Impact Factor (SJIF): 5.301

International Journal of Advance Research in Engineering, Science & Technology

e-ISSN: 2393-9877, p-ISSN: 2394-2444

Volume 5, Issue 3, March-2018

Performance evaluation of multi sensor data fusion techniques in tracking and thermal systems by modeling and simulation

Renuka S[1], Dr Abudhahir A[2]

[1] AAA College of Engineering and Technolgy, India
[2] Vel Tech Multi Tech Dr.Rangarajan Dr.Sakunthala Engineering College, Chennai, Tamilnadu, India

Abstract

The performance evaluation of parameter estimation algorithms for target tracking and thermal systems is the main issue of this article. A single measurement data from a system may not be sufficient to estimate the parameter accurately. Therefore multiple sensor data observed from the systems are fused to improve the parameter estimation by redundant and additional data available. In this paper the most preferred state estimation method known as Kalman filter is applied for the four test systems by fusing two sensors using three algorithms namely Measurement fusion (MF), State vector fusion (SVF) and Gain fusion (GF). The main purpose of this work is to implement the multi sensor data fusion algorithms in target tracking systems and thermal systems by using system models with simulated data and to evaluate all of their performances by calculating the various estimation errors namely Percentage Fit Error (PFE), Mean Absolute Error (MAE) and Mean Square Error (MSE) using MATLAB.

Keywords
Kalman filter, multi-sensor data fusion, tracking systems, measurement fusion, state vector fusion, gain fusion,MATLAB

1. Introduction

The aim of the State estimation method otherwise known as tracking method is to determine the target state with multiple measurements.[1] As the target's observation could come from diverse sensors, the objective of the state estimation in data fusion algorithms is to obtain a target state from the noisy observations. The main estimation problem is to find the values of the state (e.g., temperature, position and velocity) with the redundant observations which are error and noise corrupted.[2] Target tracking is an important job in intelligent vehicle research. Recent developments in sensor techniques and signal processing approaches have made target tracking very much simple. Temperature process control is very important in all automation industries. The state estimation of temperature is a main requirement for safe and sound process operation.[3] In specific, multi-sensor data fusion is found to be a great tool to improve the efficiency of tracking and estimation. Latest tracking systems are provided with different types of tracking sensors. In general, sensor measurements are not perfect. Due to noise there may be error in their measurements. Measurement error may be reduced by the technique Multi-sensor data fusion (MSDF).[4] MSDF is defined as the process of combining the data from multiple sensors to make the most exact and complete integrated data about an entity, activity or occurrence.[5]The most commonly used estimator in MSDF is the Kalman filter that can estimate the varying parameter of various types of processes and also the states of a dynamic system.[6]The Kalman filter can minimize the estimation error variance. In the target tracking system the continuously varying position and velocity of the target are estimated. The sensor used to measure the target range, azimuth and elevation is Radar and the sensor used to measure azimuth and elevation of the target is Infra-Red Search and Track (IRST).The measurements from these two sensors are fused in order to reduce the measurement noise. Kalman filters are implemented in control systems because in order to control a process, it is required to have an accurate estimate of the process variables.

Most of the research work in Multi sensor Data Fusion is based on the Kalman filter algorithm that filters the unwanted noise and recovers the original signal which provides a good performance on signal processing. Yourong Chen et al [3] proposed Multi Temperature and Humidity Data Fusion algorithm based on Kalman Filter. This paper also infers that under certain conditions, the proposed algorithm can be applied in temperature and humidity monitoring system based on wireless sensor networks. Bahador Khaleghi et al [7] analysed multi sensor data fusion algorithms. This paper proposed a complete review of the modern data fusion techniques. Ren C. Luo et al [2] discussed the wide applications of Multi sensor Fusion in the field of automation, military and biomedical fields. In addition to this, various future research directions in the data fusion area were highlighted and explained. B.S.Paik et al [9] proposed a new gain fusion algorithm which gives computer-efficient suboptimal estimation results and estimates without significant loss of accuracy.

In this paper the Kalman filter based fusion algorithms are applied for accurate estimation of temperature with inaccurate temperature sensor readings. In this system the continuously varying temperature is estimated by fusing the two sensor measurements. Two different sensors are used to track the moving target. Both the sensor measurements are combined to obtain a common state-vector estimate which is better than the state vector estimate of two individual sensors.

2. Fusion algorithms

The most common estimation methods are (i) the maximum likelihood and maximum posterior (ii) the Kalman filter and (iii) the particle filter.[1]The most important disadvantage of the first method mentioned is that the systematic or experimental model of the sensor is to be known to give the prior distribution and work out the likelihood function. The bias problem may be created by this method as the distribution variance can be systematically undervalued. The main disadvantage of the second method mentioned is that the huge quantity of particles is required to find a little variance in the estimator. To establish the optimal quantity of particles in advance is also difficult. The computational cost is increased significantly by the quantity of particles. The Kalman filter is mainly applied to combine low-level data for the system where the system is represented by its state model and the error is by its Gaussian noise model so as to acquire optimal statistical estimation. The multisensor data fusion can be simply executed by Kalman filter as it reduces the effect of sensor noise and bias through which significantly improves the estimation.

The Kalman filter based fusion algorithms are applied for accurate estimation of temperature, position and velocity with inaccurate sensor readings. In the proposed thermal systems the continuously varying temperature is estimated by fusing the two temperature measurements from thermocouple and hot-wire anemometer. The measurements from Radar sensor and IRST sensor are fused in the proposed target tracking systems. The fusion is done by Kalman filter based techniques namely Measurement Fusion (MF), State Vector Fusion (SVF) and Gain Fusion algorithm (GF).

2.1. Measurement Fusion

In the MF algorithm, the sensor measurements are fused directly by a measurement model and the state vector of the fused data is estimated using a single Kalman Filter.[5,8] The Kalman filter recursive algorithm is computed by the equations 1 to 6.The filtered fused state and filtered fused covariance are given by equations 5 and 6.The flow diagram for MF algorithm is given in Figure 1.

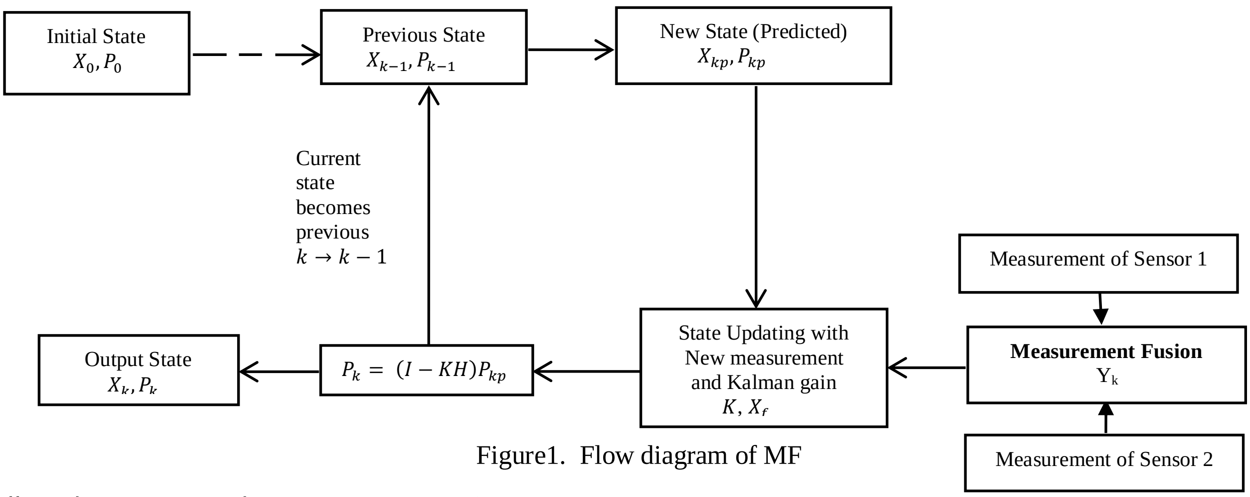

Figure1. Flow diagram of MF

$$X_{kp} = FX_{k-1} + w_k \tag{1}$$
$$P_{kp} = FP_{k-1}F^T + GQ_kG^T \tag{2}$$

The new observation is

$$Y_k = HX_{km} + v_k \tag{3}$$

The Kalman gain with predicted Covariance is

$$K = P_{kp}\, H^T\, [HP_{kp}H^T + R_k]^{-1} \tag{4}$$

The updated State and Covariance are

$$X_f = X_k = X_{kp} + K[Y_k - HX_{kp}] \tag{5}$$

$$P_k = [I - KH]P_{kp} \tag{6}$$

Where

X_{kp} – New State matrix (predicted)
P_{kp} – New Process covariance matrix
F – State transition matrix
G – Gain matrix
w_k – Process noise
Y_k – Measurement vector
H – Observation matrix
v_k – Measurement noise
Q_k – Process noise covariance matrix
R_k – Measurement noise covariance matrix
X_f – Filtered fused state
P_k – Filtered fused covariance

2.2. State Vector Fusion

In the SVF algorithm, each sensor measurement is applied to an independent Kalman filter which generates the state estimate of each sensor data. The state vector of each sensor data and its related covariance matrices are estimated using individual Kalman filter. Then at the fusion center, track-to-track correlation is carried out and the state vector after fusion is obtained.[5, 8] The time propagations of state and covariance are given by equations 7 and 8. The equation 9 gives the new observation. The Kalman gain is computed by the equation 10. With the observation from two individual sensors, the state estimates are processed. The measurement updates of state and covariance are given by equations 11 and 12.The fusion of state estimates which are obtained from two sensor measurements is carried out by the equations 13 and 14. Figure 2 illustrates the state vector fusion.

$$X_{kp} = FX_{k-1} + w_k \tag{7}$$

$$P_{kp} = FP_{k-1}F^T + GQ_kG^T \tag{8}$$

The new observation is

$$Y_k = HX_k + v_k \tag{9}$$

The Kalman gain with predicted Covariance is

$$K = P_{kp}\, H^T\, [HP_{kp}H^T + R_k]^{-1} \tag{10}$$

The updated State and Covariance are

$$X_k = X_{kp} + K[Y_k - HX_{kp}] \tag{11}$$

$$P_k = [I - KH]P_{kp} \tag{12}$$

The estimated states and the covariance matrices are fused by

$$X_f = X_k = X_{1kp} + P_{1kp}(P_{1kp} + P_{2kp})^{-1}\,(X_{2kp} - X_{1kp}) \tag{13}$$

$$P_f = P_k = P_{1kp} - P_{kp}\,(P_{1kp} + P_{2kp})^{-1} P_{kp}^T \qquad (14)$$

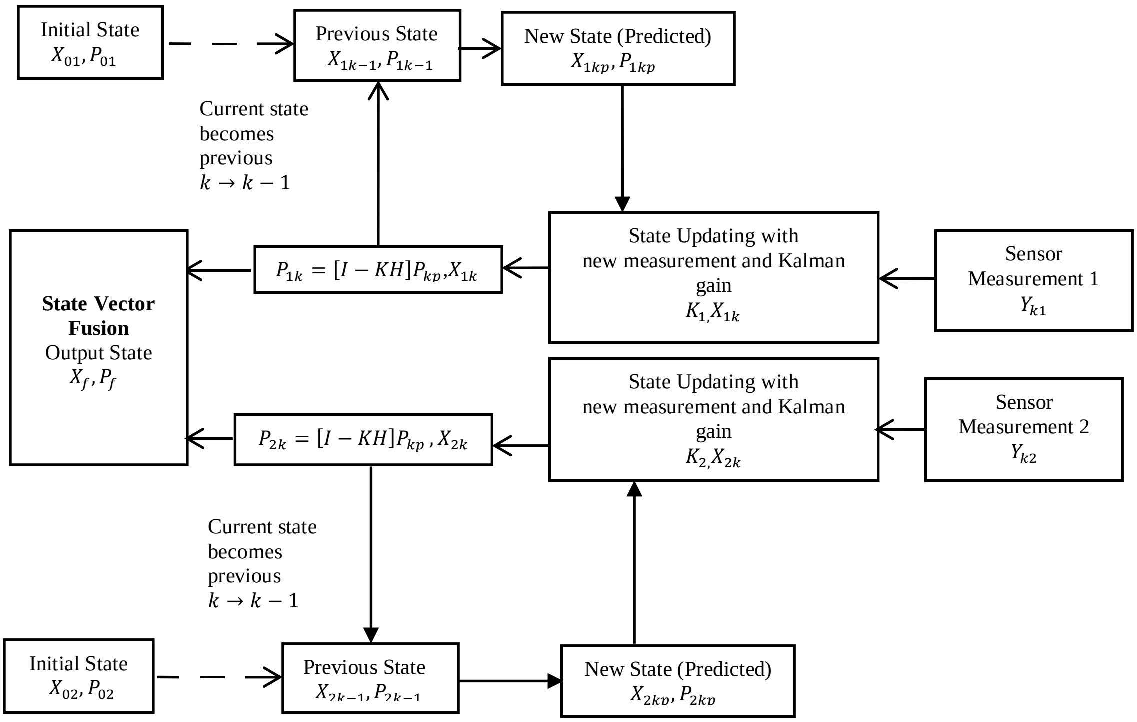

Figure2. Flow diagram of SVF

2.3. *Gain Fusion*

In the GF algorithm, the information in the form of a Kalman gain is received from local systems by a global processor and the global estimate is formulated.[9] The Kalman filter recursive algorithms for gain fusion are given in the equations 15 to 22. The state model of the system is given by equations 1 and 2.The global estimate time Propagations are given by equations 15 and 16. From the global filter, information is fed back to the local filters and this implies that the measurement data are shared between the local filters.[5] In order to get the global estimates in case of Gain fusion based algorithm, it is not needed to update the local covariance. The equations 21 and 22 give the global fused output. Figure 3 shows the flow diagram of GF.

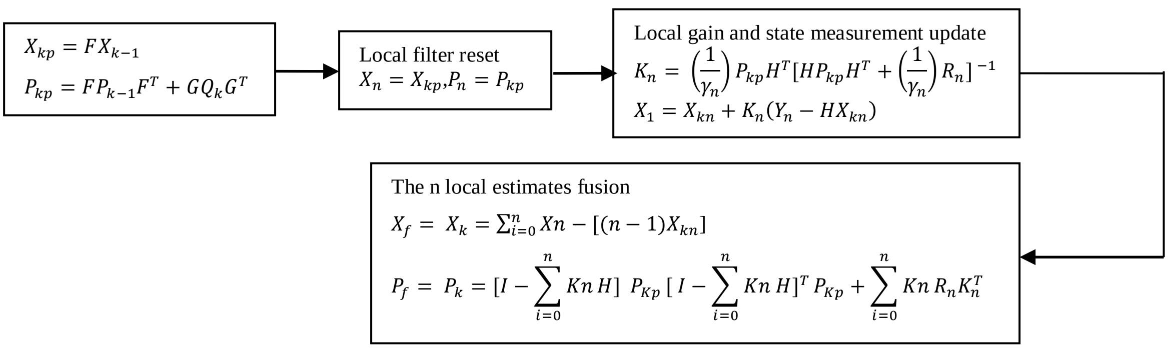

Figure 3. Flow diagram of GF

$$X_{kp} = FX_{k-1} \qquad (15)$$

$$P_{kp} = FP_{k-1}F^T + GQ_kG^T \qquad (16)$$

The local filters are reset as

$$X_n = X_{kp} \tag{17}$$

$$P_n = P_{kp} \tag{18}$$

The update of measurement for local gains and states [5, 9] is obtained by

$$K_n = (1/\gamma_n) P_{kp} H^T [H P_{kp} H^T + (^1/_{\gamma_n}) R_n]^{-1} \tag{19}$$

$$X_1 = X_{kn} + K_n (Y_n - H X_{kn}) \tag{20}$$

The n local estimates are fused globally[5, 9] by

$$X_f = X_k = \sum_{i=0}^{n} Xn - [(n-1) X_{kn}] \tag{21}$$

$$P_f = P_k = [I - \sum_{i=0}^{n} K_n H]\ P_{Kp}\ [I - \sum_{i=0}^{n} K_n H]^T\ P_{Kp} + \sum_{i=0}^{n} K_n R_n K_n^T \tag{22}$$

3. Modeling and simulation

Two target tracking systems (I and II) are considered and their 2-Degree of freedom (DOF) constant velocity model with position (x) and velocity ($\dot{x}$) components in x,y , and z directions with the state transition matrix F and gain matrix G are given below in A and B. The thermal system has an important role in our day to day life where desired temperature is maintained in order to retain the good and safe working background [10]. For the control problem the parameter estimation is more important. In addition to the tracking systems, two thermal systems (I and II) are considered by their state models with its state transition matrix F and gain matrix G. Using MATLAB the simulation is done for all the four systems.

3.1. Target tracking system I

The state model [5] of a target motion is

$$X_{(k+1)} = F X_{(k)} + G w_{(k)} \tag{23}$$

$$Y_{(k)} = H X_{(k)} + v_{(k)} \tag{24}$$

Where F is the State transition matrix, G is the Gain matrix, H is the observation matrix,

The state vector is $(k) = [x\ y\ z\ \dot{x}\ \dot{y}\ \dot{z}]$, w is the process noise,v is the measurement noise.

$var[w_{(k)}] = Q$, $var[v_{(k)}] = R$, $E[w_{(k)}] = 0$, $E[v_{(k)}] = 0$

The state model of the tracking system I [5] is

$$\text{Where } F = \begin{bmatrix} 1 & T & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & T & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & T \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix},\ G = \begin{bmatrix} T^2/2 \\ T \\ T^2/2 \\ T \\ T^2/2 \\ T \end{bmatrix}$$

3.2. Target tracking system II

The state model of the tracking system II [5] is

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

Where F is the State Transition Matrix, G is the Gain Matrix.

The state vector is $X(k) = [x\ y\ z\ \dot{x}\ \dot{y}\ \dot{z}]$

w is the process noise, H is the observation Matrix, v is the measurement noise.

$\mathrm{var}[w_{(k)}] = \mathrm{Q}\,, \mathrm{var}[v_{(k)}] = \mathrm{R}\,, \mathrm{E}[w_{(k)}] = 0\,, \mathrm{E}[v_{(k)}] = 0$

3.3. Thermal system I

The state model of the thermal system I [10] is

$$F = \begin{bmatrix} 0.9819 & -0.0024 & 0.0009 & -0.189 \\ 0.0800 & 0.5159 & 0.2760 & 0.0679 \\ 0.0270 & -0.6286 & -0.2750 & -0.2292 \\ 0.0810 & -0.0442 & -0.3830 & 0.7457 \end{bmatrix},\ G = \begin{bmatrix} 0.0005 & -0.0003 \\ -0.0001 & 0.0256 \\ 0.0018 & 0.1002 \\ -0.0085 & 0.0222 \end{bmatrix}$$

Where F is the State Transition Matrix, G is the Gain Matrix, w is the process noise,

H is the observation Matrix, v is the measurement noise.

$\mathrm{var}[w_{(k)}] = \mathrm{Q}\,, \mathrm{var}[v_{(k)}] = \mathrm{R}\,, \mathrm{E}[w_{(k)}] = 0\,, \mathrm{E}[v_{(k)}] = 0$

3.4. Thermal system II

The state model of the thermal system II [10] is

$$F = \begin{bmatrix} 0.9519 & -0.0024 & 0.009 & -0.0189 & 0 & 0 \\ 0.0800 & 0.5159 & 0.2760 & 0.0679 & 0 & 0 \\ 0.0270 & -0.6286 & -0.2750 & -0.2292 & 0 & 0 \\ 0.0810 & -0.0442 & -0.3830 & 0.7457 & 0 & 0 \\ 25.0614 & 0.9046 & -0.3986 & 1.6305 & 1 & 0 \\ -1.22297 & 0.9652 & 5.5689 & 0.9110 & 0 & 0 \end{bmatrix},\ G = \begin{bmatrix} 0.005 & -0.0003 \\ -0.0001 & 0.0256 \\ 0.0018 & 0.1002 \\ -0.0085 & 0.0222 \\ -0.0111 & -0.0168 \\ 0.0024 & -0.0019 \end{bmatrix}$$

Where F is the State Transition Matrix, G is the Gain Matrix, w is the process noise,

H is the observation Matrix, v is the measurement noise.

$\mathrm{var}[w_{(k)}] = \mathrm{Q}\,, \mathrm{var}[v_{(k)}] = \mathrm{R}\,, \mathrm{E}[w_{(k)}] = 0\,, \mathrm{E}[v_{(k)}] = 0$

4. Performance evaluation

To evaluate the performance of the estimation algorithms various performance metrics such as PFE , MSE and MAE are calculated.

The percentage fit error (PFE) is computed as the ratio of the norm of the difference between the true and estimated values to the norm of the true values. This will be zero when both true and estimated positions are exactly alike, and it will increase when the estimated values deviate from the true values. When comparing the performance of different algorithms, the algorithm that gives the least PFE is preferable.

$$PFE = 100 * \frac{norm(X_t(i) - \hat{X}(i))}{norm(X_t(i))} \qquad (25)$$

For i=1,2,..N

Where N is the number of samples

X_t is the true value

$\hat{X}$ is the estimated value, and

Norm is the operator to find the Euclidean length of the vector.

The mean absolute error (MAE) is the average of absolute error. It is calculated by

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|X_t(i) - \hat{X}(i)| \tag{26}$$

The mean square error (MSE)is the square of mean absolute error. The algorithm that gives the least MSE is preferable.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}|X_t(i) - \hat{X}(i)|^2 \tag{27}$$

5. Simulation results

The MATLAB coding for the three fusion algorithms namely - State Vector Fusion, Measurement Fusion and Gain Fusion have been developed and implemented to the target tracking systems and thermal systems proposed which are mentioned in the section 3. Performances of three fusion algorithms for the systems proposed are evaluated by MATLAB coding. The comparison for those systems is shown in the Tables 1, 2 and 3. From the tables it is observed that MF performance is better where SVF and GF performances are poor. The tables 4, 5 and 6 show the performances of two thermal systems where the MF again works better for thermal systems than for tracking systems.

Table 1. Percentage Fit Error comparisons of SVF, MF and GF in target tracking systems I and II

Error	Target Tracking Systems					
	System I			System II		
	SVF	MF	GF	SVF	MF	GF
PFE Px	0.0020	0.0005	0.0022	0.0002	0.0001	0.0002
PFE Py	0.0002	0.0005	0.0002	0.3902	0.9616	0.3978
PFE Pz	0.8452	0.0394	22.8155	10.0000	0.0000	10.0000

Table 2. Mean Absolute Error comparisons of SVF, MF and GF in target tracking systems I and II

Error	Target Tracking Systems					
	System I			System II		
	SVF	MF	GF	SVF	MF	GF
MAE Px	0.2034	0.1832	0.2579	0.2766	0.2483	0.3102
MAE Vx	0.0555	0.0149	0.1182	4.0615	0.0000	4.0619
MAE Py	0.3571	0.8368	0.3274	0.5417	1.3055	0.5545
MAE Vy	0.0338	0.0414	0.0375	0.0350	0.0163	0.0632
MAE Pz	0.3470	1.6968	0.3754	0.1000	0.0000	0.1000
MAE Vz	0.0984	0.0122	0.1056	0.0182	0.0256	0.0201

Table 3. Mean Square Error comparisons of SVF, MF and GF in target tracking systems I and II

Error	Target Tracking Systems					
	System I			System II		
	SVF	MF	GF	SVF	MF	GF
MSE Px	0.9495	0.0553	1.2104	0.9931	0.0955	1.2263
MSE Vx	0.9817	0.0033	1.7944	3.0005	0.000	3.0005
MSE Py	0.2452	1.7296	0.2452	0.4538	2.7560	0.4716
MSE Vy	0.1398	0.0925	0.1507	0.1976	0.0011	0.3777
MSE Pz	1.0563	1.5081	1.4186	1.0000	1.0000	1.000
MSE Vz	0.0098	0.0002	0.0114	0.0006	0.0010	0.0007

Table 4. Percentage Fit Error comparisons of SVF, MF and GF in thermal systems

Error	Thermal Systems					
	System I			System II		
	SVF	MF	GF	SVF	MF	GF
PFE Tx	0.1040	0.0003	0.1193	0.0683	0.0008	0.0687
PFE dTx	0.4790	0.0103	0.4887	0.3032	0.0475	0.3257
PFE Ty	0.0417	0.0154	0.2223	0.0209	0.0675	0.1774
PFE dTy	0.1000	0.0019	0.1051	0.0492	0.0052	0.0735

Table 5. Mean Absolute Error comparisons of SVF, MF and GF in thermal systems I and II

Error	Thermal Systems					
	System I			System II		
	SVF	MF	GF	SVF	MF	GF
MAE Tx	0.0310	0.0004	0.0633	0.0307	0.0008	0.0370
MAE dTx	0.0203	0.0005	0.0259	0.0205	0.0040	0.0289
MAE Ty	0.0016	0.0007	0.0105	0.0023	0.0054	0.0170
MAE dTy	0.0156	0.0005	0.0263	0.0169	0.0024	0.0415

Table 6. Mean Square Error comparisons of SVF, MF and GF in target tracking systems I and II

Error	Thermal Systems					
	System I			System II		
	SVF	MF	GF	SVF	MF	GF
MSE Tx	0.9004	0.0000	1.1835	0.9001	0.0001	0.9110
MSE dTx	0.4001	0.0002	0.4165	0.4001	0.0098	0.4618
MSE Ty	0.0020	0.0003	0.0582	0.0016	0.0164	0.1136
MSE dTy	0.1202	0.0000	0.1330	0.1017	0.0011	0.2265

6. Conclusion

The measurement value observed from a single sensor suffers from accuracy and reliability problem. The accuracy and reliability problems are rectified by getting information from multiple sensors. In this work, Kalman Filter based algorithms such as State Vector Fusion (SVF) and Measurement Fusion (MF) and also Gain Fusion based algorithm (GF) have been implemented in target tracking and thermal systems. By MATLAB simulation, the performance of all the three fusion algorithms is evaluated. From the implementation of the three algorithms for two tracking systems and two thermal systems, it is inferred that both the State Vector Fusion and Gain Fusion algorithms performed in a similar way whereas the Measurement Fusion provides better result for all the four systems especially for the thermal systems when compared to target tracking systems. Hence Kalman filter based measurement fusion algorithm is most preferable for thermal systems than for tracking systems. The Gain fusion algorithm is computer- efficient than Kalman filter based fusion algorithms. The Measurement fusion algorithm is able to provide less uncertain state estimates. However the choice of fusion algorithm depends on whether accuracy or computer complexity matters.

References

1. Federico Castanedo. A Review of Data Fusion Techniques. *The Scientific World Journal,* Volume 2013 (2013)
2. Ren C. Luo, Ying Chih Chou and Ogst Chen. Multi sensor Fusion and Integration: Algorithms, Applications and Future Research Directions. *Proceedings of the 2007 IEEE International Conference on Mechatronics and Automation*, August 5 - 8, 2007, Harbin, China.
3. Yourong Chen, Jianfen Xu, Kejing Luo and Shuli Xu, Multi-Temperature and Humidity Data Fusion Algorithm Based on Kalman Filter. *Research Journal of Applied Sciences, Engineering and Technology* 5(6): 2127-2132, 2013 ISSN: 2040-7459; e-ISSN: 2040-7467.
4. Martin Liggins, David L.Hall , James Llinas Handbook of multisensor data fusion: Theory and practice, Second edition ,*CRC Press*, *Taylor & Francis Group*, ISBN 9781420053081,2008.
5. Jitendra R. Raol. Multi-Sensor Data Fusion with Matlab. *CRC Press, Taylor & Francis Group*, ISBN 978-1-4398-0003-4, 2010.
6. Mohammad Sadegh Mohebbi Nazar, A Comparative Study of Different Kalman Filtering Methods in Multi Sensor Data Fusion. *Proceedings of the International MultiConference of Engineers and Computer Scientists* 2009, *Hong Kong* vol I.
7. Bahador Khaleghi, AlaaKhamis, Fakhreddine O. Karray, Saiedeh N. Razavi, Multisensor data fusion: A review of the state-of-the-art. *Information Fusion* 14 (2013) 28–44.
8. X.R.Li. Comparison of Two Measurement Fusion Methods for Kalman-Filter-Based Multisensor Data Fusion. *IEEE Transactions on Aerospace and Electronic Systems,* vol. 37, no. 1, pp. 273-280, 2001.
9. B.S.Paik, J.H.Oh. Gain fusion algorithm for decentralized parallel Kalman filters. *Control Theory and Applications IEE Proceedings,* vol. 147, I SSN: 1350-2379.
10. Mustapha Ramzi, Hussein Youlal, Mohamed Haloua, State Space Model Predictive Control of an Aerothermic Process with Actuators Constraints. *Intelligent Control and Automation*, 2012, 3, 50-58.
11. Jiang Dong, Dafang Zhuang, Yaohuan Huang and Jingying Fu. Advances in Multi-Sensor Data Fusion: Algorithms and Applications. *Sensors 2009,* 9, 7771- 7784.

Author biographies

Renuka S is a PhD student at Anna University, India. She is currently an associate professor with the Department of Electronics and Communication Engineering, AAA College of Engineering and Technology, Anna University, India.

Abudhahir A received the M.E. degree in Jadavpur University, India. He received his PhD from Anna University, India. He is currently a Professor with the Electrical and Electronics Engineering Department at Vel Tech Multi Tech Dr.Rangarajan Dr.Sakunthala Engineering College, Chennai, Tamilnadu, India. His areas of interest include Image Processing, Instrumentation and Nondestructive testing.