INTERACTING MULTIPLE MODEL SEEKER FILTER FOR TRACKING EVASIVE TARGETS

Shanthakumar N[1], Sudesh K. Kashyap[2], VPS Naidu[3] and Girija G[4]

[1] Scientist F, FMCD, National Aerospace Laboratories, Bangalore, nskumar@css.nal.res.in
[2] Scientist E1, FMCD, National Aerospace Laboratories, Bangalore, sudesh@css.nal.res.in
[3] Scientist C, FMCD, National Aerospace Laboratories, Bangalore, vpsnaidu@css.nal.res.in
[4] Scientist F, FMCD, National Aerospace Laboratories, Bangalore, ggirija@css.nal.res.in

ABSTRACT:. *Seeker filter is an important subsystem in modern homing guidance system of advanced intercepting missiles. Seeker filter design for homing guidance requirements are highly demanding and challenging. Very low filter lag, high noise attenuation are some of the challenges that need to be addressed. This paper presents an interacting multiple model augmented extended Kalman filter (IMM-AEKF) design to operate as seeker filter in close loop homing guidance of an interceptor to track evasive targets. The performance of the seeker filter is verified with six degree of freedom interceptor-target engagement simulation with seeker filter in guidance loop of the interceptor. Different filter performance criteria have been used to verify the performance of the seeker filter. The seeker filter efficiently handles the various seeker noise and provides a smooth estimate of target states to generate guidance command for intercepting missile. The miss distance achieved is within the acceptable limits.*

1. INTRODUCTION

RF (radio frequency) seeker is an active radar on-board an intercepting missile. Seeker filter is a target state estimator which is an important subsystem in modern homing guidance system of advanced missiles. Seeker filter is required for two reasons[1]. Firstly, the measurements provided by on-board active RF seeker of an intercepting missile are highly noisy, and are not in a form usable by the guidance law. Secondly, advanced guidance laws require additional information about the target such as its acceleration components, which cannot be provided by the on-board sensors.

RF Seeker filter design for homing guidance requirements are highly demanding and challenging. Very low filter lag (to meet very low guidance time constant for air breathing targets with evasive maneuvers at short range to go), on-line seeker filter lag control (for closed loop guidance stability and miss distance) and high attenuation of seeker noise which is correlated, non-Gaussian and modulated by radar cross section (RCS) fluctuation are some of the challenges that need to be addressed. Over and above these factors, there will be periodic data loss due to eclipsing. Air breathing targets against which homing guidance/seeker filter are being designed are capable of performing evasive maneuver. This leads to purely reactive target state estimators, often producing sluggish state estimator response in the presence of agile targets. An ideal approach to preserving the agility of the target state estimator without sacrificing its accuracy is to model the target motion with multiple target motion models that characterize the target motion all the time and a switching logic. The switching logic is then allowed to select any one of these models at any instant of time. Thus, to an estimator, at each time instant, the target motion model appears to follow one of these models. The resulting target state estimator in this case consists of a bank of Kalman filters whose outputs are blended using a hypothesis-testing algorithm. This approach is called Interacting Multiple Model (IMM) estimation technique[2]. The physical model of the target motion is assumed to be known, but the exact maneuver strategy is parameterized and then determined online together with the target states. Since the target maneuvering logic is adaptively determined, the resulting estimation scheme can be expected to have agile response to any changes in the target behavior and there by filter time lag is expected to be well under control.

This paper presents a two model interacting multiple model seeker filter with extended Kalman filter as mode-matched filter which operates in closed homing guidance loop to generate required guidance commands to intercept maneuvering air-breathing targets. The major challenge in processing the RF seeker data, especially in end game, is glint noise[3] which is a non-Gaussian noise with heavy tail distribution. The glint noise is a function of target aspect, RCS fluctuation and range to go. Obviously, when the range to go is less, the effect of glint noise (if not accounted properly) on guidance will be more and this would in turn result in large miss distances. To overcome this problem, the glint noise and radar cross section (RCS) fluctuations present in seeker data are handled as augmented states and estimated in the filter algorithm and hence the filter algorithm is named as IMM-AEKF (Interacting Multiple Model based Augmented Extended Kalman Filter). The two model in IMM-AEKF consists constant acceleration (CA) and constant jerk (CJ) models as target motion models[4] for tracking air breathing target performing evasive maneuver is discussed in section 2.

2. IMM-AEKF ALGORITHM

In target tracking applications, Kalman filters are extensively used. In general target tracking applications, the state of the target includes its position and the time-derivatives of position. For targets moving with constant velocity (CV), the state model includes the first derivative of position and for targets moving with constant acceleration (CA) it includes second derivative of position. Models with second order derivatives are preferred for tracking maneuvering targets and referred to as acceleration models. However, for rapidly maneuvering targets, higher order derivatives of position become significant. Hence models which include third order derivative of the target position, termed constant jerk (CJ) models are preferred for tracking targets executing rapid/evasive maneuvers.

When the target is maneuvering randomly, adaptive state estimation is required to track a target whose behavior pattern keeps changing with time. The Interacting Multiple Model (IMM)[2] is one such adaptive estimator which is based on the assumption that a finite number of models are required to characterize the target motion at all times. IMM approach is a sub-optimal hybrid estimator since it is characterized by both continuous valued parameters like target position, velocity and accelerations defined by the difference or differential form of state equations, as well as by the discrete stochastic process that controls the selection of a model corresponding to each behavior mode. The IMM approach, thus, performs both target state estimation as well as model selection from a given set of models. The "model set" may consist of several models, such as a CV model, CA model, CJ model and a coordinated turn (CT) model. A finite state Markov chain with known transition probabilities is used to switch from one model to another. The mode transition probabilities, which constitute the transition matrix, are the design parameters for the algorithm. Thus, the IMM algorithm, in general, consists of a set of mode matched filter modules that interact in a certain way to yield the mode-conditioned state estimates. The individual mode matched filters can either be Kalman Filters (KF) or Extended Kalman Filters (EKF) or Augmented Kalman filter (AEKF) as in the present case. The two model IMM-AEKF algorithm structure and flow chart is shown in Figure 1. The description of IMMF algorithm is given in [5].

3 TARGET MOTION MODELS

The base state model for a fixed-structure hybrid system can be described as follows

$$X(k+1) = F_j(k)X(k) + G_j(k)w_j(k) \qquad \forall \; j \in M$$
$$Z(k) = h(X(k)) + v_j(k) \qquad \forall \; j \in M; \qquad j = 1,...r \tag{1}$$

where M is a set of possible r modes and G_j denotes the process noise gain matrix. The process and measurement noises are Gaussian, mutually uncorrelated with zero mean and known covariances. The function h represents the nonlinear relation between the states X and the measurements Z. It is clear from Eq. (1) that the system transition matrix F and the noise statistics can differ from mode to mode.

3.1 State Model

State vector for CA model is

$$X_1 = \left[\Delta x, \; \Delta \dot{x}, \; a_{tx}, \; \Delta y, \; \Delta \dot{y}, \; a_{ty}, \; \Delta z, \; \Delta \dot{z}, \; a_{tz}, \; 6 \; \text{additional (augmented) states to account glint \& RCS noise} \right]$$

State vector for CJ model is

$$X_2 = \left[\Delta x, \; \Delta \dot{x}, \; a_{tx}, \; j_{tx}, \Delta y, \; \Delta \dot{y}, \; a_{ty}, \; j_{ty}, \Delta z, \; \Delta \dot{z}, \; a_{tz}, \; j_{tz}, \; 6 \; \text{augmented states to account glint \& RCS noise} \right]$$

Model 1: Constant Acceleration (CA) Model

$$\Delta \dot{x} = \Delta V_x \; ; \qquad \Delta \dot{V}_x = a_{tx} - a_{mx} \; ; \qquad \dot{a}_{tx} = -\left(\frac{a_{tx}}{\tau_x} \right); \qquad \dot{j}_{tx} = 0 \; ;$$

$$\Delta \dot{y} = \Delta V_y \; ; \qquad \Delta \dot{V}_y = a_{ty} - a_{my} \; ; \qquad \dot{a}_{ty} = -\left(\frac{a_{ty}}{\tau_y} \right); \qquad \dot{j}_{ty} = 0 \; ; \tag{2}$$

$$\Delta \dot{z} = \Delta V_z \; ; \qquad \Delta \dot{V}_z = a_{tz} - a_{mz} \; ; \qquad \dot{a}_{tz} = -\left(\frac{a_{tz}}{\tau_z} \right); \qquad \dot{j}_{jz} = 0 \; ;$$

Model 2: Constant Jerk (CJ) Model

$$\Delta \dot{x} = \Delta V_x \; ; \qquad \Delta \dot{V}_x = a_{tx} - a_{mx} \; ; \qquad \dot{a}_{tx} = j_{tx} \; ; \qquad \dot{j}_{tx} = -\left(\frac{j_{tx}}{\tau_x} \right);$$

$$\Delta\dot{y} = \Delta V_y \; ; \qquad \Delta\dot{V}_y = a_{ty} - a_{my} \; ; \qquad \dot{a}_{ty} = j_{ty} \; ; \qquad \dot{j}_{ty} = -\left(\frac{j_{ty}}{\tau_y}\right) \; ; \tag{3}$$

$$\Delta\dot{z} = \Delta V_z \; ; \qquad \Delta\dot{V}_z = a_{tz} - a_{mz} \; ; \qquad \dot{a}_{tz} = j_{tz} \; ; \qquad \dot{j}_{jz} = -\left(\frac{j_{tz}}{\tau_z}\right) \; ;$$

where, $\Delta x, \Delta y, \Delta z$ are the relative positions of the target w.r.t interceptor along three Cartesian coordinates and $\Delta V_x, \Delta V_y, \Delta V_z$ are the relative velocities of target w.r.t. interceptor, a_{tx}, a_{ty}, a_{tz} are the target accelerations, j_{tx}, j_{ty}, j_{tz} are the target jerks, a_{mx}, a_{my}, a_{mz} are the missile (interceptor) accelerations, and τ_x, τ_y, τ_z are the correlation time constants.

3.2 Measurement model

Measurement vector consists of $\begin{bmatrix} \rho & \dot{\rho} & \phi_y & \phi_z & \dot{\phi}_{y_{ig}} & \dot{\phi}_{z_{ig}} \end{bmatrix}$ during non-eclipsing period and

$\begin{bmatrix} \rho & \dot{\rho} & \phi_y & \phi_z \end{bmatrix}$ during eclipsing period

where, ρ is range-to-go (distance between interceptor and target), $\dot{\rho}$ is range rate,

ϕ_y and ϕ_z are gimbal angles in yaw and pitch planes respectively,

$\dot{\phi}_{y_{ig}}$ and $\dot{\phi}_{z_{ig}}$ are the respective line of sight (LOS) rates in inner gimbal frame.

The relative position and velocity states of the target w.r.t interceptor in inertial frame is transformed to LOS frame using:

$$\rho = \sqrt{\Delta x^2 + \Delta y^2 + \Delta z^2} \; ; \quad \dot{\rho} = \frac{\Delta x \Delta\dot{x} + \Delta y \Delta\dot{y} + \Delta z \Delta\dot{z}}{\rho} \; ; \quad \lambda_e = tan^{-1}\left(\frac{\Delta z}{\sqrt{\Delta x^2 + \Delta y^2}}\right) \; ;$$

$$\lambda_a = tan^{-1}\left(\frac{\Delta y}{\Delta x}\right); \quad \dot{\lambda}_e = \frac{\Delta\dot{z}\,\Delta x^2 + \Delta y^2 - \Delta z\,\Delta x \Delta\dot{x} + \Delta y \Delta\dot{y}}{\rho^2\sqrt{\Delta x^2 + \Delta y^2}} \; ; \quad \dot{\lambda}_a = \frac{\Delta x \Delta\dot{y} - \Delta y \Delta\dot{x}}{\sqrt{\Delta x^2 + \Delta y^2}} \tag{4}$$

The measurement model during non-eclipsing period is:

$$\begin{bmatrix} \rho \\ \dot{\rho} \end{bmatrix}_m = \begin{bmatrix} \rho \\ \dot{\rho} \end{bmatrix}; \quad \begin{bmatrix} \phi_y \\ \phi_z \end{bmatrix}_m = \begin{bmatrix} \phi_y \\ \phi_z \end{bmatrix}; \quad \begin{bmatrix} 0 \\ \dot{\phi}_{y_{ig}} \\ \dot{\phi}_{z_{ig}} \end{bmatrix}_m = C_f^g\, C_b^f\, C_i^b\, C_l^i \begin{bmatrix} -\dot{\lambda}_a\,sin\,\lambda_e \\ \dot{\lambda}_e \\ \dot{\lambda}_a\,cos\,\lambda_e \end{bmatrix} \tag{5}$$

The measurement model during eclipsing period is:

$$\begin{bmatrix} \rho \\ \dot{\rho} \end{bmatrix}_m = \begin{bmatrix} \rho \\ \dot{\rho} \end{bmatrix}; \quad \begin{bmatrix} \phi_y \\ \phi_z \end{bmatrix}_m = \begin{bmatrix} \phi_y \\ \phi_z \end{bmatrix} \tag{6}$$

where $\phi_y = tan^{-1}\left(\frac{m}{l}\right); \quad \phi_z = tan^{-1}\left(\frac{n}{\sqrt{l^2 + m^2}}\right)$ and $\begin{bmatrix} l \\ m \\ n \end{bmatrix} = C_b^f\, C_i^b\, C_l^i \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$ (7)

where DCMs $C_f^g, C_b^f, C_i^b, C_l^i$ are defined in [4].

4. INTERCEPTOR–TARGET ENGAGEMENT SIMULATION

6 degree of freedom (DoF) simulation code of air-to-air intercepting missile in FORTRAN and IMM-AEKF seeker filter in MATLAB are integrated to simulate close loop interceptor-target engagement and the seeker filter performance is validated using several realistic interceptor-target engagement scenarios. Figure 2 shows the block diagram of interceptor-target engagement simulation setup with seeker filter in the closed loop. Table 1 gives the different interceptor-target engagement scenarios considered for the present study. In order to simulate realistic target-interceptor engagement, following points are considered (as suggested by fighter pilot):

- In the presence of adversary (intercepting missile), the target (fighter aircraft) generally executes a turn and accelerates at short range to go ($R_{to-go} \approx 2$ km).
- Target turns (velocity vector) at the rate of 20 to 25 deg/sec at a speed of 300 to 400 kmph.
- Target under goes maximum roll rate (≈ 270 deg/sec) to generate glint effect.

The target performing evasive maneuver is simulated within the permissible 'g' limit of a typical fighter aircraft at different altitudes as shown in Table 1. The target starts maneuver continuously with the specified 'g' profile given in Table 1 once the specified R_{to-go} is reached.

5. PERFORMANCE OF IMM-AEKF SEEKER FILTER

The performance of the IMM-AEKF seeker filter is evaluated with 50 Monte-Carlo simulations in each case of interceptor-target engagement. Filter performance criteria like percentage fit error (PFE)[6], state error with bounds[6], innovation sequence with bounds[6], auto correlation of innovation sequence with bounds[7], root sum of squares position error (RSSPE)[6], and miss distance and noise attenuation achieved are considered to verify the performance of the seeker filter.

Figure 3 shows the interceptor-target engagement in 3D (for case no. 1 from Table 1). Table 2 gives the percentage fit error obtained with IMM-AEKF seeker filter (for simulation cases 1 and 4 from Table 1). Figure 4 shows the histogram of the miss distance achieved by the homing guidance with seeker filter in closed loop from 50 Monte-Carlo simulations (for case no. 1). It is expected that miss distance less than 10 meters is reasonably good. From the figure 3 it can be observed that most of the time the miss distance falls between 5 to 12 meters which is acceptable. Seeker measurements are highly noisy characterized by correlated thermal noise and RCS fluctuations and one of the important demand from seeker filter is to achieve very high noise attenuation. Figure 5 shows the noise attenuation achieved with IMM-AEKF seeker filter (for case no 1). The noise attenuation factor (AF) defined below is less than 0.1 most of the time which indicates that 90% of noise has been attenuated.

$$AF = \left(\frac{Y_t - \hat{Y}}{Y_t - Z} \right)$$ where Y_t, $\hat{Y}$ and Z are the true, estimated and measured value of the seeker output.

6. CONCLUDING REMARKS

In this paper, IMM based AEKF seeker filter is designed to operate in close loop homing guidance to track evasive target. The performance of the seeker filter is verified with six degree of freedom interceptor-target engagement simulation with seeker filter in closed guidance loop of the interceptor. Different filter performance criteria have been used to verify the performance of the seeker filter. The seeker filter efficiently handles the various seeker noises and provides a smooth estimate of target states used to generate guidance command for missile. The miss distance achieved is within the acceptable limits.

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Table 1:   Target trajectory simulation parameters

Case No.	Altitude (km)	Target Speed (kmph)	Maneuver (g's) pitch	yaw	Turn Rate (d/s)	Maneuver starts at $R_{to\text{-}go}$ (km)
1	0.5	485	6	-6	24.6	10
2	0.5	485	6	-6	24.6	5
3	0.5	485	6	-6	24.6	2.5
4	5.0	500	6	-6	23.7	10
5	5.0	500	6	-6	23.7	5
6	5.0	500	6	-6	23.7	2.5
7	10.0	540	6	-6	22.1	10
8	10.0	540	6	-6	22.1	5
9	10.0	540	6	-6	22.1	2.5
10	15.0	540	6	-6	22.1	10
11	15.0	540	6	-6	22.1	5
12	15.0	540	6	-6	22.1	2.5

Target azimuth orientation: Head-on with interceptor.

Table 2:   Percentage Fit Error

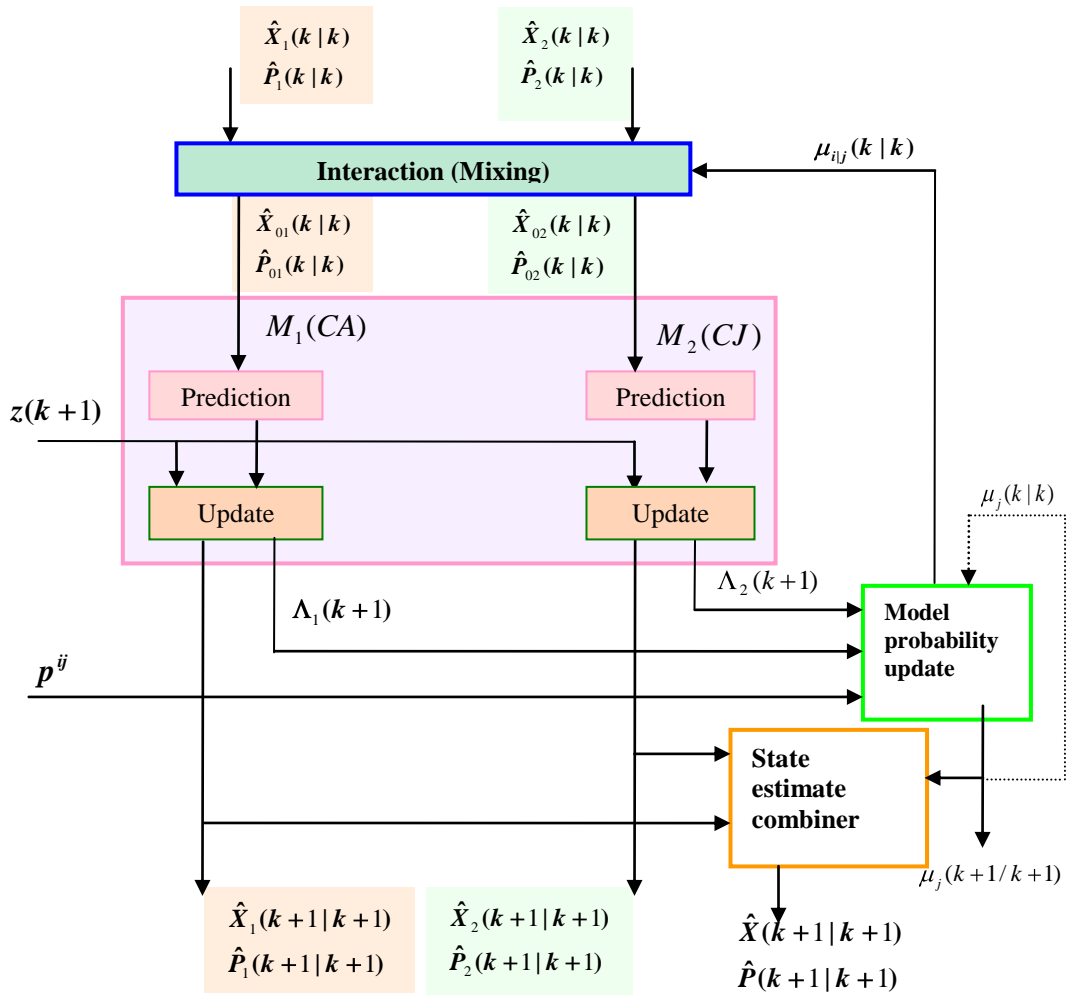|	Δx	$\Delta \dot{x}$	Δy	$\Delta \dot{y}$	Δz	$\Delta \dot{z}$
Case No. 1	0.0800	0.2239	0.3375	5.9389	0.7259	10.7550
Case No. 4	0.0662	0.2022	0.1760	4.3645	0.3561	5.1017

Figure 1: Two model IMM algorithm structure and flow chart.
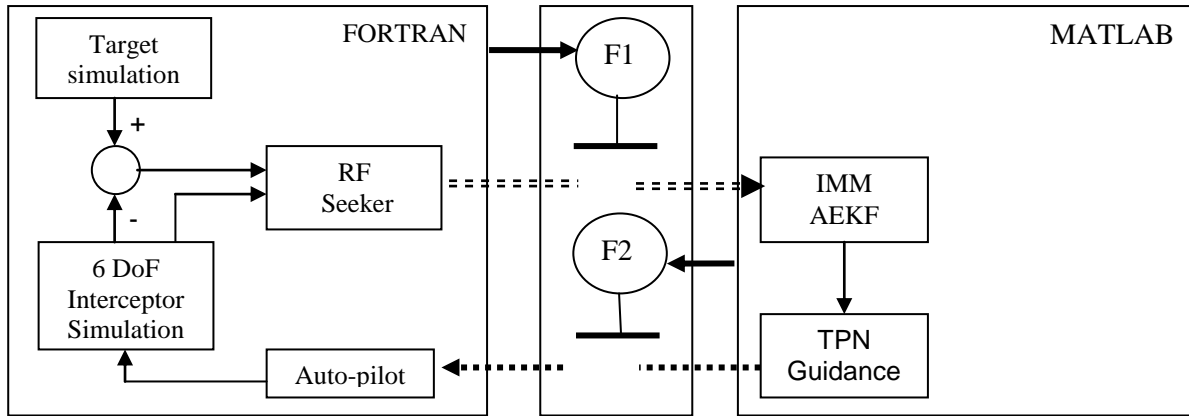
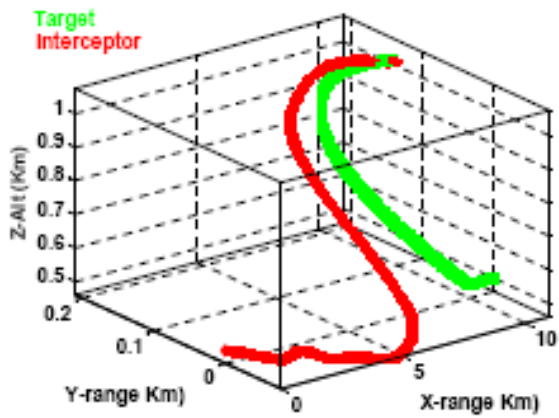Figure 2: 6 DoF Interceptor-target engagement simulation with seeker filter in closed loop
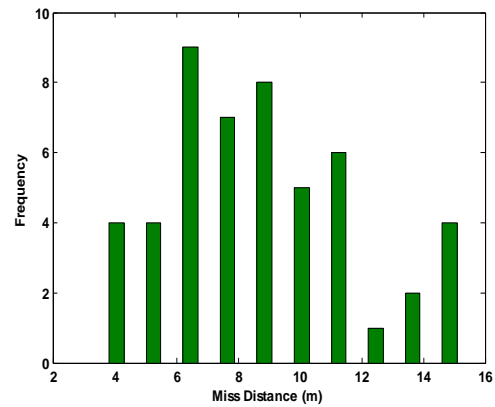
Figure 3: Interceptor-target engagement trajectory in 3D
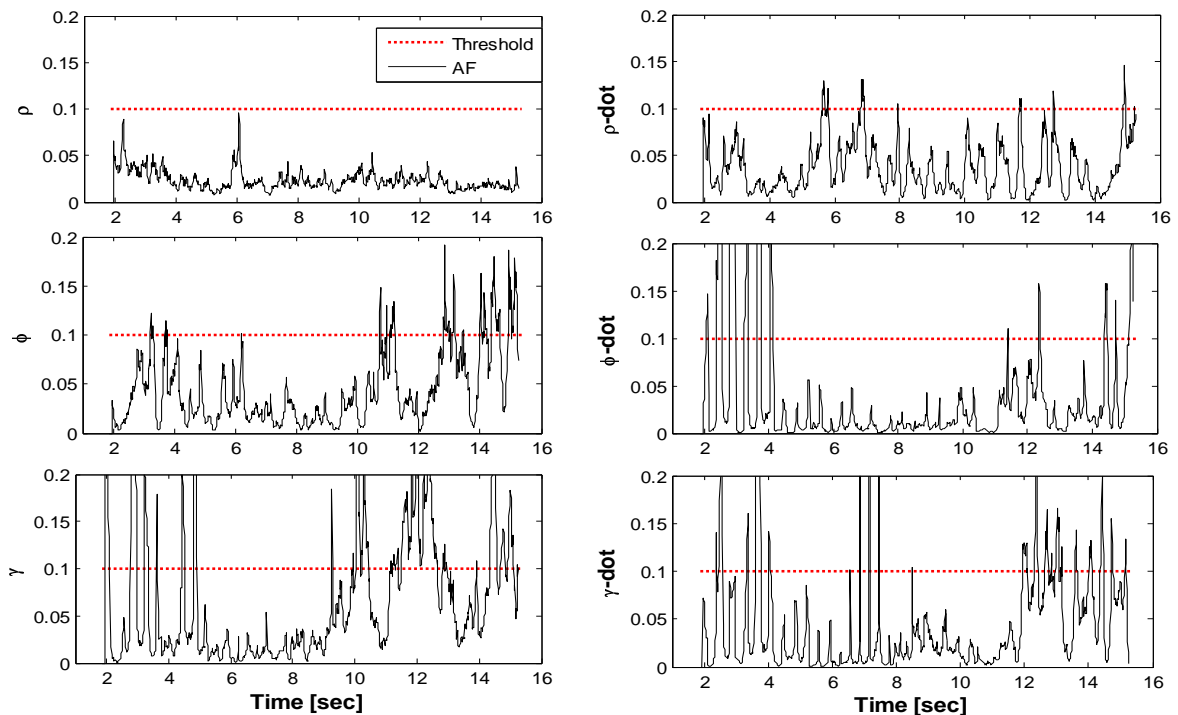
Figure 4: Histogram of miss diatnace achieved from 50 Monte Carlo simulation

Figure 5: Noise attenuation factor