MULTIPLE MANEUVERING POINT-TARGET TRACKING USING FILTER BANK IN AN IR IMAGE SEQUENCE

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ABSTRACT

Tracking of maneuvering multiple point-targets in the presence of clutter, in IR image sequences is indeed a challenging task. In real world applications, no apriori knowledge about the movement of the target is available. We propose a method to track maneuvering and nonmaneuvering targets with large motion (± 20 pixels) using multiple filter bank in an IR image sequence with occlusion due to clouds and background noise. The switch-over between the filters in the bank is based on a single-step decision logic and consequently, is computationally more efficient, and performance-wise more robust. We also present a nearest neighbor data association method using the state vector of the model.

1. INTRODUCTION

Tracking of multiple point-targets in the presence of clutter is paramount in any IRST system. Different methods for tracking multiple targets based on MHT, JPDA have been proposed ([1], [2], [3]). A Dynamic Programming Approach was proposed by Barniv [4], and the truncated SPRT is presented in [5] to detect and track targets with straight line trajectories. All these methods are computationally expensive and have little scope for real time application.

We propose a multiple point target tracking algorithm using a filter bank for each target without utilization of any apriori knowledge about target dynamics. This technique is capable of tracking both maneuvering and nonmaneuvering targets. A filter bank consists of filters with different models. This approach is different from the multiple model approach [6], because no knowledge of maneuver values is assumed.

In the proposed algorithm, filter switch-over from maneuvering to nonmaneuvering and vice-versa is performed using single-step decision logic, instead of double decision logic [7]. The proposed tracking algorithm is efficient in terms of computation. It is able to track targets in real time. Another problem in tracking multiple targets is data association, i.e. observation to track fusion. The simplest method to do so is the nearest neighbor using innovation as an error measure. We propose a nearest neighbor technique, which uses the state vector of a model to calculate error measure.

In our simulations, before the image is passed to the tracking algorithm, it is assumed that clutter and noise are removed using a target detection technique [8]. The tracking algorithm updates or deletes existing tracks and may initiate new tracks using the output of the detection phase. The paper is organized as follows: The tracking algorithm is described in Section 2. Simulation results are discussed in Section 3.

2. TRACKING USING NEW DATA ASSOCIATION TECHNIQUE AND MULTIPLE FILTER BANK

In the presence of multiple targets, data association is required to update existing tracks and to initiate a new track. Many techniques have been presented ([1], [2]) pertaining to radar tracking application. The nearest neighbor method is the most common technique used for data association. Data assignment is made, based on minimum distance, i.e. minimum error measure value. Generally, the innovation error (the difference between predicted and observed position) is used as an error measure. The validation region (gate) is formed based on this innovation error and data assignment is made using sub-optimal or optimal algorithms [9]. But the problem with this approach is that it may result in false data assignment when targets are closely spaced in an image, the reason being, for such an error measure, only position is considered. The position of the target alone, does not represent its true state. We propose a new method, which overcomes this drawback and gives better performance. In the proposed method, a state vector of the model is used to calculate minimum distance for nearest neighbor data association.

2.1. Proposed Nearest Neighbor Data Association Technique

Innovation based nearest neighbor data association is briefly described. The current set of measurements, $z(k)$ at time instant k are validated using the validation gate. It is formed based on innovation using the following procedure [2]. The predicted measurement is given by

$$\hat{\mathbf{z}}(k+1|k) = \mathbf{H}(k+1)\hat{\mathbf{x}}(k+1|k) \tag{1}$$

The true measurement at time $k+1$, conditioned upon Z^k, is assumed to be normally distributed, and is given as,

$$p[\mathbf{z}(k+1)|Z^k] = \mathcal{N}[\mathbf{z}(k+1); \hat{\mathbf{z}}(k|k+1), \mathbf{s}(k+1)] \tag{2}$$

where $Z^k = \{z(i), 1 \leq i \leq k\}$ is the set of measurements and $\mathbf{s}(k+1)$ is the innovation covariance matrix. Based on this, a region is defined in the measurement space where the measurement will be found with high probability:

$$\tilde{V}(\xi) = \{\mathbf{z} : \mathbf{v}^T(k+1)\mathbf{s}^{-1}(k+1)\mathbf{v}(k+1) \leq \xi\} \tag{3}$$

where $\mathbf{v}(k+1) = \mathbf{z}(k+1) - \hat{\mathbf{z}}(k+1|k)$ is the innovation and ξ is a parameter obtained from tables of the chi-square distribution with number of degrees of freedom equal to the dimension of measurement.

In the proposed method, $\hat{\mathbf{x}}(k-1) - \hat{\mathbf{x}}(k)$ is used to calculate an error measure (distance measure), where $\hat{\mathbf{x}}(k-1)$ and $\hat{\mathbf{x}}(k)$ are the updated state vectors at time instant $k-1$ and k respectively. This error measure value is calculated for all observations falling inside the the search window, around the predicted position given by the Kalman filter. An error measure $m(k)$ is defined as,

$$\begin{aligned} m(k) = {} & \alpha(\mathbf{x}_p(k-1) - \mathbf{x}_p(k))^2 + \\ & \beta(\mathbf{x}_v(k-1) - \mathbf{x}_v(k))^2 + \\ & \gamma(\mathbf{x}_a(k-1) - \mathbf{x}_a(k))^2 \end{aligned} \tag{4}$$

where $\alpha + \beta + \gamma = 1$ and $\mathbf{x}_p(\cdot), \mathbf{x}_v(\cdot), \mathbf{x}_a(\cdot)$ are the position, velocity and acceleration components of the state vector respectively. The values of α, β and γ are selected empirically based on the importance of the state vector components. It is possible to optimize these values for a particular application. The choice for using such criteria is dictated by following observation:

- The state dynamics of targets remains consistent during its lifetime. Overall change in state vector parameters of the target from one time instant to another is not drastic, but gradual.

In the case of a maneuver target, changes will be significant only at some particular time instants, but there will not be significant changes in the state dynamics over a time period. Error measure value calculation is done for each measurement with respect to every target in the validation gate. This is followed by Munkres' optimal data assignment algorithm [9], which is used to assign an observation to a track. The assumption made in the Munkres' algorithm is that only one observation is assigned to a single track. If Munkres' algorithm does not associate any observation to a currently existing track, it is considered as an occlusion of the target. If no measurements are associated to a track over for several consecutive image frames, then the filter bank for that target is eliminated and track is terminated.

2.2. Proposed multiple filter bank method

In a real application, target may be nonmaneuvering or maneuvering. Using a single tuned filter, it is difficult to track the target trajectory. We propose a method to track multiple point target movement using multiple filter bank. The filter bank consists of different types of filters. For example, in a bank of two filters, one could be a constant velocity filter and the other could be based on a maneuver model. This approach is different from the multiple model approach because no apriori knowledge of maneuver parameters are assumed. An approach based on the use of multiple filters has been explored earlier [7]. But in the proposed method switch-over between the filters in the bank is based on single-step decision logic, and consequently, is computationally more efficient and performance-wise more robust. The proposed method differs from the earlier approach in the following ways:

1. Only one step decision logic is required instead of double decision logic (DDL), which makes real time implementation feasible.

2. A sliding window memory is used to store the last few innovation errors. Innovations over the past few iterations characterize the observations quite well. It provides a better measure to take a decision about the behavior of a target at the next time instant.

3. The state of the target is estimated at every time instant, using current available observations. It avoids the concatenation of observations. The above steps ensure that there is no delay in decision making.

4. The need for matrix inversion or some power of the transition matrix is eliminated since the state estimation is available at every instant.

5. Reinitialization of a filter during the switch-over is not required, since all the filters update their states continuously with the current set of observations.

The constant acceleration or constant velocity based Kalman filter is able to track nonmaneuvering targets. Hence, it is preferred that at least one of the filters in the filter bank should be based on one of these models. The constant acceleration model performs well when an acceleration is in the direction of the velocity. It does not work with highly maneuvering targets. Therefore, another Kalman filter based on Singer's model [10] is used to track maneuvering targets. In this model, the acceleration is modeled as colored noise [2]. From our simulations, we observe that a filter bank with two filters, one based on constant acceleration model and the other, acceleration being modeled as colored noise, is able to track both nonmaneuvering and maneuvering targets. In order to facilitate the switch-over between the filters in the bank, we propose a single-step decision logic.

2.3. Single-step decision logic

We present a single-step decision logic, which provides a measure to characterize the behavior of the target in the absence of any apriori information.

1. At every iteration, an observation is given to all the filters in the filter bank and they update their states independent of each other.

2. The innovation error is accumulated over the past iterations for each filter in the filter bank. It is averaged and compared with that of the other filter.

Switch-over takes place from filter i to filter j if $ae_i > ae_j$ where ae_i is average innovation error from time instant $k-s+1$ to k. Here s is a sliding window size and ae_i is defined as

$$ae_i(k) = \frac{1}{s}\sum_{t=k-s+1}^{k} \mathbf{v}_i(t) \tag{5}$$

where $\mathbf{v}_i(t)$ is innovation error in position for ith filter given by (3). It is also possible to use the value of $m_i(t)$ given by (4) as an error measure in (5) instead of $\mathbf{v}_i(t)$. The above steps make it possible to track both maneuvering and nonmaneuvering multiple point targets simultaneously without any apriori knowledge about the target movement.

3. RESULTS OF SIMULATIONS

Synthetic IR images were generated using real time temperature data [11]. Intensity at different points in images is a function of the temperature, surface properties and other environmental factors. We use Gardner's method to synthesize IR clouds. For simulations, the generated frame size is 1024×256 and the target movement is ± 20 pixels per frame.

Figures (1) and (2) show the results using innovation and state vector based nearest neighbor data association techniques, respectively. It is clearly observed in Figure (1) that incorrect data association of target track to observation takes place from second frame itself and consequently, all tracks are incorrect. From Figure (2), it is clear that the proposed state vector based data association algorithm provides correct target trajectories. The value of α, β and γ were selected empirically as 0.0, 0.8 and 0.2 respectively. It demonstrates that the proper choice of these parameters can achieve the tracking of very closely spaced targets in an image sequence. Figure (3) represents another example of multiple point target tracking using the proposed scheme. All three targets are maneuvering and there is no apriori knowledge about the maneuvering parameters. The root mean square (RMS) innovation error in the position of target 2 is shown in Figure (5). It shows that innovation error over the past few iterations is sufficient to characterize the behavior of the target, i.e. to

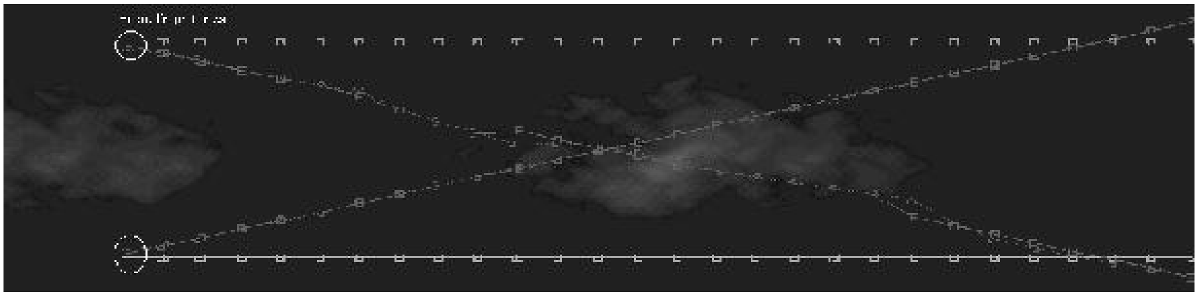

Figure 1: Target Trajectories for IR clips:4 using Innovation based data association

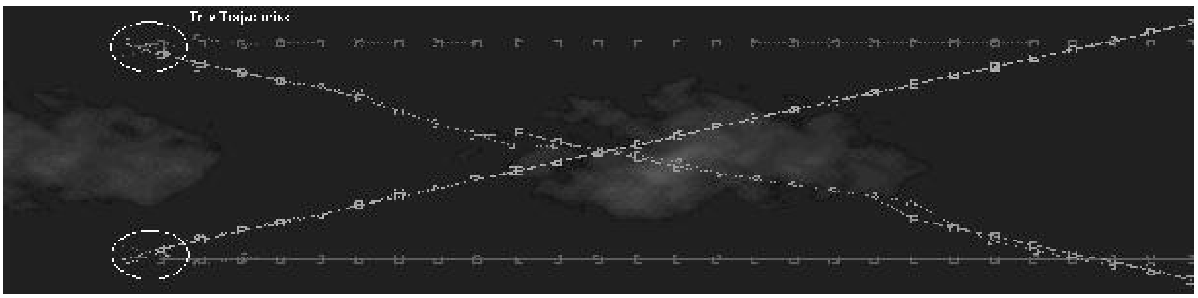

Figure 2: Target Trajectories for IR clips:4 using State vector based data association

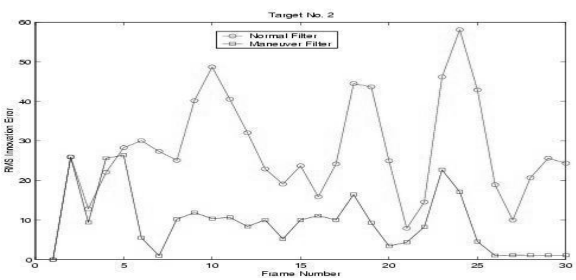

Figure 5: RMS Innovation Error (IR clips:3)

decide whether it is maneuvering or not, and consequently, helps to switch-over from nonmaneuvering filter to maneuvering filter. Multiple non-

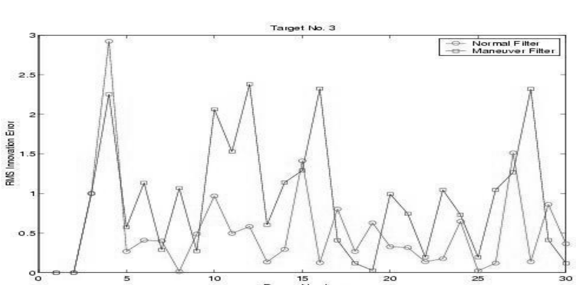

Figure 6: RMS Innovation Error (IR clips:1)

maneuvering point target results are presented in Figure (4). The RMS innovation error in the position of target 3 is shown in Figure (6).

4. CONCLUSION

The proposed method is efficient in terms of required number of computations. It can track even highly maneuvering multiple point targets in an image sequence. The proposed approach based on the incorporation of state vector of the model for calculation of minimum statistical distance for data association has proven to be a useful criterion to track targets which are very closely spaced. It provides the flexibility to choose parameter values as per application. The single-step decision logic to switch-over between filters based on innovations, avoids the calculation of the model probability and combined state estimation as required in the IMM filtering approach. Most importantly, it does not require any apriori knowledge about target dynamics.

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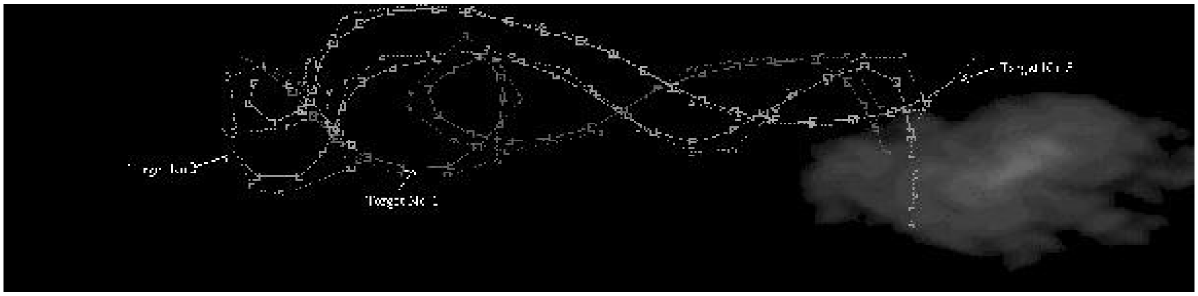

Figure 3: Target Trajectories at frame number 29 (IR clips:3) ($\alpha = 0.5, \beta = 0.3, \gamma = 0.2$)

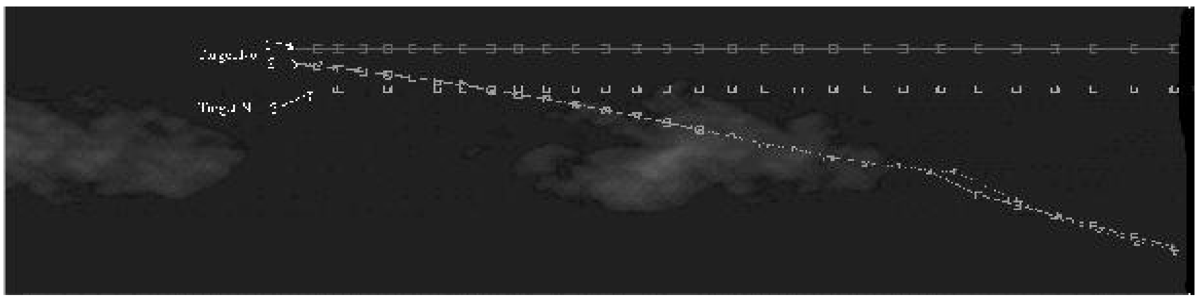

Figure 4: Target Trajectories at frame number 29 (IR clips:1) ($\alpha = 0.5, \beta = 0.3, \gamma = 0.2$)

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