TRACKING OF GROUND TARGETS WITH INTERACTING MULTIPLE MODEL ESTIMATOR

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submitted by **DUYGU ACAR** in partial fulfillment of the requirements for the degree of **Master of Science in Electrical and Electronics Engineering Department, Middle East Technical University** by,

Prof. Dr. Canan Özgen
Dean, Graduate School of **Natural and Applied Sciences** ______________

Prof. Dr. İsmet Erkmen
Head of Department, **Electrical and Electronics Engineering** ______________

Prof. Dr. Buyurman Baykal
Supervisor, **Electrical and Electronics Engineering Dept., METU** ______________

Examining Committee Members:

Prof. Dr. Kemal Leblebicioğlu
Electrical and Electronics Engineering Dept., METU ______________

Prof. Dr. Buyurman Baykal
Electrical and Electronics Engineering Dept., METU ______________

Prof. Dr. Mübeccel Demirekler
Electrical and Electronics Engineering Dept., METU ______________

Prof. Dr. T. Engin Tuncer
Electrical and Electronics Engineering Dept., METU ______________

Assist. Prof. Dr. Yakup Özkazanç
Electrical and Electronics Engineering Dept., Hacettepe University ______________

Date: ______________

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last name : Duygu ACAR

Signature :

ABSTRACT

TRACKING OF GROUND TARGETS WITH INTERACTING MULTIPLE MODEL ESTIMATOR

Acar, Duygu

M. Sc., Department of Electrical and Electronics Engineering
Supervisor: Prof. Dr. Buyurman Baykal

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Interacting Multiple Model (IMM) estimator is used extensively to estimate trajectories of maneuvering targets in cluttered environment. In the standard tracking methods, it is assumed that movement of target is applicable to a certain model and the target could be monitored via the usage of status predictions of that model. However, targets can make different maneuvering movements. At that time, expression of target dynamic model with only one model can be insufficient. In IMM approach, target dynamic model is expressed with more than one model capsulating all maneuvering movements or with one model with different noise level values. This thesis investigates the tracking of the maneuvering ground targets in cluttered environment via IMM estimator with constant velocity model with low/high process noise, coordinated turn model and move-stop-move model. The selection strategies of models are highlighted and the state errors are calculated to evaluate the performance of IMM estimator.

Keywords: Target Tracking, Interacting Multiple Model, Move-Stop-Move Model, Coordinated Turn Model

ÖZ

YER HEDEFLERİNİN ETKİLEŞİMLİ ÇOKLU MODELLEME İLE TAKİBİ

Acar, Duygu

Yüksek Lisans, Elektrik ve Elektronik Mühendisliği Bölümü
Tez Yöneticisi: Prof. Dr. Buyurman Baykal

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Etkileşimli çoklu modelleme, manevralı hedeflerin gürültülü ortamda takibi için geliştirilen bir algoritmadır. Etkileşimli çoklu modellemenin kullanılmadığı standart durumda hedefin hareketinin belli bir modele uyduğu varsayılır ve hedef o model kullanılarak takip edilir. Ancak hedefin değişik şekilde manevralı hareketler yaptığı durumda hedefin hareketinin tek bir model ile ifade edilmesi yetersiz kalabilir ve hedef takibi güçleşebilir. Böyle bir durum için etkileşimli çoklu modellemede hedef hareketi, manevralı hareketleri de kapsayacak şekilde birden fazla değişik modelle ya da aynı modelin değişik gürültü seviye değerlerine sahip halleriyle ifade edilir. Bu tezde, manevralı hedeflerin yüksek/alçak gürültü seviyesine sahip sabit hız, koordineli dönüş ve hareket et-dur-hareket et modellerini içeren etkileşimli çoklu modelleme ile gürültülü ortamda takibi incelenmektedir. Etkileşimli çoklu modelleme performansının değerlendirilmesi amacı ile model seçim stratejileri vurgulanmakta ve durum hataları hesaplanmaktadır.

Anahtar Kelimeler: Hedef Takibi, Etkileşimli Çoklu Modelleme, Hareket Et-Dur-Hareket Et Modeli, Koordineli Dönüş Modeli

To My Family

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CHAPTER 1

INTRODUCTION

In this chapter, first, methods and applications of ground target tracking will be reviewed. Then, the outline of the thesis will be presented.

1.1. Review of Ground Target Tracking in Cluttered Environment: Methods and Applications

If multiple observations are received from the scene under analysis at a given time instant, it is a crucial decision that which of the measurements should be used to update each track. This problem arises especially when tracking targets with probability of detection less than unity and in the presence of false measurements [1]. The most common approach is the nearest neighbor (NN) method which uses only one measurement (the nearest) among the received ones to discard all the others [2]. However, this solution brings easily to unsustainable estimation errors. Because of the fact that radar ignores which is the correct measurement among the validated ones, validation region approach [2] which reduces all the unlikely measurements is applied to use all the measurements. To solve the problem of measurement-origin uncertainty Bayessian approach, called probabilistic data association (PDA) [2] is used. It associates probabilistically each validated measurement at the current step to the target of interest. This probabilistic information is used in a tracking filter that accounts for the measurement origin uncertainty.

Target of interest which has evasive maneuvering movements can seldom be described by a single dynamic model [3]. Therefore, such a target is described by different modes of operation [4]. Each model is defined by its own recursive update equation, state vector dimension and process noise statistics. If the system can switch from one model to another the interacting multiple model (IMM) estimator is a powerful method [6]. It is capable of dealing with target maneuvers by introducing a set of different state space models to describe the possible target behaviors.

IMM with PDA called as IMMPDAF in the literature [2] extends PDA to include a measure of track quality. Track quality measure is used for false track discrimination. In [6], it is shown that IMMPDAF solves tracking problems such as presence of a clutter and maneuvering nature of the target with disappearances and reappearances successfully.

In this thesis we deal with the state estimation of a single ground-moving target in a cluttered environment. The purpose of this thesis is to compare and analyze IMM estimators in a realistic scenario: unknown target maneuvers, missing object detection and extraneous observations. The performances of the proposed IMM estimators are examined by simulation and compared with standard Kalman filter tracking algorithm.

1.2. Organization of the Thesis

The outline of the thesis is as follows:

In Chapter 2, background information and the problem definition are given. Target dynamic model, measurement model, noise model, observation model and target state are defined. The validation procedure is also mentioned.

In Chapter 3, Interacting Multiple Model (IMM) algorithm is given. The models used in this thesis which are constant velocity (CV) model with low process noise, constant velocity model with high process noise, coordinated turn model (CTM) and move-stop-move model (SM) are also given with mathematical expressions. The details of trajectory model utilized, assumptions made and threshold values are given with the related equations of motion.

In Chapter 4, Monte Carlo simulations are run for both IMMPDAF method and standard target tracking (standard Kalman filter with one model) method. Each run set is specific to each model mentioned above. Simulations are implemented in order to determine root mean square errors in position and/or velocity. In this chapter, overall evaluation is also given.

In Chapter 5, the thesis is concluded with the general evaluation of the simulation results obtained, and some recommendations on future work concerning effectiveness evaluation for tracking of maneuvering targets in cluttered region with multiple model approach.

CHAPTER 2

MODELING AND TRACKING DYNAMIC TARGETS

Estimation is an inference process of value of a quantity of interest from inaccurate and uncertain observations.

Decision is the best selection of one out of discrete choices. In tracking problems, decision and estimation process are applied simultaneously. In other words, before making any decision, conditional probabilities of alternatives are obtained to estimate the value of a quantity.

Tracking is the estimation process of the state of a moving object by using observations which are obtained from moving platforms or sensors at fixed locations [2]. The difference of tracking process from estimation process is that in tracking process, some data association techniques are applied to determine the right measurement because a measurement used in tracking systems may not have originated from target, but from false alarms, clutters or countermeasures.

Filtering is the estimation process of the state of a moving object in cluttered environments. In filtering process, the current state of target is estimated and the one step further state of it is predicted. States consist of position, velocity, acceleration, turn angle, turn rate, etc.

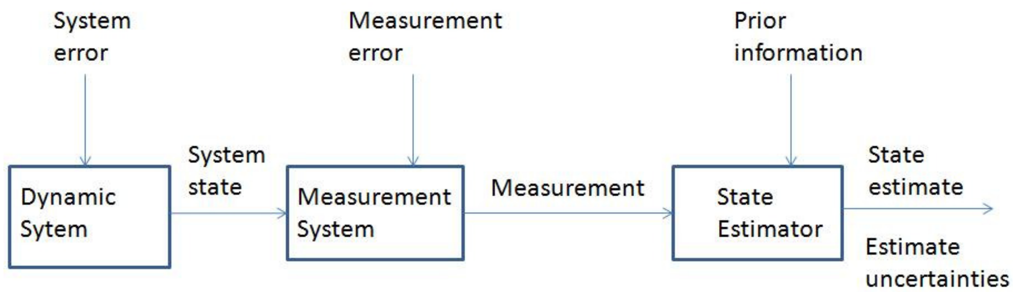

Figure 2-1: Estimation, Decision and Tracking (Figure is adapted from [2])

2.1. A Single Target in Clutter

Measurements used in tracking systems not only may have originated from target, but also from false alarms, clutters. Therefore, the validation procedure which limits the region in the measurement space is needed. Measurement space is a space that we desire to find the measurement from the target of interest. In the validation procedure, the validated region is determined. This region can also be defined as gate or association region.

Measurements outside the validation region which are unlikely to have originated from the target of interest can be ignored. This holds if the gate probability is close to unity and the model used to obtain the gate is correct. However, in the validation region, more than one detection i.e. several measurements will exist. These measurements consist of the correct measurement and the undesirable measurements (clutter or false-alarm originated) [2].

The problem of tracking a single target in clutter considers the situation where there are possibly several measurements in the validation region (gate) of a target. It is assumed that the measurement contains all the information that could be used to discard the undesirable measurements. Therefore, any measurement that has been validated could have originated from the target of interest. A situation with several validated measurements is depicted in Figure 2-2 [2].

The validation region is two dimensional ellipsoid region. It is centered at the predicted measurement. All the measurements in the validation region can be said to be not too unlikely to have originated from the target of interest, even though only one is assumed to be the true one. The reason of this assumption is that there is a single target, so other undesirable measurements constitute a random interference. In this thesis, the mathematical model for such false measurements is that they are uniformly distributed in the measurement space. As an example, when the number of scans is 10, true measurement and false alarms in target trajectory can be seen from Figure 2-3.

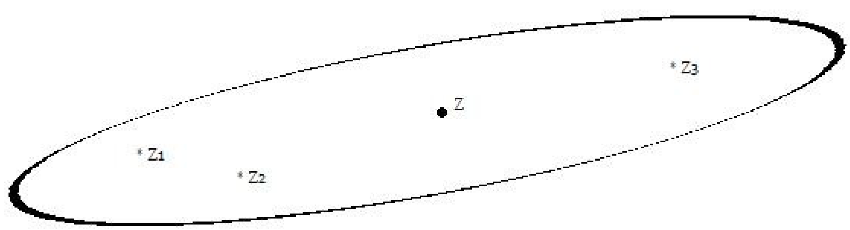

Figure 2-2: Several measurements in the validation region of a single target (Figure is adapted from [2])

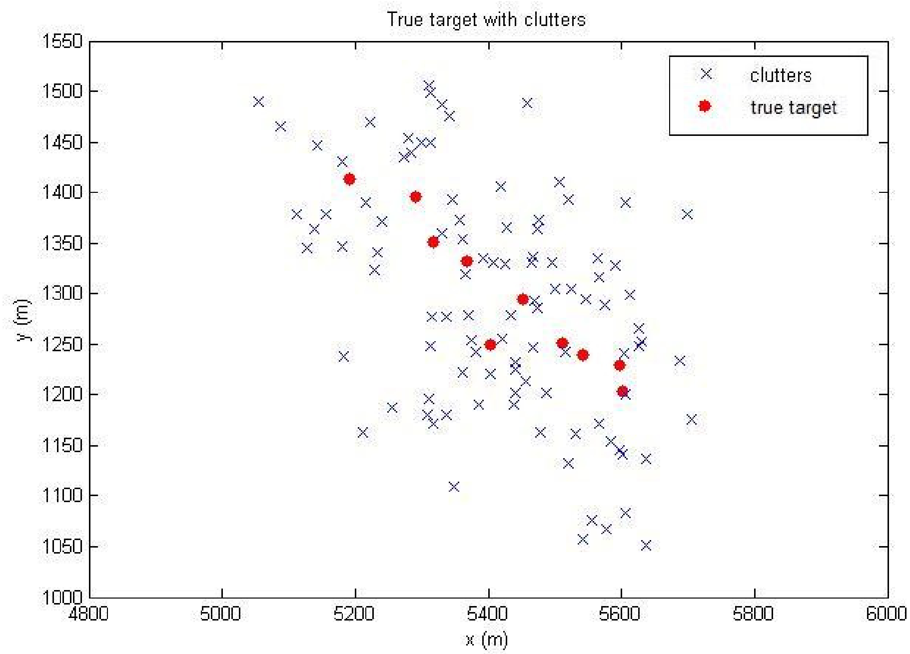

Figure 2-3: True target with clutters

2.1.1. Target Dynamic Model

In this thesis, the target of interest moves both off-road and on-road. Target dynamic models are different in off-road and on-road conditions.

If the target is off road, the models below are used,

- Constant velocity model with a low uncertainty
- Constant velocity model with a high uncertainty reflected by a strong noise
- A stop model when the target is assumed to have a zero velocity

If the target is on road, the models below are used,

- Constant velocity model with a low uncertainty
- A coordinated turn model with a high uncertainty
- A stop model when the target is assumed to have a zero velocity

The transition between the models is a Markovian process. Markov model will be explained in Section 3.1.1.

The detailed explanation of the models is given in Section 3.2.

2.1.2. Target State

Target can be expressed by different state variables at each model used. As an example, at constant velocity model, states are 2 dimensional position and velocity [x(k) V_x(k) y(k) V_y(k)], but at turn model, states are defined as [x(k) y(k) h(k) w(k) s(k)] where s is the magnitude of target velocity, h is the heading angle of target velocity, w is dh/dt, turn ratio or angular velocity and k is the sample number.

In such a case, before model states and covariances are combined for composite estimation, they are converted to common dimension [7]. For the case above and also in this thesis, common states are position and velocity.

Target state is given as,

$$\mathbf{x}(k) = \left[x(k)\ \ V_{x}(k)\ \ y(k)\ \ V_{y}(k)\right]^{T} \tag{2-1}$$

2.1.3. Observation Model

If Ground Moving Target Indicator (GMTI) radar is thought as a sensor, the measurement vector **z**(k) consists of range r(k) and azimuth θ(k), which are given as in [8] and by

$$r(k) = \sqrt{x^{2}(k) + y^{2}(k)} \tag{2-2}$$

$$\theta(k) = \tan^{-1}\left[\frac{y(k)}{x(k)}\right] \tag{2-3}$$

The corresponding measurement model is given by

$$\mathbf{z}(k) = [r(k) \quad \theta(k)]^T + \mathbf{v}(k) \tag{2-4}$$

The measurement noise **v**(k) is a 2x1 zero-mean Gaussian vector with the covariance matrix R.

$$\mathbf{R} = \begin{bmatrix} \sigma^2{}_R & 0 \\ 0 & \sigma^2{}_\theta \end{bmatrix} \tag{2-5}$$

where $\sigma_R(k)$ is the range standard deviation (STD) and $\sigma_\theta(k)$ is the azimuth standard deviation. In this thesis, $\sigma_R(k)$ is taken as 30 m and $\sigma_\theta(k)$ is taken as 0.001 rad.

In this thesis, elevation information obtained from the radar is ignored.

The polar measurements (range and azimuth) obtained by a GMTI radar are converted into a Cartesian coordinate. Then, the measurement model for the unbiased converted measurements can be written as,

$$\mathbf{z}^C(k) = \begin{bmatrix} x(k) \\ y(k) \end{bmatrix} + \mathbf{v}^C(k) \tag{2-6}$$

2.1.4. Target and Measurement Models

There is only one target of interest whose state evolves according to a dynamic equation driven by process noise. The state of the target of interest is assumed to evolve in time according to the equation given in (2-7) [9], [10].

$$\mathbf{x}_i(k+1) = \mathbf{F}_i \mathbf{x}_i(k) + \mathbf{G}_i \mathbf{w}_i(k) \tag{2-7}$$

where $\mathbf{F}_i$ is the state transition matrix for i^{th} model, $\mathbf{G}_i$ is the process noise matrix for i^{th} model, $\mathbf{x}_i$ is the state vector for i^{th} model and $\mathbf{w}_i$ is Gaussian random process noise for i^{th} model.

Assuming that the measurement models are linear, time invariant and with additive independent Gaussian random measurement noise, the equation below is written [9], [10].

$$\mathbf{z}(k) = \mathbf{H}_i \mathbf{x}_i(k) + \mathbf{v}(k) \tag{2-8}$$

where $\mathbf{z}$ is the measurement vector of target, $\mathbf{H}_i$ is the measurement matrix for i^{th} model and $\mathbf{v}$ is Gaussian random measurement noise.

Measurements originated from the target are common for all models. However, due to the fact that the dimension of the state vector of each model can be different from each other, there can be different measurement matrix ($\mathbf{H}_i$) for each model. In this thesis, for constant velocity and stop model $\mathbf{H}_{CV}$ and for turn model $\mathbf{H}_T$ are used [7].

$$\mathbf{H}_{CV} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{2-9}$$

$$\mathbf{H}_{T} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \tag{2-10}$$

$\mathbf{w}$(k) and $\mathbf{v}$(k) are zero-mean mutually independent white Gaussian noise sequences with known covariance matrices $\mathbf{Q}$(k) and $\mathbf{R}$(k) respectively.

2.1.5. Process Noise Model

The uncertainty in state estimation due to random target dynamics or mismodeling of target dynamics is typically represented by the process noise covariance matrix. Therefore, the process noise covariance matrix is specific to each model.

In this thesis, for constant velocity model, the process noise matrix is defined as [11],

$$\mathbf{Q}_{\mathrm{CV}} = \begin{bmatrix} T^4/4 & T^3/2 & 0 & 0 \\ T^3/2 & T^2 & 0 & 0 \\ 0 & 0 & T^4/4 & T^3/2 \\ 0 & 0 & T^3/2 & T^2 \end{bmatrix} \sigma^2{}_{CV} \tag{2-11}$$

The process noise matrix of stop model is defined as in the case of constant velocity model.

However, the process noise matrix of turn model is defined as in [7],

$$\mathbf{Q}_{\mathrm{T}} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & T^3\sigma^2{}_w/3 & T^2\sigma^2{}_w/2 & 0 \\ 0 & 0 & T^2\sigma^2{}_w/2 & T\sigma^2{}_w & 0 \\ 0 & 0 & 0 & 0 & T\sigma^2{}_s \end{bmatrix} \tag{2-12}$$

2.2. Multiple Model Filtering

Target maneuvers are typically abrupt deviations from basically straight-line target motion. It is very difficult to represent the movement of a target of interest with a single maneuver model. Therefore, for tracking maneuvering targets, multiple models, representing different potential target maneuver states are run in parallel and continuously evaluated using filter residual histories [7].

2.2.1. Interacting Multiple Model Filtering

Interacting Multiple Model (IMM) estimator is used extensively to estimate trajectories of maneuvering targets. IMM estimator considers fixed mode sets. In other words, it is assumed that, the target trajectory evolves according to one of a finite number of pre-determined models.

The unique feature of the IMM approach is the manner in which the state estimates and the covariance matrices from these multiple models are combined according to a Markov model for the transition between target maneuver states [7].

The process described in Figure 2-4 begins at the point just after the formation of filtered state estimates and covariance matrices for each of the multiple models at scan k-1. Observation data are used to update each model's filtered state estimate and covariance matrix. That is, validation procedure and data association are carried out respectively before IMM mixing process. Then, using the assumed Markov transition properties between models, new filtered state estimates and covariance matrices are computed for each model via the mixing process.

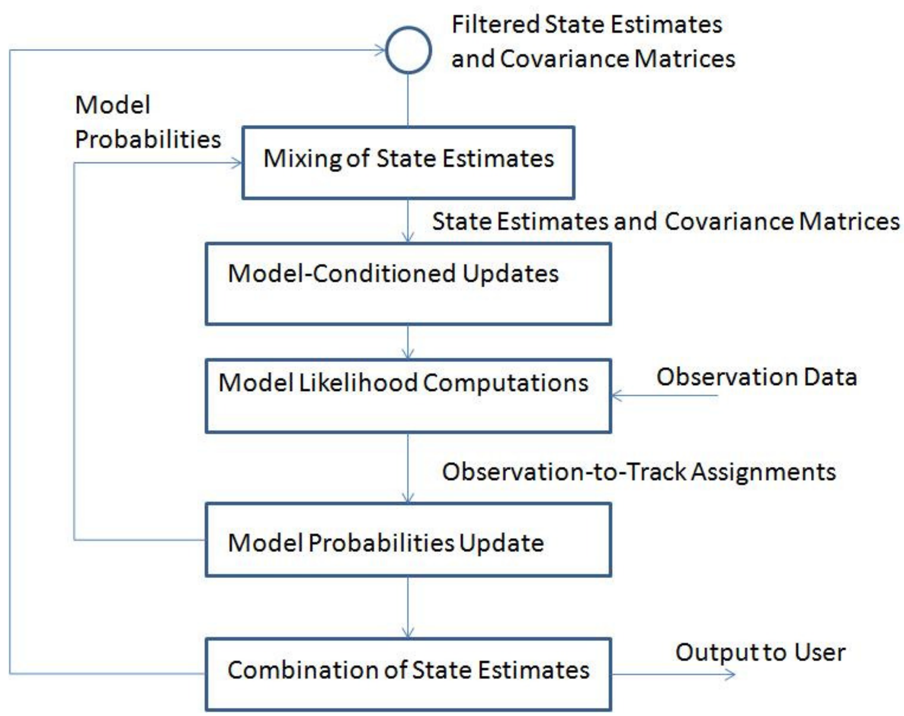

Figure 2-4: IMM flowchart (Figure is adapted from [2])

2.3. The Validation Procedure: Gating

Gating is used as a screening mechanism to determine which observations are valid candidates to update existing tracks. Therefore, the size of gate is crucial to performance in terms of root mean square error (RMSE) [12]. This validation procedure is performed primarily to reduce unnecessary computations by the association and maintenance functions.

In this thesis, gate threshold value is calculated same as in [2] and [7]. While calculating the gate threshold, three parameters are needed basically. These parameters are radar detection probability (P_D), innovation covariance (S) and extraneous return density (β).

2.3.1. Gate Threshold Calculation

First of all, the predicted value (mean) of the measurement $\tilde{\mathbf{z}}(k+1|k)$ and the associated covariance $\mathbf{S}(k+1)$ are obtained for the current step by the equations (2-13), (2-14) and (2-15) [2];

$$p[\mathbf{z}(k+1)|\mathbf{Z}^k] = N[\mathbf{z}(k+1); \tilde{\mathbf{z}}(k+1|k), \mathbf{S}(k+1)] \tag{2-13}$$

$$\tilde{\mathbf{z}}(k+1|k) = \mathbf{H}(k)\mathbf{x}(k+1|k) \tag{2-14}$$

$$\mathbf{S}(k+1) = \mathbf{H}(\mathrm{k})\mathbf{P}(k+1|k)\mathbf{H}(k)^{\mathrm{T}} + \mathbf{R}(k) \tag{2-15}$$

H is the measurement matrix and **R** is the measurement covariance matrix.

In [2], it is assumed that the true measurement will be in the validation region with probability determined by the gate threshold γ. That is, the number of measurements falling in the validated region is obtained by using this threshold value.

CHAPTER 3

INTERACTING MULTIPLE MODEL (IMM)

Interacting Multiple Model (IMM) is an algorithm that is implemented for the aim of tracking the maneuvering targets. IMM tracks maneuvering targets in cluttered environment by using PDA (for one target tracking) algorithm. In IMM approach, more than one dynamic model is used together at the same time.

In the standard tracking methods at which IMM is not used, it is assumed that the movement of target is applicable to a certain model and the target could be monitored via the usage of status predictions of that model. However, targets can make different maneuvering movements. At that time, expression of the target dynamic model with only one model can be insufficient, and then target tracking will be very difficult. For this kind of conditions, in IMM approach, target dynamic model is expressed with more than one model capsulating all maneuvering movements or with one model which has different noise level values.

Assuming that the movement of target is applicable to one of these maneuvering models, by filtering each measurement at every step with each model in parallel way, state and covariance of target according to each model are estimated. For these models, mode probabilities are calculated and then by using these mode probabilities, estimations are combined. In this way, composite estimation has been obtained. At this point, right choice of models is the best way to increase success.

3.1. IMM Algorithm with PDA Filter

IMM algorithm combined with PDA filter is as follows [7] and [9]:

Step 1: Defining Markov model

Step 2: Mixing of State Estimates

Step 3: Model-Conditioned Updates

Step 4: Model-Likelihood Computations

Step 5: Model Probabilities Update

Step 6: Combination of State Estimates

The process of conversion of state vectors and covariance matrices to own model dimensional or common dimensional state vectors and covariance matrices for each model is carried out before model-conditioned updates or combination of state estimates respectively.

Conversion procedure is given in Section 3.2.2.

3.1.1. Definition of Markov Model (Transition Matrix)

Markov model used in IMM is given as constant or time varying transition matrix. Due to the fact that the movement of target can change at every step, the transition matrix expresses transition probabilities of the model. If there are N models, dimension of Markov transition matrix is N x N. In this thesis, IMM algorithm consists of 3 models for both on road and off road conditions in Scenario-2, Scenario-3 and Scenario-4, so the time invariant transition matrix is expressed as,

$$\mathbf{P}_{\mathrm{T}} = \begin{bmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{bmatrix} \tag{3-1}$$

Every row gives probabilities of transitions that may occur from one model to itself and to other models. Addition of probabilities in a row is 1.

$$\sum_{j=1}^{N} \mathbf{P}_{ij} = 1 \tag{3-2}$$

where N is the number of models

The diagonal values of Markov transition matrix are chosen to be higher than other values. The rationale for this choice is that the target of interest changes current mode with a relatively low probability. However, if the assumed probability is low, the filter will be slow in adapting to it.

3.1.2. Mixing of State Estimates

This process starts with prior state estimates $\mathbf{x}_j(k-1|k-1)$, state error covariances $\mathbf{P}_j(k-1|k-1)$ and the associated probabilities $\mu_j(k-1)$ for each model. The mixed state estimate for model j at t_k is calculated as [7],

$$\mathbf{x}^0{}_j(k-1 \mid k-1) = \sum_{i=1}^{N} \mathbf{x}_i(k-1 \mid k-1)\mu_{i\,j}(k-1 \mid k-1) \tag{3-3}$$

where

$$\mu_{i\,j}(k-1 \mid k-1) = \frac{1}{C_j(k-1)} \mathbf{P}_{ij}\mu_i(k-1) \tag{3-4}$$

with

$$C_j(k-1) = \sum_{i=1}^{N} \mathbf{P}_{ij}\mu_i(k-1) \tag{3-5}$$

The mixed error covariance is calculated as,

$$\mathbf{P}^0{}_j(k-1|k-1) = \sum_{i=1}^{N} \mu_{i\,j}(k-1|k-1)\left[\mathbf{P}_i(k-1|k-1) + \mathbf{DP}_{ij}(k-1)\right] \tag{3-6}$$

$$\mathbf{DP}_{ij}(k-1) = \mathbf{Dx}_{ij}(k-1)\mathbf{Dx}_{ij}(k-1)^T$$
$$\mathbf{Dx}_{ij}(k-1) = \left(\mathbf{x}_i(k-1|k-1) - \mathbf{x}_j^0(k-1|k-1)\right) \tag{3-7}$$

$\mathbf{x}_i(k-1|k-1)$ is the filtered state estimate at scan k-1 for Kalman filter model i.

$\mathbf{P}_i(k-1|k-1)$ is the covariance matrix at scan k-1 for Kalman filter model i.

$\mu_i(k-1)$ is the probability that the target is in model state i as computed just after data are received on scan k-1.

$\mu_{ij}(k-1)$ is the conditional probability given that the target is in state j that the transition occurred from state i while $\mathbf{P}_{ij}$ represents the conditional probability that the transition from state i to state j occurs given that the target is initially in state i.

$C_j(k-1)$ is the probability after interaction that the target is in state j.

$\mathbf{DP}_{ij}(k-1)$ is an increment to the covariance matrix to account for the difference in the state estimates from models i and j.

N is the number of models.

The result of this process is that state estimates and covariance matrices are transitioned according to the probability that the true target state makes a transition.

3.1.3. Model-Conditioned Updates

The PDAF [9] equations provide the model-conditioned updates using the mixed estimates and error covariances.

In this process, for each track the following probability weighted composite quantities are computed to use for gating and data association [7].

$$\mathbf{x}(k \mid k+1) = \sum_{j=1}^{N} C_j(k-1)\mathbf{x}_j(k \mid k-1) \tag{3-8}$$

$$\mathbf{P}(k \mid k+1) = \sum_{j=1}^{N} C_j(k-1)\mathbf{P}_j(k \mid k-1) \tag{3-9}$$

3.1.4. Model Likelihood Computations

This process [7], [13] is computation of a likelihood function Λ_i for each IMM mode i that includes N data association hypothesis corresponding to each observation (j=1, 2,…, N) in the gate and the hypothesis that none of the observations is valid:

$$\Lambda_i(k) = (1 - P_D P_G)\beta + \sum_{j=1}^{N} \frac{P_D}{\sqrt{(2\pi)^M \mid S_i(k) \mid}} e^{-d_{ij}^2/2} \tag{3-10}$$

where d_{ij} is the distance of the j^{th} measurement to the i^{th} model, N is the number of measurements falling in the gate, P_D is the probability of target detection, P_G is the probability that the target-originated measurement falls in the validation region, β is the extraneous return density and M is the measurement dimension.

3.1.5. Model Probabilities Update

At the end of filtering, by using these likelihood values, mode probabilities, μ_j are calculated as in [7],

$$\mu_j(k) = \frac{1}{C} \Lambda_j(k) C_j(k-1) \tag{3-11}$$

$$C = \sum_{i=1}^{N} \Lambda_i(k) C_i(k-1) \tag{3-12}$$

3.1.6. Combination of State Estimates

After finding mode probabilities, model estimations are combined with mode probabilities, so final state and covariance estimations are obtained. Combination procedure is made as in [9],

$$\mathbf{x}(k \mid k) = \sum_{i}^{N} \mu_i(k)\mathbf{x}_i(k \mid k) \tag{3-13}$$

$$\mathbf{P}(k \mid k) = \sum_{i=1}^{N} \mu_i(k)\left[\mathbf{P}_i(k \mid k) + \mathbf{DP}_i(k)\right] \tag{3-14}$$

$\mathbf{DP}_i(k)$ is an increment to the covariance matrix to account for the difference in the state estimates.

$$\mathbf{DP}_i(k) = \left[\mathbf{x}_i(k \mid k) - \mathbf{x}(k \mid k)\right]\left[\mathbf{x}_i(k \mid k) - \mathbf{x}(k \mid k)\right]^T \tag{3-15}$$

3.2. IMM Models Used in Simulations

In this thesis, the models used in simulations are listed as;

1. White noise constant velocity model with low process noise
2. White noise constant velocity model with high process noise
3. Coordinated turn model
4. Move-stop-move model

3.2.1. White Noise Constant Velocity Model

As mentioned in Section 2.2.1, it is assumed that, the target trajectory evolves according to one of a finite number of pre-determined models. These models can differ in their noise levels. There are two constant velocity models: CV with low process noise and CV with high process noise.

As in [11] and [9], the state of the target of interest is assumed to evolve in time according to the equation given below,

$$\mathbf{x}_i(k+1) = \mathbf{F}_i\mathbf{x}_i(k) + \mathbf{G}_i\mathbf{w}_i(k) \tag{3-16}$$

where

$$\mathbf{x} = \begin{bmatrix} x & V_x & y & V_y \end{bmatrix}^{\mathrm{T}} \tag{3-17}$$

The transition matrix is given as,

$$\mathbf{F}_i = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{3-18}$$

$\mathbf{F}_i(1,2)$ and $\mathbf{F}_i(3,4)$ elements of transition matrix are taken as T. We calculate x or y position of target for the next state as,

$$x(k+1) = x(k) + V_x(k)T \tag{3-19}$$

$$y(k+1) = y(k) + V_y(k)T \tag{3-20}$$

In this thesis, for constant velocity model the process noise matrix is given as,

$$\mathbf{Q}_{\mathrm{CV}} = \mathbf{G} \times \begin{bmatrix} \sigma^2{}_{CV} & 0 \\ 0 & \sigma^2{}_{CV} \end{bmatrix} \times \mathbf{G}^{\mathrm{T}}$$

$$= \begin{bmatrix} T^2/2 & 0 \\ T & 0 \\ 0 & T^2/2 \\ 0 & T \end{bmatrix} \times \begin{bmatrix} \sigma^2{}_{CV} & 0 \\ 0 & \sigma^2{}_{CV} \end{bmatrix} \times \begin{bmatrix} T^2/2 & 0 \\ T & 0 \\ 0 & T^2/2 \\ 0 & T \end{bmatrix}^{\mathrm{T}} \tag{3-21}$$

$$
= \begin{bmatrix} T^4/4 & T^3/2 & 0 & 0 \\ T^3/2 & T^2 & 0 & 0 \\ 0 & 0 & T^4/4 & T^3/2 \\ 0 & 0 & T^3/2 & T^2 \end{bmatrix} \sigma^2{}_{CV}
$$

As mentioned before, the constant velocity models are differed with noise levels. CV model with low process noise uses $\sigma^2{}_{CVL}$. CV model with high process noise uses $\sigma^2{}_{CVH} > \sigma^2{}_{CVL}$.

Target can maneuver suddenly, so for the aim of not to lose the track (to maintain the track), the constant velocity model with high process noise is used.

Assuming that the measurement models are linear, time invariant and with additive independent Gaussian random measurement noise, measurement model and measurement matrix can be written as,

$$
\mathbf{z}(k) = \mathbf{H}_{\mathrm{CV}} x_i(k) + \mathbf{v}(k) \tag{3-22}
$$

$$
\mathbf{H}_{\mathrm{CV}} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{3-23}
$$

3.2.2. Coordinated Turn Model with Nearly Constant Velocity

The white noise constant velocity and stop models are basically designed for tracking systems in which the filters are uncoupled such that, for example, tracking in the x and y directions is independent. However, target maneuvers, such as target performing a coordinated turn, will produce a motion which is highly correlated across the tracking directions. Therefore, in such cases, the horizontal motion and vertical motion of the target are considered to be decoupled and therefore tracked separately [7]. In this thesis, turn model is restricted to horizontal motion of the target.

Horizontal turn model uses speed (s) as a filter state. The choice of the state vector is given by,

$$[x \quad y \quad h \quad w \quad s]^{\mathrm{T}} \tag{3-24}$$

where s is the magnitude of target velocity, h is the heading angle of target velocity and w is dh/dt, turn ratio or angular velocity.

The state of the target of interest is assumed to evolve in time according to the equation given below,

$$\mathbf{x}_i(k+1) = \mathbf{F}_i\mathbf{x}_i(k) + \mathbf{G}_i\mathbf{w}_i(k) \tag{3-25}$$

Assuming a constant turn ratio, predicted target position components are calculated as in [7], [14] and [15],

$$\begin{aligned} x(k+1) &= x(k) + \int_{t_k}^{t_k+1} V_x(\tau \mid t_k)\, d\tau \\ &= x(k) + s\int_0^T \cos(h + w\tau)\, d\tau \\ &= x(k) + sT[SW\cos(h) - CW\sin(h)] \end{aligned} \tag{3-26}$$

$$y(k+1) = y(k) + sT[SW\sin(h) + CW\cos(h)] \tag{3-27}$$

where

$$\begin{aligned} SW &= \frac{\sin(wT)}{wT} \\ CW &= \frac{1-\cos(wT)}{wT} \end{aligned} \tag{3-28}$$

Given the estimates $\hat{h}(k)$, $\hat{w}(k)$ and $\hat{s}(k)$, (3-26) and (3-27) can be used to compute predicted position components. Other predicted estimates are,

$$\hat{h}(k+1|k) = \hat{h}(k|k) + \hat{w}(k|k)T$$
$$\hat{w}(k+1|k) = \hat{w}(k|k) \qquad (3\text{-}29)$$
$$\hat{s}(k+1|k) = \hat{s}(k|k)$$

Then, the transition matrix $\mathbf{F}_i$ can be written as,

$$\mathbf{F}_i = \begin{bmatrix} 1 & 0 & 0 & 0 & \Phi_{15} \\ 0 & 1 & 0 & 0 & \Phi_{25} \\ 0 & 0 & 1 & T & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \qquad (3\text{-}30)$$

where T is the interval time and the elements are

$$\Phi_{15} = T\left(SW.\cos(\hat{h}) - CW.\sin(\hat{h}) \right)$$
$$\qquad (3\text{-}31)$$
$$\Phi_{25} = T\left(SW.\sin(\hat{h}) + CW.\cos(\hat{h}) \right)$$

where

$$SW = \frac{\sin(\hat{w}T)}{\hat{w}T} \qquad (3\text{-}32)$$
$$CW = \frac{1-\cos(\hat{w}T)}{\hat{w}T}$$

In this thesis, known and constant turn ratio is used for all analysis. The value of this parameter is assumed and taken as the ratio of maximum acceleration that the target of interest can make in one interval time to maximum speed that the target of interest can have during maneuver as in [16], [17]. Therefore, turn ratio is taken as 10/20=0.5 for all scenarios. In other words, in this model, angular velocity is increased linearly by using known and constant turn ratio value. Then, the model is linear.

The process noise covariance matrix is a 5 x 5 matrix and shown as,

$$\mathbf{Q}_{\mathrm{T}} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & T^3\sigma^2{}_w/3 & T^2\sigma^2{}_w/2 & 0 \\ 0 & 0 & T^2\sigma^2{}_w/2 & T\sigma^2{}_w & 0 \\ 0 & 0 & 0 & 0 & T\sigma^2{}_s \end{bmatrix} \tag{3-33}$$

where $\sigma^2{}_w$ is the noise variance of turn rate and $\sigma^2{}_s$ is the noise variance of speed.

In this thesis, it is assumed that the target of interest moves with nearly constant speed. Therefore, this model is introduced by using a small value for the process noise entering the system through the speed state. In other words, σ_s is in general taken as smaller than σ_w.

Assuming that the measurement models are linear, time invariant and with additive independent Gaussian random measurement noise,

$$\mathbf{z}(k) = \mathbf{H}_{\mathrm{T}}\mathbf{x}_i(k) + \mathbf{v}(k) \tag{3-34}$$

$$\mathbf{H}_{\mathrm{T}} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \tag{3-35}$$

As can be seen above, the target can be expressed by different state variables at each model used. While at constant velocity model, states are 2 dimensional position and velocity [x V_x y V_y], at 2 dimensional turn model, state is expressed as [x y h w s]. In such a case, before model vectors and covariance matrices are combined for composite estimation, they are converted to common dimension. In addition, as indicated in IMM with PDAF definition, state vectors and covariance matrices at common dimension are converted back to model dimensions. In other words, there are two types of conversions; one is model dimension to common dimension and the other is common dimension to model dimension.

In this thesis, the common states are position and velocity. In this case, it is not needed to convert constant velocity model. It is just turn model with constant velocity to be converted.

For state vector conversion from model dimension to common dimension, relations in (3-36) are used.

$$
\begin{aligned}
&x=x \\
&y=y \\
&V_x = s.\cos(h) \\
&V_y = s.\sin(h)
\end{aligned}
\tag{3-36}
$$

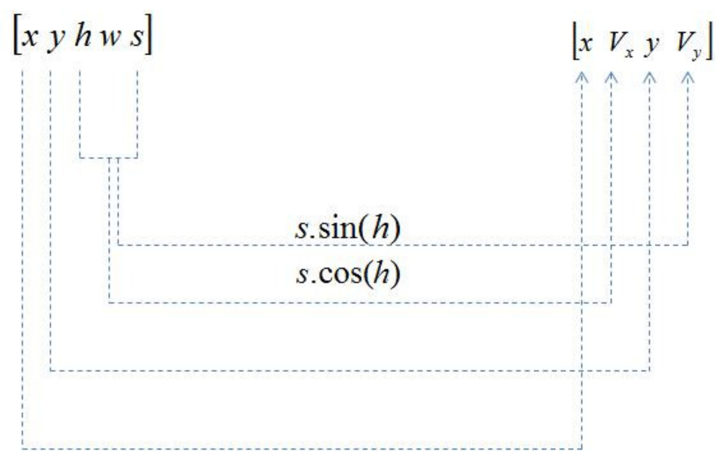

Figure 3-1: State vector conversion method-1

As can be seen from (3-36) and Figure 3-1, usage of w is not needed.

For conversion of covariance matrices to common dimensional covariance matrices, conversion matrix whose dimension is N x M is provided. N is the dimension of the common state vector and M is the dimension of the state vector which is to be converted.

$$\mathbf{A}_{TC} = \begin{bmatrix} \mathbf{A}_{TC}(1,1) & \mathbf{A}_{TC}(1,2) & \dots & \mathbf{A}_{TC}(1,M) \\ \mathbf{A}_{TC}(2,1) & \dots & & \\ \dots & & & \\ \mathbf{A}_{TC}(N,1) & \dots & & \mathbf{A}_{TC}(N,M) \end{bmatrix} \qquad (3\text{-}37)$$

$$\mathbf{A}_{TC} = \left.\frac{\partial \mathbf{x}_T^C}{\partial \mathbf{x}_T}\right|_{\hat{\mathbf{x}}_{TC}} \qquad (3\text{-}38)$$

$\mathbf{x}_{TC}$ is the converted state vector and $\mathbf{x}_T$ is the state vector to be converted, i.e. turn model state vector.

In this thesis, N is 4 and M is 5 because the model to be converted is turn model with nearly constant velocity. Then, the conversion matrix for turn model with constant velocity is

$$\mathbf{A}_{TC} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & -s.\sinh & 0 & \cosh \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & s.\cosh & 0 & \sinh \end{bmatrix} \qquad (3\text{-}39)$$

Using the conversion matrix above, the covariance matrix of turn model is converted to common dimension as,

$$\mathbf{P}_{TC} = \mathbf{A}_{TC}\mathbf{P}_T\mathbf{A}_{TC}^T \qquad (3\text{-}40)$$

where $\mathbf{P}_T$ is 5 x 5 (model dimension) covariance matrix of turn model and $\mathbf{P}_{TC}$ is 4 x 4 (common dimension) covariance matrix of turn model.

Similarly, for the state vector conversion from common dimension to model dimension, relations in (3-41) are used.

$$\begin{aligned} x &= x \\ y &= y \end{aligned} \qquad (3\text{-}41)$$

$$h = \arctan(\frac{V_y}{V_x})$$

$$w = 0.5 \text{ (taken as constant)}$$

$$s = \sqrt{V_x^{\,2} + V_y^{\,2}}$$

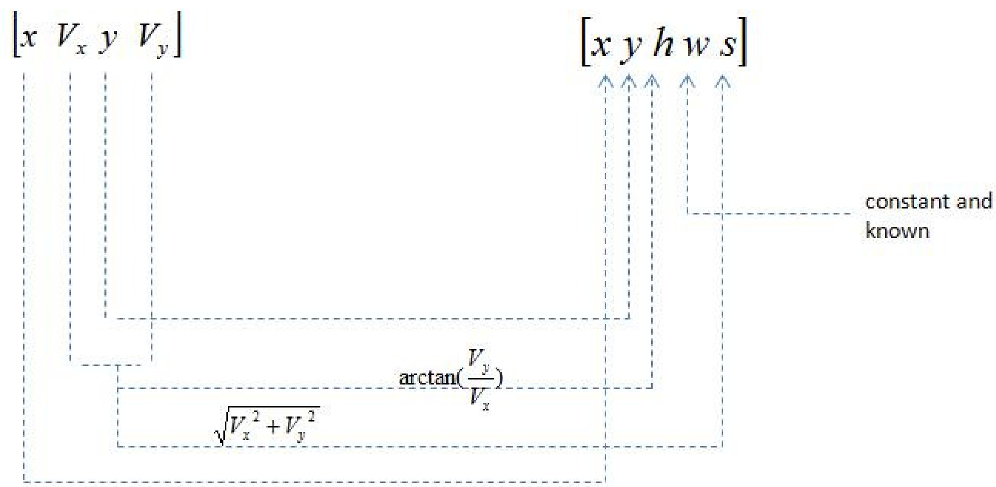

Figure 3-2: State vector conversion method-2

For covariance matrix conversion from common dimension to model dimension, it is needed to define other conversion matrix $\mathbf{A}_{CT}$. In this case, while finding elements of this conversion matrix, we use the common state vector as to be converted one and the turn model state vector as converted one.

$$\mathbf{A}_{CT} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & A_{32} & 0 & A_{34} \\ 0 & 0 & 0 & 0 \\ 0 & A_{52} & 0 & A_{54} \end{bmatrix} \tag{3-42}$$

where the elements are;

$$A_{32} = \frac{-V_y}{s^2} \quad or \quad \frac{-s.\sin(h)}{s^2}$$

$$A_{34} = \frac{V_x}{s^2} \quad or \quad \frac{s.\cos(h)}{s^2}$$

$$A_{52} = \frac{V_x}{s} \quad or \quad \frac{s.\cos(h)}{s} \qquad (3\text{-}43)$$

$$A_{54} = \frac{V_y}{s} \quad or \quad \frac{s.\sin(h)}{s}$$

Using the conversion matrix above, the dimension of covariance matrix is converted to model dimension as,

$$\mathbf{P}_{CT} = \mathbf{A}_{CT}\mathbf{P}_{C}\mathbf{A}_{CT}^{T} \qquad (3\text{-}44)$$

where $\mathbf{P}_C$ is 4 x 4 (common dimension) covariance matrix of turn model and $\mathbf{P}_{CT}$ is 5 x 5 (model dimension) covariance matrix of turn model.

3.2.3. Move-Stop-Move Model

GMTI sensor uses a moving target's Doppler radar return to distinguish it from surface clutter and makes it possible to detect and track moving targets. Targets can deliberately stop for some time before moving again to avoid detection by GMTI radar. The GMTI radar does not detect a target when the radial velocity (along the line-of-sight from the sensor) falls below a certain minimum detectable velocity (MDV).

In [8] and [18], it is developed a new approach by using state-dependent mode transition probabilities to track move-stop-move targets.

In a real scenario, the maximum deceleration is always limited. That is, a target can not stop from a high speed in one interval T. Therefore, the Markov transition matrix of the mode switching has mode transition (jump) probabilities dependent on the target kinematic state [8].

In this thesis, the state dependent approach is implemented. The predetermined values, assumptions and simulation results are given in Section 4.3.4.

The state of the target of interest is assumed to evolve in time according to the equation given below,

$$\mathbf{x}_i(k+1) = \mathbf{F}_i\mathbf{x}_i(k) + \mathbf{G}_i\mathbf{w}_i(k) \tag{3-45}$$

where

$$\mathbf{x} = \begin{bmatrix} x & V_x & y & V_y \end{bmatrix}^T \tag{3-46}$$

$$\mathbf{F}_i = \begin{bmatrix} 1 & T/10 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T/10 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{3-47}$$

$\mathbf{F}_i(1,2)$ and $\mathbf{F}_i(3,4)$ element of the transition matrix are taken as T/10. Because, when estimated velocity of the target of interest falls below the predetermined threshold velocity value (MDV), we assume that the target will probably stop and for the stop model we calculate the x or y position of target as,

$$x(k+1) = x(k) + V_x(k)\frac{T}{10} \tag{3-48}$$

$$y(k+1) = y(k) + V_y(k)\frac{T}{10} \tag{3-49}$$

In [8], it is stated that it is not guaranteed that the target will stop exactly in one sampling interval, so non-zero process noise for the stop model should be used.

In this thesis, the process noise matrix is given as,

$$\mathbf{Q}_{STOP} = \begin{bmatrix} T^4/4 & T^3/2 & 0 & 0 \\ T^3/2 & T^2 & 0 & 0 \\ 0 & 0 & T^4/4 & T^3/2 \\ 0 & 0 & T^3/2 & T^2 \end{bmatrix} \sigma^2{}_{STOP} \tag{3-50}$$

Assuming that the measurement models are linear, time invariant and with additive independent Gaussian random measurement noise,

$$\mathbf{z}(k) = \mathbf{H}_i \mathbf{x}_i(k) + \mathbf{v}(k) \tag{3-51}$$

$$\mathbf{H}_{CV} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{3-52}$$

State–Dependent mode transition probability calculation [8]:

$\mathbf{E}_s$: The speed of the target is below a stopping limit

$\mathbf{E}_f$: The speed of the target is above a stopping limit

For the event $\mathbf{E}_s$, the transition matrix can be written as,

$$\left[p_{ij}\right]^{Es} = \begin{bmatrix} p_{11}{}^{Es} & p_{12}{}^{Es} & p_{13}{}^{Es} \\ p_{21}{}^{Es} & p_{22}{}^{Es} & p_{23}{}^{Es} \\ p_{31}{}^{Es} & p_{32}{}^{Es} & p_{33}{}^{Es} \end{bmatrix} \tag{3-53}$$

For the event $\mathbf{E}_f$, the transition matrix can be written as,

$$\left[p_{ij}\right]^{Ef} = \begin{bmatrix} p_{11}{}^{Ef} & p_{12}{}^{Ef} & 0 \\ p_{21}{}^{Ef} & p_{22}{}^{Ef} & 0 \\ p_{31}{}^{Ef} & p_{32}{}^{Ef} & 0 \end{bmatrix} \tag{3-54}$$

The third column of the matrix above is all 0 because in the fast stage target can not stop in one interval time. Therefore, the transition probability to this mode is 0.

In this thesis, in on-road conditions, M_1: NCV with low process noise, M_2: NCV with high process noise and M_3: stop model; in off-road conditions, M_1: NCV with low process noise, M_2: turn model with high process noise and M_3: stop model.

Target speed V under the stop model has a Rayleigh distribution and its probability density function (pdf) is given by,

$$f(V) = \frac{V}{\sigma^2{}_{STOP}T^2}\exp\left(-\frac{V^2}{2\sigma^2{}_{STOP}T^2}\right) \tag{3-55}$$

where $$V = \sqrt{V_x{}^2 + V_y{}^2} \tag{3-56}$$

V_x and V_y values are obtained from the filtered state estimates.

The minimum detectable value or stopping limit V_{ST} can be written as,

$$V_{ST} = a_M T + V_0 \tag{3-57}$$

where a_M is the maximum deceleration value. The choices for these parameters are given in related simulation results.

V_0 is the maximum speed deviation and calculated by,

$$V_0 = \sqrt{6}\sigma_{STOP} T \tag{3-58}$$

The events $\mathbf{E}_s$ and $\mathbf{E}_f$ can be described by,

$$\mathbf{E}_s = \{V \le V_{ST}\} \tag{3-59}$$

$$\mathbf{E}_f = \{V > V_{ST}\} \tag{3-60}$$

Then the stage probabilities conditioned on mode i can be obtained by,

$$\begin{aligned} p_{E\,s,i}(k-1) &= P\{E_S(k-1) \mid M_i(k-1), Z^{k-1}\} \\ &= P\{V(k-1) \le V_{ST} \mid M_i(k-1), Z^{k-1}\} \end{aligned} \tag{3-61}$$

$$p_{E\,f,i}(k-1) = 1 - p_{E\,s,i}(k-1) \tag{3-62}$$

In particular, the stage probabilities conditioned on the stop mode at time k-1 are given by,

$$p_{E\,s,0}(k-1) = P\{V(k-1) \le V_{ST} \mid M_0(k-1), Z^{k-1}\}$$
$$= P\{V(k-1) \le V_{ST} \mid V(k-1) \le V_0, Z^{k-1}\} = 1 \quad (3\text{-}63)$$

$$p_{E\,f,0}(k-1) = 0 \quad (3\text{-}64)$$

Using the total probability theorem,

$$p_{i\,j} = [p_{i\,j}]^{Es} \cdot p_{E\,s,i}(k-1) + [p_{i\,j}]^{Ef} \cdot p_{E\,f,i}(k-1) \quad (3\text{-}65)$$

CHAPTER 4

SIMULATIONS AND DISCUSSION

The tracking methodology and the algorithms that are used for maneuvering ground target tracking are given in the previous chapters. In this chapter, the estimates of these algorithms and their performances will be discussed and compared.

4.1. Initializations

The track initializations are made by,

$$\mathbf{R} = \begin{bmatrix} 400 & 0 \\ 0 & 400 \end{bmatrix}$$

where **R** is the measurement covariance matrix.

$$\mathbf{x}_{0|0} = \begin{bmatrix} \mathbf{Z}_{\text{converted}}(1) & 0 & \mathbf{Z}_{\text{converted}}(2) & 0 \end{bmatrix}^T$$

where $\mathbf{Z}_{\text{converted}}$ is the converted measurement.

$$\mathbf{P}_{0|0} = \begin{bmatrix} \mathbf{R}(1,1) & 0 & 0 & 0 \\ 0 & 4\mathbf{R}(1,1) & 0 & 0 \\ 0 & 0 & \mathbf{R}(2,2) & 0 \\ 0 & 0 & 0 & 4\mathbf{R}(2,2) \end{bmatrix}$$

4.2. Performance Evaluation

The filter performances are analyzed by simulation runs (Monte Carlo Test) and using the designed 4 target tracking scenarios. Estimation errors are calculated by comparing IMMPDAF estimators with each other or with PDA filtering. In Section 4.3.1, 4.3.2, 4.3.3 and 4.3.4, simulation results and evaluations are provided.

Root-Mean-Square Error (RMSE) of the state estimate is the main criterion of performance evaluation and calculated as,

Nr is the number of runs and Nk is the number of time steps.

$$RMSE_p = \frac{1}{Nr}\sum_{i=1}^{Nr}\sqrt{\frac{1}{Nk}\sum_{k=1}^{Nk}\left(\mathbf{x}(k)(1)-\tilde{\mathbf{x}}(k \mid k)(1)\right)^2+\left(\mathbf{x}(k)(3)-\tilde{\mathbf{x}}(k \mid k)(3)\right)^2} \qquad (4\text{-}1)$$

$$RMSE_v = \frac{1}{Nr}\sum_{i=1}^{Nr}\sqrt{\frac{1}{Nk}\sum_{k=1}^{Nk}\left(\mathbf{x}(k)(2)-\tilde{\mathbf{x}}(k \mid k)(2)\right)^2+\left(\mathbf{x}(k)(4)-\tilde{\mathbf{x}}(k \mid k)(4)\right)^2} \qquad (4\text{-}2)$$

In statistical terminology, sample errors, rather than the expected value for velocity and position errors are also calculated in every time step and are shown as,

$$RMSE_p(k) = \frac{1}{Nr}\sum_{i=1}^{Nr}\sqrt{\left(\mathbf{x}(k)(1)-\tilde{\mathbf{x}}(k \mid k)(1)\right)^2+\left(\mathbf{x}(k)(3)-\tilde{\mathbf{x}}(k \mid k)(3)\right)^2} \qquad (4\text{-}3)$$

$$RMSE_v(k) = \frac{1}{Nr}\sum_{i=1}^{Nr}\sqrt{\left(\mathbf{x}(k)(2)-\tilde{\mathbf{x}}(k \mid k)(2)\right)^2+\left(\mathbf{x}(k)(4)-\tilde{\mathbf{x}}(k \mid k)(4)\right)^2} \qquad (4\text{-}4)$$

Another performance evaluation criterion, namely Normalized Estimation Error Squared (NEES) is alternatively calculated as [2],

$$NEES(k) = \frac{1}{Nr}\sum_{i=1}^{Nr}\left\{\left(\mathbf{x}(k)-\tilde{\mathbf{x}}(k \mid k)\right)^T \tilde{\mathbf{P}}(k \mid k)^{-1}\left(\mathbf{x}(k)-\tilde{\mathbf{x}}(k \mid k)\right)\right\} \qquad (4\text{-}5)$$

In addition, the tracked target trajectory is given in each simulation run to observe the actual path and the estimated position of the target of interest.

4.3. Scenarios and Results

The design of an IMM estimator consists of;

- selection of the models for the various modes of behavior of the system
- selection of the Markov chain transition probabilities among the models
- selection of the parameters of the various models such as process noise levels, threshold values.

IMM models, selected Markov chain transition matrices, process noise levels, threshold values and if any, assumptions will be given in related scenario part.

4.3.1. Scenario-1

In this scenario, IMM estimator is implemented with 2 models same as in on-road and off-road conditions: one is constant velocity with low process noise; the other is constant velocity with high process noise.

For CV with low process noise model, σ_{CV} is taken as 2.5. For CV with high process noise model, σ_{CV} is taken as 30.

In this scenario, the process noise standard deviation values of each model are acceptable values. They are determined by regarding Monte Carlo test results for this scenario.

The Markov chain matrix is given as,

$$\begin{bmatrix} 0.8 & 0.2 \\ 0.2 & 0.8 \end{bmatrix}$$

The detection and gate probabilities are taken as P_D=0.99 and P_G=0.99.

There are clutters and a true target in every beginning of each step.

The time interval T is taken as 1.

The number of runs, N is 100.

IMMPDAF results are compared with PDA filter (standard Kalman filtering with one model) results. It is assumed that PDA filter uses standard deviation values of process noise, σ_{PDAF} as 2.5 and 10 separately in process noise model.

The target of interest decreases own speed while approaching to the junction points and then increases while going away from junctions which are either from off-road to road or from road to another road. The actual velocity graph is given in Figure 4-1.

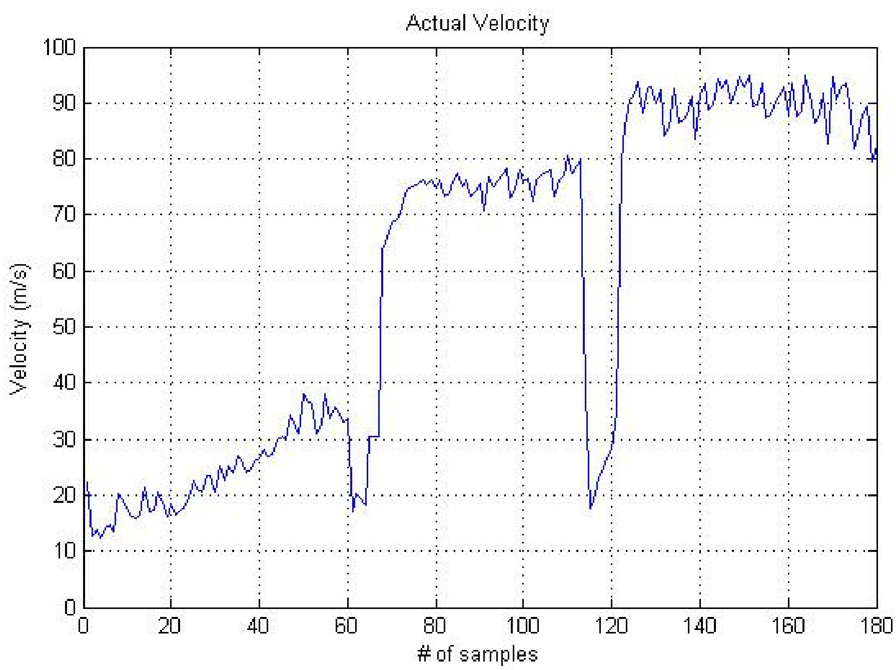

Figure 4-1: Actual Velocity (Scenario-1)

The target trajectory and sample IMM estimations on map are given in Figure 4-2.

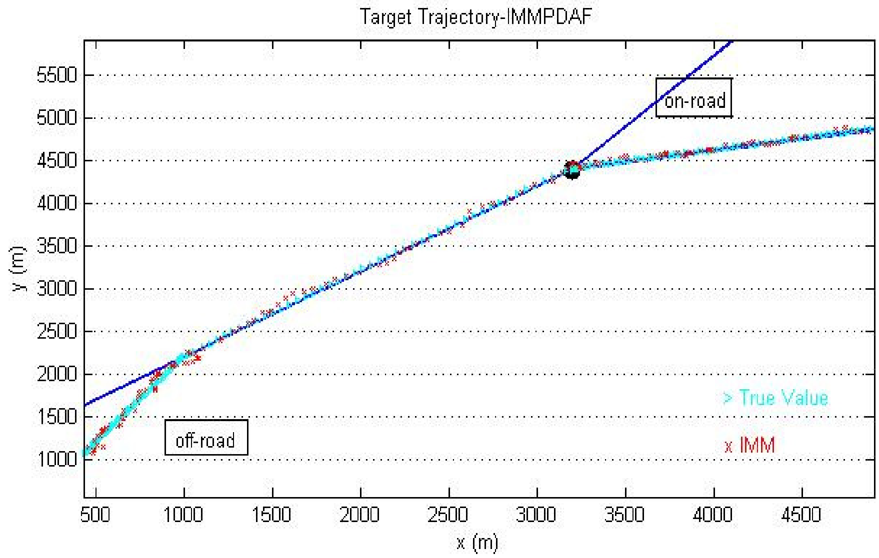

Figure 4-2: Target trajectory-IMMPDAF (Scenario-1)

The position RMS errors belonged to both IMMPDAFs and PDA filter:

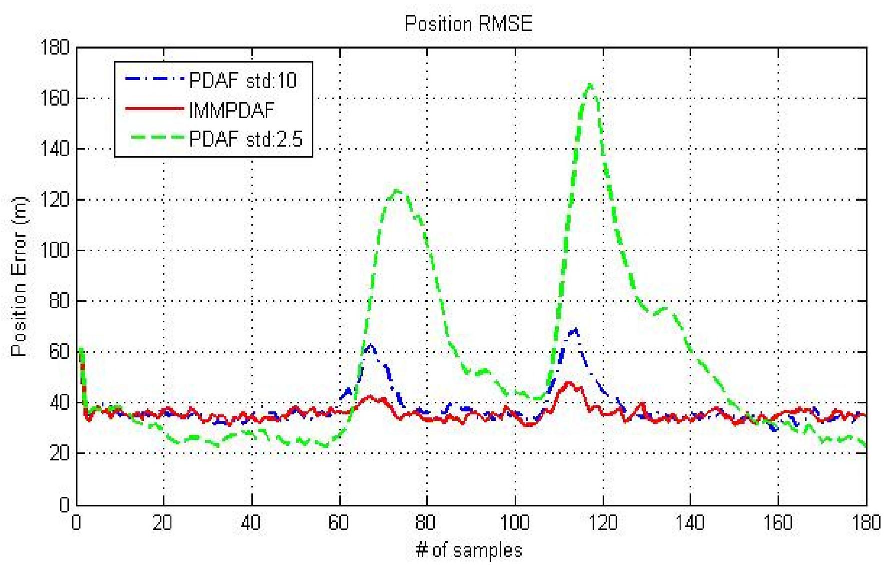

Figure 4-3: Position RMSE Comparison (Scenario-1)

Result-1: As can be seen from Figure 4-3, if we use the deviation of the process noise of PDA filter as 2.5, the position error of PDA filter is smaller than the error of

IMMPDAF during the straight portion of the trajectory. However, the position error of PDA is at least 3 times higher than the one of IMMPDAF when the target of interest passes through the junction points. If we use the deviation of the process noise of PDA filter as 10, the position error of PDA filter is nearly same with the error of IMMPDAF. The reason for these results is that the second value of process noise deviation of PDA filter is nearly mean of the process noise deviations of the two models used in IMMPDAF. Therefore, 10 is preferable value for the process noise deviation of PDA filter.

The velocity RMS errors belonged to both IMMPDAFs and PDA filter:

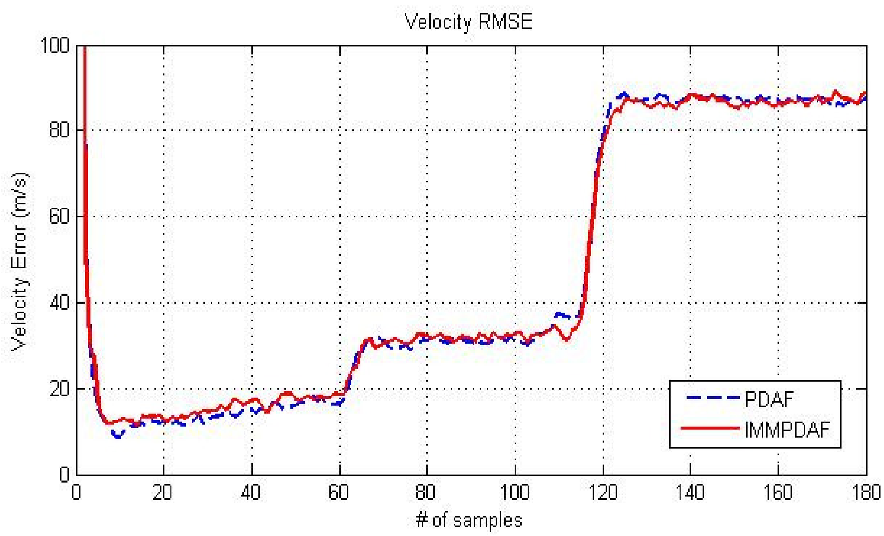

Figure 4-4: Velocity RMSE Comparison (Scenario-1)

Result-2: In this scenario, at approximately 62nd and 118th samples, the target passes through the junctions. Because of this maneuvering movement, it is reasonable that the velocity estimation error increases at these two points. As can be seen from Figure 4-4, the velocity error of PDA filter is nearly same with the velocity error of IMMPDAF.

The overall velocity and position RMS errors belonged to both IMMPDAFs and PDA filter:

Table 4-1 IMMPDAF with 2 CV model vs. Single model

Tracking Algorithm	RMSE in position (m)	RMSE in velocity (m/s)
IMMPDAF with 2 CV models	**40.7902**	**56.1072**
Single model (PDAF) with noise deviation 2.5	**74.6454**	**55.6459**
Single model (PDAF) with noise deviation 10	**44.5743**	**55.8883**

Result-3: The RMSE values calculated for both position and velocity are listed in Table 4-1**.** The RMSE values are nearly same with each other, but the smallest RMSE in position belongs to IMMPDAF with 2 CV models.

4.3.2. Scenario-2

In this scenario, IMM estimator is implemented with 3 models. However, at this time the models used in on-road or off-road conditions are different. In off-road conditions, the models used are CV with low process noise, turn model and stop model. In on-road conditions, the models used are CV with low process noise, CV with high process noise and stop model. Stop model is out of analysis in this scenario. It just acts as a CV model with low process noise.

In both on-road and off-road conditions, for CV with low process noise model, σ_{CV} is taken as 2.5 and for stop model, σ_{STOP} is taken as 2.5. In just on-road condition, for CV with high process noise model, σ_{CV} is taken as 30.

In just off-road conditions, for turn model, σ_W is taken as 30 and σ_S is taken as 10.

In this scenario, the process noise standard deviation values of each model are acceptable values. They are determined by regarding Monte Carlo test results for this scenario.

The Markov chain matrix for IMMPDAF is given as,

$$\begin{bmatrix} 0.85 & 0.05 & 0.1 \\ 0.2 & 0.6 & 0.2 \\ 0.1 & 0.1 & 0.8 \end{bmatrix}$$

The detection and gate probabilities are used as P_D=0.99 and P_G=0.99.

There are clutters and a true target in every beginning of each step.

The time interval T is taken as 1.

The number of runs, N is 100.

IMMPDAF results are compared with PDA filter (standard Kalman filtering with one model) results. It is assumed that PDA filter uses σ_{PDAF} as 2.5 in the process noise model.

The target of interest moves off road in between [1-125] samples and on road in between [125-180] samples. In this section, off road conditions are focused.

The speed of the target of interest changes in between [30-70] m/s. The actual velocity graph is given in Figure 4-5.

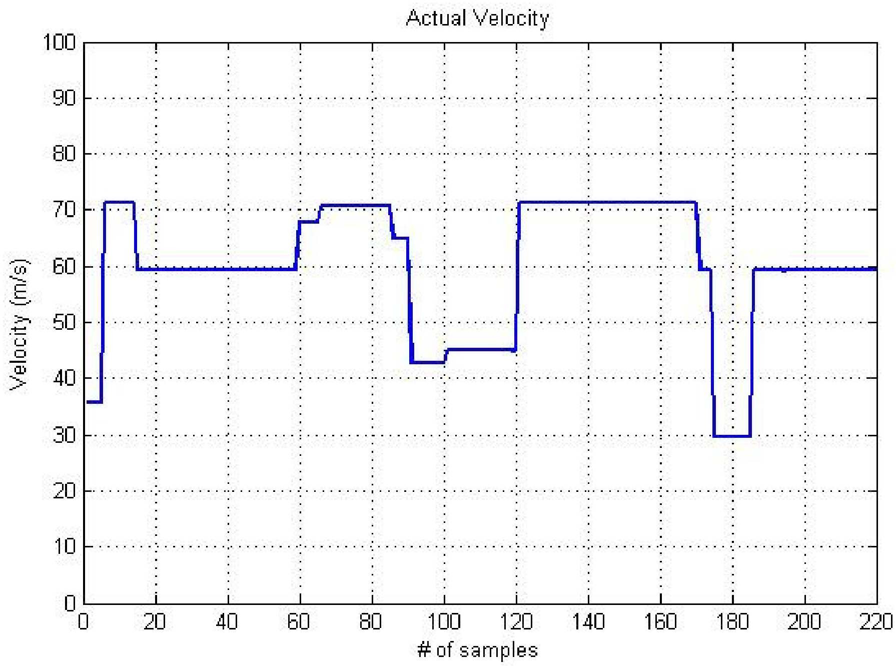

Figure 4-5: Actual Velocity (Scenario-2)

The target of interest makes 6 maneuvers in approximately 5000 m range in off-road conditions and then enters the road. The turn angles are in between [0, π/2]. In other words, the maneuvers are in general continuous but blunt.

The target trajectory and sample IMM estimations on map are given in Figure 4-6.

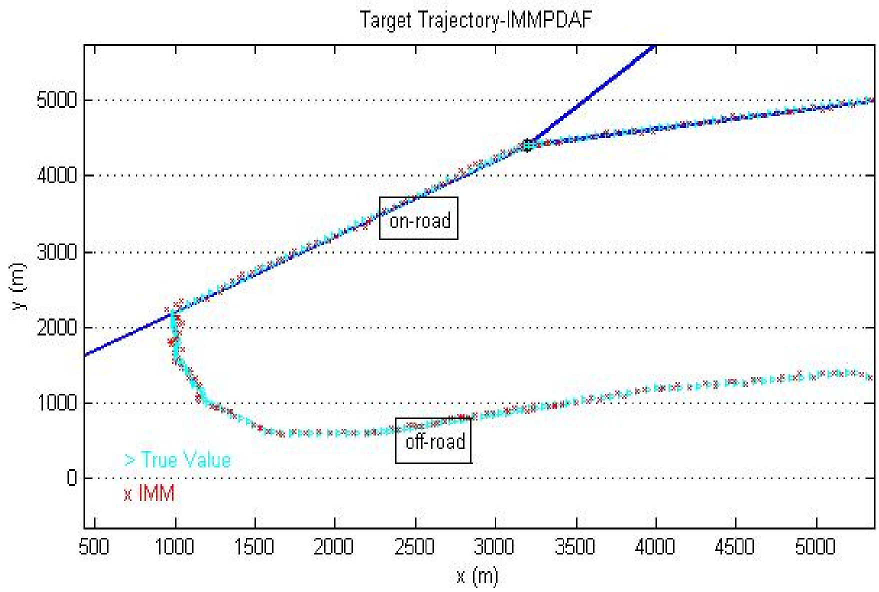

Figure 4-6: Target Trajectory-IMMPDAF (Scenario-2)

The position RMS errors belonged to both IMMPDAFs and PDA filter:

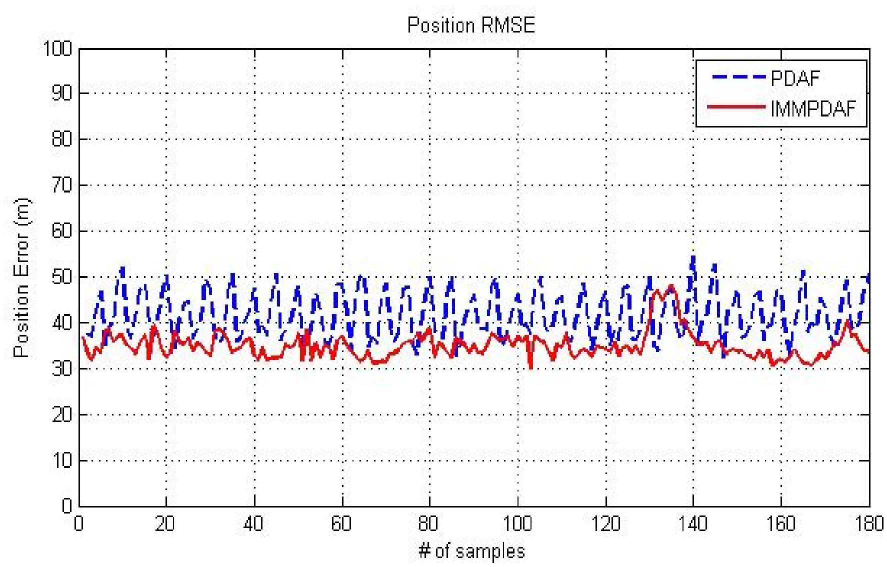

Figure 4-7: Position RMSE Comparison (Scenario-2)

Result-1: As can be seen from Figure 4-7, in off-road conditions (in 1-125 samples), both IMMPDAF and PDA filter catch up maneuvers. However, the position error of PDA filter which is 45 m in average is always higher than the position error of IMMPDAF which is 35 m in average. In addition, the error variance of IMMPDAF is lower than the one of PDA filter. That is, IMMPDAF responses to maneuvers quickly.

The velocity RMS errors belonged to both IMMPDAFs and PDA filter:

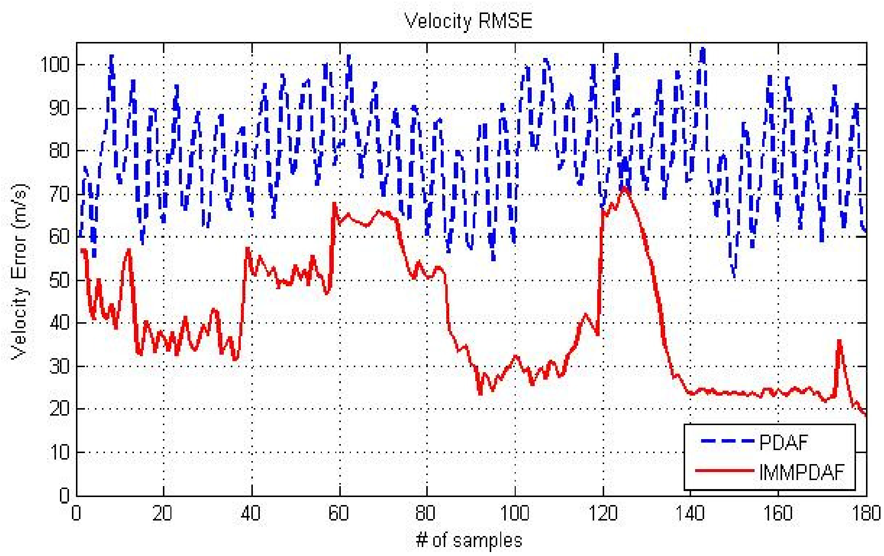

Figure 4-8: Velocity RMSE Comparison (Scenario-2)

Result-2: As can be seen from Figure 4-8, as in the case which is the position error performance, PDA filter does not react to maneuvers. The velocity error of PDA filter is always high when it catches up the maneuver or not. However, for example, IMMPDAF gives response to the maneuver at 76th sample, and then decreases the velocity error to approximately 25 m/s at 91st sample.

The NEES values belonged to both IMMPDAFs and PDA filter:

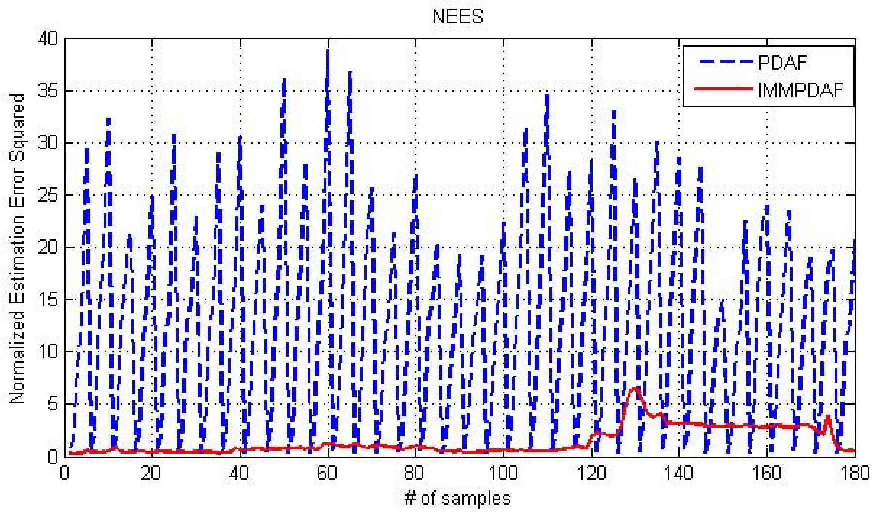

Figure 4-9: NEES Comparison (Scenario-2)

Result-3: Normalized Estimation Error Squared (NEES) also takes estimated covariance into account. When the target of interest is not maneuvering, the NEES of IMMPDAF is nearly smooth. However, it peaks at the onset of the maneuver until it catches up the maneuver. In any case, as can be seen from Figure 4-9, in on-road conditions, the NEES of IMMPDAF is smooth; during maneuver, it is fluctuating; while passing through junction, it makes highest value of own. However, the NEES of PDA filter always takes high values.

The overall position and velocity RMS errors belonged to both IMMPDAFs and PDA filter:

Table 4-2 IMMPDAF with 3 models vs. Single model

Tracking Algorithm	RMSE in position (m)	RMSE in velocity (m/s)
IMMPDAF with 3 models	**39.3108**	**44.0666**
Single model (PDAF)	**47.2748**	**90.7647**

Result-4: As can be seen from Table 4-2, the IMMPDAF errors both in position and velocity are lower than those of PDA filter. Especially, the RMSE in velocity is too high to be acceptable for the case of PDA filter. In addition, although IMMPDAF maintains 3 models, its performance is still much better than PDA filter.

4.3.3. Scenario-3

In this scenario, IMM estimator implemented with 3 models will be compared with IMM estimator implemented with 2 models in only off-road conditions. In off-road conditions, first IMM estimator use 3 models such as CV with low process noise, turn model and stop model while second IMM estimator use 2 models such as CV with low process noise and CV with high process noise. Actually, turn model (TM) effectiveness will be evaluated especially in turn points in this scenario. Stop model is out of analysis in this scenario. It just acts as a CV model with low process noise.

In off-road conditions, for CV with low process noise model, σ_{CV} is taken as 2.5, for stop model, σ_{STOP} is taken as 2.5. σ_{CV} is taken as 10 for CV with high process noise model at first, but the value σ_{CV} is increased to 30 for this scenario since it (former choice) gives very high RMSE results whose figures are not shown but RMSE error values are given in Table 4-3.

In off-road conditions, σ_W is taken as 10 and σ_S is taken as 10 for turn model at first. Then, the value of σ_W is changed to 30 to increase efficiency and decrease errors.

In this scenario, the process noise standard deviation values of each model are acceptable values. They are determined by regarding Monte Carlo test results for this scenario.

For IMMPDAF with 2 CV models, the Markov chain matrices are given as respectively,

$$\begin{bmatrix} 0.6 & 0.4 \\ 0.4 & 0.6 \end{bmatrix} \qquad \text{(noise STD is 10)}$$

$$\begin{bmatrix} 0.8 & 0.2 \\ 0.2 & 0.8 \end{bmatrix} \qquad \text{(noise STD is 30)}$$

For IMMPDAF with turn model, Markov chain matrices are given as respectively,

$$\begin{bmatrix} 0.5 & 0.36 & 0.14 \\ 0.24 & 0.1 & 0.66 \\ 0.26 & 0.54 & 0.2 \end{bmatrix} \qquad \text{(noise STDs are 10-10)}$$

$$\begin{bmatrix} 0.8 & 0.1 & 0.1 \\ 0.2 & 0.7 & 0.1 \\ 0.1 & 0.1 & 0.8 \end{bmatrix} \qquad \text{(noise STDs are 30-10)}$$

The detection and gate probabilities are used as P_D=0.99 and P_G=0.99.

There are clutters and a true target in every beginning of each step.

The time interval T is taken as 1.

The number of runs, N is 100.

The speed of target of interest changes in between [11-53] m/s. The actual velocity graph is given in Figure 4-10.

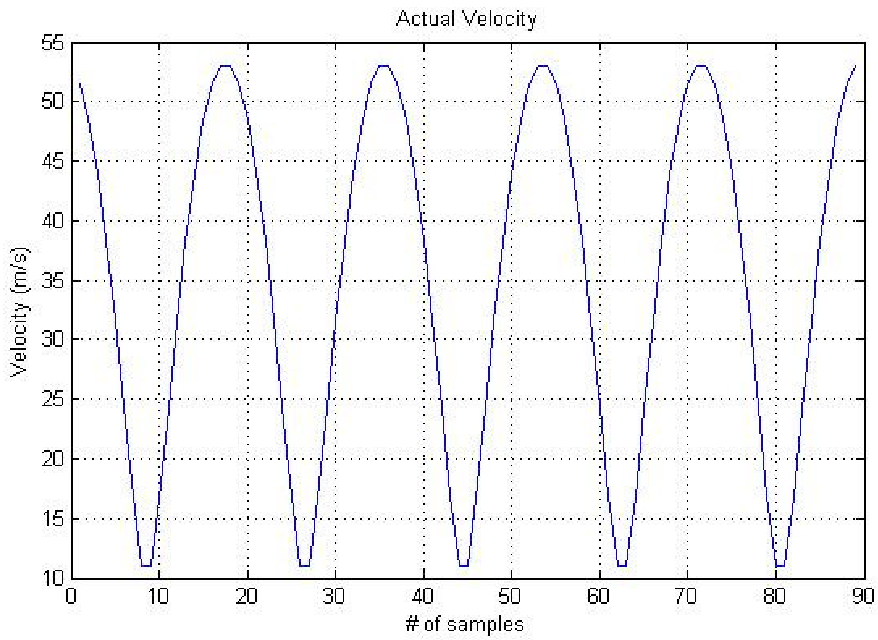

Figure 4-10: Actual Velocity (Scenario-3)

The target of interest makes 5 maneuvers in approximately 3000 m range in off-road situation. The turn angles are in between [π/2, π]. In other words, the maneuvers are frequent and sharp. The target trajectory and sample IMM estimations on map are given in Figure 4-11.

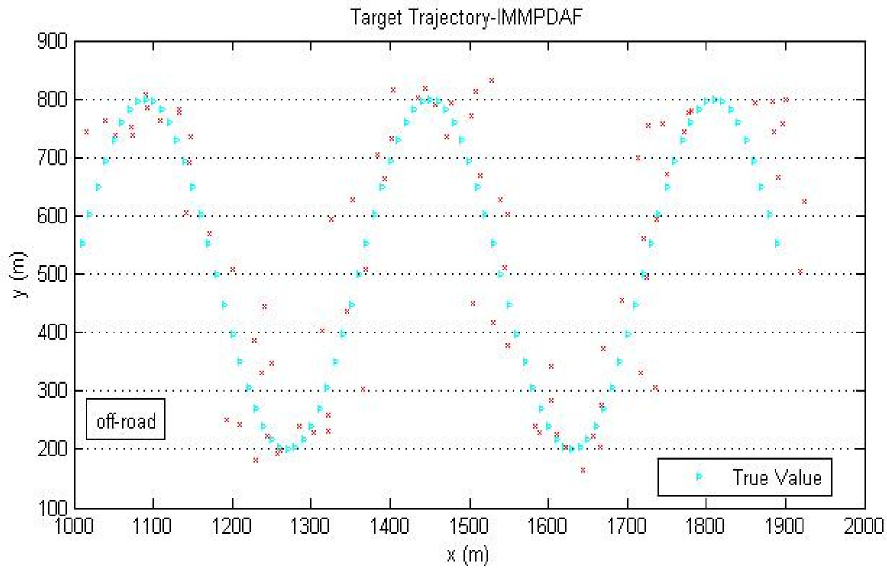

Figure 4-11: Target Trajectory-IMMPDAF with turn model-[30-10] (Scenario-3)

The position RMS errors belonged to both IMMPDAFs:

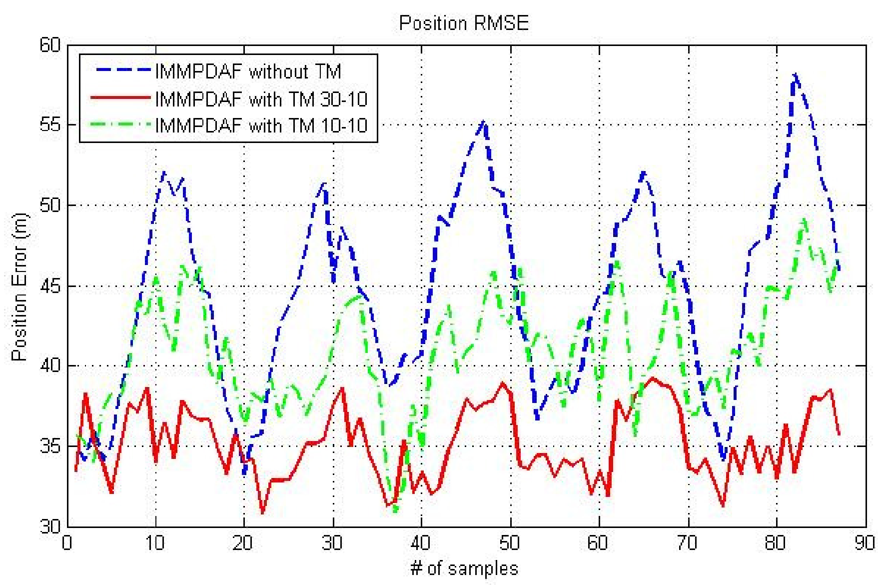

Figure 4-12: Position RMSE Comparison (Scenario-3)

Result-1: As can be seen from Figure 4-12, IMMPDAF with turn model whose process noise standard deviations are 30 and 10, is more applicable in the position estimation than both IMMPDAF with 2 CV models whose high process noise standard deviation is 30, and IMMPDAF with turn model whose process noise standard deviations are 10 and 10. When IMMPDAF with turn model catches up maneuver in turn points, the position error values increase up to peak values for a while. However, it decreases and stabilizes the position errors in smooth portions of path after maneuvering. On the other hand, IMMPDAF with 2 CV models also decreases the errors after maneuvers, but not stabilizes. That is, the error compensation process is too slow. In addition, IMMPDAF with 2 CV models whose high process noise standard deviation is 10 does not work in such scenarios including frequent and sharp maneuvers.

The velocity RMS errors belonged to both IMMPDAFs:

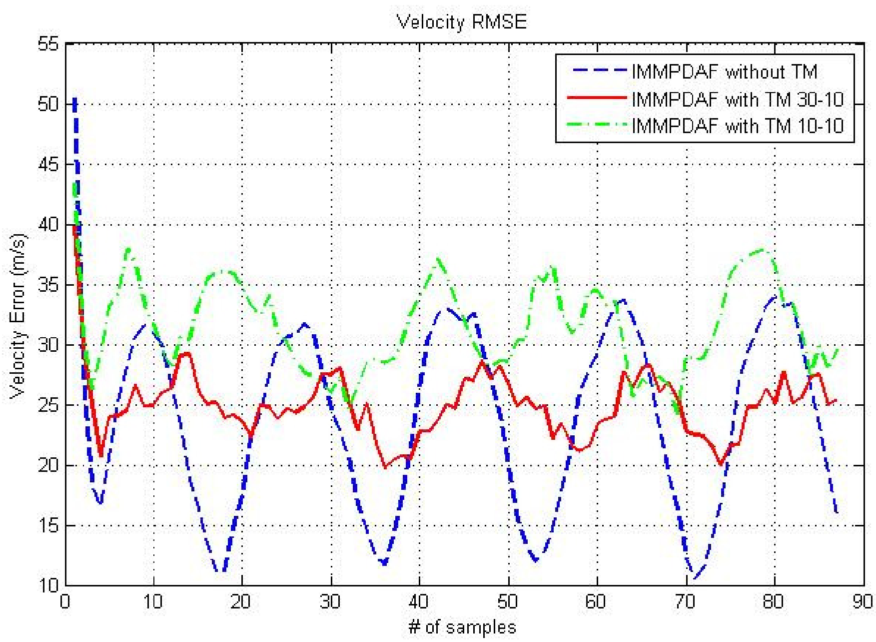

Figure 4-13: Velocity RMSE Comparison (Scenario-3)

Result-2: It is easily seen from Figure 4-13 that performances of both IMMPDAFs seem to be approximately same. The first difference between these results obtained from two IMMPDAFs is the variance of velocity error distributions. IMMPDAF with turn model, whose process noise levels are 30-10, tries to stabilize the error not only during maneuver but also after turn points. It is seen that the velocity error range of that model is in between [20-30] m/s. The second difference is that in IMMPDAF without turn model, the velocity errors in turn points increase gradually after each maneuver.

The NEES values belonged to both IMMPDAFs:

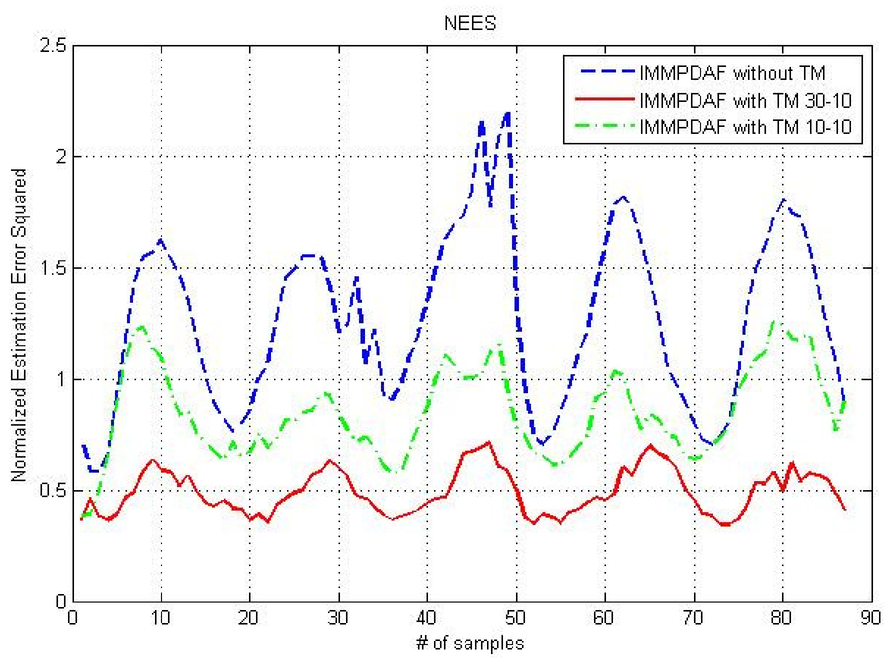

Figure 4-14: NEES Comparison (Scenario-3)

Result-3: Result-2 can also be observed from Figure 4-14. In addition, since NEES consists of both position and velocity errors, in which range NEES takes which values is very important issue. According to the NEES figure above, it can be said that IMMPDAF with turn model whose turn model process noise levels are 30-10, is much more applicable than the other filter/estimator.

The overall RMS errors belonged to both IMMPDAFs:

Table 4-3 IMMPDAF with turn model vs. IMMPDAF with 2 CV model

Tracking Algorithm	RMSE in position (m)	RMSE in velocity (m/s)
IMMPDAF with turn model (turn model noise standard deviations:10-10)	**45.3462**	**34.7316**
IMMPDAF with 2 CV models (high process noise standard deviation:10)	**200.0607**	**63.0750**
IMMPDAF with turn model (turn model noise standard deviations:30-10)	**40.0596**	**28.3063**
IMMPDAF with 2 CV models (high process noise standard deviation:30)	**48.4350**	**25.2202**

Result-4: As can be seen 2^{nd} row of the table above, it is not possible in such scenarios to track the target of interest with 2 CV models whose process noise standard deviations are 2.5 and 10. Although, the velocity RMS errors of IMMPDAFs with/without turn model seem to be same, there is ~8,5 m distance difference in the position RMS errors of these estimators.

Mode probability analysis: Mode probabilities depend on the probability transition values belonged to the Markov transition matrices. Therefore, the choice of Markov transition matrix plays an important role in performance of an estimator. In general, if model set of IMM consists of turn model, mode probabilities of turn model are equal to or higher than the mode probabilities of constant velocity model in turn points. However, in straight portions of the trajectory, mode probabilities of constant velocity model are equal to or higher than the mode probabilities of turn model. In this scenario, we can observe the mode transitions between each other by making the stop model disable and by using the suitable Markov transition matrix to focus the turn model effectiveness.

In Figure 4-15, approximately at 15th, 25th, 45th and 85th samples (turn points) the mode probability of turn model increases, but then decreases in straight portions of trajectory.

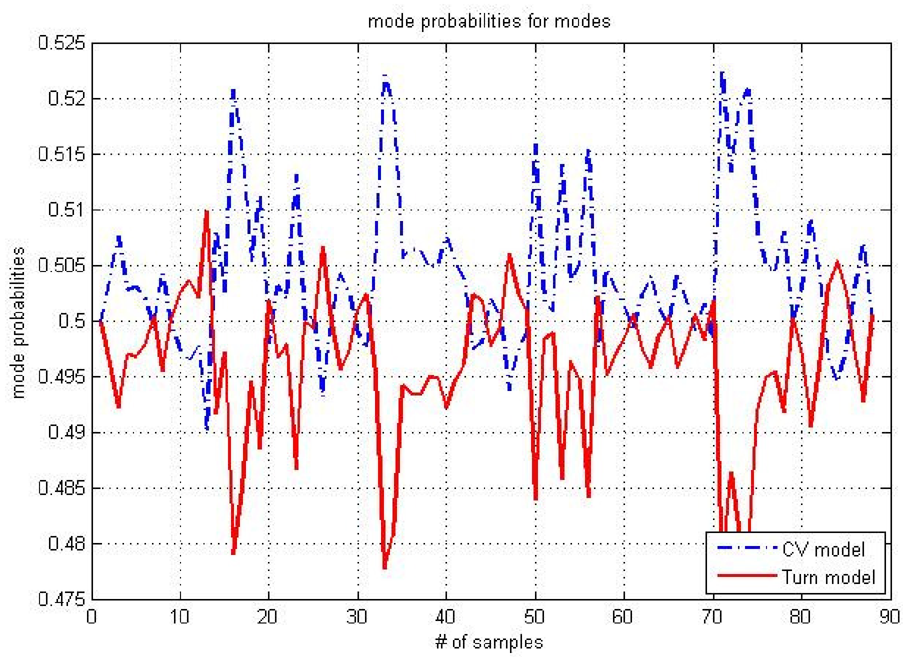

Figure 4-15: Mode Probabilities for Modes (Scenario-3)

4.3.4. Scenario-4

In this scenario, stop model effectiveness will be evaluated in both on-road and off-road conditions. In off-road conditions, IMM estimator use 3 models such as CV with low process noise, turn model and stop model while IMM estimator use 3 models such as CV with low process noise CV with high process noise and stop model in on-road conditions.

In off-road conditions, for CV with low process noise model σ_{CV} is taken as 2.5, for stop model σ_{STOP} is taken as 2.5 and for turn model σ_W is taken as 10, σ_S is taken as 1. In on-road conditions, for CV with low process noise model σ_{CV} is taken as 2.5, for CV with high process noise model σ_{CV} is taken as 10 and for stop model σ_{STOP} is taken as 2.5.

In this scenario, the process noise standard deviation values of each model are acceptable values. They are determined by regarding Monte Carlo test results for this scenario.

The Markov chain matrix is given as,

$$\begin{bmatrix} 0.5 & 0.14 & 0.36 \\ 0.24 & 0.66 & 0.1 \\ 0.26 & 0.2 & 0.54 \end{bmatrix}$$

For the event E_s, transition matrix is written as,

$$\left[p_{ij}\right]^{Es} = \begin{bmatrix} 0.5 & 0.1 & 0.4 \\ 0.2 & 0.3 & 0.5 \\ 0.6 & 0.1 & 0.3 \end{bmatrix}$$

For the event E_f, transition matrix is written as,

$$[p_{ij}]^{Ef} = \begin{bmatrix} 0.7 & 0.3 & 0 \\ 0.8 & 0.2 & 0 \\ 0.8 & 0.2 & 0 \end{bmatrix}$$

a_M used in equation $V_{ST} = a_M T + V_0$ is taken as 5.

where $V_0 = \sqrt{6}\sigma_{STOP} T = \sqrt{6}.\ 2.5.T$

The detection and gate probabilities are used as P_D=0.99 and P_G=0.99.

There are clutters and a true target in every beginning of each step. However, at stopped points, the measurements include just clutters.

The time interval T is taken as 1.

The number of runs, N is 100.

The target of interest decreases own speed gradually and stops (radial velocity is 0) in 35-40 and 120-125 steps. The actual velocity graph is given in Figure 4-16.

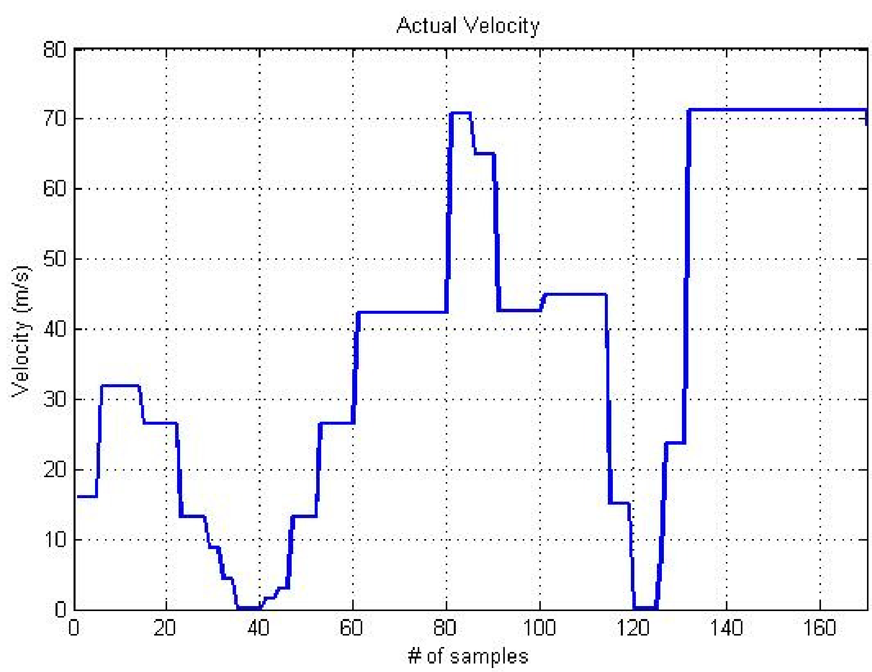

Figure 4-16: Actual Velocity (Scenario-4)

The target stops at [x~1000, y~1030] m in off-road and at [x~2255, y~3480] m in on-road. The target trajectory and sample IMM estimations on map are given in Figure 4-17.

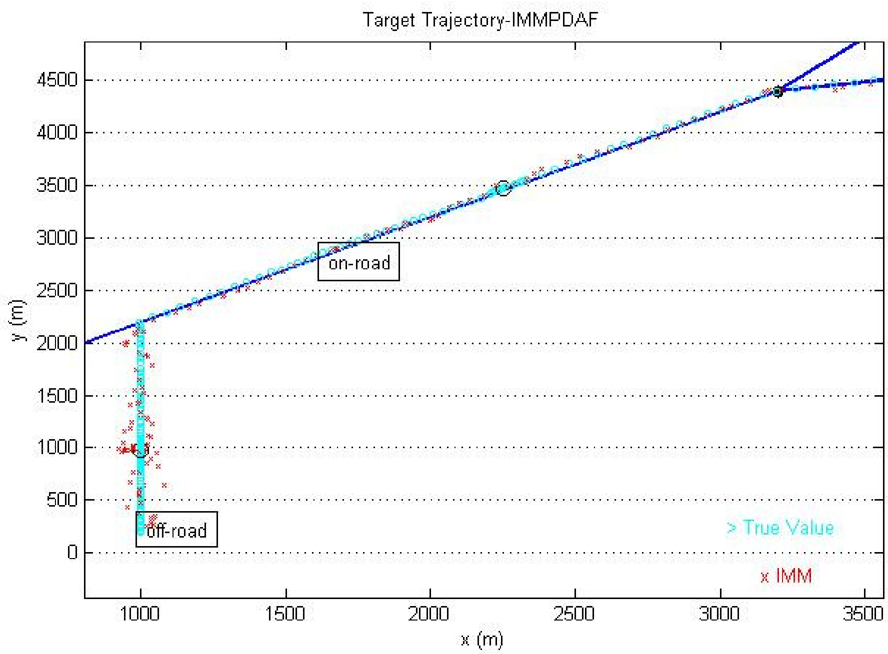

Figure 4-17: Target trajectory-IMMPDAF with stop model (Scenario-4)

The position RMS errors belonged to IMMPDAF:

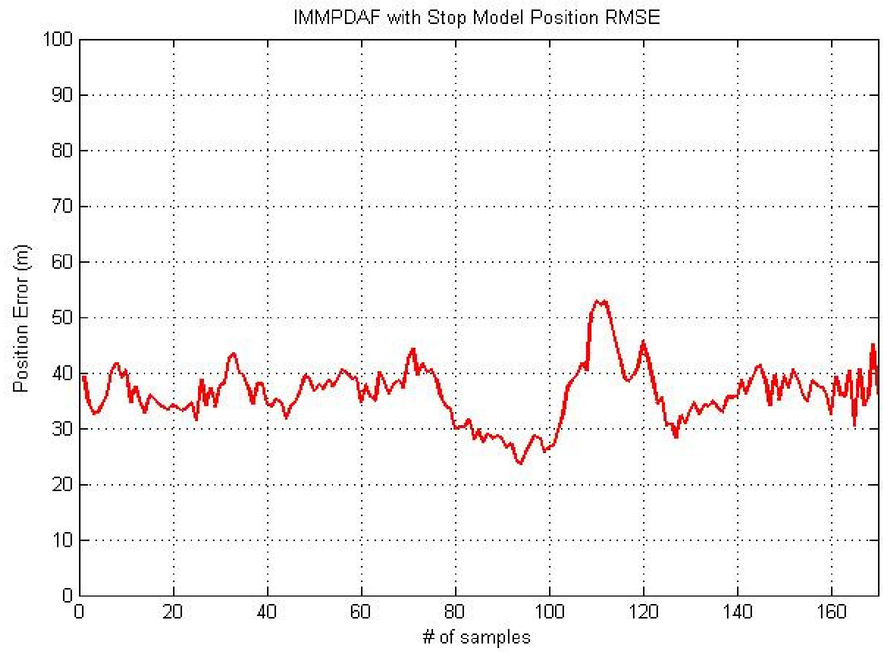

Figure 4-18: IMMPDAF with stop model position RMSE (Scenario-4)

Result-1: As can be seen from Figure 4-18, the position error increases and then decreases with in 30-40 steps and 110-120 steps but in general, the position error is stabilized to values with in the range of 30-40 m. When the target of interest decreases own velocity below the minimum detection velocity, IMMPDAF with stop model starts to run. At these points, either current track can be dropped and then new track can be initialized or target can be tracked again without any track initiation and drop. Therefore, at these points, the estimated values may belong to a clutter and the estimated position may be far away from actual position. The important issue here is the error stabilization after stopping points.

The velocity RMS errors belonged to IMMPDAF:

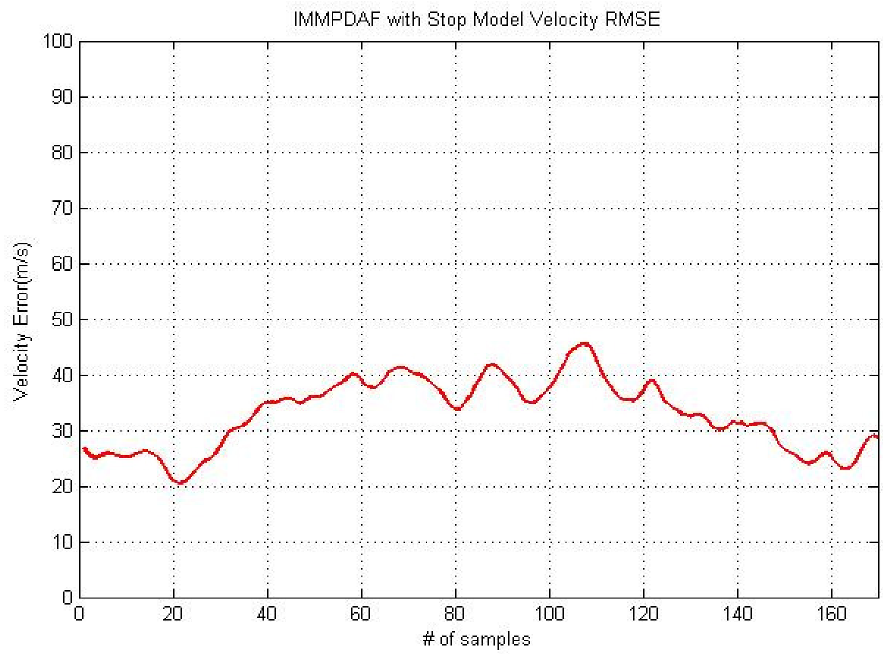

Figure 4-19: IMMPDAF with stop model velocity RMSE (Scenario-4)

The actual and related estimated velocities at each sample are given in Figure 4-20.

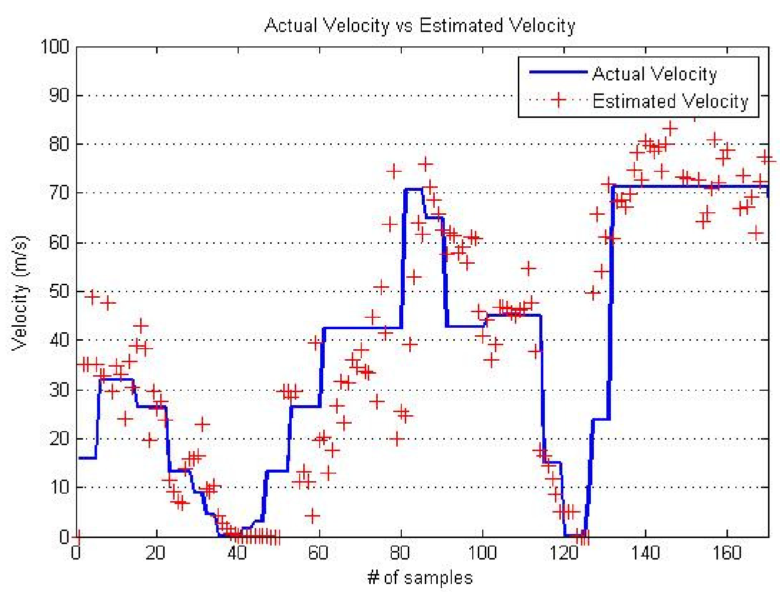

Figure 4-20: IMMPDAF Actual velocity vs. Estimated velocity (Scenario-4)

Result-2: It is easily seen from Figure 4-16; the velocity of target of interest decelerates and accelerates certainly in 20-60 and 110-130 steps. Also, the target stops in 35-40 and 120-125 steps. The error values belonged to stopped target are not contributed to the velocity RMS error calculation. Therefore, as can be seen from Figure 4-19, the velocity error of IMMPDAF does not make any fluctuation. That is, the target of interest is tracked successfully before and after stopping point. Also, 1 run velocity estimation of IMMPDAF can be observed from Figure 4-20.

4.4. Overall Evaluation

As in Scenario-1, the errors of IMMPDAF are sometimes larger, sometimes smaller than ones in PDA filter. This is typical of adaptive algorithms like IMMPDAF. For overall better performance, IMMPDAF with two models which are CV with low process noise and CV with high process noise is more applicable than PDA filter because we do not need to adjust the process noise levels specifically while tracking.

As in Scenario-2, the target of interest can make maneuver to any direction in off-road conditions, so turn model with optimized noise level deviation and Markov matrix should be used especially in off-road conditions to minimize error. The way of responses to maneuvers is also an important issue. IMMPDAF handles the maneuvers quickly. However, PDA filter does not react to maneuvers. That is, the velocity and position errors are always high. In Scenario-2, the number of estimated samples (number of confirmed track) in PDA filtering method is 40 samples smaller than the other. In other words, PDA filter is able to catch up soft and continuous maneuvers but not sharp and frequent ones.

As in Scenario-3, because of the fact that IMMPDAF with 2 CV models whose high process noise standard deviation is chosen as 10, does not work in scenarios including frequent and sharp maneuvers, high level noise deviation should be adjusted to higher values to work with 2 CV models in this kind of maneuvering situations. In addition, it is not known which maneuver the target of interest makes or when target of interest makes a maneuver. Therefore, stabilizing (decreasing) error with in fewer steps after or during turn points is very important issue. That is, the error compensation process is too slow in IMMPDAF with 2 CV model estimators.

As in Scenario-4, move-stop-move model should be used not to lose the track (or to track true target not a clutter). In addition, stop model should be supported by track initiation and drop algorithm [7]. It is also shown in [1] that IMMPDAF with stop model achieves the best results among the various estimators.

CHAPTER 5

CONCLUSIONS

In this thesis, ground target tracking via interacting multiple model estimator is examined and four target dynamic models are studied in this context. The dynamics of targets are presented and system is estimated using designed interacting multiple model (IMM) estimators. The performances of these estimators are evaluated by Monte Carlo simulations and compared with standard one model tracking algorithm which is chosen as standard Kalman filter.

Initially, a single target in clutter is examined. Thereafter, target dynamic model, measurement model, observation model, target state and process noise model are given in detail. Then, gating procedure which is used as a screening mechanism to determine which observations are valid candidates to update existing tracks is described briefly. Then, chosen multiple model filtering method which is interacting multiple model estimator is described in general and flowchart of the system is given.

After the target dynamic model and validation algorithm are described, interacting multiple model estimator is presented. First, the reason for the selection of IMM, which is probably the most widely used estimation algorithm for maneuvering ground target tracking systems and models used in this thesis are discussed. Thereafter, brief information about combination process of PDA and IMM is given. Afterwards, IMM models used in simulations are described with all formulations. Process noise levels, Markov chain matrices, state vectors and covariance matrices are given in detail. The dimension conversion process is reviewed since state vector dimension of turn coordinated model is different from dimensions of other models. The design of conversion matrices needed for this process is given in detail.

In order to measure the performance of the estimators presented, sample scenarios are provided. In each scenario, models used in simulations are analyzed one by one. Both IMMPDAF with two CV models and IMMPDAF with turn model are compared with standard Kalman filter algorithm to observe the effectiveness of multiple model algorithms. IMMPDAF with two CV models is also compared with IMMPDAF with turn model to measure the performance of turn model. Also, IMMPDAF with stop model is investigated to show that even if target of interest stops or decreases own velocity below the minimum detectable velocity threshold in any part of the trajectory, it is possible to continue tracking the true target. Because, other tracking algorithms most probably lose the track in the event that target stops.

One of the important and expected results of the simulations is that IMMPDAF estimates almost all target trajectories with minimum position and velocity errors when it uses optimized process noise level and Markov model.

The most important result is as follows:

Interpretation of IMMPDAF performances is related to scenarios. Although, IMMPDAFs with two CV models seem to be effective with non-maneuvering target trajectories or it can catch up soft maneuvers, if target stops or maneuvers sharply and frequently, turn model and stop model are certainly required. Because it is not known which maneuver target of interest makes or when target of interest makes a maneuver. Therefore, the ability of error compensation should exist in IMMPDAF. That is, these models should be in the model set of IMMPDAF.

As a future work, the tracking algorithms can be modified so that it will be possible to vary the set of models in the IMMPDAF based on some criteria to yield better estimates. IMM algorithm expressed in this thesis requires the mode set which includes as many modes as necessary to handle the varying target motion characteristics. However, this situation results excessive computational resources to be required. Therefore, Variable Structure IMM (VS-IMM) estimator where the mode set not only differs across targets, but also varies with time for a given target of interest can be used for tracking ground targets in cluttered environments. In VS-IMM estimator, filter modules are adaptively modified, added or removed depending on the terrain topography, for tracking on-road and off-road targets within the same framework [19], [20].

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