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RADAR TARGET DETECTION USING HIDDEN MARKOV MODELS

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Abstract—Standard radar detection process requires that the sensor output is compared to a predetermined threshold. The threshold is selected based on a-priori knowledge available and/or certain assumptions. However, any knowledge and/or assumptions become inadequate due to the presence of multiple targets with varying signal return and usually non stationary background. Thus, any fixed predefined threshold may result in either increased false alarm rate or increased track loss. Even approaches where the threshold is adaptively varied will not perform well in situations when the signal return from the target of interest is too low compared to the average level of the background. Track-before-detect techniques eliminate the need for a detection threshold and provide detecting and tracking targets with lower signal-to-noise ratios than standard methods. However, although track-before-detect techniques eliminate the need for detection threshold at sensor's signal processing stage, they often use tuning thresholds at the output of the filtering stage. This paper presents a Hidden Markov Model based target detection method that avoids any thresholding at any stage of the detection process. Moreover, since the proposed Hidden Markov Model method is based on the target motion models, the output of the detection process can easily be employed for maneuvering target tracking.

1. INTRODUCTION

The purpose of target detection is to detect all objects of interest within the area of observation. Generally speaking, target detection would be an easy task if the targets were located in front of an otherwise clear or empty background. In such a case, the echo signal can

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simply be compared to a fixed threshold, and targets are detected whenever the signal exceeds this threshold. In real life applications, however, the target practically always appears before a background filled with clutter and frequently the location of this background clutter is, additionally, subject to variations in strength, time and position. Therefore, using a fixed threshold may cause problems. For instance if the threshold is selected too low the false alarm rate will increase whereas a too high threshold will result in an increased level of misdetection. This fact calls for adaptive signal processing techniques operating with a variable detection threshold to be determined in accordance to the local clutter situation. However, in the presence of multiple targets and/or where the echo signal is below the local clutter information obtained in a window around the radar test cell, even varying the threshold level may not perform well. Track-before-detect (TBD) techniques eliminate the need for a detection threshold and help detecting and tracking targets with lower signal-to-noise ratios.

Numerous studies can be found on TBD techniques in the literature. Most of TBD algorithms have been proposed to detect and track small moving objects in optical images corrupted by high cluttered noise [1, 2]. Dynamic Programming (DP) and particle filter based implementations are the most well-known techniques. In [3–5], DP based TBD methods were proposed for detecting and tracking low SNR targets. The analysis in [3] showed that the tracking performance of the DP algorithm is poor, even though detection performance is good and track separation phenomenon is one of the factors that deteriorate the tracking performance. An alternative approach is the Particle Filtering (PF), which has been used extensively for TBD [6, 7]. It is a numerical approximation technique that uses randomly placed samples to solve the non-linear function of the target state, which describes target's kinematic evolution. Although, PF based TBD approximation produce good results, it was reported that reducing the number of particles degrades performance too much [8].

Although TBD techniques eliminate the need for detection threshold at sensor's signal processing stage, they often use tuning thresholds at the output of the filtering stage. It is the motivation in this work to propose a novel method for detection which does not use any thresholding at any stage. In this paper, we propose a methodology for applying Hidden Markov Model (HMM) to detection of targets from unprocessed radar data available at the output of the sensor. HMM is a doubly stochastic process where an underlying stochastic (and Markovian) process that is not directly observable (i.e., "hidden") is observed through another set of symbols which are also stochastic processes. Discrete HMM corresponds to the particular case where the number of possible states is finite. In recent years, HMM based methods have become indispensable in applied mathematics and modern pattern recognition. HMMs are especially known for their application in temporal pattern recognition such as speech, sound, handwriting and image recognition. In fact the use of HMMs is an obvious choice for complex, nonstationary stochastic processes that produce time sequence of random observations. In most cases remote sensor outputs fit the description given above very well. Therefore, there are many examples of HMMs being employed in detection, tracking and identification using the observations obtained by remote sensors such as radar and sonar. For instance in [9] the problem of frequency line tracking is tackled by employing HMMs and in [10] the problem is extended to multiple frequency line tracking with ambiguous detections in which the problem was formulated in terms of HMM to produce MAP track estimates via the Viterbi algorithm. Tracking and target motion analysis (TMA) were performed in [11] by discretizing the target states in a grid of possible positions and speeds where the target state evolutions were assumed to be stochastic. In [12] a new strategy, in which wave fronts and resonances are used simultaneously, was presented and wave-based matched-pursuits algorithm was employed in the context of a HMM for target identification.

This paper presents a HMM based target detection method for employing with TBD techniques. HMM is a powerful statistical method to characterize the observed data samples of a discrete time series. The underlying assumption of the HMM is that the data samples can be well characterized as a parametric random process and the parameters of the stochastic process can be estimated in a well-defined framework. In addition to detection of existence of a target, the proposed algorithm also detects target maneuver which plays an important role in target tracking applications. Tracking of maneuvering targets is an important problem in air surveillance and traffic control applications and it has received considerable attention for many years [13, 14]. Maneuver detection is one of the key points for tracking of maneuvering targets because, an early and accurate detection of the target maneuver leads to a better result in tracking. In the proposed HMM based method clutter and target models have been constructed, in which, in order to detect the target maneuver, the target model is divided into 3 sub models as Coordinated Turn (CT), White Noise Acceleration (WNA) and Wiener Process Acceleration (WPA). The radar coverage area is assumed to be consisted of 4096×4096 resolution cells, which were grouped into 128×128 blocks corresponding to observation sequences. Therefore, the search over all the cells is narrowed into a much smaller area and detection process performed only on the corresponding blocks between subsequent scans. The size of the blocks is chosen assuming that target remains in the same block during six consecutive radar scans. Clutter and target models have been trained by Baum-Welch algorithm with sufficient amount of observation data. Finally, detection process was performed on radar observations by using Viterbi algorithm.

The rest of the paper is organized as follows: The following section gives a brief overview of HMM whereas Section 3 details how the HMM is applied to radar target tracking. Section 4 outlines the measurement and motion models employed in the study and the HMM structure used in the study is explained in Section 5. Performance of the proposed model is discussed compared to the PF approach in Section 6. Finally some conclusions are given in the last section.

2. BRIEF REVIEW OF HMM

HMM is a model of a stochastic process that characterizes a sequence of random observation vectors at discrete times according to an underlying Markov chain. HMM consists of a set of N states, each of which is associated with a set of M possible observations. At each observation time, the Markov chain may be in one of the states and, given that the chain is in a certain state, there are probabilities of moving to other states. These probabilities are called the transition probabilities.

The word "hidden" in hidden Markov models comes from the fact that the states are hidden or not directly observable. Given an observation vector at time, there are probabilities that the chain is in each state. The actual state is described by a probability density function, which can either be continuous or discrete. The probability density functions describing the states define the probabilities of the observations conditioned upon the chain being in the associated state. Initial state probabilities are also assigned.

Thus, HMM is characterized by three sets of probability density functions: the transition probabilities, the state probability density functions, and the initial probabilities. Furthermore, HMM is called continuous if the observation probability density functions are continuous and discrete if the observation probability density functions are discrete. The parameters of the HMM include:

- An initial matrix, π, of state probabilities whose elements, π_i; $i \in [1, N]$ describe the position distribution probabilities of the target over the initial state set at the beginning when time $t = 1$.

- A transition matrix A, whose elements a_{ij}; $i, j \in [1, N]$ are the transition probabilities from state i to state j.
- An observation matrix B, whose elements b_{im} are the probabilities of observing symbol $m \in [1, M]$ given that the system is at the state $i \in [1, N]$.

The HMM parameter set is denoted by $\lambda = (A, B, \pi)$. The transition probabilities express which type the model is, i.e., ergodic, left-right or coupled. Three basic problems have to be address with the HMM [15]:

- Evaluation problem: What is the probability of the observation O, given the model λ, i.e., $P(O|\lambda) = ?$
- Decoding problem: What is the most likely state sequence given the observation O, i.e., $\arg_s [\max P(O|\lambda)] = ?$
- Estimation problem: How can one estimate the parameters given the training observation sequences, $\lambda^* = \arg_\lambda [\max P(O|\lambda)] = ?$

3. HIDDEN MARKOV MODELS FOR TARGET DETECTION

In the proposed method, the HMM is used to detect not only targets but also its maneuver in the presence of clutter. Both detecting the existence of a target and its maneuver are of great importance as each detection scheme is usually followed by a tracking mechanism. Thus, the proposed method not only distinguishes targets in a highly cluttered environment but also provides an input to the tracking algorithm that would help reduce estimation errors.

Let each radar measurements be represented by a sequence of measurement vector or observations O, defined as

$$O = o_1, o_2, \ldots, o_T \tag{1}$$

The target detection problem can then be regarded as that of computing

$$\arg\max_i \{P(w_i | O)\} \tag{2}$$

where w_i is the ith detection. In this study, detections are divided into two main classes as clutter and target. In order to detect target maneuver model, target class is divided into three subclasses as CT, WPA and WNA. If needed, more subclasses can be constructed. For example, clutter class can be divided into sea and land clutter. The probability given in Eq. (2) is not computable directly; however, Bayes' Rule yields

$$P(w_i | O) = \frac{P(O | w_i) P(w_i)}{P(O)} \tag{3}$$

Thus, for a given set of prior probabilities $P(w_i)$, the most probable detection depends only on the likelihood $P(O|w_i)$. If the dimensionality of the observation sequence O is considered, the direct estimation of the joint conditional probability $P(o_1, o_2, \ldots | w_i)$ from examples of radar measurements is not practical. However, if a parametric model of the radar measurement production (such as a Markov model) is assumed, then estimation from data is possible since the problem of estimating the class conditional observation densities $P(O|w_i)$ is replaced by the much simpler problem of estimating the Markov model parameters [16].

In HMM based target detection, it is assumed that the sequences of observed radar measurement vectors corresponding to each detection are generated by a Markov model as shown in Fig. 1. A Markov model is a finite state machine which changes state once every time unit (in this application time unit is a radar scan) and each time t that a state j is entered, a radar measurement vector is generated from the probability density $b_j(o_t)$. Furthermore, the transition from state i to state j is also probabilistic and represented by the discrete probability a_{ij}. The joint probability that O is generated by the model M moving through the state sequence X is calculated as the product of the transition probabilities and the output probabilities. So, for the state sequence X given in Fig. 1.

$$P(O, X|M) = a_{12}b_2(o_1)a_{22}b_2(o_2)a_{23}b_3(o_3)\ldots \tag{4}$$

In practice, only the observation sequence O is known and the underlying state sequence X is hidden.

Given that X is unknown; the required likelihood is computed by taking the sum over all possible state sequences (Bayesian approach)

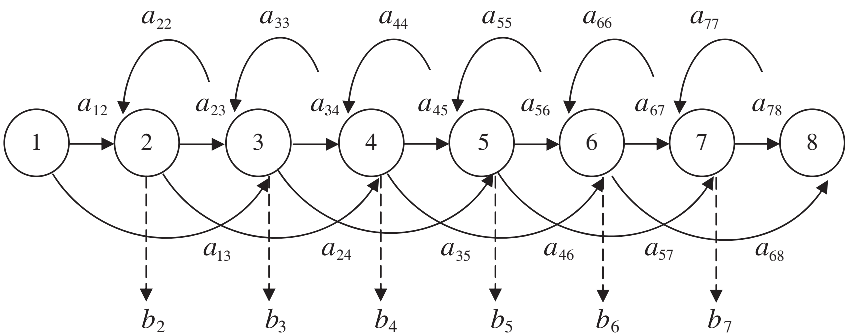


Figure 1. The Markov generation model.

$X = x(1), x(2), \ldots, x(T)$, that is

$$P(O\,|M) = \sum_X a_{x(0)x(1)} \prod_{t=1}^{T} b_{x(t)}(o_t) a_{x(t)x(t+1)} \tag{5}$$

where $x(0)$ is constrained to be the model entry state and $x(T+1)$ is constrained to be the model exit state.

As an alternative to Eq. (5), the likelihood can be approximated by considering the most likely state sequence that is (Viterbi approach)

$$\hat{P}(O\,|M) = \max_X \left\{ a_{x(0)x(1)} \prod_{t=1}^{T} b_{x(t)}(o_t) a_{x(t)x(t+1)} \right\} \tag{6}$$

Given a set of models, M_i, corresponding to detections w_i, Eq. (2) is solved by using Eq. (3) and assuming that

$$P(O\,|w_i) = P(O\,|M_i) \tag{7}$$

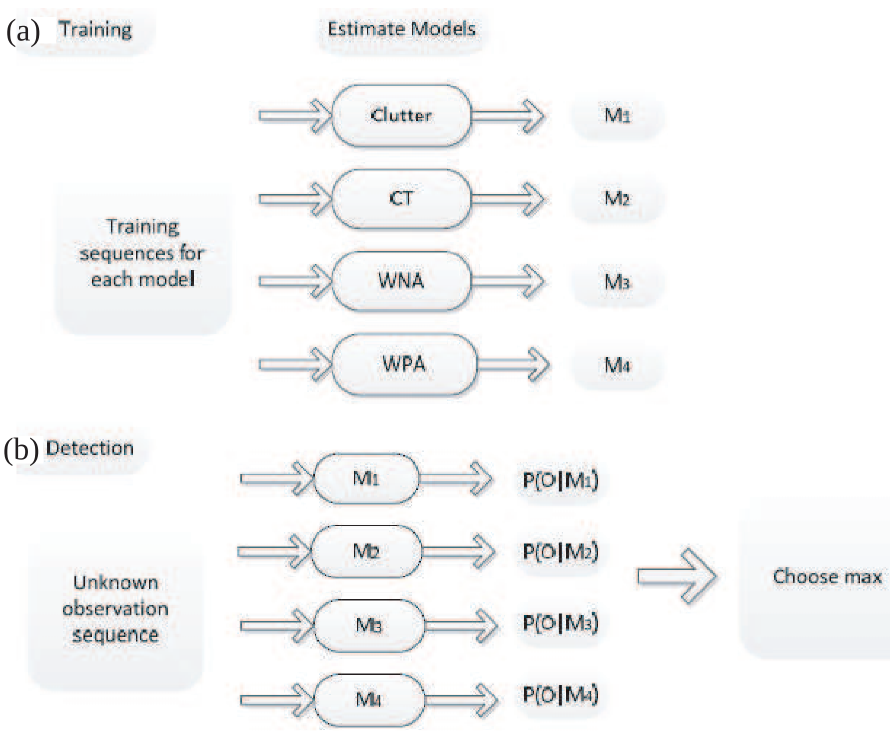


Figure 2. Using HMMs for target detection.

Given sufficient number of training examples of each detection, a HMM can be constructed which implicitly models all of the many sources of variability inherent in real radar measurements. Fig. 2 summarizes the use of HMMs for target detection. Firstly, a HMM is trained for each detection using a number of examples of that detection. In this case, four detection models: "clutter", "CT", "WPA" and "WNA" models are used. Secondly, to detect some unknown radar measurements, the likelihood of each model generating that measurement is calculated and the most likely model identifies the detection.

4. MEASUREMENT AND MOTION MODELS

4.1. Measurement Model

Each radar scan contains 4096×4096 resolution cells whose rows and columns are assumed to be bearing and range cells respectively where each cell contains a signal originated either from clutter or target. The measurement in each cell at time k, $z_k^{(i,j)}$, is assumed to be the magnitude of a windowed complex sinusoid in Gaussian noise. Thus, the measurement signal will be Ricean distributed if there is a target present, or Rayleigh distributed if there is no target. Then the pdf for measurements is,

$$p\left(z_k^{(i,j)}\middle|\, x_k\right) = \frac{2z_k^{(i,j)}}{\sigma^2}\exp\left(-\frac{\left[z_k^{(i,j)}\right]^2 + h^{(i,j)}(x_k)^2}{\sigma^2}\right) \times I_0\left(\frac{2z_k^{(i,j)}h^{(i,j)}(x_k)}{\sigma^2}\right) \quad (8)$$

If the target is present, or

$$p\left(z_k^{(i,j)}\right) = \frac{2z_k^{(i,j)}}{\sigma^2}\exp\left(-\frac{\left[z_k^{(i,j)}\right]^2}{\sigma^2}\right) \quad (9)$$

if there is no target, where σ^2 is the variance of the measurement noise. The term $h^{(i,j)}(x_k)$ is the contribution in cell i, j from the target, which depends on the point spread function of the window, the target location and the target signal amplitude. $I_0(\cdot)$ is the modified Bessel function [8].

4.2. White Noise Acceleration (WNA) Motion Model

White noise acceleration model is the basic model for the target motion where the target acceleration is assumed to be white Gaussian with zero mean and known variance. This model is also called the nearly constant velocity model and considered as the nominal motion model [14]. Any deviation from this model is classified as a maneuver.

$$x_{k+1} = Fx_k + Gw_k \tag{10}$$

$$F = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix}, \quad G = \begin{bmatrix} T^2/2 \\ T \end{bmatrix} \tag{11}$$

where T is the sampling period and w_k the constant acceleration at time k.

4.3. Wiener Process Acceleration (WPA) Motion Model

In this model acceleration is assumed as a Wiener process. This model is also known as constant acceleration model.

$$x_{k+1} = Fx_k + Gw_k \tag{12}$$

$$F = \begin{bmatrix} 1 & T & T^2/2 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}, \quad G = \begin{bmatrix} T^2/2 \\ T \\ 1 \end{bmatrix} \tag{13}$$

where T is the sampling period and w_k is the acceleration at time k and assumed as zero mean white noise.

4.4. Coordinated Turn (CT) Motion Model

In this model target moves constant velocity v and turns with constant angular velocity ω.

$$\dot{x}(t) = \begin{bmatrix} \dot{x}(t) \\ -\omega\dot{y}(t) \\ \dot{y}(t) \\ \omega\dot{x}(t) \end{bmatrix} + Bw(t) = A(\omega)x(t) + Bw(t) \tag{14}$$

$$A(\omega) = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & -\omega \\ 0 & 0 & 0 & 1 \\ 0 & \omega & 0 & 0 \end{bmatrix}, \quad B = \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} \tag{15}$$

Discrete time state equation defined as,

$$x_{k+1} = F_{ct}(\omega)x_k + w_k = \begin{bmatrix} 1 & \frac{\sin\omega T}{\omega} & 0 & -\frac{1-\cos\omega T}{\omega} \\ 0 & \cos\omega T & 0 & -\sin\omega T \\ 0 & \frac{1-\cos\omega T}{\omega} & 1 & \frac{\sin\omega T}{\omega} \\ 0 & \sin\omega T & 0 & \cos\omega T \end{bmatrix} x_k + w_k \tag{16}$$

5. HMM STRUCTURE FOR DETECTION

The measurements, feature set and HMM structure determine the overall performance of the detection system designed. Signal strength measurements from the target as well as range and bearing have been used as feature vectors.

5.1. Training Set

In order to train the HMM models, a radar model must be designed to create target and clutter measurements.

The training set comprises;

- Clutter measurements for 50 radar scans.
- Target measurements whose signal level is above the average clutter level. 300 different target trajectories have been used for each target maneuver model for training purposes. 100 different target trajectories have been created for test purposes.

Target initial positions were randomly assigned between 1–120 km in range and 0–359° in bearing. Angular velocity for the CT maneuver model and the acceleration for the WPA motion model are randomly assigned between 0–5 °/sec and 0.01–0.05 m/sec^2 respectively where the target velocities are also randomly assigned between -500 to 500 m/sec. The process noise used in CT, WPA and WNA kinematic models are 0.1, 1 and 0.01 respectively.

5.2. HMM Topology

To determine the number of states in the HMM numerous tests have been performed and it was found that state number is closely related with the number of consecutive radar scans used for detection. As it is seen from Fig. 3, best detection accuracy is obtained if six consecutive radar scans are utilized for detection. For this reason, each clutter and target detections were modeled by an 8 state HMM as shown in Fig. 1, where states 1 and 8 are entry and exit states of the HMM respectively. Also, states 2–7 are the emitting states that correspond to measurements obtained from sequential radar scans.

Clutter and target maneuver models were trained separately in which the feature set consists of signal strength, range and bearing values that are collected at each radar scan interval. Although these measurements are sufficient for separating clutter from target [17], they are inadequate for determining maneuver models. For this reason in addition to the feature set mentioned above, their delta, acceleration and third differential coefficients are also used which gives a total of 12 coefficients. Delta, acceleration and third differential coefficients are calculated through

$$d_t = \frac{\sum_{\theta=1}^{\Theta} \theta(c_{t+\theta} - c_{t-\theta})}{2\sum_{\theta=1}^{\Theta} \theta^2} \tag{17}$$

where d_t is a delta coefficient at time t and Θ the window size. The same formula is applied to the delta coefficients to obtain the acceleration coefficients.

Finally, the measurements that were used for training were not used for testing and the HTK toolkit [16] was used to perform HMM training and testing processes.

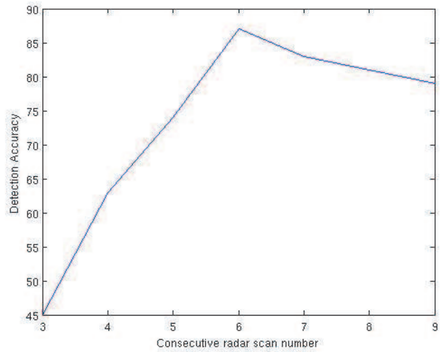


Figure 3. Effect of number of consecutive radar scans employed on detection performance.

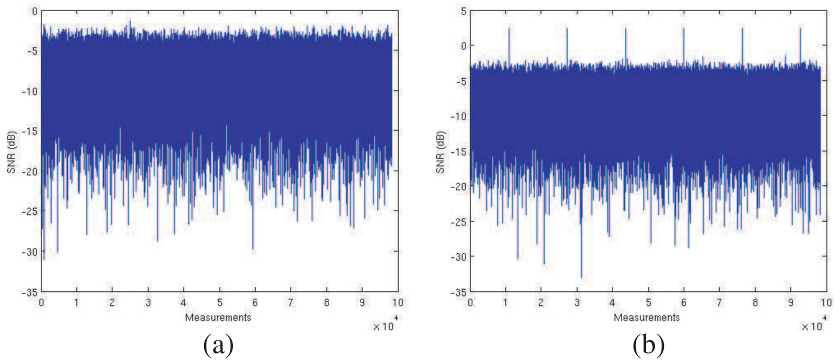


Figure 4. Sample observation sequence. (a) Clutter. (b) Target.

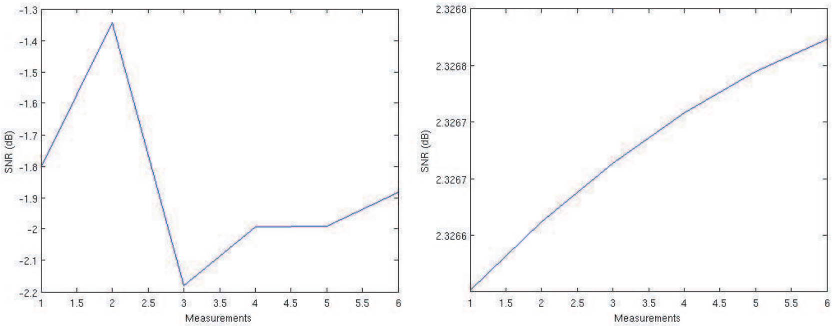
6. SIMULATION RESULTS

Detection process starts with forming the observation sequence, that is, by collecting six consecutive radar scans. There is no assumption as to which part of the target trajectory is sampled in the observation sequence and the aim of the HMM detection is to perceive the target trajectory through observation sequences. Each radar scan is assumed to have 4096×4096 range and bearing bins whose size is determined by radar's range and bearing resolution. In order to narrow down the search space, the 4096×4096 matrix is divided into 128×128 grids. Each observation sequence comprises 6 of these smaller 128×128 grids across consecutive scans, where it is assumed that the target remains within this grid while processing the observation sequence. Through this, trajectory search over all 4096×4096 cells is narrowed into a much smaller area and detection process performed only in the corresponding grids between sequential scans. Each cell in the observation sequence is assumed to contain information, thus, there are 16384 measurements in a grid and since we assume this is a single target tracking application with a unity probability of detection[†] (PD), only one of them is target originated. Fig. 4 shows clutter and target only cells which were decided by the proposed method based on the strongest signal selection criteria described above.

Once the six consecutive radar scans are accumulated then at each time, a radar scan is added in a sliding window fashion while the oldest scan is discarded. The size of the grid can be adjusted for different types of targets performing different target motions, for instance for a highly maneuvering target a bigger grid size may be needed. As each grid contains a vast amount of clutter measurements, reduction for these measurements is needed. It is assumed that, measurements originated from the target of interest have a signal level above average clutter level. This assumption gives an opportunity to reduce the measurement number in each grid which is, measurements from only the biggest signal level in each scan interval is considered. Then, HMM detection was applied on these grids from scan to scan. Detection was performed by applying the Viterbi algorithm on these grids to find the most likelihood model, i.e., whether the measurement has been originated from a target or from clutter, then at the end of the detection process measurements in each grid is marked as clutter or target.

100 different maneuvering targets, which had not been used for training, were selected for testing the proposed method. Strongest

† Unity P_D assumption stems from the fact that with this study we aim to demonstrate the applicability of the HMM to radar detection without any thresholding. However, unity P_D assumption can easily be relaxed with inclusion of a simple scheme to handle less than perfect detection conditions.



(a) (b)

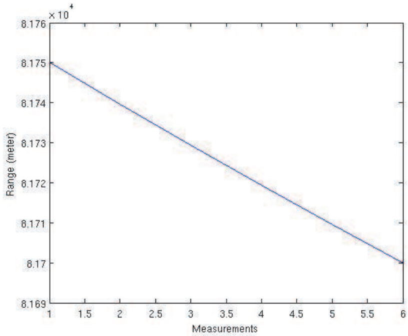
Figure 5. Variation of the signal power in a selected observation sequence. (a) Clutter. (b) Target.

Table 1. Maneuver detection performance of the HMM approach.

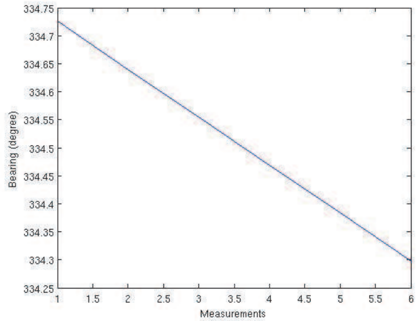
Models	Clutter	WNA	WPA	CT
Clutter	100%	0	0	0
WNA	0	100%	0	0
WPA	0	0	56.66%	43.34%
CT	0	0	0	100%

signals in each observation sequence have been determined and applied to the Viterbi algorithm in order to declare whether this sequence belongs to a target or it is clutter originated. Fig. 5 depicts sequences of clutter and target originated measurements in an observation sequence and as it can be seen, clutter is a noise like signal and has no apparent relation from scan to scan, whereas measurements from a target, which moves according to WNA maneuver model, display strong relation as we move along the radar scans.

In order to test the reliability of the Viterbi decision making, a whole radar scan consisting of only clutter measurements have been fed to the proposed algorithm. As expected the proposed algorithm has correctly labeled each measurement as clutter. Finally, Fig. 6 gives the range and bearing variation of the detected target whose signal power variation is shown in Fig. 5(b). Both range and bearing variation in Fig. 6 suggests that that the detected target obeys the WNA motion model. Simulation results have revealed that the proposed method has successfully detected the target of interest in heavy clutter without employing any thresholding.



(a)



(b)

Figure 6. Range and bearing variation of the detected target. (a) Range. (b) Bearing.

Moreover, the proposed method not only detects targets in clutter using raw radar data but also it provides information pertaining to the type of the maneuver that the target is performing at the time of detection. Maneuvering information is of particular information as the performance of any tracking algorithm that follows detection process will be greatly improved by using this information. Since this work mainly focuses on the detection performance of the HMM approach we shall not further discuss how the tracking performance is improved. However, Table 1 summarizes the maneuver detection performance of the proposed method.

As it can be seen from Table 1, the proposed method can perfectly label clutter and benign motion (WNA model) measurements. On the other hand the method has difficulty differentiating measurements obeying WPA motion model from measurements obeying CT motion model. However, as far as detecting the maneuver is concerned, this does not constitute a problem as the maneuver is labeled is correctly.

Particle filtering (PF) is a commonly used method for target detection [19, 20] and tracking [21, 22] in radar applications. When particle filters are used for detection, like the proposed method, the raw radar data is utilized. In this respect the PF method constitutes a good candidate for performance comparison. The idea behind the PF, is to approximate the posterior pdf, $p(x_k | Z_k)$, by a set of random samples, $\{x^i, q^i\}_{i=1}^{M}$, where $\{x^i\}_{i=1}^{M}$ is the set of support points, called particles, $\{q^i\}_{i=1}^{M}$ is a set of corresponding "weights", i.e., probability masses, and M is the number of particles used in the approximation [18]. Here a very brief discussion of the PF method is given and the reader is referred to numerous comprehensive publications for details. In particle filtering the posterior pdf can be approximated as

$$p\left(x_k \middle| Z^k\right) \approx \sum_{i=1}^{M} q^i \delta\left(x_k - x_k^i\right) \tag{18}$$

where the state x_k is assumed to be a nonlinear function of the state from the previous scan x_{k-1} and the process noise w_k. Also the measurements y_k are assumed to be a nonlinear function of the state and the measurements noise v_k. The PF algorithm can be simply outlined as follows [19]:

Step 1: Draw samples $\left\{w_{k-1}^i\right\}_{i=1}^M$ according to the initial distribution of the state and compute $\left\{x_k^i\right\}_{i=1}^M$.

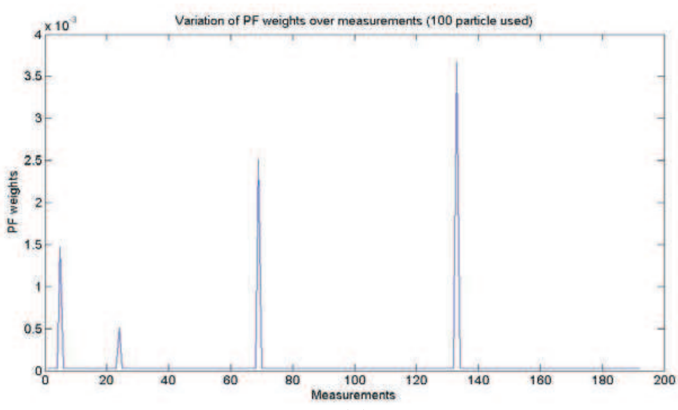
Step 2: Compute weights $q^{*t} = p(y_k \left| x_k^i \right.)$, $i = 1, \ldots, M$ and $q_k^i = q^{*i} \Big/ \sum_{i=1}^{M} q^{*i}$.

Step 3: Resample M times from $\hat{p}(x_k \left| Z^k \right.) = \sum_{i=1}^{M} q_k^i \delta(x_k - x_k^i)$ and obtain $\{x_k\}_{i=1}^M$ to construct $\hat{p}(x_k \left| Z^k \right.) = \sum_{i=1}^{M} \frac{1}{M} \delta(x_k - x_k^i)$.

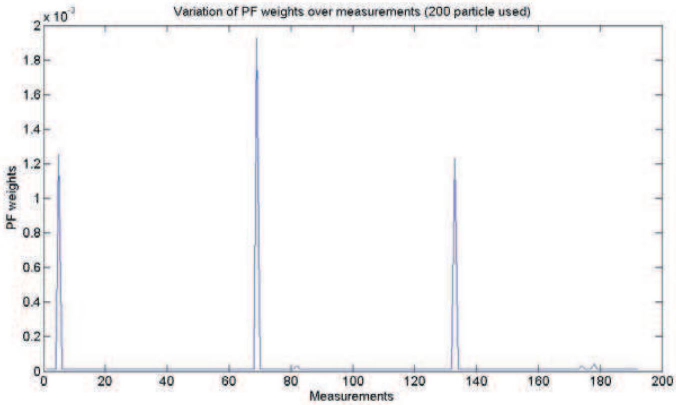
Step 4: Go to Step 1.

In the PF approach detection is performed using the output and likelihood ratio

$$L(y_k) = \frac{p(y_k \left| H_1 \right.)}{p(y_k \left| H_0 \right.)} \tag{19}$$



(a)



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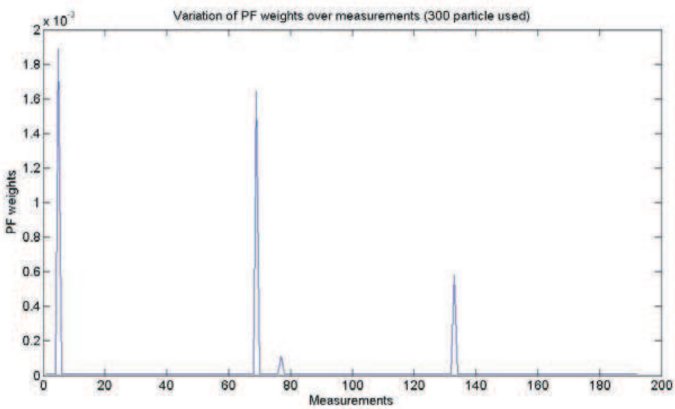

(c)

Figure 7. Presence of a target during 3 consecutive radar scans. (a) 100 particles. (b) 200 particles. (c) 300 particles.

where $p(y_k\,|H_1) \approx \frac{1}{M}\sum_{i=1}^{M} q_k^{*i}$ and H_0 and H_1 represent the absence or presence of the target, respectively. A signal is declared to be present whenever the likelihood, $L(y_k)$ exceeds a predetermined threshold τ where the choice of the threshold is a compromise between false alarms and probability of detection [20]. In Eq. (19), $p\,(y_k|\,H_0)$ is the pdf of the measurement noise, i.e., no target present, and is assumed known, then the likelihood function depends only on the variation of $p\,(y_k|\,H_1)$ which renders the computation of particle weights an important factor for the detection process when using the PF approach. Particle weights are directly affected by accuracy of the system dynamic models, clutter density and target maneuver. Thus, mis-modeling the target motion and/or varying clutter density between scans will lead to less accurate particle weights which will deteriorate the performance in return.

PF based simulations intend to display the dependence of the approach on the number of particles used as well as the difficulty in selecting the right threshold for the optimum performance. For this purpose similar to the HMM scenario, a single target that moves according to the WNA model is used. Like in the proposed method, the resolution area consists of 4096×4096 cells; however, since only target detection is intended, in order to reduce the computational load, measurements are grouped into a smaller size of 8×8 grids and the observation sequence comprises three 8×8 grids from three consecutive radar scans. The PF algorithm is then set to declare a target present if the likelihood ratio is above the predetermined threshold for three consecutive radar scans. Dependence of the particle weights on so many factors will make the $p\left(y_k \middle| H_1\right)$, hence the likelihood ratio, vary from scan to scan making it rather hard to determine an appropriate threshold value. In the simulations it is assumed that we know the target motion and clutter density does not change from scan to scan.

Figure 7 shows the calculated particle weights for 100, 200 and 300 particles. As it is seen from the figure, particle weights from scan to scan and also as the number of particles change. This would require that the threshold for target detection should be varied as well for improved performance.

Note that although the PF method employed in this paper is the basic one and modifications to it have been proposed for improved performance [20], even the improved PF method requires utilization of a threshold in which the problems related to thresholding still prevails.

7. CONCLUSION

In this paper a HMM based target detection method, that is suitable to be used TBD applications, was presented. The proposed method detects target existence without any prior knowledge on the target dynamics or the clutter as long as the return from the target is above the average clutter level. Simulations showed that proposed method not only has a potential to detect targets in heavily cluttered environments but also detect target maneuver type which is an important aspect in target tracking. Proposed algorithm successively separates the grids consisting of target measurements from clutter only grids. Performance of the proposed algorithm has been compared to that of a PF based method and it has been shown that the detection performance of the PF based algorithm heavily depends on the a-priori knowledge regarding the system dynamics is available and when selection of the threshold has been carried out accordingly.

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