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Obstacle avoidance capability for an Autonomous Underwater Vehicle (AUV) is of high interest for the French defence and especially GESMA centre which is involved in the development of decisional autonomy for AUV for several years. In addition to its original mission, the vehicle must ensure its own survival and must therefore understand the environment in safety. The use of a Forward Looking Sonar (FLS) on AUV is one of the most efficient solutions to detect unexpected and potentially dangerous changes of the environment, like the presence of obstacles or seabed slope. Like this, a FLS can prevent the vehicle from obstacles or terrain that may endanger the underwater vehicle. A process model has been derived based on navigation data in order to predict the motion of a ground target which has been detected in the sonar image. This model has been used in the prediction step of a Kalman filter that enables still targets tracking through successive frames. The article gives an overview of the overall architecture with a focus on Kalman filtering. An assessment will be done on synthetic and real data recorded in April 2006 during sea trials organized by GESMA.

1 Introduction

Autonomous Underwater Vehicles (AUVs) have to fulfill their mission safely. In this article, a Forward Looking Sonar is used by an AUV to ensure its survival. To do it, sector scan sonar images are processed in order to classify any obstacle that can endanger the vehicle and lead to the interruption of the mission. To have enough time to characterize and finally avoid an obstacle, this latter has to be detected and tracked through the images sequence.

Some works published on the tracking of objects on sonar images use optical flow on moving objects and data association techniques [1, 2]. Other works use still objects tracking to estimate the AUV motion with respect to the seabed [3].

In contrast our tracking algorithm takes into account navigation data to robustly track detected ground obstacles even if the vehicle changes its speed and/or its attitude. Indeed a Kalman filter which takes navigation data as input has been derived from the AUV process model. The Kalman filtering of successive detections gives a good estimation of the trajectory of the obstacle in sight. The process model has been presented last year and will be briefly reminded in the third part [4]. Detection process is presented in the following part and the Kalman filtering will be detailed in the fourth part. After some words on data association for multi-target tracking in the fifth part, the last part is dedicated to assessment on real RESON 8101 data recorded in April 2006 during sea trials organized by GESMA.

2 Detection step

Sonar images are corrupted by a well-known multiplicative noise that is speckle noise [5]. By considering amplitude modulus of the reflected wave, pixels level follows a Rayleigh law. Under this hypothesis, we have derived a simple adjustment test that only consists in verifying the relation of proportionality that exists between the mean and the standard deviation of pixels. In practice, we divide the sonar image into snippets and test for each of them the value of the ratio between the standard deviation value and mean value of pixels levels. If this ratio is too far from the expected value (about 0.52) we consider that a target is in sight. By thresholding the image, we can see areas whose pixels level does not follow a Rayleigh distribution. The centre of inertia of each area is set as a detected point or measurement and can initiate a Kalman filter.

3 Process model [4]

The state equation is based on the process model that provides the sonar coordinates (d,δ) of a detected object given the AUV motion. This model is obtained in several steps.

In the mobile reference frame the target is located by means of the following equations:

$$\begin{cases} \left(m_r^x\right)^2+\left(m_r^y\right)^2+\left(m_r^z\right)^2=d^2 \\ m_r^y=\sin\delta.d \\ -\sin\theta.m_r^x+\cos\theta.\sin\varphi.m_r^y+\cos\theta.\cos\varphi.m_r^z=h \end{cases} \quad (1)$$

Where $\boldsymbol{m_r}=\left(m_r^x,m_r^y,m_r^z\right)$ stands for the coordinates of an object laying on the seafloor, h is the AUV altitude and (φ,θ,ψ) stand for the Euler angles.

From this system, we can derive the function f_a such that:

$$\begin{pmatrix} m_r^x \\ m_r^y \\ m_r^z \end{pmatrix}=f_a\begin{pmatrix} d \\ \delta \end{pmatrix} \quad (2)$$

and f_c such that: $\left(\dot{d},\dot{\delta}\right)= f_c\left(\dot{m}_r^x,\dot{m}_r^y,\dot{m}_r^z,d,\delta\right)$ (3)

Besides we have the following vehicle model :

$$\boldsymbol{p_a}-\boldsymbol{m_a}=-R_{euler}(\varphi,\theta,\psi)\cdot\boldsymbol{m_r} \quad (4)$$

where $\boldsymbol{p_a}=\left(p_a^x,p_a^y,p_a^z\right)$ stands for the coordinates of the AUV (we supposed its location merged with all the other sensors) and $\boldsymbol{m_a}=\left(m_a^x,m_a^y,m_a^z\right)$ stands for the coordinates of the object in the absolute reference frame.

By derivating the last equation, we get:

$$\begin{pmatrix}\dot{m}_r^x\\ \dot{m}_r^y\\ \dot{m}_r^z\end{pmatrix}=-R_{euler}^T\dot{R}_{euler}\cdot\begin{pmatrix}m_r^x\\ m_r^y\\ m_r^z\end{pmatrix}-\boldsymbol{v_r}=f_b\left(m_r^x,m_r^y,m_r^z,\boldsymbol{v_r},\varphi,\theta,\psi,\dot{\varphi},\dot{\theta},\dot{\psi}\right) \quad (5)$$

where $\boldsymbol{v}_r=\left(v_r^x,v_r^y,v_r^z\right)$ stands for the speed of the AUV.

We can now give the expression of a moving object in function of its initial position and navigation data:

$$\left(\dot{d},\dot{\delta}\right)= f_c o f_b o f_a\left(d,\delta,\boldsymbol{v_r},\varphi,\theta,\psi,\dot{\varphi},\dot{\theta},\dot{\psi}\right) \quad (6)$$

4 Kalman filtering

4.1 State equation

The state vector is composed of the sonar coordinates, i.e. $x=\left(d \quad \delta\right)^T$. Considering the previous paragraph and Eq.(6), we can then write the state equation in the discrete domain:

$$x_{k/k-1}=f\left(x_{k-1/k-1},u_{k-1}\right)+v_{k-1} \quad (7)$$

where the vector input u_{k-1} is derived from navigation data such that $u_{k-1}=\left(\boldsymbol{v_r} \quad \varphi \quad \theta \quad \psi \quad \dot{\varphi} \quad \dot{\theta} \quad \dot{\psi}\right)_{k-1}^T$, v_{k-1} stands for the white Gaussian state noise whose covariance matrix is Q_{k-1} (detailed farther) and $f = f_c o f_b o f_a$ is a non linear state function determined at paragraph 3.

4.2 Measurement equation

Our measurement consists of obstacle coordinates on the screen. The measurement equation is then:

$$y_{k/k-1}=H_k x_{k/k-1}+w_{k-1} \quad (8)$$

where w_{k-1} stands for the white Gaussian measurement noise whose covariance matrix is R_{k-1} (detailed farther),

$[H_k]=[H]=\begin{bmatrix}\frac{1}{\Delta d} & 0\\ 0 & \frac{1}{\Delta\delta}\end{bmatrix}$, $\forall k$, is the measurement matrix, with Δd (*resp.* $\Delta\delta$) stands for the along track (*resp.* across track) sampling rate.

4.3 Implementation

4.3.1 Covariance matrices

State and measurement noises as well as initial state are Gaussian and mutually independent.

By taking into account theoretical precisions of navigation sensors, we can estimate the following state variances:

$$Q_k=Q=10^{-6}\begin{bmatrix}0.48 & 0\\ 0 & 0.024\end{bmatrix}, \forall k$$

To compute measurement variances at the initial step (k=0), we consider a measurement precision about hundred pixels along track and half a pixel across track according to sonar resolution. In other words, $R_0=\begin{bmatrix}100^2 & 0\\ 0 & 0.5^2\end{bmatrix}$.

For the other steps (k>0), measurement precision depends on the innovation, i.e. the difference between the measurement y_k and its prediction $\hat{y}_{k/k-1}$ converted into pixels.

4.3.2 Initialisation

The initial state $x_{0/0}$ consists of the coordinates of the centre of inertia of the detected obstacle. In other words $x_{0/0}=\hat{x}_{0/0}=\left(d_0 \quad \delta_0\right)^T$.

From uncertainties about 5 meters in range and 5 degrees in azimuth, we can derive the initial covariance matrix $P_{0/0}=\begin{bmatrix}(100\Delta d)^2 & 0\\ 0 & (3\Delta\delta)^2\end{bmatrix}$.

4.3.3 Prediction stage

For this stage we have to compute the new state $\hat{x}_{k/k-1}$ given the previous one $\hat{x}_{k-1/k-1}$.

Prediction step is carried out by performing an unscented transform of $x_{k-1/k-1}$ because of the strong non linearity of the state function *f* [6] as follows:

1. Creation of Sigma points $\chi_{k-1/k-1}^i$, for i=1 to 2n+1 with respective weight W_i: points that are uniformly distributed on an ellipsoid such that their mean and covariance are $\hat{x}_{k-1/k-1}$ and $P_{k-1/k-1}$ (n=length of $\hat{x}_{k-1/k-1}$) [7].
2. Computation of $\chi_{k/k-1}^i=f\left(\chi_{k-1/k-1}^i,u_{k-1}\right)$ for i=1 to 2n+1

3. Predicted state is then $\hat{x}_{k/k-1} = \sum_{i=0}^{2n} W_i \chi^i_{k/k-1}$ and the associate covariance matrix $P_{k/k-1} = \sum_{i=0}^{2n} W_i \left[\chi^i_{k/k-1} - \hat{x}_{k/k-1}\right]\left[\chi^i_{k/k-1} - \hat{x}_{k/k-1}\right]^T$.

4.3.4 Correction stage

For this stage we have to estimate the actual measurement $\hat{y}_{k/k-1}$ given the actual state $\hat{x}_{k/k-1}$ and we can do the correction by applying Kalman equations in the linear case this once:

$$\begin{cases} \hat{x}_{k/k} = \hat{x}_{k/k-1} + K_k\left(y_k - \hat{y}_{k/k-1}\right) \\ K_k = P_{k/k-1}H_k^T\left(H_k P_{k/k-1} H_k^T + R_k\right)^{-1} = P_{k/k-1}H_k^T\left(R_k^\upsilon\right)^{-1} \\ P_{k/k} = P_{k/k-1} - K_k R_k^\upsilon \left(K_k\right)^T \end{cases} \quad (9)$$

where y_k is the real measurement (detection). If no detection occurs at this step, we take the previous detection but the corresponding covariance matrix becomes $R_k = R_{\max} = \begin{bmatrix} 10^{15} & 0 \\ 0 & 10^{15} \end{bmatrix}$ in order not to take into account this detection.

We can notice here the impact of the innovation term $\upsilon_k = y_k - \hat{y}_{k/k-1}$.

5 Data association

Data association techniques can be divided into the two following categories [8]:

- Approaches that focus primarily on target selecting measurements that only fall within « validation gates » generated by existing tracks,
- Approaches that focus on measurements finding an existing track or creating a new one if necessary.

The second one is more suitable for our context, i.e. for trackable target with sufficient geographic information to be well localized. Practically for each measurement we search the closest track by considering the Euclidean distance in meters. Two cases can occur: if this distance is two big (>15m) a new Kalman filter is initialized, otherwise this measurement (or average measurement if more than one measurement is found) is taken into account in the correction step of the Kalman filtering.

Another point concerns tracking interruption. Complex tests like the sequential probability ratio test of Wald or statistical tests of Mehra and Peschon seemed to be interesting because these tests are based on the innovation values [9, 10]. Unfortunately these tests were difficult to use here because of hazardous implementation and tuning for the first one and because of lack of statistical samples (innovation values) for the others. For these reasons, we chose a simpler test that is to say that if no measurement is associated to a given track three times one after the other this track is interrupted.

6 Experimental results

6.1 Data description

6.1.1 Avoidance sonar data

The *Redermor* is an experimental platform deployed from the French Navy ship *BEGM Thetis*. In its last release, avoidance means of Redermor consist of a network of 10 *Tritech* echosounders and a *Reson Seabat 8101* Forward Looking Sonar (FLS). In this article sonar data come from the *Reson Seabat 8101* FLS operating in a sector scan mode. The system can play a beamformed image over a 15° (vertical) × 60° (horizontal) sector with an azimuth resolution Δδ equal to 1.5° and a range resolution Δd equal to 5cm. The sonar has been oriented 15° from the horizontal plane.
In order to test the capability of the *Redermor* vehicle to react when obstacles are encountered on its way, GESMA organized an experimental trial in April 2006, named DEVITOBS'06 "DETection et EVITement d'OBStacles".

6.1.2 Navigation data

Navigation is performed knowing data from a Doppler Velocity Log (DVL) and a Motion Reference Unit (MRU). The DVL gives the vehicle speed in relation to the seafloor. The MRU gives the vehicle orientation and its acceleration in relation to the earth (or absolute) reference frame (X : geographical North, Y : East, Z : gravity direction).

6.2 Results on synthetic sonar data

Synthetic data consist of two punctual ground objects embedded in the background image of an *empty* real sonar sequence. Doing this it was possible to quantify the tracking performance for different levels of noise on measurements. We observed that filtering works well while a white Gaussian noise with a standard deviation less than 2m was applied.

An example of filtering with noisy measurements (standard deviations of 20 pixels in range and 1 pixel in azimuth) is given hereafter.

Fig. 1 is a snapshot of the tracking of the two embedded targets and Fig. 2 gives trajectories and variances for one of them.

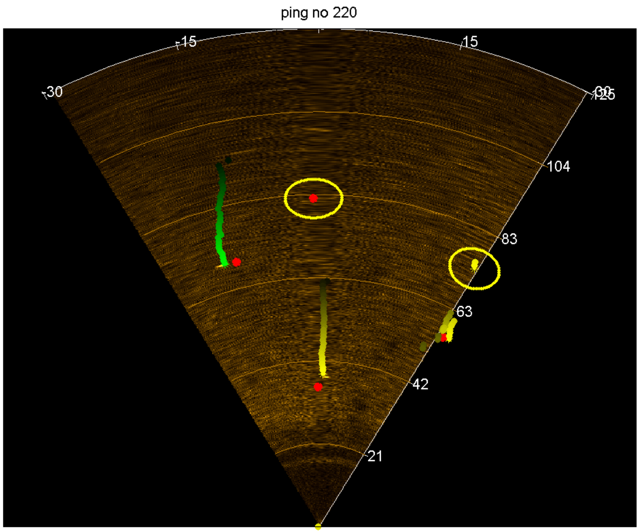

Figure 1: Snapshot of multiple Kalman filtering (measurements in red – tracks in green or yellow with their corresponding ellipses of uncertainty)

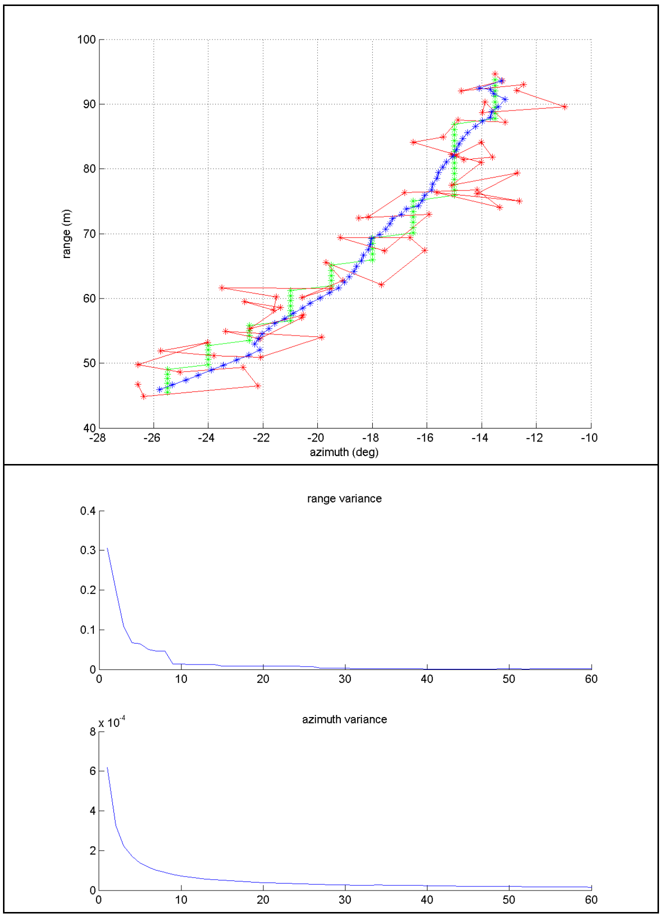

Figure 2: Target 1
Up: filtering (green: reference trajectory, red: measurements, blue: estimated trajectory)
Down: variances evolution along the sequence

6.3 Results on real sonar data

We show here results on a sequence where a shipwreck lies on the seafloor (a large echoes area followed by a large shadow area).

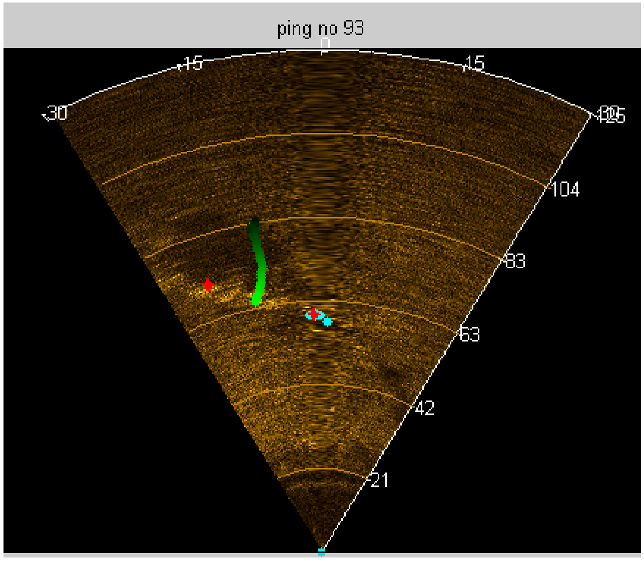

Figure 3: Snapshot of Kalman filtering on a shipwreck (measurements in red, tracks in green and cyan)

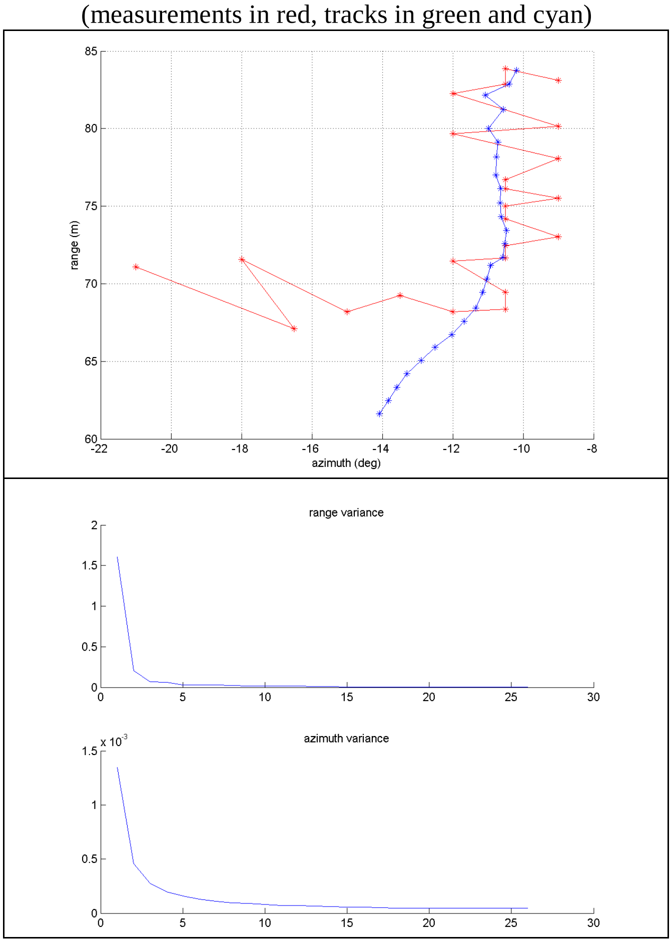

Figure 4: Shipwreck sequence
Up: filtering (green: reference trajectory, red: measurements, blue: estimated trajectory)
Down: variances evolution along the sequence

7 Conclusion

In this paper a multiple-target tracking has been presented for sector-scan sonar images. This algorithm is designed for still target lying on a flat seafloor and it would fail if one of these hypotheses is strongly violated. It is based on a Kalman filter that takes navigation data as input. The state equation is based on the process model of the vehicle which is non-linear. That is why an Unscented Kalman Filter has been implemented. Results on synthetic and real *Reson Seabat 8101* FLS sonar data have been showed. This study is of high interest for GESMA involved in the development of experimental AUVs such as the Redermor for several years [11]. These results will also be useful in the context of the covert REA (Rapid Environmental Assessment) AUV named “Daurade” [12]. The objective of this project is to describe the seabed and the water column by means of an AUV. This project is realized in collaboration with the SHOM, the French Navy Hydrographic and Oceanographic Service. As this AUV is equipped with a Blueview 450 FLS, the multiple-target tracking algorithm will be soon tested on it.

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