TRACKING MULTIPLE MANEUVERING POINT TARGETS USING MULTIPLE FILTER BANK IN INFRARED IMAGE SEQUENCE

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ABSTRACT

Performance of any tracking algorithm depends upon the model selected to capture the target dynamics. In real world applications, no apriori knowledge about the target motion is available. Moreover, it could be a maneuvering target. The proposed method is able to track maneuvering or nonmaneuvering multiple point targets with large motion (± 20 pixels) using multiple filter bank in an IR image sequence in the presence of clutter and occlusion due to clouds. The use of multiple filters is not new, but the novel idea here is that it uses single-step decision logic to switch over between filters. Our approach does not use any apriori knowledge about maneuver parameters, nor does it exploit a parameterized nonlinear model for the target trajectories. This is in contrast to: (i) Interacting Multiple Model (IMM) filtering which required the maneuver parameters, and (ii) Extended Kalman Filter (EKF) or Unscented Kalman Filter (UKF), both of which require a parameterized model for the trajectories. We compared our approach for target tracking with IMM filtering using EKF and UKF for nonlinear trajectory models. UKF uses the nonlinearity of the target model, where as a first order linearization is used in case of EKF. RMS for the predicted position error (RMS-PPE) obtained using our proposed methodology is significantly less in case of highly maneuvering target.

1. INTRODUCTION

Target tracking in the presence of multiple targets and clutter is paramount in any InfraRed Search and Track system. Different methods to track multiple targets based on Multiple Hypothesis Tracking, Joint Probabilistic Data Association have been proposed ([1],[2],[3]) respectively. All these methods are computationally expensive and have little scope for real time application. In real life application, target may be maneuvering. It is difficult to track the target trajectory using one particular type of filter. 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 or nonmaneuvering targets. 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 [4]. The proposed tracking algorithm is efficient in terms of computation. It is able to track targets in real time.

Our approach does not use any apriori knowledge about maneuver parameters, nor does it exploit a parameterized nonlinear model for the target trajectories. This is in contrast to: (i) IMM filtering [5] which required the maneuver parameters, and (ii) EKF or UKF [6], both of which require a parameterized model for the trajectories.

We have also compared our approach with the IMM algorithm [7], consisting of constant acceleration (CA), Singer's maneuver model (SMM) and coordinated turn (CT) model. In our simulation, to preserve the nonlinearity associated with the CT model we have also used UKF. In simulation, before the image is passed to the tracking algorithm, it is assumed that clutter and noise are removed using a target detection technique developed in [8]. A tracking algorithm updates or deletes existing tracks. It is possible to initiate new tracks if image sequence is preprocessed to form a candidate target list using target detection module. If no measurement is associated with a track for several consecutive image frames, then the filter bank for that target is eliminated and the track is terminated.

2. TRACKING MULTIPLE MANEUVERING TARGETS USING 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]. 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

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

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

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

where $Z^k = \{z(i), 0 \leq k\}$ is the set of measurement and $\mathbf{s}(k+1)$ is the innovation covariance matrix defined as,

$$\mathbf{s}(k+1) = E[\tilde{\mathbf{z}}(k+1|k)\tilde{\mathbf{z}}^{'}(k+1|k)|Z^k] \quad (3)$$

Based on this, a region is defined in the measurement space where the measurement will be found with high probability:

$$\tilde{V}(\xi) = \{\mathbf{z} : \tilde{\mathbf{z}}^T(k+1)\mathbf{s}^{-1}(k+1)\tilde{\mathbf{z}}(k+1) \leq \xi\} \quad (4)$$

where $\tilde{\mathbf{z}}(k+1) = \mathbf{z}(k+1) - \hat{\mathbf{z}}(k+1|k)$ 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. 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 measurement is associated with a track over for several consecutive image frames, then the filter bank for that target is eliminated and track is terminated.

2.1. 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. The performance of the nonmaneuvering model based tracking filter degrades when the target maneuvers, on the other hand the performance of the maneuver based filter degrades when there is no maneuver. 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. For example, in case of coordinated turn model, the value of angular turn rate parameter is required.

An approach based on the use of multiple filters has been explored earlier [4]. 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, 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 and consequently, 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 constant acceleration or constant velocity model. The constant acceleration model performs well when an acceleration is in the direction of velocity. It does not work with highly maneuvering target. Therefore, we add one more filter; a Kalman filter based on Singer's model [10], which 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 based on acceleration being modelled as colored noise, is able to track both nonmaneuvering and maneuvering targets.

2.2. 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.

Let the average innovations error ae_i for i-th filter at time instant k be defined as

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

where $\mathbf{v}_i(m)$ is the RMS value of innovation, which is given by (4), for i-th filter at time instant m. Here s is size of sliding window. Switch-over takes place from filter i to filter j if $ae_i(k) > ae_j(k)$ at time instant k. 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. SIMULATION RESULTS

Synthetic IR images were generated using real time temperature data [11]. Intensity at different points in images is a function of temperature, surface properties and other environmental factors. We use Gardner's method to synthesize IR clouds. For simulation, the generated frame size is 1024×256 and very high target movement of ± 20 pixels per frame. Maneuvering trajectories are generated using B-Spline function. It is important to note that these generated trajectories do not follow any specific model.

Figure 1 depicts the tracks formed using the proposed scheme for IR clips:3 (ir18_i). All three targets are maneuvering and there is no apriori knowledge about the maneuvering parameters. Multiple nonmaneuvering point targets tracking result is presented in Figure 2 for IR clips:1 (ir1). The root mean square (RMS) innovation error in the position of a target number 2 in IR clips:3 is shown in Figure 3(a). The RMS innovation error in position of a target number 3 in IR clips:1 is shown in Figure 3(b). It shows that innovation error over the past few iterations is sufficient to characterize the behavior of the target, i.e. to decide whether it is maneuvering or not, and consequently, helps to switch-over from nonmaneuvering filter to maneuvering filter.

Table I represent RMS predicted position error for the targets in different IR clips using our proposed method, where filter bank consists of constant acceleration (CA) filter and Singer's maneuver model (SMM) filter, named as CASMM approach. 'Tr.' represents target trajectory number in respective IR clip. We have also tested our approach by adding coordinated turn model (CT) along with

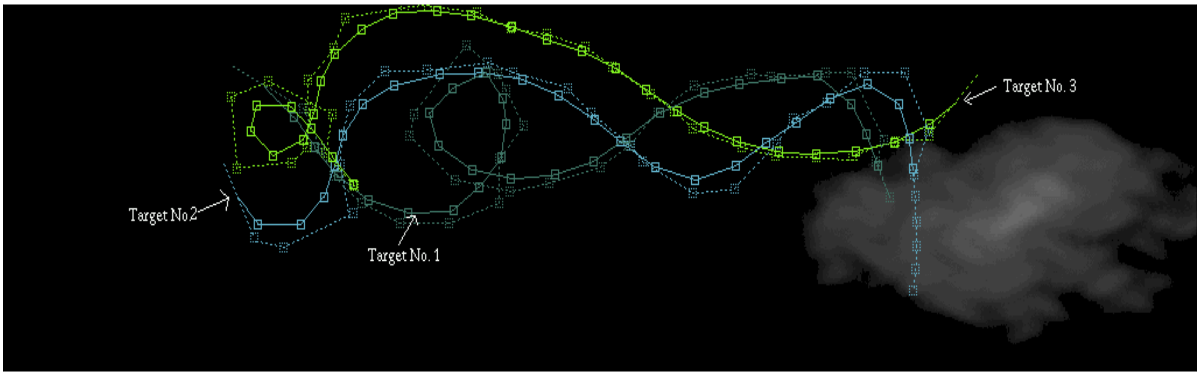


Fig. 1. Target Trajectories at frame number 29 (IR clips:3)

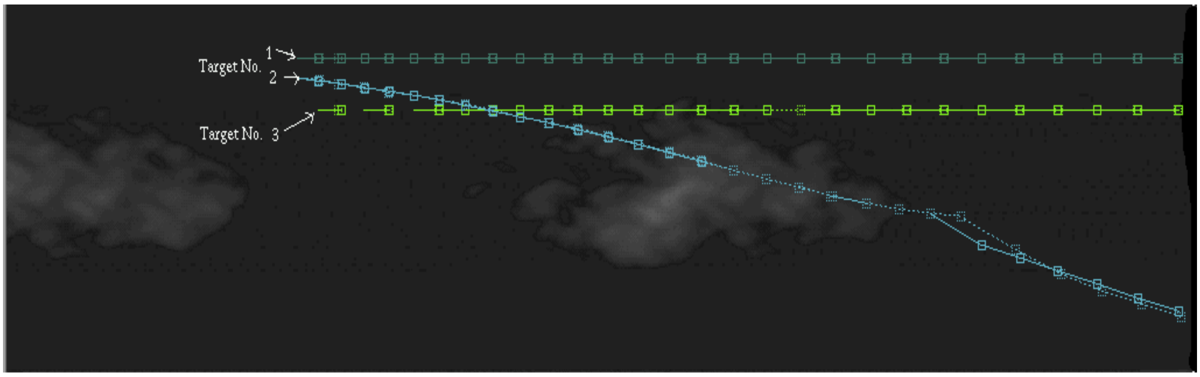
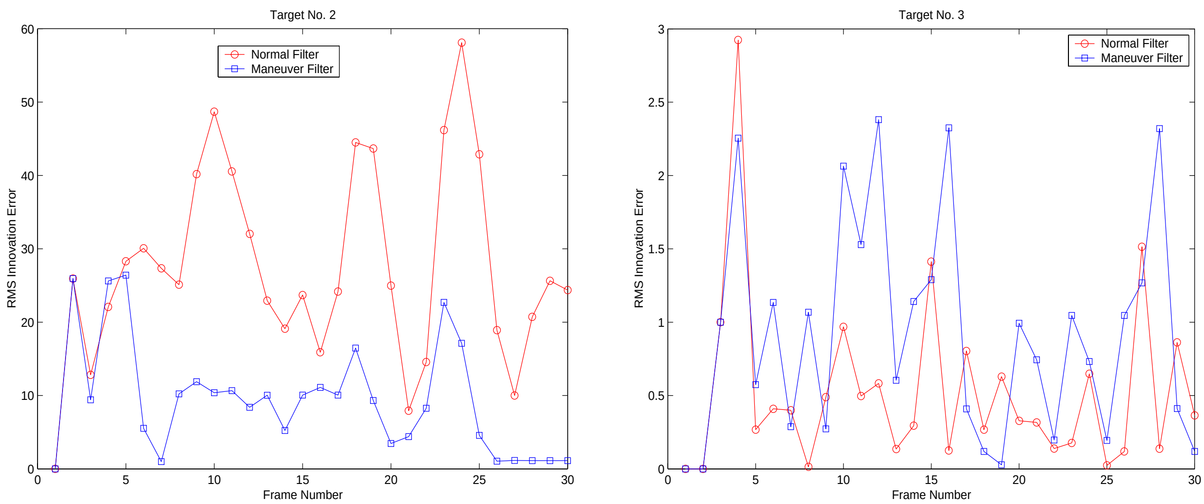


Fig. 2. Target Trajectories at frame number 29 (IR clips:1)



(a) for (IR clips:3) (b) for (IR clips:1)

Fig. 3. RMS Innovation Error

CA and SMM (CASMMCT approach). In our simulation, to test single step switch over logic, an active filter is initialized as SMM in case of nonmaneuvering targets and as CA for maneuvering targets. Figure 4 shows switch over of the filter from CA to SMM filter for three maneuvering targets in IR clips:3.

In table II, we depict the combined RMS-PPE for different IMM filtering approaches, (i) IMM using discrete models for CA, SMM and CT, abbreviated as IMM_Dis filtering approach, (ii) IMM using the same three models with EKF being used for CT model, abbreviated as IMM_EKF and (iii) IMM using the same three model with UKF being used for CT model, abbreviated as IMM_UKF. The CASMM filtering approach gives less error in

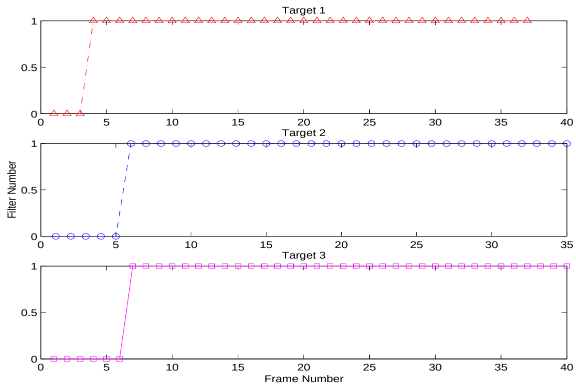


Fig. 4. Single step filter switch over (IR clips:3)

comparison with the other approaches for two IR video clips ir18_i and ir50_i (refer table I, RMS-PPE for SMM in CASMM filtering approach) with substantially less amount of computations and with only two filters in the filter bank.

Due to space limitation, model probability plots for IMM filtering using UKF and EKF are not included. It shows that a single-step decision logic is sufficient to switch over from CA filter to SMM and it can be compared with plots for evolution of the model probabilities in case of IMM approach. For the proposed method CASMM, RMS-PPE=8.4065, for IMM_EKF RMS-PPE=11.9056 and for IMM_UKF RMS-PPE=12.0032 is obtained for target 1 in IR clips:3 (ir18_i), which consists of highly maneuver targets.

RMS Position Error Table - I					
Tr.	CASMM		CASMMCT		
	CA	SMM	CA	SMM	CTurn
Sequence ir18_i					
1	29.2858	8.4065	19.5274	8.4065	26.6414
2	23.8033	7.5490	29.2858	7.5490	22.8071
3	19.9325	8.6224	23.8033	8.4291	19.5274
Sequence ir49_i					
1	3.7155	2.3760	3.7155	2.3760	9.1296
2	4.5295	2.8121	4.5295	2.8121	9.2744
Sequence ir50_i					
1	4.8520	2.2176	4.8520	2.2176	8.5792
2	3.6508	1.9787	3.6508	1.9787	7.7607

Combined RMS Position Error Table - II (IMM)			
Tr.	IMM_Dis	IMM_EKF	IMM_UKF
Sequence ir18_i			
1	8.4898	11.9056	12.0032
2	7.5492	10.4007	10.4453
3	8.0187	7.7725	7.8390
Sequence ir49_i			
1	1.8974	2.0316	2.0571
2	2.2631	2.1712	2.0730
Sequence ir50_i			
1	2.2572		2.4465
2	2.0195		2.1692

4. CONCLUSION

RMS for the predicted position error (RMS-PPE) obtained using our proposed methodology is significantly less in case of highly maneuvering target. As demonstrated through simulation, it can track even highly maneuvering multiple point targets. 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. The proposed method is computationally less demanding as compared to IMM filtering using EKF or UKF. Most importantly, it does not require any apriori knowledge about target dynamics. Use of multiple filter bank using a single-step decision logic to switch over between the filters gives a better result for tracking targets in presence of multiple target and clutter.

5. REFERENCES

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