Adaptive Clutter Density in Multi-Hypothesis Tracking

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Abstract: In underwater surveillance active sonar is an important technological asset. Compared to passive sonar it features higher detection ranges and enables the detection of silent objects. As a drawback the interaction of sound waves with the seabed and the water surface causes false alarms, named clutter. False alarms usually appear randomly and variable in time and space. To distinguish false alarms from true contacts the Multi-Hypothesis Tracking approach can be used. This approach incorporates the density of sonar contacts to extract possible target tracks. Thus, the assumed clutter density influences, amongst others, the performance of this tracking approach.
This paper presents a method for determining the clutter density adaptively. It considers positions of all sonar contacts within one measurement and thereby approximates the actual clutter density precisely. The influence on the tracking results using adaptive clutter density in a multi-hypothesis tracker is shown by applying the algorithm to two multistatic sonar datasets and comparing it to results obtained by tracking using constant clutter density. Tracking performance is quantified by existing tracking performance metrics.

1 Introduction

The technological development of submarines has advanced enormously since the end of the Second World War. Modern submarines can stay submerged for weeks or even months. In addition they are not detectable by radar systems due to the high attenuation of electromagnetic waves in the water. Hence SONAR, a technology using sound waves, is used to detect and track submarines. Modern submarines are remarkably quiet, making them hard to detect by passive sonar. Therefore, active sonar is used. It can not only detect silent submarines but also features high detection ranges. As a drawback the interaction of the actively emitted sound waves with the seabed and the water surface can cause high amounts of false detections, also called clutter. This results in the necessity of automatic tracking and data association methods. One of these methods is Multi-Hypothesis Tracking (MHT) which is used to distinguish false alarms from true contacts. Using MHT, track

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hypotheses are calculated from all contacts and weighted according to their probability of being a target-originated contact.
The tracking performance of MHT algorithms is heavily influenced by certain input parameters such as the clutter density which is the spatial density of false detections. In many tracking realizations it is assumed that the clutter density is constant at any location [vK98]. But as the seabed is not uniformly shaped and the water surface changes permanently, the clutter density actually varies with time and space.
In the following we present a method to calculate the variable clutter density based on the location of all sonar contacts detected from one sonar transmission, named ping. The variable clutter density is included into a MHT algorithm. Tracking results are obtained by applying the algorithm to the ARL:UT and SEABAR07 datasets and evaluated by different tracking-performance metrics proposed in [CdT06]. Tracking results are compared to results of the MHT for which a constant clutter density is used.
This paper is structured as follows: Section 2 presents the Multi-Hypothesis Tracking algorithm. In section 3 the method to calculate a variable clutter density is described. The tracking results and the comparison are shown in Section 4. A conclusion and an outlook is given in section 5.

2 Multi-Hypothesis Tracking

MHT is based on sequential state estimation realized by Kalman filtering. The idea of MHT described in [KKU06] is to generate tracks by stating different hypotheses for association of noisy sonar contacts to target tracks. Thereby, the decision, whether a contact is target-originated or a false contact is delayed until enough information is available. Despite missing detections and high false alarm rates the MHT can generate tracks consisting of target-originated contacts. The association of clutter contacts results in unlikely hypotheses represented by low hypothesis weights. The MHT includes an estimation step to provide accurate target state estimates. Due to the nonlinearities between the sonar measurement and the target state, estimation is realized by a nonlinear variant of the Kalman filter, namely the Unscented Kalman filter [JU04]. Since the number of sonar contacts within one ping may be high, the number of hypotheses representing one target track increases fast with time. Thus, different methods to limit the number of hypotheses are included in the MHT.

2.1 System modeling

In the considered model, tracking is done in the Cartesian plane. Hence, a state vector at time t_k is defined by

$$\boldsymbol{x}_k = (x, v_x, y, v_y)^\top. \tag{1}$$

x and y are the Cartesian coordinates of the target's position and v_x and v_y are the corresponding velocities. Choosing a *Nearly Constant Velocity* model [BSRLK01] for the

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assumed target behavior, the system dynamic is linear:

$$\boldsymbol{x}_k = \boldsymbol{A}\boldsymbol{x}_{k-1} + \boldsymbol{w}_{k-1}. \tag{2}$$

$\boldsymbol{A}$ is the system matrix, and the process noise representing deviations from the assumed behavior is modeled as white Gaussian noise $\boldsymbol{w}_{k-1}$.
The measurement vector $\boldsymbol{y}_k$ consists of the bearing φ and the distance r between receiver and target:

$$\boldsymbol{y}_k = (r, \varphi)^\top. \tag{3}$$

The functional relation between the measurement and the state vector is described by the nonlinear function h distorted by additive white Gaussian noise $\boldsymbol{v}$ modelling the unavoidable measurement errors:

$$\boldsymbol{y}_k = h(\boldsymbol{x}_k) + \boldsymbol{v}_k. \tag{4}$$

2.2 Kalman filtering

The estimation of the target state $\boldsymbol{x}$ includes the stochastic components $\boldsymbol{w}$ and $\boldsymbol{v}$. Thus, a Kalman filter is used [WB06] to incorporate knowledge on these components in the estimation procedure. The process of filtering is divided into two steps: time update and measurement update.
In the time update step an *a priori* estimation $\hat{\boldsymbol{x}}_{k|k-1}$ of the target state $\boldsymbol{x}_k$ at time step t_k is obtained by using the assumptions on the target dynamics. The *a priori* estimation considers all measurements up to the time step t_{k-1} as it is indicated by the subscript $k|k-1$. The measurement update processes the new measurement $\boldsymbol{y}_k$ and calculates the *a posteriori* estimation $\hat{\boldsymbol{x}}_{k|k}$ based on all measurements up to the current time step t_k.
The Kalman filter algorithm is described in [WB06] in detail. Due to the nonlinear function h the Unscented Kalman filter [JU04] is used in this paper.

2.3 Building up Hypotheses

In order to take multiple contacts at each time step into account, the target state is represented by different hypotheses states. Having a set of hypotheses states $\boldsymbol{X}_{k-1} = \{\hat{\boldsymbol{x}}^1_{k-1|k-1}, \hat{\boldsymbol{x}}^2_{k-1|k-1}, ..., \hat{\boldsymbol{x}}^{\hat{n}_{k-1}}_{k-1|k-1}\}$ at t_{k-1} with $\hat{n}_{k-1}$ being the number of states, hypotheses states at t_k can be obtained by associating each element of $\boldsymbol{X}_{k-1}$ with each element of the set of contacts $\boldsymbol{Y}_k = \{\boldsymbol{y}^1_k, \boldsymbol{y}^2_k, ..., \boldsymbol{y}^{n_k}_k\}$. n_k is the number of contacts at t_k.
The probability of a hypothesis state being the actual target state is given by the weight w.
The preliminary weights are calculated as [KKU06]

$$\hat{w}^{ij}_k = \begin{cases} w^i_{k-1}\frac{P_d}{f_c}\mathcal{N}(\boldsymbol{y}^j_k; h_{UT}(\hat{\boldsymbol{x}}^i_{k|k-1}), \boldsymbol{S}^{ij}_k), & j > 0 \\ w^i_{k-1}(1 - P_d), & j = 0 \end{cases} \tag{5}$$

with $1 \leq i \leq \hat{n}_{k-1}$ and $0 \leq j \leq n_k$. i is the index of a hypothesis state at t_{k-1} and j is the index of the contact associated with this state. $h_{UT}(\hat{\boldsymbol{x}}^i_{k|k-1})$ is the result of the Unscented

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Transformation of $\hat{\boldsymbol{x}}^i_{k|k-1}$, representing the *a priori* estimation of the Kalman filter. $\boldsymbol{S}$ is the innovation covariance resulting from the Kalman filter measurement update. $j = 0$ considers the case that none of the contacts belongs to the target. f_c denotes the clutter density whose determination is described in section 3.
The actual probabilities are obtained by normalizing the preliminary weights:

$$w_k^{ij} = \frac{\hat{w}_k^{ij}}{\sum_{i=1}^{\hat{n}_{k-1}} \sum_{j=0}^{n_k} \hat{w}_k^{ij}}. \tag{6}$$

As the number of hypotheses increases by the factor $n_k + 1$ each time step the computability could not be ensured without reducing the number of hypotheses. For this purpose different techniques such as *gating*, *pruning* and *merging* are used [DE10].

2.4 Track Confirmation and Termination

In general, there is no *a priori* information about the time of occurrence of targets. In fact each contact might be target-originated. Hence the tracking procedure is initiated at any contact, i.e. each contact is considered to be the starting point of a new track where hypotheses are generated independently from hypotheses of other tracks.
Assuming a severely cluttered environment, many sonar contacts are processed from which at most one contact is target-originated for every target present. Thus, most of the tracks are false tracks. To distinguish false and true tracks, sequential track extraction (STE) is applied [vK98]. STE is based on a likelihood ratio test and can be described as follows:
Let $a = 1, 2, ..., m_k$ be the index of a track and m_k the number of tracks at t_k. Furthermore two hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$ are stated. $\mathcal{H}_0$ considers that the contacts $\boldsymbol{Y}_1^a, \boldsymbol{Y}_2^a, ..., \boldsymbol{Y}_k^a$ used to generate the hypotheses of a certain track $\mathcal{T}_k^a$ are false alarms only. $\mathcal{H}_1$ considers that the contacts are target-originated *and* false alarms. The likelihood ratio $L(\mathcal{T}_k^a)$ is defined as

$$L(\mathcal{T}_k^a) = \frac{p(\mathcal{T}_k^a|\mathcal{H}_1)}{p(\mathcal{T}_k^a|\mathcal{H}_0)}. \tag{7}$$

Hypothesis $\mathcal{H}_1$ is accepted and the track $\mathcal{T}_k^a$ is confirmed if $L(\mathcal{T}_k^a) > B$. The track $\mathcal{T}_k^a$ is terminated if $L(\mathcal{T}_k^a) < A$. In this case, $\mathcal{H}_0$ is accepted. A and B are thresholds which have to be chosen appropriately. The ratio $L(\mathcal{T}_k^a)$ can be calculated as the sum of unnormalized hypothesis weights [KKU06]:

$$L(\mathcal{T}_k^a) = \sum_{i=1}^{\hat{n}_k^a} \hat{w}_i \quad . \tag{8}$$

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3 Calculating Variable Clutter Density

As indicated by eq. (5) the hypothesis weights depend, among other variables, on the clutter density f_c which is the spatial density of false contacts. Clutter occurs randomly from time step to time step with respect to number and position. In addition the positions are statistically independent from each other as well as from the target. Although it is assumed in [vK98] that "clutter targets" are uniformly spaced with density f_c, the actual spatial distribution is usually not uniform. In fact, the density can be very high at certain spots and very low at other spots and might change from time step to time step. It is simply variable and not constant.

In order to take this fact into account when tracking the variable clutter density must be quantified in some ways. Usually the density can be calculated by dividing the number of contacts by the size of the area in which they are. This method is not suitable for calculating a variable clutter density due to the smooth transition between areas of high density and those of low density and the resulting difficulty of setting up appropriate area boundaries (size, shape and position of the area). To overcome this problem the method proposed here does not calculate the clutter density for certain areas but for each contact position individually.

The main idea behind the proposed method is that each contact provides density contributions to all other contacts. This represents an extension to the determination of a measure of clutter density proposed in [MMLS05] where only the closest contact is considered. Here, the sum of all density contributions a contact receives represents the clutter density for the position of this specific contact. The density contribution F of one contact i to another contact j depends on the Euclidean distance between the contacts [Ngu10]. It is defined as

$$F(i,j) = \begin{cases} \dfrac{1}{\hat{d}_{ij}^2}, & i \neq j \\ 0, & i = j \end{cases}, \tag{9}$$

with

$$\hat{d}_{ij} = \begin{cases} d_{min}, & d_{ij} < d_{min} \\ d_{ij}, & \text{else} \end{cases} \tag{10}$$

and d_{ij} being the Euclidean distance between the contacts. d_{min} is a lower bound for the distance $\hat{d}_{ij}$.

Finally the clutter density f_{c_j} at the position of the contact j is defined as

$$f_{c_j} = \frac{C}{n_k} \sum_{i=1}^{n_k} F(i,j) \tag{11}$$

with n_k being the number of contacts at time step t_k and C being a normalization factor. f_{c_j} is used in the Kalman filter measurement update step to weight the association between the predicted track hypothesis and the considered sonar contact. The clutter density refers to the density within the considered association gate. Thus, C normalizes the density to the gate volume V_G with $C \propto V_G$. The gate volume V_G of an ellipsoidal gate G, as it is used here, is defined as [BP99]

$$V_G = \pi \sqrt{\det(\boldsymbol{S})} G \tag{12}$$

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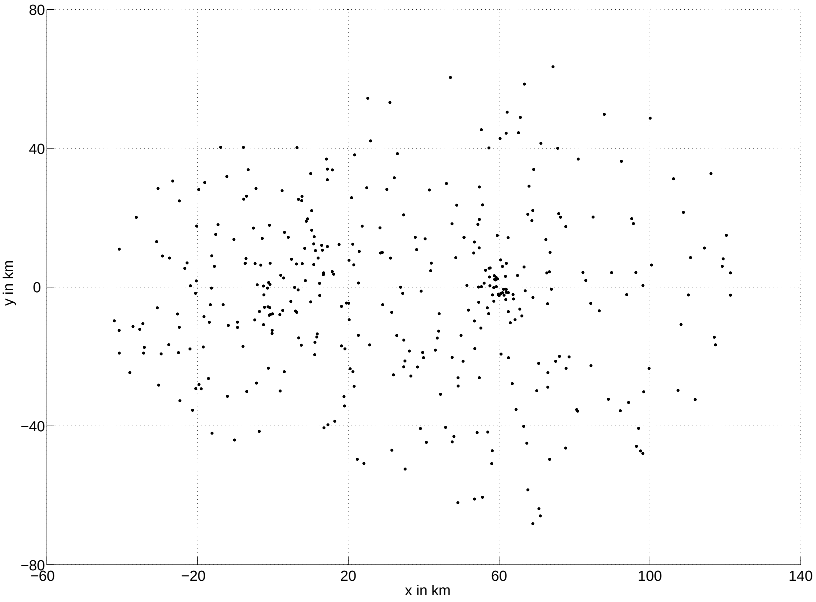
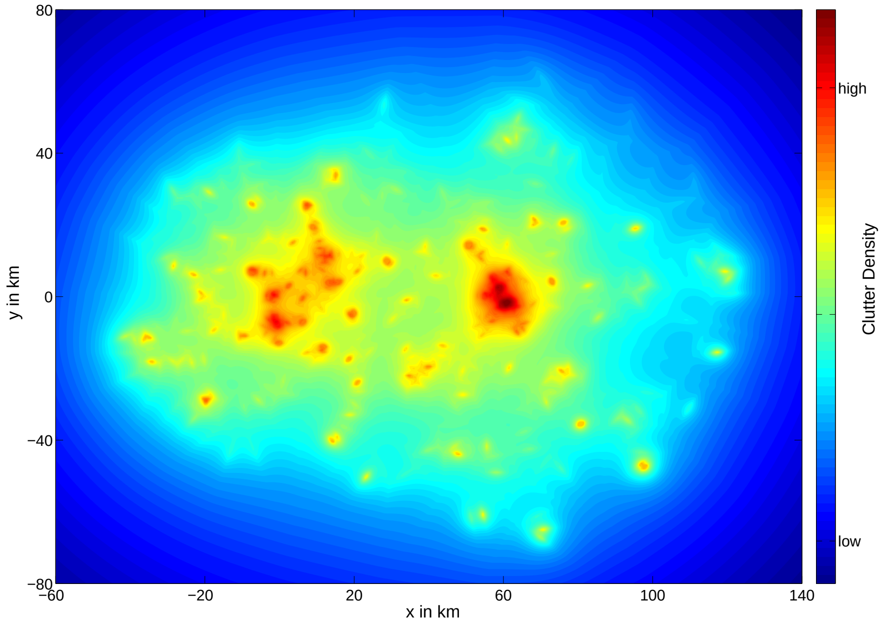


(a)



(b)

Figure 1: All contacts of a certain ping (a) and the corresponding clutter density map (b).

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for two-dimensional measurements as given in (4). G defines the size of the gate set appropriately and $\boldsymbol{S}$ is the innovation covariance matrix.
To limit the complexity of the algorithm the consideration of each individual gate volume is avoided by the approximation of

$$\sqrt{\det(\boldsymbol{S})} \approx T^2 \frac{m}{s^2} \tag{13}$$

with $T = t_k - t_{k-1}$ denoting the measurement interval. Thereby, an approximated gate volume $\tilde{V}_G$ is used for normalization.
As an example the described method has been applied to all contacts within one ping shown in Fig. 1(a). The resulting density map is shown in Fig. 1(b). As can be seen areas with a high and those with a low density were visualized appropriately. Note, that Fig. 1(b) is just a visualization for the area covered by the contacts. The method itself only calculates the density for the contact positions.

4 Tracking Simulations and Results

The presented method of calculating a variable clutter density has been implemented in the MHT algorithm and applied to the multistatic sonar datasets ARL:UT and SEABAR07. For each dataset tracking has been performed twice, once using a variable and once using a fixed clutter density. To compare the results several tracking-performance metrics according to [CdT06] have been determined. Due to the multistatic sensor systems used in both scenarios a suitable data fusion technique is necessary. For this paper, the data fusion is performed by a centralized fusion strategy [SSH10].

4.1 The ARL:UT and SEABAR07 datasets

The ARL:UT sonar dataset is a *hybrid* dataset. As described in [LCCL06], [LC07] real experimental sonar data have been collected by a distributed buoy sonar system. The system consists of one source S and two receivers R1 and R2 which record the acoustic echoes of the data which was sent every 120 seconds. The duration of the scenario is 120 minutes resulting in 60 sonar transmissions. Two simulated targets were injected into the recorded data. These targets move with a constant velocity during the scenario. Target 1 moves slowly from east to west with a speed of approximately 2 knots and target 2 is moving from south-west to north-east. Its velocity is about 10 knots. The geometry of ARL:UT is shown in Fig. 2(a).
The data of SEABAR07 was collected during a sea trial in 2007 which was carried out by the NATO Undersea Research Centre (NURC). In the scenario three receivers R1, R2 and R3 and one transmitter source S were used. R1 was only active during a few pings. Thus, it is not taken into account for any analysis. The target moves along a zig-zag track. The scenario consists of 90 pings and the interping time is 60 seconds. The geometry of the dataset is shown in Fig. 2(b).

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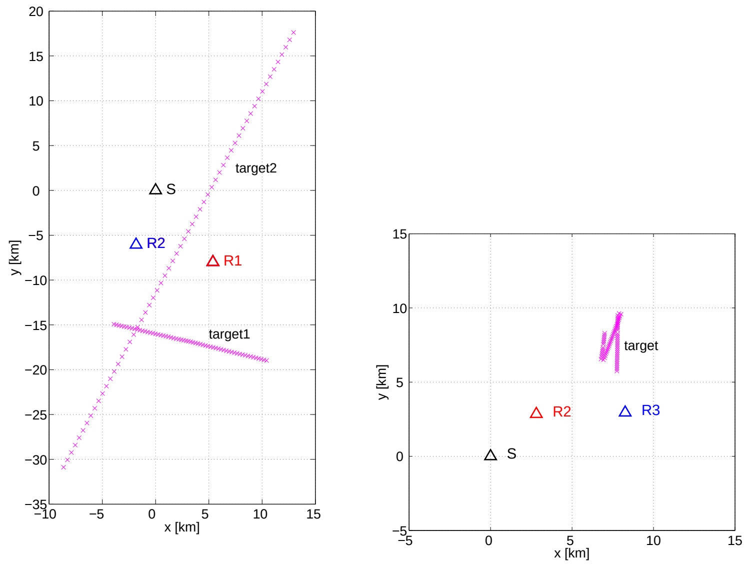

(a) (b)

Figure 2: Run geometries of the ARL:UT dataset (a) and the SEABAR'07 data (b).

4.2 Tracking Results

Applying the approach of a variable clutter density to the above described datasets has a positive influence on the overall tracking result. Fig. 3(a) shows all tracks that have been extracted during the scenario using a variable clutter density. For comparison, in Fig. 3(b) all tracks extracted with the MHT using a constant clutter density are shown. It can be seen, that with an adaptively determined clutter density the number of extracted false tracks can be significantly reduced. Table 1 lists several tracking performance met-

Table 1: Tracking performance metrics ARL:UT.

	fixed clutter density	adaptive clutter density
TPD [target 1/ target 2]	0.95/0.78	0.87/0.78
NFT	30	17
TLE [target 1/ target 2]	35/106	37/110

rics. From the table it can be read, that the number NFT of false tracks is reduced from 30 under a constant clutter density to 17 by the inclusion of a variable density. Further metrics describe the track probability of detection TPD, the ratio of the time the target is tracked to the time the target is present, and the mean track-localization error TLE. For target 1 the TPD decreases in case a variable clutter density is implemented. This

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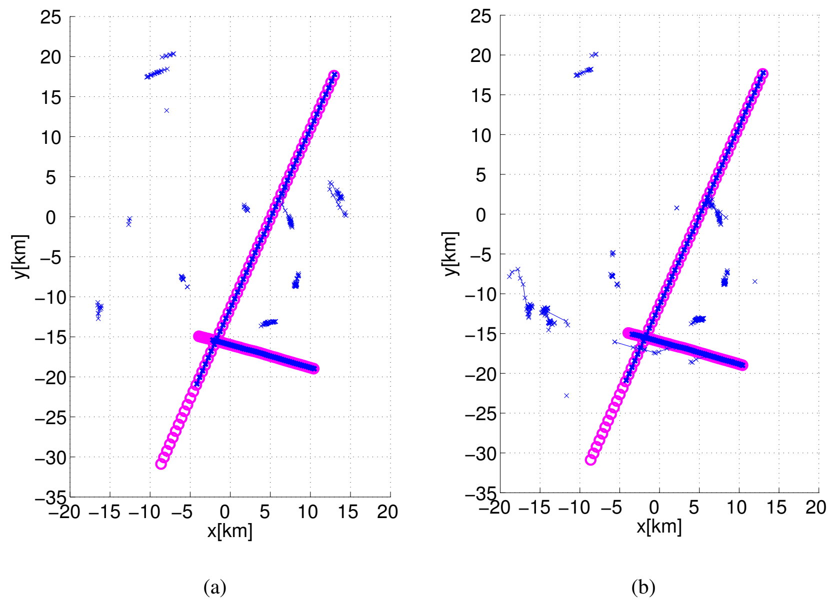

Figure 3: Tracking results for the ARL:UT dataset when applying an adaptive clutter density (a) and with a fixed clutter density (b).

is because the track is initialized in a dense cluttered area where the STE takes longer for track extraction. Further performance metrics for both targets are hardly influenced by the implementation of the variable clutter density.
Fig. 4(a) and Fig. 4(b) show the results obtained by applying the presented approach on the SEABAR'07 dataset. It can be seen that the results are similar to those obtained with the ARL:UT data. The number of extracted false tracks is reduced from 29 to 12 tracks. Simultaneously, further tracking performance metrics are not significantly changed as table 2 shows.

Table 2: Tracking performance metrics SEABAR'07.

	fixed clutter density	adaptive clutter density
TPD	0.93	0.92
NFT	29	12
TLE [m]	131	135

In general, the number of false tracks is determined pessimistically for the two datasets since there are three known wreck positions and an oil platform in the surveillance area. Thus, tracks which are extracted at these positions are expected.

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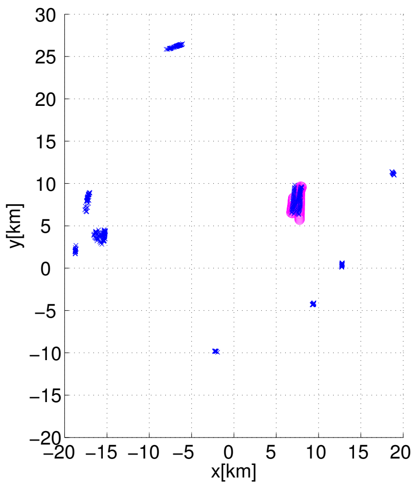
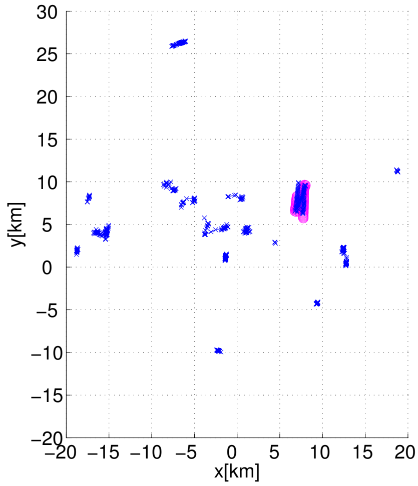


(a)



(b)

Figure 4: Tracking results for the SEABAR'07 dataset when applying an adaptive clutter density (a) and with a fixed clutter density (b).

5 Conclusion and Outlook

In this paper the influence of a variable clutter density on the performance of a Multi-Hypothesis Tracking algorithm has been analyzed. It has been shown that using a variable clutter density increases the tracking performance. The density was calculated for each contact position individually. The main concept of the proposed method is that each contact provides density contributions to all other contacts within the same ping. The amount of the density contribution depends on the Euclidean distance between two contacts and the sum of all density contributions a contact receives represents the clutter density.
Tracking results were obtained by applying a MHT algorithm to two datasets. They show that in both cases the usage of a variable clutter density reduces the number of false tracks significantly compared to the usage of a fixed clutter density. Furthermore the track localization error and the track probability of detection remained almost unchanged. Thus, the presented approach reduces the number of false tracks without effecting other tracking performance metrics. Only for one target of one dataset the TPD was slightly decreased.
To verify the results the approach needs to be applied to further datasets. These should be obtained in different sea areas with different clutter structures. Moreover, an extensive testing should be done for datasets with targets moving through dense cluttered areas in order to analyze the effect of a variable clutter density holistically.

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References

[BP99] S. Blackman and R. Popoli. *Design and Analysis of Modern Tracking Systems*. Artech House Radar Library, 1999.

[BSRLK01] Y. Bar-Shalom, X. Rong Li, and T. Kirubarajan. *Estimation with Applications to Tracking and Navigation*. John Wiley & Sons, 2001.

[CdT06] S. Coraluppi and P. de Theije. Benchmark Evaluation of Multistatic Trackers. In *Proceedings of the 9th International Conference on Information Fusion*, Florence, Italy, July 2006.

[DE10] M. Daun and F. Ehlers. Tracking Algorithms for Multistatic Sonar Systems. *EURASIP Journal on Advances in Signal Processing*, 2010:28, 2010.

[JU04] S. Julier and J. K. Uhlmann. Unscented Filtering and Nonlinear Estimation. *Proceedings of the IEEE*, 92:401–422, 2004.

[KKU06] W. Koch, J. Koller, and M. Ulmke. Ground target tracking and road map extraction. *ISPRS Journal of Photogrammetry & Remote Sensing*, 61:61, 2006.

[LC07] B. La Cour. Bayesian Multistatic Tracking with Doppler-Sensitive Waveforms. In *Proceedings of OCEANS 2007*, Aberdeen, Scotland, 2007.

[LCCL06] B. R. La Cour, C. W. Collins, and J. L. Landry. Multi-everything Sonar Simulator (MESS). In *Proceedings of the 9th International Conference on Information Fusion*, Florence, Italy, July 2006.

[MMLS05] D Musicki, M. Morelande, and B. La Scala. Non Parametric Target Tracking in Non Uniform Clutter. In *Proceedings of the 8th International Conference on Information Fusion*, Philadelphia, USA, July 2005.

[Ngu10] V. D. Nguyen. Analysis of the Influence of the variable Clutter Density on the Tracking Result. Diplomarbeit (master thesis), Institute for Circuit and Systems Theory, Christian-Albrechts-Universität zu Kiel, 2010. (in German).

[SSH10] K. Seget, A. Schulz, and U. Heute. Multi-Hypothesis Tracking and Fusion Techniques for Multistatic Active Sonar Systems. In *Proceedings of the 13th International Conference on Information Fusion*, Edinburgh, Scotland, July 2010.

[vK98] G. van Keuk. Sequential Track Extraction. *IEEE Transactions on Aerospace and Electronic Systems*, 34(4):1135–1148, October 1998.

[WB06] G. Welch and G. Bishop. An Introduction to the Kalman Filter. Technical report, UNC Chapel Hill, 2006.