TRACKING UNDERWATER OBJECTS USING LARGE MIMO SONAR SYSTEMS

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Abstract: *MIMO sonar systems can offer great capabilities for area surveillance especially in very shallow water with heavy cluttered environment. We present here a MIMO simulator which can compute synthetic raw data for any transmitter/receiver pair in multipath and cluttered environment. Synthetic moving targets such as boats or AUVs can also be introduced into the environment. For the harbour surveillance problem we are interested in tracking all moving objects in a particular area. So far the tracking filter of choice for multistatic systems has been the MHT (Multiple Hypothesis Tracker). The reason behind this choice is its capability to propagate track identities at each iteration. The MHT is an extension of a mono object tracker to a multi object problem and therefore suffers from a number of drawbacks: the number of targets should be known and the birth or death of new tracks are based on heuristics. A fine ad hoc parameter tuning is then required and there is a lack of adaptivity in this process. To overcome those restrictions we will be using the HISP (Hypothesised multi-object filter for Independent Stochastic Population) filter recently developed. The HISP filter relies on a generalisation of the concept of point process that integrates a representation of distinguishability. As a consequence, this filter deals directly with the multi-object estimation problem, while maintaining track identities through time without using heuristics. While filters track the objects after processing in the digital domain, we show as well in this paper that we can adapt acoustical time reversal techniques to track an underwater target directly with the MIMO system. We will show that the proposed modified DORT technique matches the prediction / data update steps of a tracking filter.*

Keywords: *MIMO sonar systems, tracking, time reversal.*

1. INTRODUCTION

Multiple Input Multiple Output sonar systems have raised a lot of interest during the recent years mainly in the ASW community. Multi-static sonars overcome monostatic sonar systems in target localisation and detection performances [1]. CMRE in particular developed a deployable low frequency multi-static sonar system called DEMUS. The DEMUS hardware consists of one source and three receiver buoys and can be denominated as a SIMO (Single Input Multiple Output) system. A lot of the efforts were focussed on the data fusion and the target tracking problems. Several trackers including centralised and decentralised MHT (Multi-Hypothesis Tracker) [2] or TBD (Track Before Detect) trackers [3] have been developed and applied to the DEMUS datasets.

In this paper we present a full 3D MIMO simulator which can compute synthetic raw data for any transmitter/receiver pair in multipath and cluttered environment. Synthetic mid-water targets can also be added to the environment. MIMO image formation will be discussed and MIMO autofocus techniques will be demonstrated. We show in particular that the depth of a mid water target can be estimated with great accuracy. The principles of the MHT filters will be discussed and the HISP filter will be presented. The HISP deals directly with the multi-object estimation problem, while maintaining track identities through time without using heuristics. Finally we will show that large MIMO systems offer an ideal platform for time reversal techniques. We will present in particular an unfocussed time reversal mirror algorithm capable of tracking automatically moving targets.

2. MIMO SIMULATOR

2.1. Seabed interface

To model the seabed interface we generate 2D fractional Brownian motion using the Incremental Fourier Synthesis Method developed by Kaplan and Kuo [4]. The main idea is to model the 1st and 2nd order increments I_x, I_y and I_2. I_2 for example is given by:

$$I_2(m_x,m_y) = \quad B(m_x+1,m_y+1)+B(m_x,m_y) \quad -B(m_x,m_y+1)-B(m_x,m_y+1) \tag{1}$$

where B is the 2D fBm. Those 1st and 2nd order increments can be computed thanks to their FFTs. The 2nd order increment FFT is given by:

$$S_2(\omega_x,\omega_y) = \frac{32\sqrt{\pi}\sin^2(\omega_x/2)\sin^2(\omega_y/2)\Gamma(2H+1)\sin(\pi H)}{\sqrt{\omega_x^2+\omega_y^2}^{\,2H+2}} \tag{2}$$

where H is the Hurst parameter. Figure 1 displays an example of 2D fractional Brownian surface generated using this technique.

2.2. Bistatic reverberation level

The bistatic scattering strength is computed using the model developed by Williams and Jackson [5]:

$$S_b(\theta_s,\phi_s,\theta_i) = 10\log[\sigma_{br}(\theta_s,\phi_s,\theta_i)+\sigma_{bv}(\theta_s,\phi_s,\theta_i)] \tag{3}$$

where $\sigma_{br} = [\sigma_{kr}^{\eta}+\sigma_{pr}^{\eta}]^{1/\eta}$ is the bistatic roughness scattering which includes the Kirchhoff approximation and the perturbation approximation. σ_{bv} is the sediment bistatic volume scattering. S_b depends on the bistatic geometry as well as the sediment physical properties. Figure 2 displays the bistatic scattering strength for a Tx/Rx pair situated 141m apart and both at 7.5m from the seafloor. The S_b is computed for

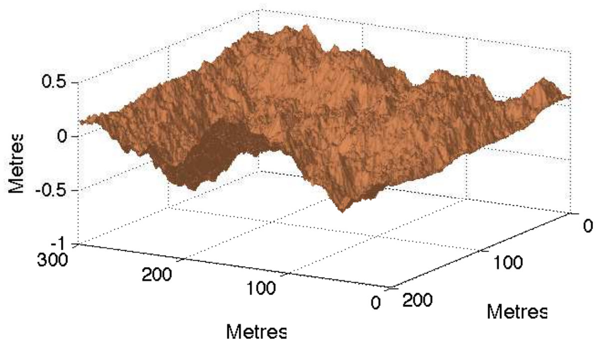
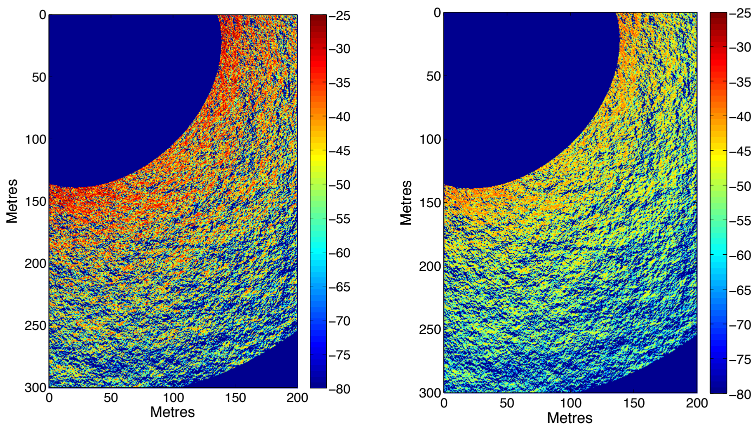


Fig. 1: Example of 2D fBm with H = 0.8 (fractal dimension = 2.2)

two different sediment types (coarse sand and sandy mud) for the same fBm interface. There is around 10dB difference is the S_b for the two sediments which can plays a role in the detection/tracking process. We will consider these two sediment types later on.



(a) (b)

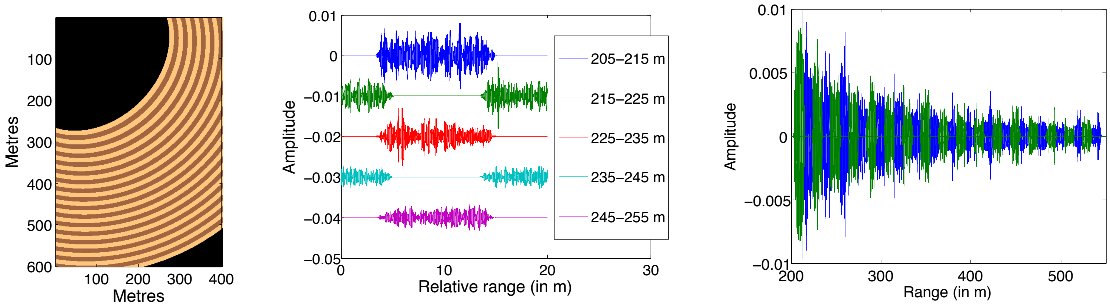
Fig. 2: Bistatic scattering strength relative to one Tx located at [0m,100m] and a Rx located at [100m,0m] for (a) a coarse sand sediment type and (b) a sandy mud sediment type.

2.3. Propagation

Sound propagation in shallow water can become extremely complex. Because we are modelling harbour environment we assume a constant sound speed through the water column. To model the multipath we are using the mirror theorem. In conjunction with a constant sound speed ray tracing techniques are used to compute the different propagation paths. The simulations done in this paper consider a maximum of three bounces. The reason behind this choice is that the coherent MIMO processing done on the next section suppresses greatly incoherent echoes.

To synthesise time echo a random scatterer point cloud including random position and random intensity is generated for each cell in the seabed. Note that once the point cloud is generated, it can be saved for other simulations with the same configuration.

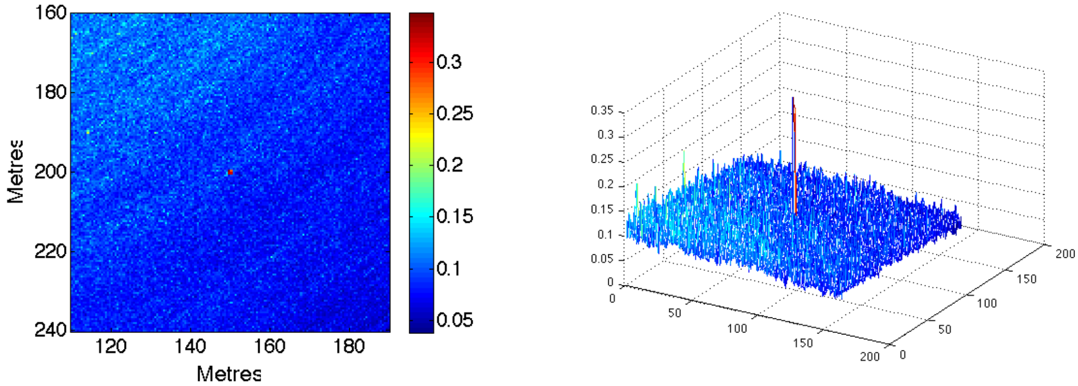
In our case we want to synthesise time echo from 400 $\times$ 600 cells $\times$ 20 scatterers per cell $\times$ 100 MIMO pairs which represents around half a billion paths to compute (direct paths only). Brute force computation using MatLab on a standard laptop requires around 2 months of computation. Hopefully a handful of tricks can reduce drastically this time. One of them is to use sparsity with the the circular convolution properties of the DFT. The main tool to propagate a signal is free water is the well known FFT property: $f(t-u) \Leftrightarrow e^{-iu\omega}\hat{f}(\omega)$. If we consider the echo related to one cell, this echo is extremely sparse over a 600m range signal. The idea is to compute the propagated signal over a much smaller window. Figure 3 draws the outlines of the algorithm: the full scene is divided into range bands, on Fig. 3(a) each colour band represents a 10m range division. The echoes relative to each band are computed independently on a small window of 20m (cf. figure 3(b)). The echoes are then recombine to give the full range bistatic response as seen in figure 3(c). Using those techniques greatly reduces the computation time from 2 months to around 10 hours.



(a) (b) (c)

Fig. 3: (a) of the observed scene in 10m range band. (b) Individual range band echo contribution. (c) Full echo response recomposition.

2.4. MIMO imaging and autofocus



(a) (b)

Fig. 4: Synthetic aperture MIMO image of a mid water -30dB target on a coarse sand sediment background, (a) 2D image, (b) 3D image.

In order to image the output of the MIMO system we will use the multi-static back- projection algorithm which is a variant of the bistatic back-projection algorithm developed by the SAR community. Further details can be found in [6]. Using the back-projection algorithm the Synthetic Aperture Sonar (SAS) image is computed by integrating the echo signal along a parabola. In the bistatic case the integration is done along ellipses. For the multi-static scenario the continuous integration is replaced by a finite sum in which each term corresponds to one transmitter/receiver pair contribution. Figure 4 displays a synthetic aperture MIMO image: the background is a fractal coarse sand seafloor, a mid-water target is present at the location [200m, 150m].

As it has been mentioned before synthetic aperture MIMO imaging shares a lot of features with standard SAS imaging. In particular the image is projected onto a plane or a bathymetry estimate. The image of a mid water target will then appear unfocused for this particular projection. By moving the projection plane through the water column the MIMO target image will focus at its actual depth. Using simple autofocus algorithm it is then possible to estimate the depth of the target even if the MIMO system is coplanar. For a mid water target at 400m range in a 15m depth environment it is possible to estimate its depth with 10 to 50 cm accuracy. Figure 5 displays the autofocus results and the estimated target depth compared with the ground truth.

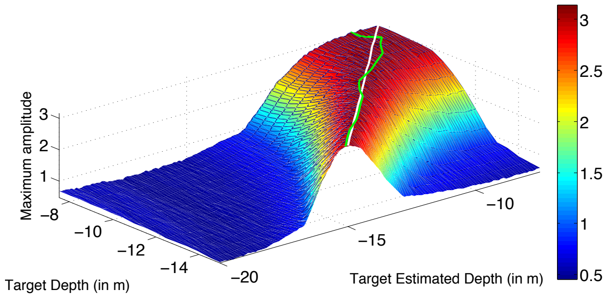
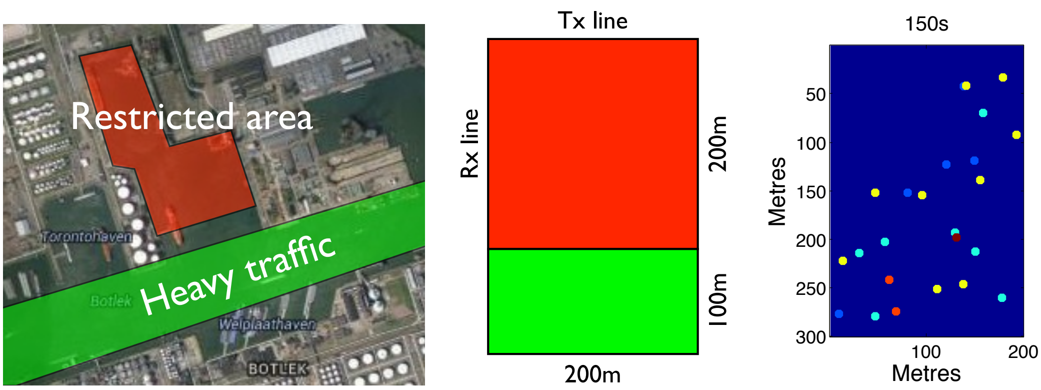


Fig. 5: Autofocus algorithm results based on maximising the scattering response: ground truth (white curve) and estimated depth (green curve).

3. HARBOUR SURVEILLANCE SCENARIO USING MIMO SONAR SYSTEMS

Figure 6(a) displays the overall scenario: in a harbour environment a restricted area is located close a traffic area. The goal is to protect the restricted area from underwater threats. Figure 6(b) displays the geometry of the synthetic environment: 300 $\times$ 200 m area to survey, 15m average depth with coarse sand or sandy mud sediment. The MIMO systems is composed of 11 Tx located on the top and 11 Rx located on the right, all the transducers are located at 7.5m depth. The central frequency for the MIMO system is 30kHz and the resolution cell 50cm. Figure 6(c) displays the input to the multi-object tracker. Note that the detection have been colour coded only for display purposes.



(a) (b) (c)

Fig. 6: (a) Harbour scenario. (b) geometry of the MIMO simulation. (c) Colour coded detections: (light blue) static bottom object, (dark blue) false alarm, (yellow) fish, (orange) boat, (red) AUV.

4. MULTIPLE OBJECT TRACKING

After the derivation, in the 1960's, of the first principled single-object filter, known as the Kalman filter, the problem of tracking multiple targets in a cluttered environment rapidly arose. As a consequence, gradually sophisticated methods for handling the complexity of data association have been introduced. These methods can be seen as bottom-up approaches, as they build up multiple target tracker from the Kalman Filter. One of the most successful of these methods is the MHT [7], which principles and limitations are summarised in Section 4.1. Since early 2000, another class of methods, which we will describe as "top-down", have been introduced. These methods are presented in Section 4.2.

4.1. The MHT filter

The MHT, for Multiple Hypothesis Tracking, is a multi-target tracker that handles data association in a probabilistic way. It can be seen as one of the most sophisticated bottom-up tracker, building on the idea behind techniques such as the GNN, for Global Nearest Neighbour, or JPDA, for Joint Probabilistic Data Association, while incorporating the concept of hypothesis. However, the MHT also have shortcomings, *(a)* it is much more computationally demanding than the GNN or JPDA, and is known to be intractable for complicated target tracking problems, and *(b)* it inherits from the ad-hoc management of birth and death found in any bottom-up approach.

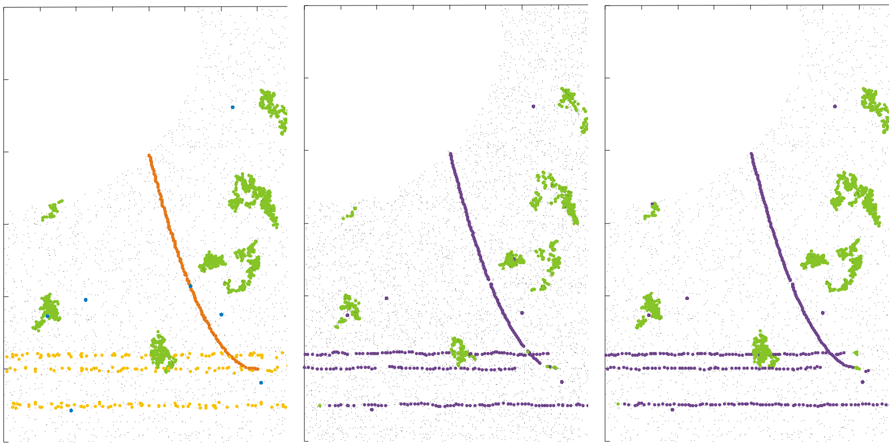
4.2. The PHD and HISP filters

In 2003, the PHD filter [8], for Probability Hypothesis Density, has been introduced in order to address the limitations of the MHT. It can be seen as one of the first top-down approaches to the problem of multiple target tracking. The PHD filter, and other similar filters, are based on the principled modelling of the multiplicity which is inherent to target tracking, and allow for the integration of birth and death of targets in a probabilistic and consistent way. The issue of computational complexity is also addressed by assuming that tracks are not distinguishable, so that they can be represented by a single distribution over the state space. However, track identities are lost as a consequence, and additional algorithms have to be used in order to recover the estimated state of each track. The impact of this limitation is strengthen by the use of multiple dynamical models for the propagation of each track, or when classification is required.

Recently, a new multi-target tracking algorithm called the HISP filter, for Hypothesised filter for Independent Stochastic Populations, has been introduced [9, 10]. The HISP filter presents the same advantages as the PHD filter but maintains track identities. This is made possible through the introduction of distinguishability into the multi-target representation. As a consequence, any single-object filter can be used within this multi-target framework, including classification, as demonstrated below.

4.3. Results

The output of a Gaussian Mixture implementation of the HISP filter, or GM-HISP, is pictured in Figure 7 with two different types of seabed: Figure 7b for coarse sand and Figure 7c for muddy sand. These figures show that the HISP filter managed to separate the fishes from the other targets. This is made possible by estimating two different multi-target populations with two different dynamical models. In order to distinguish the static targets from the boats and the UAV, a Sequential Monte Carlo implementation of the HISP filter, or SMC-HISP, would be required, as dynamical models excluding small velocities are non-Gaussian. More specifically, the coarse sand scenario 7b has more false alarms than the muddy



(a) Ground truth (b) Coarse sand (c) Muddy sand

Fig. 7: Accumulated view of the HISP filter's output (7b & 7c) compared against ground truth (7a). Ground truth: • observations — • fish — • static targets — • boat — • UAV. Estimated: • observations — • fish — • UAV, boat, static target.

sand scenario 7c. As a result, the estimation is made more difficult, e.g. the estimated positions of the fishes are not as consistent as the one given for the muddy sand scenario, the latter being closer to the ground truth.

5. ACOUSTICAL TRACKER

Prada et al. in [11] described the iterative time reversal process for a static scene. The MIMO problem formulation can written as:

$$\mathbf{R}(\omega) = \mathbf{K}(\omega)\mathbf{E}(\omega) \tag{4}$$

where $\mathbf{E}(\omega)$ is the column vector of the FFT of the transmit signals, $\mathbf{R}(\omega)$ is the column vector of the FFT of the received signals and $\mathbf{K}(\omega)$ the channel matrix. Given a received signal $\mathbf{R}_n(\omega)$, the next output signals is given by: $\mathbf{E}_{n+1} = \mathbf{R}_n^*(\omega) = \mathbf{K}^*(\omega)\mathbf{E}_n^*(\omega)$. With this formulation and collocated Tx and Rx, the $2n^{th}$ input signals is:

$$\mathbf{E}_{2n}(\omega) = [\mathbf{K}^*(\omega)\mathbf{K}(\omega)]^n\mathbf{E}_0(\omega) \tag{5}$$

Prada shows the convergence of the $[\mathbf{K}^*(\omega)\mathbf{K}(\omega)]^n$ operator to the brightest scattering point of the scene. Effectively the MIMO array focus the sound to this scattering point. For a dynamic scene $\mathbf{K} = \mathbf{K}(\omega,t)$ varies with time. We note $\mathbf{K}_n(\omega)$ the channel matrix at time step n. We can now write: $\mathbf{R}_n = \mathbf{K}_n\mathbf{E}_n$. In order to track an underwater target in motion we propose to defocus the input signal $\mathbf{E}_{n+1}$ accordingly to the maximum speed of the target. $\mathbf{E}_{n+1}$ becomes $\mathbf{E}_{n+1} = \mathbf{G}\mathbf{K}_n^*\mathbf{E}_n^*$. Equation 5 then becomes

$$\mathbf{E}_{2N} = \left[\prod_{2n=2}^{2N} \mathbf{G}\mathbf{K}_{2n-1}^*\mathbf{G}^*\mathbf{K}_{2n-2}\right]\mathbf{E}_0 \tag{6}$$

It is interesting to note that the iterative defocussed time reversal process it equivalent to the general approach taken by digital tracking filters. Tracking algorithms proceed in two steps:

$$p_k(X_k|Z^{(k)}) \rightarrow p_{k+1|k}(X_{k+1}|Z^{(k)}) \rightarrow p_{k+1}(X_{k+1}|Z(k+1)) \tag{7}$$

The first step is a prediction step and is equivalent to the defocus operator $\mathbf{G}$. The second step is the data update is equivalent to the channel matrix operator $\mathbf{K}_n$.

6. CONCLUSIONS

In this paper a full 3D realistic MIMO sonar simulator was presented. We showed the value of large MIMO sonar systems for underwater surveillance. In particular we studied the problem of harbour surveillance and underwater object tracking. The traditional MHT and PHD filter approaches were discussed and results using the HISP filter were presented. Finally we proposed a time reversal approach to tracking using defocused output signals.

7. ACKNOWLEDGEMENT

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