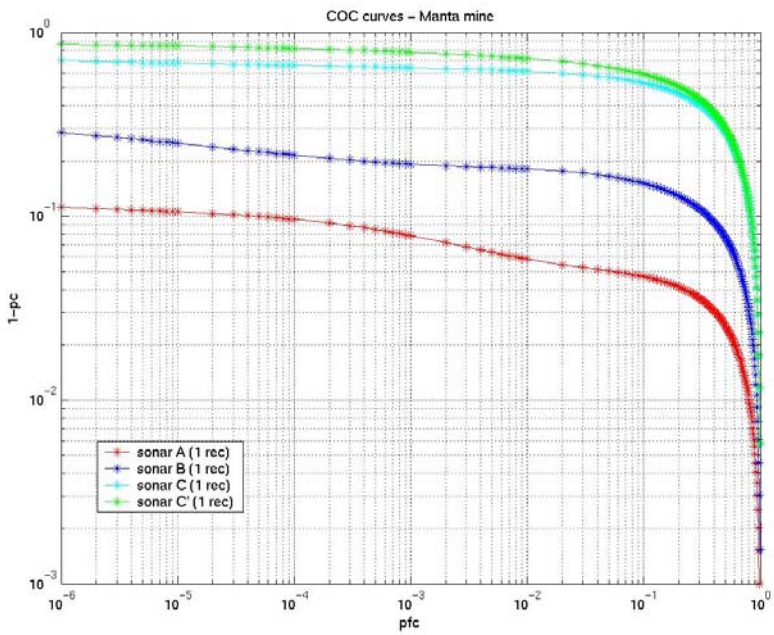


Figure 4: COC curves for one ping - MANTA Mine

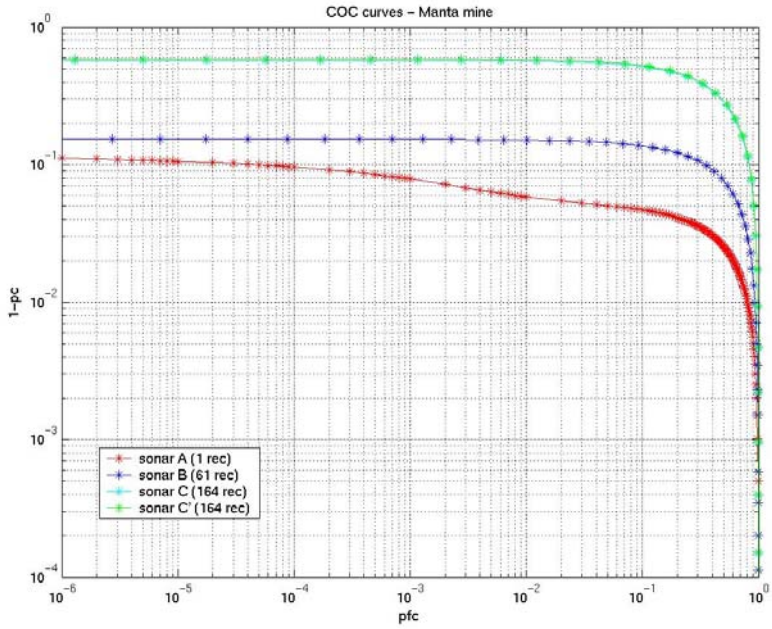


Figure 5: COC curves for multiple pings - MANTA Mine

Two different images are plotted for each sonar, in order to show the differences of the image qualities that are obtained with the different simulated sonar systems. The left images show the MANTA shadows and the right images show NOMBO shadows.

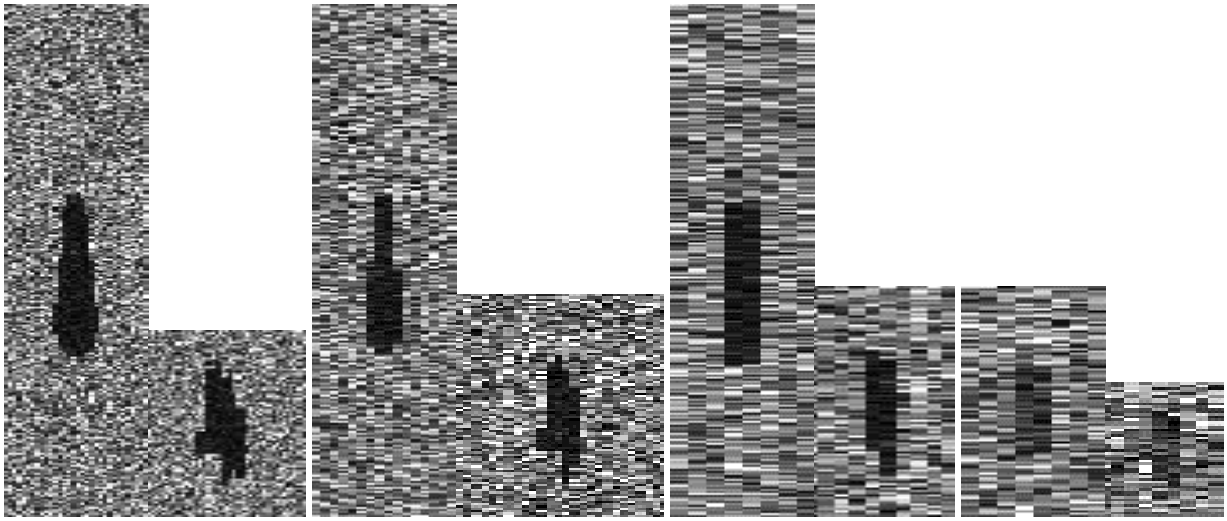


Figure 6: Simulated Shadows of a MANTA and a NOMBO as viewed with respectively sonar systems A, B, C, C'

4. CONCLUSION

The COC curves, that include an evaluation of operational risk and operational inefficiency are proposed as the right way to evaluate classification sonar.
A technique, said DMC (Delta-Mask Classification), designed to evaluate COC curves, for a given sonar, a mine and given conditions of environment has been developed. The case of the classification from multiple pings has been examined.
This technique was implemented and estimated in simulation and on the basis of real sonar images.
The behaviour of classification sonar according to the environment and to the seabed type was evaluated quantitatively. A key point of the modelling is certainly the characterisation of NOMBO. A reference database of masks for this type of objects has been established.

The DMC technique is thus relevant both as a tool for sonar systems conception and for tactical and operational use. Indeed, it is a way to relate the calculation of the performances of shadow classification to the characteristics of the sonar, the environment and the threat.
On the basis of simulations, the operational performances of mine hunting sonar have been better quantified by taking into account data, characteristics and inputs, not only related to detection but also to classification. This was illustrated by plotting COC curves corresponding to some configurations of sonars, threats and environment.

5. ACKNOWLEDGEMENT

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