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Performance Evaluation of Adaptive H-Infinity Filter

Reshma Verma [a]
Raol, J.R. [b]

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Abstract

This study is related to the use of adaptive H-infinity filter ($AHIF$) for multi sensor data fusion ($MSDF$) based tracking. AHIF can work efficiently in the presence of uncertainties using sliding window concept. In the present use of $AHIF$, the length of window size is varied to eliminate/minimize the estimation errors and predict almost precise location of a target. Simulation experiments are conducted to evaluate performance of $AHIF$ in comparison with Kalman and H-Infinity filters for mild and evasive maneuvering targets. $AHIF$ Performs better in terms location accuracy and position fit error.

Author correspondence:
Reshma Verma,
Asst. Professor, Dept. of Electronics and Communications,
MSRIT, and Research Scholar, Jain University, Bangalore.
Email address : *reshmaverma11@gmail.com*

1. Introduction

Target tracking is widely used in the military (Durišić, *et al.,* 2012), civil domains, battlefields (Oracevic & Ozdemir, 2014), smart transportation (Tubaishat, *et al.,* 2009), unmanned aircraft systems (Frew, *et al.,* 2008), geophysics (Shen, *et al.,* 2012) and aerospace applications (Eykhoff, 1972). In practical real time application to achieve highly efficient tracking, a robust and effective system design is required (Kashyap & Raol, 2008; Raol, 2010) to adopt $MSDF$ techniques. There are few problems which arise while developing target tracking systems for real-time practical applications such as sensor data communication errors, sensor measurement errors, developing & maintenance costs, large computational complexity and sensor incompatibility in adverse surroundings (Wang, *et al.,* 2017).

It has been a practice to use adaptive filters for handling varying amount of noise in the data. In this paper we use the MSDF in the context of target tracking for which the AHI filter is used. The performance of non-adaptive HIF would be satisfactory in the case of linear devices; however, for non-linear problem, the use of adaptive filter would be highly beneficial.

[a] Jain University, Bangalore, India
[b] MSRIT, Bangalore, India

Simulation study to evaluate performance of HIF and $AHIF$ for maneuvering targets (mild and evasive) is presented. Performance of $AHIF$ is compared with fuzzy KF (FKF) and HIF for non-maneuvering target tracking. Results are very encouraging.

2. Materials and Methods

Adaptive H-Infinity Filter for MSDF based tracking

An adaptive problem can be reshaped into space prediction problem of standard states by appropriately recasting to achieve adaptive filtering (Sayed & Kailath 1994). In this framework, we can use many standard sliding window patterns of different lengths as shown in Figure 1. Here, we can get a physical exposition of transformations with negative Gramian and corresponding information loss can be measured.

$$scan\ i \left\{ \underbrace{(x_{i-1} \quad y_{i-1})(x_{i-l+1} \quad y_{i-l+1})(x_i \quad y_i)}_{Length\ l_i = 1} \right.$$

$$scan\ i+1 \left\{ \underbrace{(x_{i-1} \quad y_{i-1})(x_{i-l+1} \quad y_{i-l+1})(x_i \quad y_i)(x_{i+1} \quad y_{i+1})}_{Length\ l_{i+1} = l+1} \right.$$

$$scan\ \ i+2 \left\{ \underbrace{(x_{i-l+1} \quad y_{i-l+1})(x_i \quad y_i)(x_{i+1} \quad y_{i+1})(x_{i+2} \quad y_{i+2})}_{Length\ l_{i+2} = l+1} \right.$$

Figure 1 sliding window length with varying window length

Here, sliding window length can be measured as $l_i \geq 0$. And $(x_i \quad y_i)$ can be referred as data points. Figure 1 represents a time variant sliding window length where we can have a window length $l_i = l$ at scan i at first instant. For following time instant, to alter the sliding window length as $l_{i+1} = l + 1$ we can add another data points as $(x_{i+1} \quad y_{i+1})$. Similarly, for next instant, to alter the sliding window length as $l_{i+2} = l + 1$ we can add another data points as $(x_{i+2} \quad y_{i+2})$. Some other standard patterns of sliding window can be considered. The new time index k can easily replace the old scan i. The time index k posses some unique properties as time index k is incremented in any condition either data points are added to the window or discarded from the window. If window length is l_i at any scan i then the new time index k can be represented as $2i - l_i + 1$. This can be better explained as:

1. The new time index k incremented, each time a data point (x_i, y_i) added at scan$i$ and which can be defined as,
$$\bar{y}_k = y_i\ , \bar{x}_k = \ x_i\ , and\ \bar{R}_k = 1. \tag{1}$$
2. The new time index k can be incremented even if each time a data point (x_{i-l_i}, y_{i-l_i}) is removed at scan$i$ and which can be defined as,
$$\bar{y}_k = y_{i-l_i}\ , \bar{x}_k = \ x_{i-l_i}\ , and\ \bar{R}_k = -1. \tag{2}$$

The similar method can be used to build a state space model which is partially equal to indefinite quadratic form $\bar{J}_k$. Therefore, the state space models are defined as follows,

$$x(k\ +\ 1) = \ Fx(k) + Gw(k), \tag{3}$$

$$y(k) = \ Hx(k) + \ v(k), \tag{4}$$

Where x represents a state vector, F is a state transition matrix, G is process noise gain-matrix, w is used to represent white Gaussian process noise with zero mean and covariance matrix Q. The sensor measurement vector is y , H is the sensor dynamic matrix and v is used to represent white Gaussian measurement noise with zero mean and covariance matrix R . The current state /scan number is k. From these equations we can conclude sliding window adaptive filtering a follows:

a) The data points $(x_i \quad y_i)$ at scan i can be updated as,

$$\hat{x}_i(k+1) = F\hat{x}_i(k) + K_i\big(y_i(k+1) - H_iF\hat{x}_i(k)\big) \tag{5}$$

Where estimate $\hat{x}_i(k+1)$ is stated to enclose all the data of sliding window from scan j to scan i and where,

$$K_i = P_i(k+1)H_i^t(I + H_iP_i(k+1)H_i^t)^{-1}. \tag{6}$$

Where P_k satisfies this adaptive filtering method as,

$$P_i(k+1) = FP_i(k)F' + GQG' - FP_i(k)[H_i^t \quad L_i^t]R_i^{-1}\begin{bmatrix} H_i \\ L_i \end{bmatrix}P_i(k)F', \tag{7}$$

Where for every sensor $i \in m$ in $MSDF$, where m are the total number of sensors considered. Let x represent a vector, its estimation is represented using $\hat{x}_i$ with covariance given as $P_i = cov(\tilde{x}_i)$. Estimation error is represented using $\tilde{x}_i = \hat{x}_i - x$. Two matrices $L_i$and H_i are initialized and defined by unity matrix I. Covariance time propagation of HIF for the i^{th}sensor is defined as,

$$R_i = \begin{bmatrix} I & 0 \\ 0 & -\gamma^2 I \end{bmatrix} + \begin{bmatrix} H_i \\ L_i \end{bmatrix}P_i(k)[H_i^t \quad L_i^t]. \tag{8}$$

b) The data points $(x_i \quad y_i)$ at scan i can be down dated as $\{x_{i-l_i} \quad y_{i-l_i}\}$ and can be expressed as,

$$\hat{x}_i(k+1) = F\hat{x}_i(k) + K_i\left(y_{i-l_i}(k+1) - H_{i-l_i}F\hat{x}_i(k)\right) \tag{9}$$

Where,

$$K_i = P_i(k+1)H_{i-l_i}^t(I + H_iP_i(k+1)H_i^t)^{-1}. \tag{10}$$

Where P_k satisfies this adaptive filtering method as,

$$P_i(k+1) = FP_i(k)F' + GQG' - FP_i(k)[H_i^t \quad L_i^t]R_i^{-1}\begin{bmatrix} H_i \\ L_i \end{bmatrix}P_i(k)F', \tag{11}$$

Where,

$$R_i = \begin{bmatrix} -I & 0 \\ 0 & -\gamma^2 I \end{bmatrix} + \begin{bmatrix} H_{i-l_i} \\ L_{i-l_i} \end{bmatrix}P_i(k)\big[H_{i-l_i}^t \quad L_{i-l_i}^t\big]. \tag{12}$$

Where, $P_i(k+1)$ always remain as minimum and R_i can be of two types and first is, when recursion type is updating,

$$R_i = \begin{bmatrix} I & 0 \\ 0 & -\gamma^2 I \end{bmatrix} + \begin{bmatrix} H_i \\ L_i \end{bmatrix}P_i(k)[H_i^t \quad L_i^t] > 0 \tag{13}$$

Second is when recursion type is down dating,

$$R_i = \begin{bmatrix} -I & 0 \\ 0 & -\gamma^2 I \end{bmatrix} + \begin{bmatrix} H_{i-l_i} \\ L_{i-l_i} \end{bmatrix}P_i(k)\big[H_{i-l_i}^t \quad L_{i-l_i}^t\big] < 0 \tag{14}$$

By changing the size of sliding window, adaptive filtering can be done and it would help reduce estimation errors.

3. Results and Discussions

Performance Evaluation

The $AHIF$ is evaluated using MATLAB and Fuzzy logic toolbox. Performance of $AHIF$ is compared with HIF for non-linear systems i.e. maneuvering targets. Mild maneuvering and evasive maneuvering target tracking cases are evaluated.

3.1 Target tracking for maneuvering objects using HIF and AHIF

Two sets of maneuvering conditions are used to evaluate the performance: mild and evasive maneuvering target tracking. Data for simulation are generated using kinematic model defined in Eq. (3). In the experiments for maneuvering objects, sampling time $T = 1\, sec.$ is considered. Total number of scans k considered for simulation is 25 . The state transition matrix F and process noise gain matrix G considered are:

$$F = \begin{bmatrix} 1 & T & T^2/2 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix} \tag{15}$$

$$G = [T^2/2 \quad T \quad 1] \tag{16}$$

Sensor measurements are obtained as per Eq. (4) with sensor dynamic matrix H defined as

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}. \tag{17}$$

Process noise variance $Q = 0.1$; it is assumed that $Q_{xx} = Q_{yy} = Q$ and $R_{xx} = R_{yy} = R$ where measurement noise variance $R = 25$. Initial state of the system: $(x, \dot{x}, \ddot{x}, y, \dot{y}, \ddot{y}) = (100, 30, 0, 100, 20, 0)$. To simulate maneuvering targets additional acceleration of (x_{ac}, y_{ac}) is introduced at scan number 8 and acceleration of $(-x_{ac}, -y_{ac})$ at scan 15. Data simulation for maneuvering targets is carried out with process noise vector $w\ (2 \times 1)$; i.e. $w(1)$, $w(2)$ defined as

$$w(1) = \begin{Bmatrix} \left(Gauss() \times \sqrt{Q_{xx}}\right) & \forall\, k : k \neq 8{,}15 \\ \left(Gauss() \times \sqrt{Q_{xx}}\right) + x_{ac} & k = 8 \\ \left(Gauss() \times \sqrt{Q_{xx}}\right) - x_{ac} & k = 15 \end{Bmatrix} \tag{18}$$

$$w(2) = \begin{Bmatrix} \left(Gauss() \times \sqrt{Q_{yy}}\right) & \forall\, k : k \neq 8{,}15 \\ \left(Gauss() \times \sqrt{Q_{yy}}\right) + y_{ac} & k = 8 \\ \left(Gauss() \times \sqrt{Q_{yy}}\right) - y_{ac} & k = 15 \end{Bmatrix} \tag{19}$$

Initialization of fuzzy logic systems in $AHIF$ is carried out using procedure mentioned in [7]. Mild maneuvering and evasive maneuvering targets are simulated by varying acceleration parameters $x_{ac}$and y_{ac}.

3.2 Case 1 - Target tracking for mild maneuvering objects using HIF, FKF and $AHIF$

Acceleration magnitudes of $x_{ac} = 6\ m/s^2$ and $y_{ac} = -6\ m/s^2$ are introduced at scan 8. At scan 15 acceleration magnitudes of $x_{ac} = -6\ m/s^2$and $y_{ac} = 6\ m/s^2$ are introduced to simulate mild maneuver. Uniform initial states close to true values are considered for HIF, $FKF$and $AHIF$. For both filters initial state covariance matrices are assumed to be unity. The true and estimated positions obtained using $AHIF$ are shown in Figure 2 considering window lengths: 3, 5 and 7. Estimation errors of position, velocity and accelerations are computed as: root sum square position error-$RSSPE$, root sum square velocity error-$RSSVE$ and root sum square acceleration error–$RSSAE$. For mild maneuvering target tracking $RSSPE$ results obtained from $AHIF$ for different window length 3, 5 and 7 are shown in Figure 3.

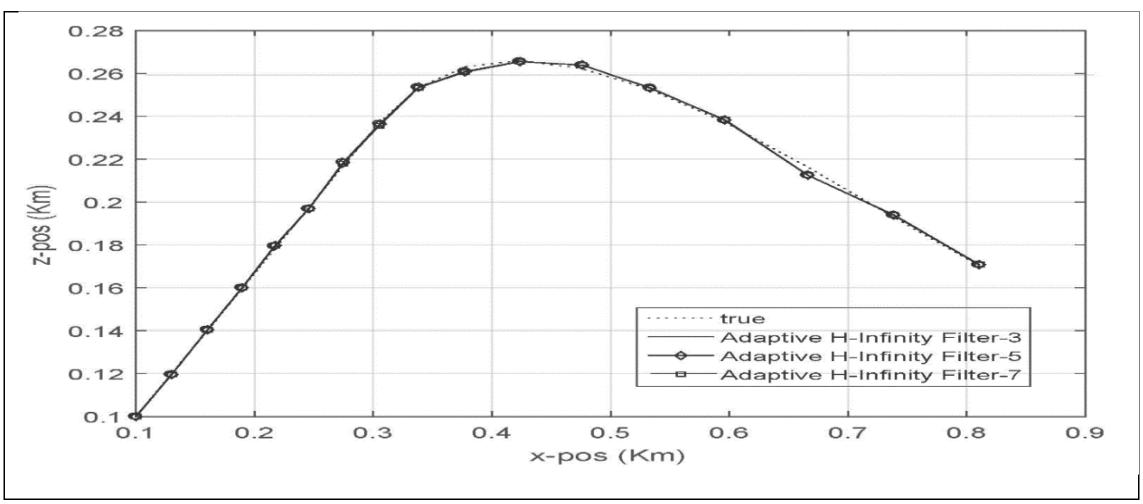

Figure 2 Case 1- Mild maneuvering tracking results for true positions and estimated positions using AHIF considering window length – 3, 5 and 7

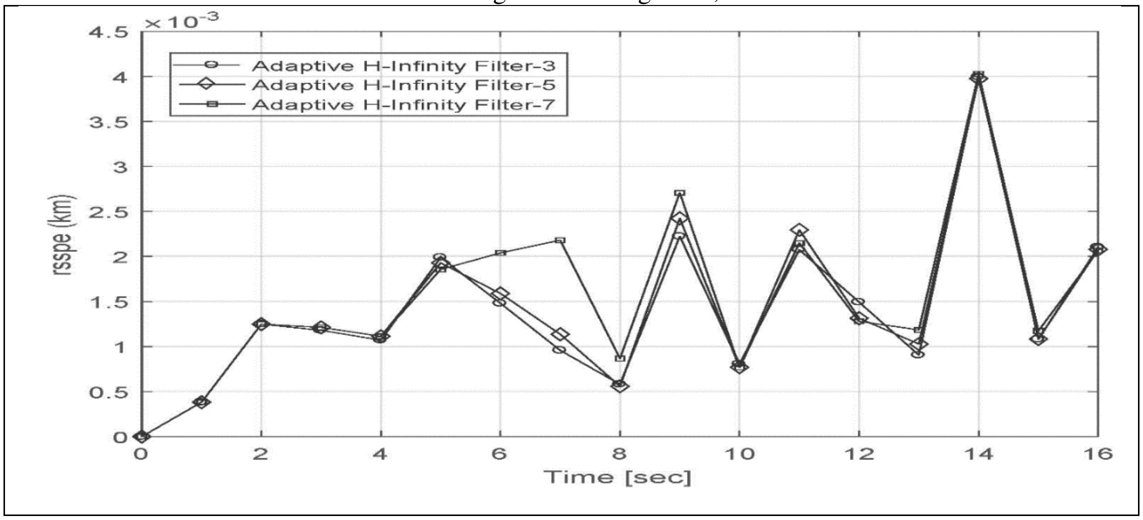

Figure 2 RSSPE comparison plots considering AHIF for mild maneuvering target tracking for window length 3, 5 and 7

Percentage Fit Error (PFE) is computed as

$$PFE^a = 100 \times \left(\frac{norm(\hat{x}^a - x^a_{True})}{norm(x^a_{True})}\right), \tag{20}$$

Where variable a is used to represent position axis X, Y, Z, x_{True} represents True trajectories of objects, and $\hat{x}^a$ is estimated trajectories of tracked objects obtained from $FKF, HIF, AHIF$. Results are shown in Table 1 for different window lengths as $WL = 3{,}5{,}7$. Lowest PFE is reported for X position estimates in $AHIF$ for $WL - 3$. Similarly, lowest PFE is reported for Y position estimates in $AHIF$ for $WL - 3$. Lower PFE is observed in $AHIF - 3$ when compared to $HIF\ and\ FKF$ considering X, Y positions estimates proving better performance.

Table 1
PFE in X, Y position considering HIF, FKF and $AHIF$ for mild maneuvering

Algorithm	PFE^X (%)	PFE^Y (%)
HIF	0.368054937	1.176292633
FKF	0.299506842	0.78021731
AHIF – 3	0.21335349	0.6432287
AHIF – 5	0.213577993	0.662656686
AHIF – 7	0.233267274	0.701457035

3.3 Assertion of suitable sliding window length in AHIF

To estimate exact position we have tested our model considering different sliding window lengths as $WL = 3, 5\ and\ 7$. On introducing acceleration variables, tracking of maneuvering objects is better in case of $AHIF$ for window length 3 when compared to $AHIF$ for window length 5 and 7 concluded from table 1. The tracking estimation of maneuvering objects is more precise when sliding window length is minimum, since it adapts the estimation very quickly. The true positions and estimated positions obtained using HIF, FKF and $AHIF - best$ for window length-3 are shown in Figure 4. Errors observed for position estimation are maximum during mild maneuvering phase of targets in HIF and lowest in $AHIF - best$ for window length -3 as shown in Figure 5.

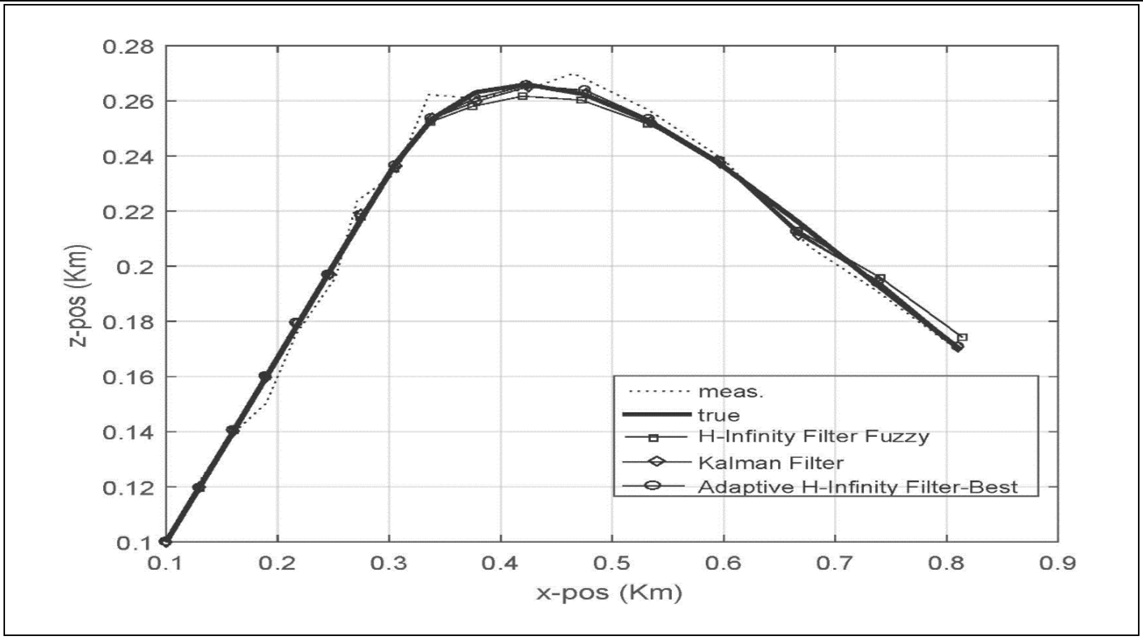

Figure 3. Case 1- Mild maneuvering tracking results for true positions and estimated positions using HIF , FKFand AHIF

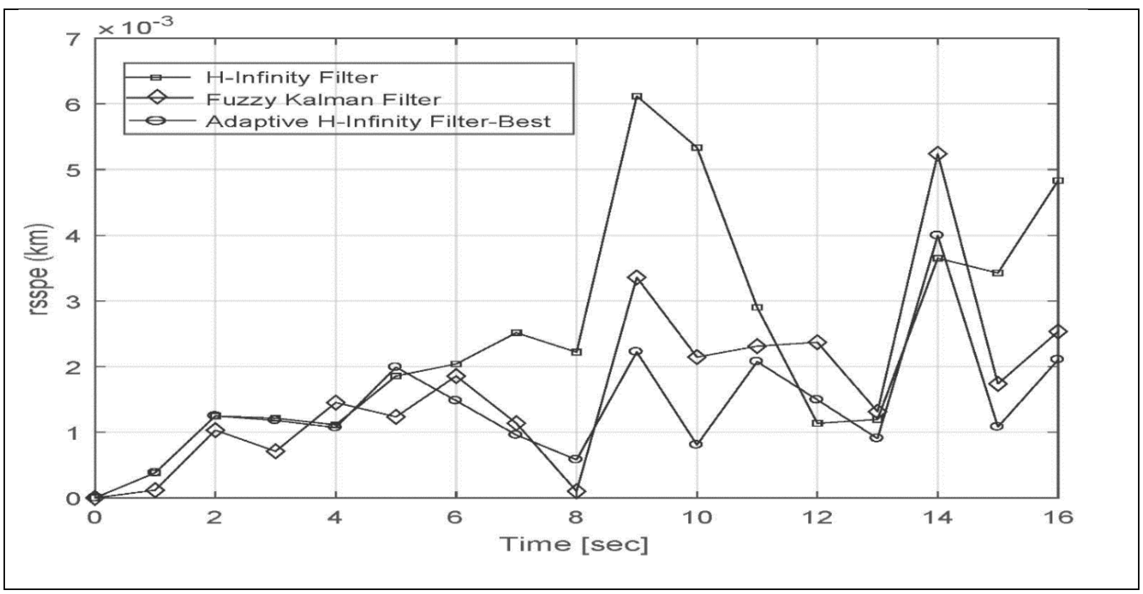

Figure 4. Case 1 - RSSPE comparison plots considering HIF, $FKF$and $AHIF$ for mild maneuvering target tracking

Performance comparison considering $HIF, FKF$and $AHIF$

Results obtained for PFE measures considering FKF, HIF and $AHIF - Best$ is shown in Table 2. $AHIF - Best$ Performance is more superior in comparison to FKF and HIF filters.

Table 2
PFE in X, Y position considering HIF, FKF and AHIF for mild maneuvering

Algorithm	PFE^X (%)	PFE^Y (%)
HIF	0.368054937	1.176292633
FKF	0.299506842	0.78021731
AHIF - Best	0.21335349	0.6432287

$AHIF$ considering window length-3 can reduce errors $RSSPE$ for X-position by 42.03% and 28.76% and for Y-position by 45.31% and 17.55 % for mild maneuvering target estimation against HIF and FKF respectively. While $AHIF$ considering window length-5 can reduce errors $RSSPE$ for X-position by 41.97% and 28.69% and for Y-position by 43.66% and 15.06% for mild maneuvering target estimation against HIF and FKF respectively. Similarly, $AHIF$ considering window length-7 can reduce errors $RSSPE$ for X-position by 36.62% and 22.11% and for Y-position by 40.36% and 10.09 % for mild maneuvering target estimation against HIF and FKF respectively. Experimental results presented prove better maneuvering target tracking performance is exhibited by $AHIF$ when compared to HIF and FKF filter.

Case 2 - Target tracking for evasive maneuvering objects using HIF and AHIF:

To simulate evasive maneuvering targets 25 scans are considered. Large acceleration magnitudes at scan 8 introduced are $x_{ac} = 392\ m/s^2$ and $y_{ac} = -392\ m/s^2$. At scan 15, $x_{ac} = -392\ m/s^2$ and $y_{ac} = 392\ m/s^2$ is considered. Initial state covariance matrices for HIF and $AHIF$ are assumed to be unity. The true and estimated positions of evasive maneuvering obtained using $AHIF$ are shown in Figure 6 considering window length-3, 5 and 7. For evasive maneuvering target tracking $RSSPE$ results obtained considering $AHIF$ for different window length 3, 5 and 7 are shown in Figure 7.

Results obtained for PFE measures are shown in Table 3. Lowest PFE is reported for X and Y position estimates in $AHIF$ considering $WL = 3$. Lower PFE is observed in $AHIF - 3$ when compared to HIF and FKF considering X, Y positions estimates proving better performance. The experimental results demonstrates that $AHIF$ estimates position precisely when window length considered as minimum. The accuracy of estimation a decreases as the window length increases.

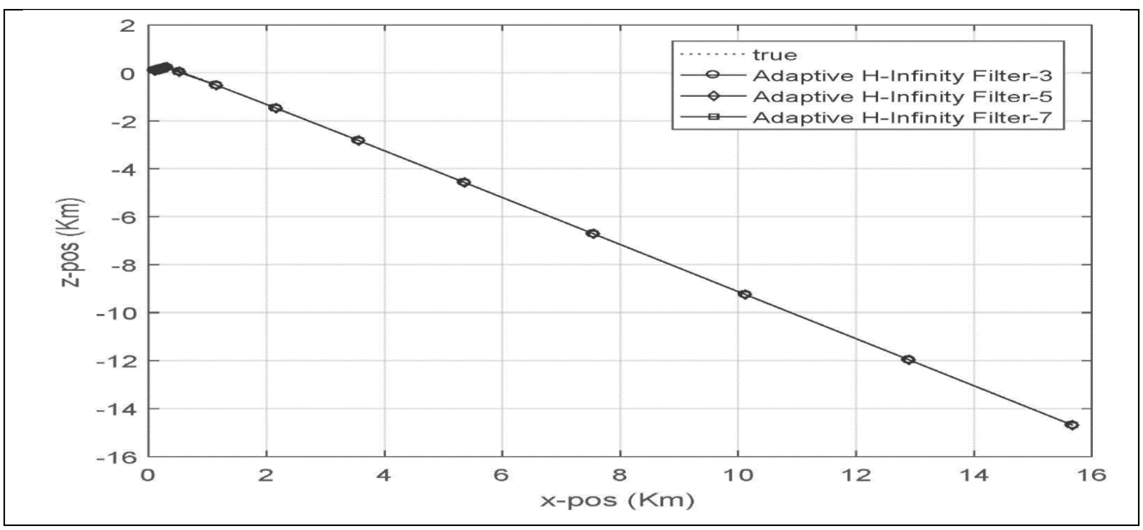

Figure 5. Case 2- Evasive maneuvering tracking results for true positions and estimated positions using AHIF considering window lengths -3, 5 and 7

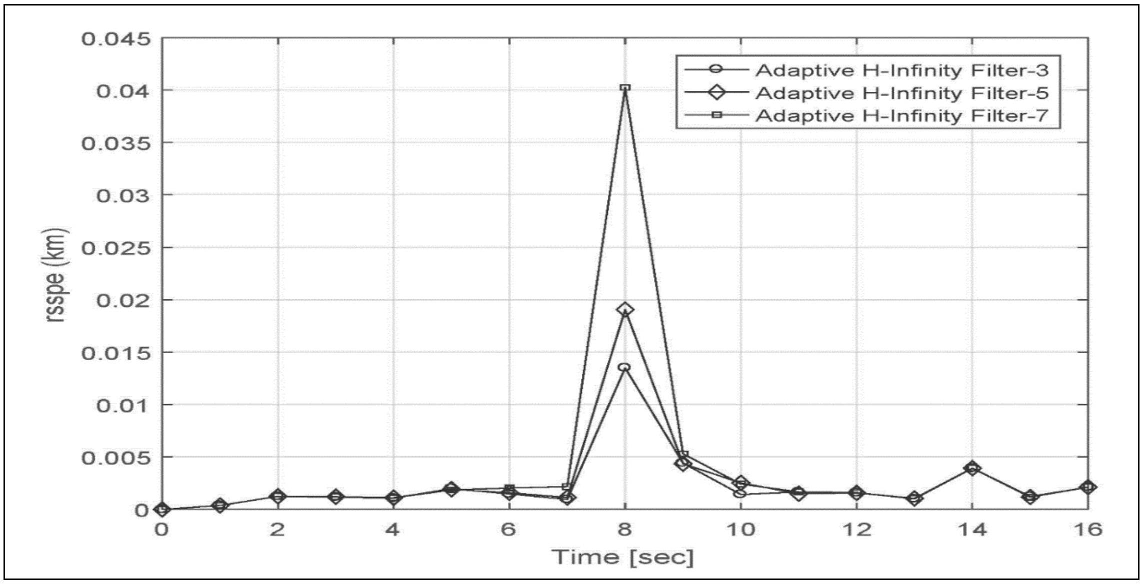

Figure 6. Case 2 - RSSPE comparison plots considering $AHIF$ for evasive maneuvering target tracking for WL-3, 5 and 7

Table 3
PFE in X, Y position considering HIF, FKF and $AHIFF$ for evasive maneuvering

Algorithm	PFE^X (%)	PFE^Y (%)
HIF	2.028645072	2.224569761
FKF	0.564246727	0.61066931
AHIF – 3	0.043088829	0.049574268
AHIF – 5	0.05855819	0.064330919
AHIF – 7	0.117524236	0.127203565

Assertion of suitable sliding window length in $AHIF$

To estimate exact position we have tested our model considering different sliding window lengths as $WL = 3, 5\ and\ 7$. On introducing acceleration variables, tracking of maneuvering objects is better in case of $AHIF$ for window length 3 when compared to $AHIF$ for window length 5 and 7 concluded from table 3. The true and estimated positions$-best$ for window length-3 are shown in Figure 8. Errors observed for position estimation are maximum during mild maneuvering phase of targets in HIF and lowest in $AHIF - best$ for window length -3 as shown in figure 9.

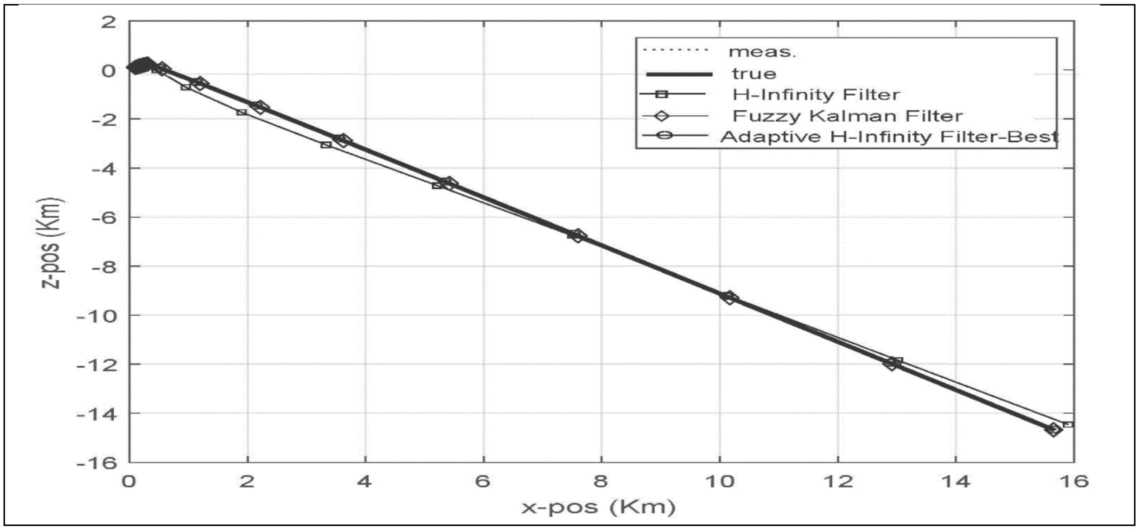

Figure 7 Case 2 Evasive maneuvering tracking results for true positions and estimated positions using HIF, FKF and $AHIF$ considering Best window lengths -3

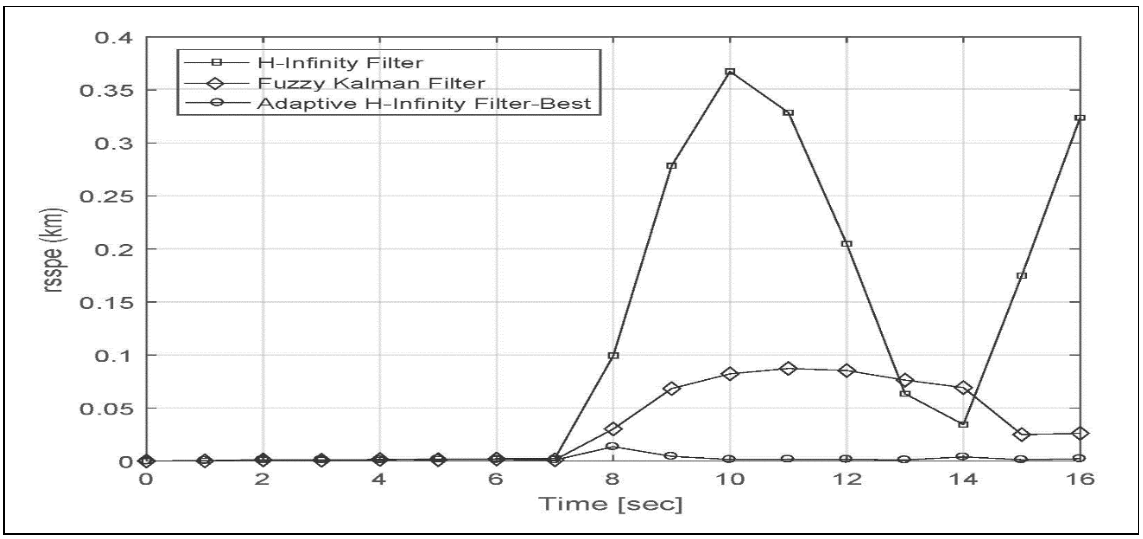

Figure 8 Case 2 - RSSPE comparison plots considering HIF, FKF and AHIFfor evasive maneuvering target tracking for best WL-3

Performance comparison considering $HIF, FKF and\ AHIF$

Results obtained for PFE measures considering FKF, HIF and $AHIF - Best$ is shown in Table 4. $AHIF - Best$ Performance is more superior in comparison to FKF and HIF filters.

Table 4
PFE in X, Y position considering HIF, FKF and $AHIFF$ for evasive maneuvering

Algorithm	PFE^X(%)	PFE^Y(%)
HIF	2.028645072	2.224569761
FKF	0.564246727	0.61066931
$AHIF - Best$	0.043088829	0.049574268

Estimation error of target position increase when evasive maneuvering is initiated during scan 8 or at 8 seconds of simulation time. Overall lower evasive maneuver target estimation errors for the position are reported in $AHIF$ compared to $HIF\ and\ FKF.$ $AHIF$ considering window length-3 can reduce errors $RSSPE$ for X-position by 97.87% and 92.36% and for Y-position by 97.77% and 91.88% for evasive maneuvering target estimation against HIF and FKF respectively. While $AHIF$ considering sliding window length-5 can reduce errors $RSSPE$ for X-position by 97.11% and 97.10% and for Y-position by 89.62% and 89.46% for evasive maneuvering target estimation against HIF and FKF respectively. Similarly, $AHIF$ considering window length-7 can reduce errors $RSSPE$ for X-position by 94.20% and 94.28% and for Y-position by 79.17% and $79.16\ \%$ for evasive maneuvering target estimation against HIF and FKF respectively. Experimental results presented prove better evasive maneuvering target tracking performance is exhibited by $AHIF$ when compared to HIF and FKF filter.

4. Conclusion

In the studied application of AHIF, the size of sliding window is varied to estimate target location precisely in adaptive filtering and it also used to eliminate local estimation errors at filter level. An additional adaptive filtering is considered in HIF to minimize estimation errors and ill-effects of outliers at fusion level. The PFE comparisons for different window lengths are presented to verify the robustness of the model for target tracking performance. The results presented to prove that AHIF exhibits better performance than AKF and HIF. Hence, to estimate the exact position and location of target AHIF can be very effective method for MSDF based non-linear tracking.

Conflict of interest statement and funding sources

The author(s) declared that (s)he/they have no competing interest. The study was financed by the authors.

Statement of authorship

The author(s) have a responsibility for the conception and design of the study. The author(s) have approved the final article.

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Biography of Authors

	Reshma Verma is Assistant Professor in E&C department at M.S. Ramaiah Institute of Technology Bangalore, She Graduated with B.E. degree in Electronics and Communication Engineering. She did M.Tech with specialization in Power Electronics Engineering from VTU. She is currently working towards the Ph.D. degree. Her research interests include image processing and Fuzzy Logic. *Email: reshmaverma11@gmail.com*
	Jitendra, R, Raol has BE and ME degrees from M. S. University of Baroda (1971/1974) and Ph.D. from McMaster University, Canada, 1986. He worked in CSIR-NAL, Bangalore from 1975 to 1981 on human pilot modeling infix- and motion-based simulators, and from 1986 to 2007, on parameter estimation, filtering, and data fusion. He retired as Scientist-G & Head, FMCD (CSIR-NAL) in July 2007. He has been a senior member of the IEEE (USA), the fellow of IEE/IET (UK), and he is life fellow of Aero. Soc. of India, and a life member of Syst. Soc. of India. He has won several awards/prizes. He has severed as a chairman and member of several technical/administrative committees and has also evaluated several doctoral theses. He is a reviewer for several national/international technical and research journals. He has authored (singly and jointly) six books, published by IEE, UK, and CRC Press, USA. He has published more than 130 research papers. He has carried out several sponsored R&D projects in several areas. He had visited several countries on deputation to conduct R&D and to present papers at some technical conferences. His current activities include parameter estimation, nonlinear filtering, sensor data fusion, and soft computing. He has been Professor Emeritus in the depts. of Instrumentation Technology and E & C Engg., of M. S. Ramaiah Institute of Technology, Bangalore for a number of years. He is the chief editor of Control and Data Fusion e-Journal, an online open access journal started very recently. He is also an author of some literary works.