Different tools for clutter mapping

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Abstract: Stationary clutter arises in a wide area of different radar or sonar applications. Without adaption to a non-uniform clutter distribution, tracking algorithms try to initialize tracks in these areas repeatedly while - in most cases - there is no target to be found.

The intention of this paper is to discuss different ways to enable clutter mapping in order to use this as an efficient tool for target tracking algorithms. The methods will be applied to the Range/Doppler tracking task in a multistatic passive radar application, and the performances of the different algorithms are discussed.

1 Introduction

Passive radar systems use illuminators of opportunity, no additional emitting source is necessary. This provides the advantage that the sensor does not reveal its own position, and in view of the application to air surveillance it is an important aspect that a passive system does not need a frequency permission. However, the signal waveforms are usually not perfectly suited for radar applications. Therefore passive radar systems usually deliver less precise measurements than active radar systems. Moreover, the measurements are often ambiguous. Thus, a fusion/tracking algorithm is needed to display the target information to the operator reliably.

In this paper we focus on DAB and DVB-T transmitters as illuminators of opportunity. A characteristic property of passive radar systems using DAB/DVB-T is the arrangement of the illuminators in so called single frequency networks (SFNs). As a consequence we cannot distinguish between measurements of individual illuminators within the same SFN. This means that the association of measurement and illuminator is a priori unknown and has to be solved by the tracking algorithm.

To handle the association problem in SFNs, a multi-stage tracking strategy is proposed in [DK08]. The first tracking stage operates in target parameters, i.e. bistatic range, bistatic Doppler and (if available) also azimuth. The main task of Range/Doppler (R/D) tracking is to remove false alarms before handling the association problem. A good performance of next tracking stage, the Cartesian tracking, is therefore highly dependent on the performance of the R/D tracking.

In the multistatic passive radar application that is studied here, clutter regions take shape as thin stripes spreading in Doppler. This paper shall not give an explanation for their appearance, but discusses ways to deal with this problem in context of R/D tracking.

Different approaches will be shown. In the first part of this paper, the Gaussian mixture reduction (GMR) algorithms by M. West [Wes93] and A. R. Runnalls [Run07] shall be shortly presented. Thereafter, there will be a revision of the Expectation Maximization (EM) algorithm, which is used in order to optimize the results of the other algorithms. The next part treats a greedy EM algorithm presented by Vlassis and Likas in 2000 [VL00]. After this, we will see different ways to use and combine the presented solutions, so that we can conclude the effect of clutter map usage on tracking algorithms. The algorithms are applied to real data of the Fraunhofer FHR [KMH07, KHSO09, OKH+10] and the resulting improvements with respect to R/D tracking are pointed out.

Due to space limitations we only give an outline of the algorithms and achieved results here, for details we refer to the long version of this paper which can be found in the electronic version of the proceedings.

2 Problem formulation

A common approach to create a clutter map is to divide the observation area into predefined clutter cells and to count the number of measurements appearing in the respective cell on a given time interval [MSMM05].

The focus of this paper is the representation of a clutter map by a Gaussian Mixture. The idea is that each measurement is represented by an expectation and a covariance matrix. Thus, from the view of a clutter statistic, a single measurement increases the clutter probability at the position of the expectation and its vicinity, whereas the expansion is described by the covariance.

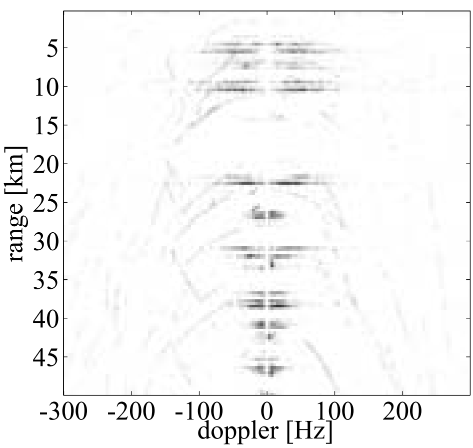


Figure 1: Representation of the observed area by a Gaussian mixture over 200 time scans. The stationary clutter regions appear as stripes of similar range.

In our specific application, a measurement at time t_i contains measurements of the bistatic range and Doppler given by $\mathbf{z}^{(i)} = (r^{(i)}, d^{(i)})$. The set of measurements at time t_i is further given by $\mathcal{Z}^i = \{\mathbf{z}_1^{(t_i)}, \ldots, \mathbf{z}_{N^{t_i}}^{(t_i)}\}$. A single measurement is by assumption Gaussian distributed, thus the set of measurements can be visualized by Gaussian mixture (GM), where for each $\mathbf{z}_j^{(t_i)}$ one summand $w_j^{t_i}\mathcal{N}(\mathbf{y}, \mathbf{z}_j^{(t_i)}, \mathbf{R}_j^{t_i})$ with weights $w_j^{t_i}$ and equally chosen covariances $\mathbf{R}_j^{t_i} = \text{diag}(\sigma_r^2, \sigma_d^2)$ is defined for each pair i, j, so that the calculation of

$$f(\mathbf{y}) = \sum_{i=1}^{t_{max}} \sum_{j=1}^{N^{t_i}} w_j^{t_i}\mathcal{N}(\mathbf{y}, \mathbf{z}_j^{(t_i)}, \mathbf{R}_j^{t_i}), \quad \mathbf{y} \in \mathbb{R}^d. \tag{1}$$

To visualize (1) we place a grid on the section of interest and derive the $f(\mathbf{y})$-values for all grid points seperately; the result is shown in figure 1. One can observe some horizontal oriented lines which are interpreted as the unwanted clutter, as well as tracks of some targets which cause the parabolic curves in the current R/D system[1]. Accumulating the data of more than a few time steps increases the complexity within the tracking algorithm. An efficient algorithm has to be found to decrease the information to its substance. With this motivation, we will compare and combine different algorithms and contrast their performance with respect to reduction of the Gaussian components.

3 Two GMR algorithms, EM algorithm and greedy EM.

To approximate clusters of points by only a few Gaussians, we use different methods to reduce the number of components of the Gaussian mixture in (1), i.e. we need to find a similar expression with a reduced number of K summands to approximate the old sum.

GMR algorithms We use and compare two algorithms for Gaussian mixture reduction following the approaches of M. West [Wes93] and A. R. Runnalls [Run07], referred to as GMR West and GMR Runnalls in the follwing.

The basic idea of GMR West is to delete the summand with lowest weight by merging it to its nearest neighbour, and then go on inductively, so that summands with little relevance will be sorted out first. Summands with weight 0 will be totally ignored.

The GMR Runnalls [Run07] has a more complicated structure than the rather straightforward solution by West. Runnalls' thought is to compare all possible pairs of summands in each merging step and to combine the two summands with highest compatibility. The comparison factor in this case is based on the so called *Kullback-Leibler discrimination*, which describes a divergence measure between two general probability density functions.

The EM and greedy EM algorithms The GMR techniques of Runnalls and West give us quite promising tools to reduce the number of GM components. However, it is recommendable to smooth the results of the GMR algorithms afterwards. We therefore use the Expectation Maximization (EM) algorithm as given in [VL00] and [OT96].

One more tool to build a clutter map is the greedy EM algorithm presented by Vlassis and Likas [VL00]. The strategy behind it has a slightly other view on our task since it does not try to merge certain summands like Runnalls and West proposed, but initializes by just one single Gaussian and later tries to reconstruct the old cluster inductively. This is provided by sequentially adding new components to the initialization, which fit best on the underlying old setting and simultaneously optimizing the Gaussians by the classical EM.

4 Application to multistatic passive radar data

Due to the wide multi-functionality of Gaussian mixtures, the introduced algorithms are very suitable for a vast number of circumstances. In this part of the paper we would like to present the tools in context of clutter map computation which occurs as a problem of target tracking. The clutter map is set up in Range/Doppler coordinates to assist the R/D tracking [DK08]. All algorithms will be tested with real sensor data from passive radar experiments with the passive radar demonstrator CORA, conducted at Fraunhofer FHR. A detailed description of CORA is given in [KHMA08].

[1] The little gap at Doppler zero is caused by an *a priori* clutter filtering at the receiver.

The data used for the clutter map analysis were obtained during a military exercise in Germany in 2007, where numerous aircraft operations and electronic warfare applications were trained. Illumination was provided by three local DAB single frequency networks.

Independent of the algorithms currently used, we will always start based on the following setting: The data that are to be analysed are stored in range and Doppler coordinates with units $[km]$ and $[Hz]$. The calculations are processing along 200 time steps, and for each time step, there will be approximately 100 measurements. Here we assume that the clutter is stationary during 200 time steps. In each step, the new data is added to the Gaussian and then optimized in different ways.

4.1 Creating the clutter map

Default setting The data that are to be analysed are stored in range and Doppler coordinates with units $[km]$ and $[Hz]$. The calculations are processing along 200 time steps $t_0, \dots, t_{199}$, and for each time step t_i, there will be approximately $N^{t_i} \approx 100$ measurements. Here we assume that the clutter is stationary during 200 time steps. In each step, the new data is added to the Gaussian and then optimized in different ways, where one or two of the presented algorithms will be combined.

Implementation problems of the EM and greedy EM algorithms The EM algorithm assumes i.i.d. samples on the distribution that is to be approximated. In our application, the measurements are interpreted as Gaussian samples of a true target, a Clutter target or a false alarm, described by an expectation and a covariance. We apply the EM on two different settings, on the one hand as an intermediate step in the greedy EM algorithm, and on the other hand independently, where it needs i.i.d. samples of the Gaussian mixture that is to be optimized. In the latter case, it is necessary to add a covariance matrix $\mathbf{R} = \text{diag}(\sigma_r^2, \sigma_d^2)$ to the covariances of the Gaussians, as justified in the large version of this paper. With this approach we overcome difficulties of the EM due to small sampling numbers (causing non positive definite covariances) and therefore overcome computational problems.

The initialization of the greedy EM algorithm requires a very sensitive choice. In our case, accuracy is improved by choosing just one element of the original data set at random, setting the weight of it to 1.

Results of clutter map generation In Fig. 2, the result of the combination of greedy EM algorithm and the classical EM is shown.

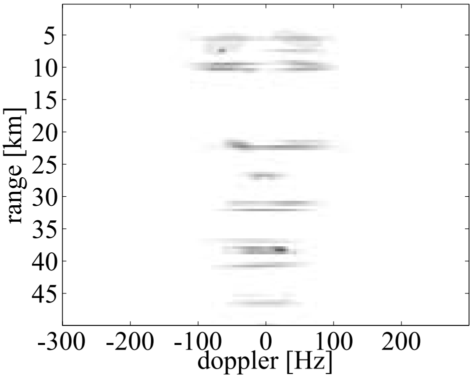


Figure 2: greedy EM algorithm and classical EM

The greedy EM algorithm gives an initialization based on the first 20 time steps and then, the classic EM algorithm is applied in every of the following time steps.

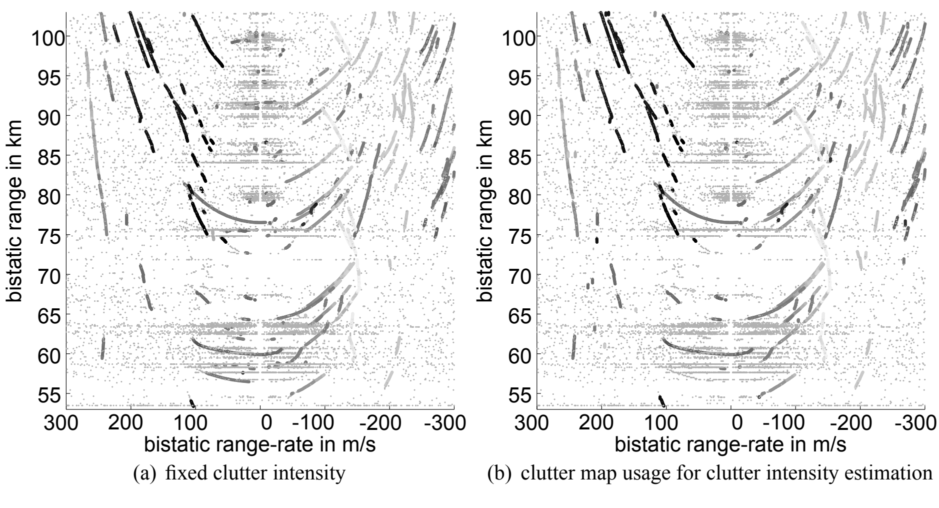
This scenario performs with high accuracy and displays the clutter map with only 63 Gaussian summands; hence we will use the Gaussian sum produced by the two EM routines for the tracking algorithm. Please see the full version of this paper for more results on clutter map generation.

4.2 The clutter map as a tool for target tracking

After the discussion of the different tool combinations, we will now explore the efficiency of using clutter maps in tracking algorithms. For generating R/D tracks we use Multi-hypothesis Tracking (MHT) [KKU06]. It is applied with different parameter settings of the Clutter value ϱ_F. The data deliver additional measurements of the azimuth direction, that is processed in the R/D tracking algorithm, but not considered in the R/D clutter map generation. For the azimuth we assume here a uniform false measurement background.

In the standard target tracking scenario we assume a uniform false alarm background, which means that ϱ_F is chosen to be fixed. This assumption is not suited for modelling the clutter distribution, which is reflected in the tracking results, see Fig. 3(a). A large number of false tracks is extracted in the regions of enhanced clutter intensity, since the tracker notices a deviation from the background model.

This effect can be counteracted by calculating a clutter map over several time scans. The results of the clutter map (with only 63 Gaussian components) generated by combination of Greedy EM initialization and EM (fig. 3(b)) give a better performance, generation of false tracks is significantly reduced. For the other tracks the tracking performance is quite comparable, but we can note some slight degradation for the clutter map approach. A track at range between 55km and 60km (lying close to clutter region) is not found by the tracker, when estimating the false alarm intensity using the clutter map.



(a) fixed clutter intensity

(b) clutter map usage for clutter intensity estimation

Figure 3: Doppler-Range Tracking Results of real data of the Fraunhofer FHR/PSK: The measurements are shown by black dots, whilst the tracks are illustrated in different colors (representing the value of the azimuth estimate).

5 Conclusion and Acknowledgements

As the results in the last section show, clutter map computation is of great importance in order to reduce the amount of false alarms by a tracking algorithm. Based on the underlying Gaussian mixture representation of the clutter map, different algorithms were shown that reduce Gaussian mixtures and optimize the reduction results. It could be observed that, despite the loss of a few tracks that coincide with high appearance of clutter, the usage of a clutter map generated by the greedy EM algorithm can improve the R/D tracking by sorting out most of the generated false tracks.

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