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Multiple Target Tracking Based on Self Stabilised IMM Estimator Model

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Abstract: Multiple target tracking is more difficult if the target in motion is maneuvering. The behaviour of maneuvering targets is modelled in the form of various target motion dynamics called as Interacting Multiple Model (IMM) filters. IMM uses a probabilistic switching mechanism between the several possible models for target's motion. Due to overmodeling at these maneuvering times in the Interacting Multiple Model (IMM) method, there will be continuous switching between different models which will eventually degrade the tracking precision and smoothness. This paper proposes a new Self Stabilised IMM filter estimator model based on adaptive mode probability and vigorous switching technique. The results of the simulations demonstrate the feasibility and the superiority of the proposed model when combined with Particle Filter (PF) measurement model.

Keywords: Multiple Target Tracking (MTT), Air Surveillance Systems, Particle Filter, Interactive Multiple Model (IMM), Maneuvering target tracking

I. INTRODUCTION

Target tracking is the process of filtering the measurement data from one or more sensors such as radar, sonar, IR or camera devices such that best estimate of the target state is achieved at real time. The key to successful target tracking lies in the effective use of tracking model for the extraction of suitable information about the target's state from noisy measurement data [1]. An optimal tracking model of the target will certainly facilitate this information extraction to a great extent. A model-based tracking algorithm will greatly outperform any model-free tracking algorithm if the underlying model best fits in the different tracking scenarios. Modern tracking systems are based on two models, kinematic model and measurement model. The target state between two consecutive time increments is best described by kinematic model because prior knowledge of target motion is available. The measurement model links the target state to the actual set of measurements.

Target motions are broadly classified into maneuvering and nonmaneuvering motions. A nonmaneuvering motion is the straight and uniform motion at a constant velocity whereas all other random motions which are described by target acceleration are called target maneuvers [7]. There are four basic models used to track maneuvering targets. Constant Velocity (CV) and Constant Acceleration (CA) model, Constant turn Model (CT) and Current Statistical (CS) model separately built for different target motions[12]. Interacting Multiple Model Filter (IMMF) uses a few of these target motion models, one model may for the uniform straight level targets and other models for different target maneuvers. IMMF also maintains an estimate of the probability with which the target is moving accordingly with each model [1]. Depending on these probabilistically assigned weights for each model, It is always challenging to switch between these motion models occurs to best fit the target state to the actual set of measurements [2].

IMMF algorithm can adaptively switch these models to link underlying measurement model. However, there is another challenge; it is that the model switched time is slightly deviate to the real time of the maneuver occurred and degrade the tracking performance due to lack of smooth switching. This paper proposes a new Smooth Switching based IMMF model fit for different kinds of target motions in order to ensure the effective tracking. Section 2 of this paper highlights the IMM approach from literature. Section 3 details the basic IMM approach. Section 4 describes the proposed Self Stabilised IMM model to deal with the change of manoeuvrability and Self Stabilised IMM (SSIMM) algorithm. Finally simulations scenarios and results are presented in Section 5.

II. RELATED WORK

Maneuvering target tracking is widely used in military, civil and robotics fields. It is always challenging to track the target in motion with maneuvers. The tracking and filtering algorithm should have ability to adapt maneuvers by tuning the target state and measurement noise - covariance. In modern tracking systems, a Kalman Filters (KF) can be used for automatic tuning of absolutely benign maneuvers. KF can also be used to reduce adequate noise for the time period when targets are not maneuvering [15]. In most tracking scenarios, an Interacting Multiple Model (IMM) kalman

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filtering method has been found to perform better than other filtering methods [].Various filtering & estimation algorithms based on motion models have been proposed in literature. The first basic Multiple Model (MM) method was pioneered by Magill and Laintis [3][4] and applied by Maybeck and others in [5][6][8].The second generation IMM algorithm was proposed by blom [6] which enhanced MM estimation with effective applications in target tracking. IMM developed and more popularised by Bar-Shalom [7] where it investigated with self-adjusting variable-bandwidth filter for effective maneuvering targets tracking.
To be more precise, different variations and advancement in IMM proposed in [9] to [11]. The Reweighted IMM (RIMM) method is proposed in [12] where new filtering method is incorporated in IMM. The third generation variable structure IMM is proposed and it becomes as a standard for Multiple Model (MM) estimation [16]. VSIMM [15] can decrease potential loss of accuracy, but this method requires prior information to select a probable model set [17]. Recently extended IMM algorithm are proposed in [19][20] which shows some improvement with moderate computational cost. The Multiple Model Particle Filter (MMPF) combines Particle Filters (PF) with multiple model based approach. Branko et al. (2004) [] highlighted the use of MMPF with its simplicity and its proven performance.
However the performance of IMM algorithm is totally depends on selection of optimal motion model set and switching mechanism between these models and it is hard to decide without some prior knowledge. To solve the above-mentioned problem, an improved IMM algorithm with smooth switching strategy is proposed in this paper.

III. INTERACTING MULTIPLE MODEL FILTER ALGORITHM

Interacting Multiple Model filter uses several possible target motion models and switching strategy between these models. Practically this algorithm is implemented with the help multiple parallel kalman filters where each filter would correspond to one of the multiple models. During each sample interval of time, all filters are in action and algorithm calculates overall state estimate which is a combination of state estimates from individual kalman filters.

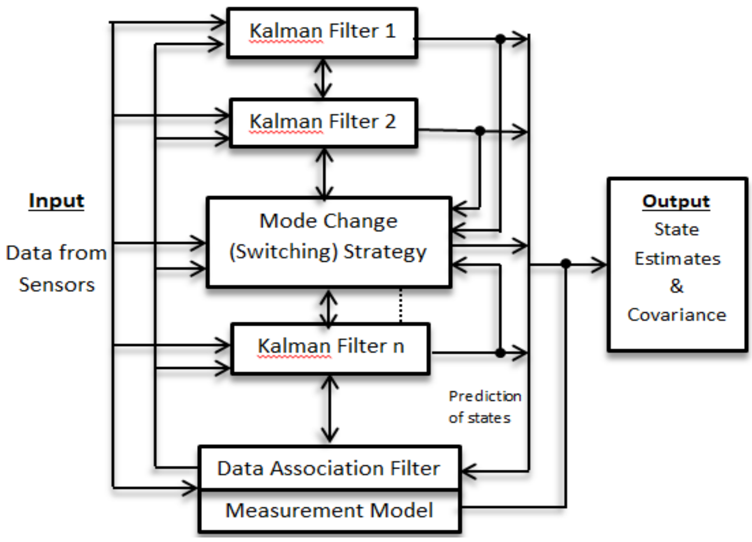

Fig 1: General Structure of Interaction Multiple Model (IMM) Filter

Figure 1 highlights the basic structure of the IMM filter. The IMMF algorithm includes four major steps as interaction & mixing of probabilities, Kalman Filtering, mode probability update, and combination of state estimates [12]. These major steps are explained with details in below sections.

A. Interaction & Mixing of Probabilities:
Assume there are total ‘M’ motion models in consideration; let the initial model probability is given by.

$$\mu_0^{(j)} = p_j\ , \qquad j = 1, \ldots, M, 0 \le p_j \le 1 \ and \ \sum_{j=1}^{m} p_j = 1 \qquad eq. (1)$$

Mode probability is given by,

$$\mu_k^{(i)} = i\frac{\mu_{k-1}^{(i)} - L_k^{(i)}}{\sum_{j=1}^{m} \mu_{k-1}^{(j)} - L_k^{(j)}} \qquad eq. (2)$$

$$where \text{ Model likelihood } L_k^{(i)} \triangleq p\left[\check{z}_k^{(i)} | M_{(i)}^k, z^{(k-1)}\right] \qquad eq. (3)$$

B. KALMAN Filtering

Kalman Filter (KF) equations are used with target motion models to update mixed state estimate. Predicted state x and covariance P matched with model M1 is calculated [18].

C. Mode Probability Update

Once each model is updated with measurement z(k+1) in current scan, and likelihood function given in eq.(3) is matched with filter $L_j^{(i)}$. Thus the mode probability is updated by,

$$\mu_{k+1}^{(i)} = \frac{1}{C}\,\mu_k^{(i)} L_j^{(i)} \qquad eq.(4)$$

$$where\ \ the\ stability\ coeffiecient\ C\ is\ calculated\ as := \sum_{i=1}^{m} \mu_k^{(i)} L_k^{(i)} \qquad eq.(5)$$

The stability coefficient is calculated by taking past m history scans in consideration and calculating the sum of their mode probabilities. Here i= 1, 2, 3 as the window size w=3. Hence past 3 history scans are considered.

D. Combination of State Estimates

The overall state estimate X and corresponding covariance is calculated by combining state estimate and covariance from each filter employed by:

$$\mu_{k+1}^{(i)} = \frac{1}{C}\,\mu_k^{(i)} L_j^{(i)} \qquad eq.(6)$$

IV. PROPOSED METHODOLOGY

A. **Self-Stabilised IMM Method**

In the traditional IMM filtering algorithm explained above, the current mode probability reflects the real motion feature of the maneuvering target during current time period. This mode probability will change prominently when the target motion mode changes, and short-term model transition will take small interval of time. But several intervals later, the model probability will tend to a stable value and new model best fits the target motion change. This is because of the IMM method takes a lot of time for calculations and the probabilistic weight of models has not been solved properly.

In order to reduce this time interval taken for smoothening and stability of tracking process, the attentional prioritizations is done by analysing history of target models adapted by IMM during the past three scans. The cumulative model probability is calculated whenever there is a sudden changes target's estimates and possibility of maneuvers. This step is done by coefficient using ESIMM method as given in equation 4 and 5. Assume the mode probability at time I, w denotes the window size factor

where $0<w<3$ … window size=3 and t denotes the number of time steps requires to fit the model during switching and become stable & smooth. This time interval is calculated by analysing past maneuvers in history scans. As stated in equation 4, mode probabilities of past w scans are considered, which are used to identify the real motion mode due to the sudden occurrence of maneuvers. Thus there is need of change of motion model from next scans.

Calculate and compare $P_{IMM} < P_M$

If the model probability calculated by basic IMM algorithm (P_{IMM}) from equation 2 is lower than the current model probability (P_{M}), then there is a huge chance of incorrect judgement of the real motion mode. This is due to the sudden occurrence of high maneuvers whose motion change cannot model properly. In these scenarios, proposed SSIMM algorithm calculates the model probabilities using history scan given in equation 4, aftermath basic IMM algorithm adapt this newly calculated model probabilities and change motion mode accordingly. Otherwise for all other normal nonmaneuvering scenarios where motion model remain unchanged, basic IMM filtering method will be applied.

B. **Proposed SSIMM Algorithm:**

Step 1: Initialise basic IMM filtering parameters as given in equations from table 1.

Step 2: Calculated mode probability update at each scan.

Step 3:When the motions changes and maneuver occurs, then calculate PSSIMM by basic IMM and also calculates model probabilty as per the SSIMM method.

Step 4: If there is incorrect judgement of real motion mode is found by comparing current mode probability as: $P_{CurrentM} < P_{IMM} <$ PSSIMM then goto step 5 Otherwise go to step 2

Step 5: Adapt ESIMM method and change mode from PCureentM -> PSSIMM

Step 6: Initialise filtering parameters for SSIMM method as given in equation 4 to equation 7 and implement this method for interval k+t where k= current time step. t= time interval required to fit the model smoothly.
Modify state estimates and covariance between time k and k+t.

Go to step 2

Step 7: end

V. SIMULATIONS

The proposed tracking algorithm is simulated using three tracking scenarios for Constant Velocity (CV), Constant Turn (CT) and accelerating targets with high maneuvers. Simulation is carried out for 300 scans with sampling interval of 2 seconds. Assume there are two maneuvering targets which takes uniform motion in first 10 seconds. Then it takes motion with constant turn for next 5 seconds and then it starts to take accelerated motion with high maneuvers between 15 to 25 seconds interval. Finally it takes nonmaneuvering motion with constant velocity in last 15 seconds. Figure 1 and 2 gives the position and velocity error for the considered 40 seconds tracking scenario. Proposed SSIMM algorithm uses three models, first Constant Velocity (CV) model is employed then it switches to Constant Turn (CT) model and for maneuvering motion it switches to accelerated motion model. Algorithm uses CT model in last 15 seconds for non maneuvering target motion. Comparative analysis of standard IMM and proposed algorithm shows that Proposed SSIMM algorithm has the higher accuracy to the standard IMM algorithm. To be more precise, accuracy is higher when it takes turns and maneuvers. The reason is that the proposed algorithm can switch the motion models smoothly by analysing past history of motion models and acquire more stability than the traditional IMM method. Thus we can conclude that proposed SSIMM algorithm uses effective switching strategy and has better and stable performance than other tracking methods.

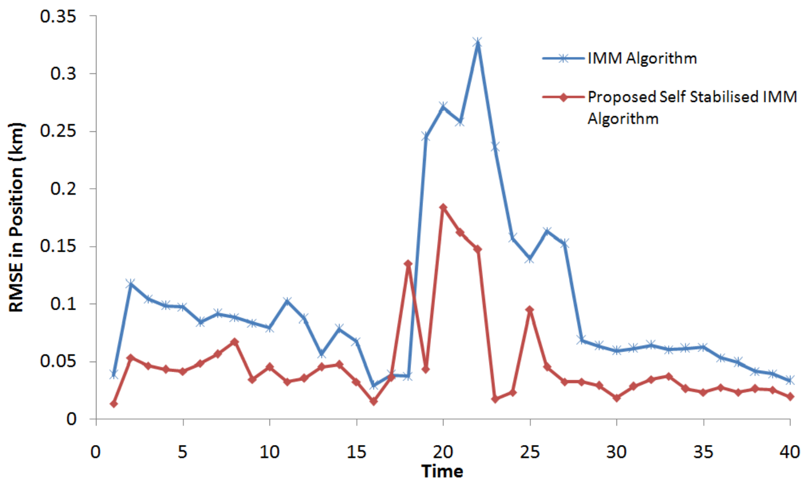

Fig. 2 Positioning Error comparison of Proposed Method in Different Scenarios

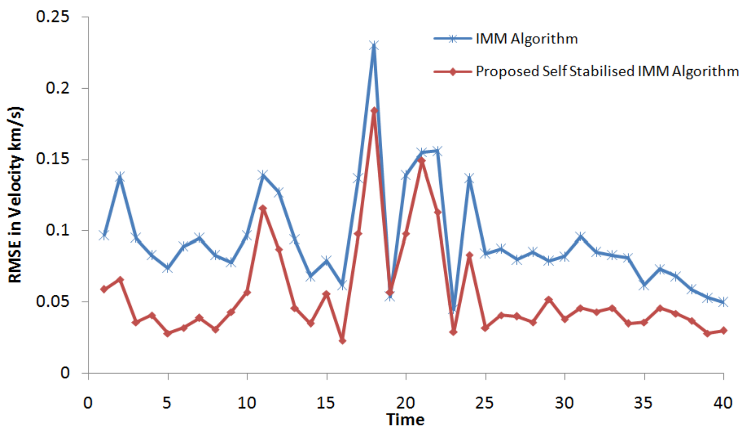

Fig. 3 Velocity Error comparison of Proposed Method in Different Scenarios

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VI. CONCLUSION

The Interactive Multiple Model (IMM) method and model switching based on different scheme have been the emerging trend in modern tracking systems. The effectiveness of IMM method mainly depends on the collection of different motion models and the smooth switching strategy. This paper proposes a tracking method based on Self Stabilised IMM (SSIMM) estimator model in order to solve the frequent switching between motion model and thereby degradation of tracking performance due to lack of smooth and stable switching. Simulation results show that the proposed method has an enhanced performance with stable switching strategy in maneuvering target tracking.

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