Multi Sensor Data Fusion Algorithms for Target Tracking using Multiple Measurements

R.Anitha[1], S.Renuka[2], A.Abudhahir[1]

[1] Department of Electronics and Instrumentation Engineering, National Engineering College, Kovilpatti, India

[2]Department of Electronics and Instrumentation Engineering, Sree Sowdambika College of Engineering, Aruppukottai, India

(anitha.ramamorthy@gmail.com, renukathirumurugan@gmail.com, abudhahir74@yahoo.co.in)

Abstract – **Multi-Sensor Data Fusion (MSDF) is very rapidly growing as an independent discipline to be considered with and finds applications in many areas. Surplus and complementary sensor data can be fused using multi-sensor fusion techniques to enhance system competence and consistency. The objective of this work is to evaluate multi sensor data fusion algorithms for target tracking. Target tracking using observations from several sensors can achieve improved estimation performance than a single sensor. In this work, three data fusion algorithms based on Kalman filter namely State Vector Fusion (SVF), Measurement Fusion (MF) and Gain fusion (GF) are implemented in a tracking system. Using MATLAB, these three methods are compared and performance metrics are computed for the evaluation of algorithms. The results show that State Vector Fusion estimates the states well when compared to Measurement Fusion and Gain Fusion.**

Keywords - **Kalman filter, sensor fusion, target tracking**

I. INTRODUCTION

Multi-sensor data fusion (MSDF) is defined as the process of combining information from multiple sources to produce the most precise and complete unified data about an entity, activity or event [3]. MSDF is the combination and application of many conventional disciplines and new areas of engineering. A broad idea of multi sensor data fusion is represented in Fig. 1. The measurement value taken from a single sensor is not accurate and not reliable. It consumes more time. The spatial coverage of a single sensor is also low. Compared to the single sensor measurement, the MSDF gives more accurate, reliable and timely data. It covers a larger geometrical area and the results obtained are fault tolerant. In this paper three different fusion algorithms are considered and employed in a tracking system [8]. The performance metrics are computed and the results obtained are reported descriptively.

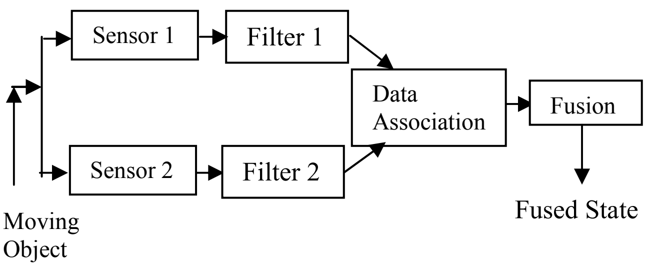

Figure1. Concept of Multi Sensor Data Fusion

II. RELATED LITERATURE AND MOTIVATION

Most of the research work in Multi sensor Data Fusion is based on the Kalman filter algorithm that filters the noise well and recovers the signal and thus providing a good performance on signal processing.

Bahador Khaleghi et al [3] reviewed multi sensor data fusion algorithms. This paper proposed a comprehensive review of the data fusion state of the art. Ren C. Luo et al [7] discussed the wide application spectrum of Multi sensor Fusion and Integration (MFI) in automation, military and biomedical fields. In addition, several future directions of research in the data fusion community were highlighted and described. B.S.Paik et al [4] proposed a new gain fusion algorithm which gives computer-efficient suboptimal estimation results and estimates without significant loss of accuracy.

Jiang Dong et al [6] presented an overview of recent advances in multi-sensor satellite image fusion.

III. DATA FUSION ALGORITHMS

A. *State Vector Fusion*

State Vector Fusion (SVF) is a Kalman Filter (KF) based data fusion. The KF [1] is given for each set of observations, i.e., the algorithm is applied independently for each sensor (data) and generates state estimates. As shown in Fig. 2 each sensor uses an estimator that obtains an estimate of the state vector and its associated covariance matrices (of the tracked target) from the data of that associated sensor. Then at the fusion center, track-to-track correlation is carried out and the fused state vector is obtained [9].

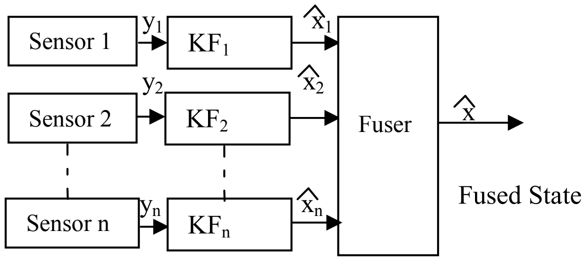

Figure 2. State Vector Fusion

The state model of the system is given by

$$X_{(k+1)} = \Phi X_{(k)} + G\, w_{(k)} \quad (1)$$

$$Z_{(k+1)} = H X_{(k)} + v_{(k)} \quad (2)$$

Where

X is the state vector,
Φ is the state transition matrix;
G is the gain matrix,
w is the process noise,
Z is measurement vector,
H is the observation matrix,
v is the measurement noise

The kalman filter recursive algorithm is computed by the equations (3) to (7). The state and covariance time propagations are given by

$$\hat{X}_{(k+1)} = \Phi \hat{X}_{(k)} \quad (3)$$

$$\hat{P}_{(k+1)} = \Phi \hat{P}_{(k)} \Phi^T + G\, Q\, G^T \quad (4)$$

State and covariance measurement updates are given by

$$K_{(k+1)} = \tilde{P}_{(k+1)} H^T [H \tilde{P}_{(k+1)} H^T] \quad (5)$$

$$\hat{X}_{(k+1)} = \tilde{X}_{(k+1)} + K_{(k+1)} [Z_{(k+1)} - H \tilde{X}_{(k+1)}] \quad (6)$$

$$\hat{P}_{(k+1)} = [\, I - K_{(k+1)} H] \tilde{P}_{(k+1)} \quad (7)$$

Where

$\hat{X}_{(k)}$ is the State vector of the sensor at the instant *k*

$\hat{P}_{(k)}$ is the covariance of the sensor which is the square of difference between desired state vector and the Sensor's state vector

$K_{(k+1)}$ is the kalman gain

$\hat{X}_{(k+1)}$ is the filtered state estimate

$\hat{P}_{(k+1)}$ is the filtered covariance estimate

B. *Measurement Fusion*

Measurement fusion (MF) algorithm fuses the sensor observations directly via a measurement model and uses one KF [1, 2] to estimate the fused state vector. Fig. 3 shown below depicts the measurement fusion.

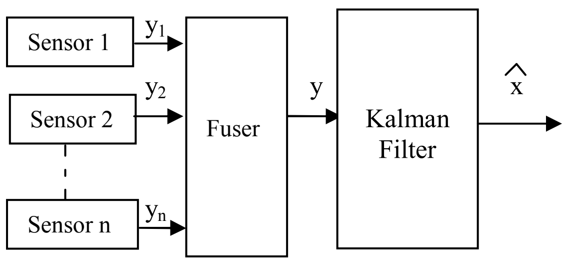

Figure 3. Measurement Fusion

The kalman filter recursive algorithm is computed by the equations (8) to (12). State and covariance time propagations are given by

$$\tilde{X}^f_{(k+1)} = \Phi \hat{X}^f_{(k)} \quad (8)$$

$$\tilde{P}^f_{(k+1)} = \Phi \hat{P}^f_{(k)} \Phi^T + GQG^T \quad (9)$$

The state and covariance measurement data updates are given by

$$K^f_{(k+1)} = \tilde{P}^f_{(k+1)} H^T [H \tilde{P}^f_{(k+1)} H^T + R]^{-1} \quad (10)$$

$$\hat{X}^f_{(k+1)} = \tilde{X}^f_{(k+1)} + K^f_{(k+1)} [Z_{(k+1)} - H \tilde{X}^f_{(k+1)}] \quad (11)$$

$$\hat{P}^f_{(k+1)} = [I - K^f_{(k+1)} H] \quad (12)$$

Where

$\hat{X}^f_{(k+1)}$ is the filtered fused state

$\hat{P}^f_{(k+1)}$ is the filtered fused covariance

C. *Gain Fusion*

In the Gain fusion (GF) algorithm [4, 5], a global processor receives the information in the form of a kalman gain from local systems and formulates the global estimate. The kalman filter recursive algorithm for gain fusion is given in the equations (13) to (16). Time Propagations of global estimate are given by

$$\tilde{X}^f_{(k+1)} = \Phi \hat{X}^f_{(k)} \quad (13)$$

$$\tilde{P}^f_{(k+1)} = \Phi \hat{P}^f_{(k)} \Phi^T + G\, Q\, G^T \quad (14)$$

The local filters are reset as,

$$\tilde{X}^m_{(k+1)} = \tilde{X}^f_{(k+1)} \quad (15)$$

$$\tilde{P}^m_{(k+1)} = \tilde{P}^f_{(k+1)} \quad (16)$$

Where

m is the number of sensors

$\hat{X}^f_{(k+1)}$ is the filtered fused state

$\hat{P}^f_{(k+1)}$ is the filtered fused covariance

IV. SIMULATION RESULTS

A. *Implementation of Fusion Algorithms*

Implementations of SVF, MF and GF algorithms in the tracking system [8] are graphically shown in Fig. 4, Fig. 5 and Fig. 6. Fig. 7 and Fig. 8 show the IR and RADAR sensor states respectively.

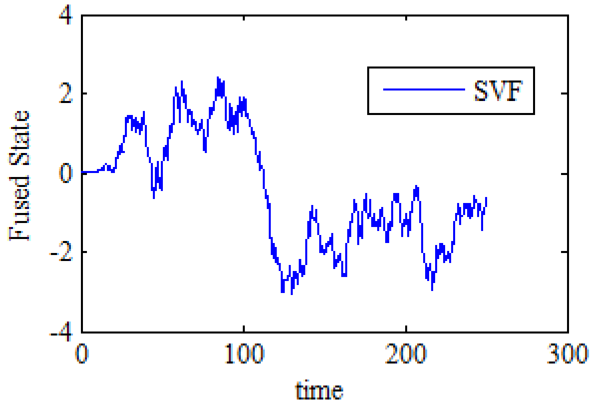

Figure 4. Graphical output of SVF

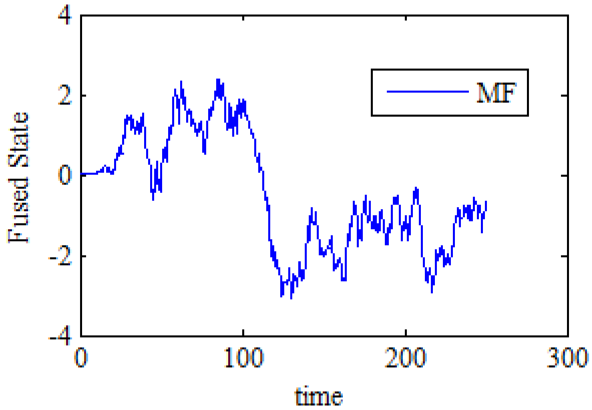

Figure 5. Graphical output of MF

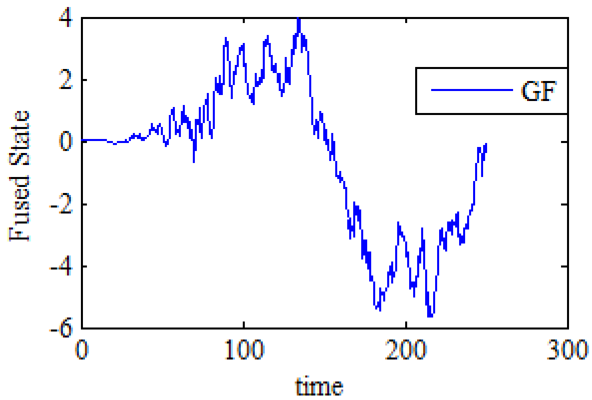

Figure 6. Graphical output of GF

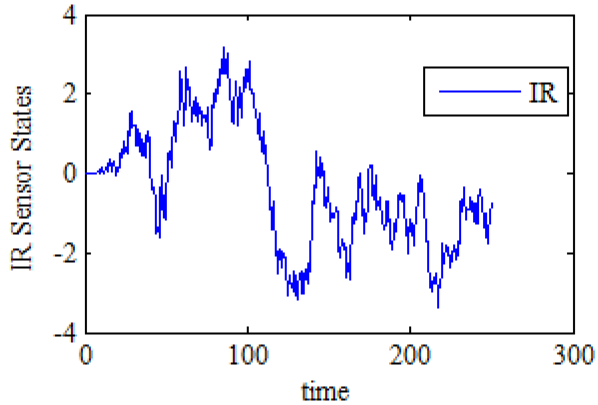

Figure 7. Graphical output of the states of IR Sensor

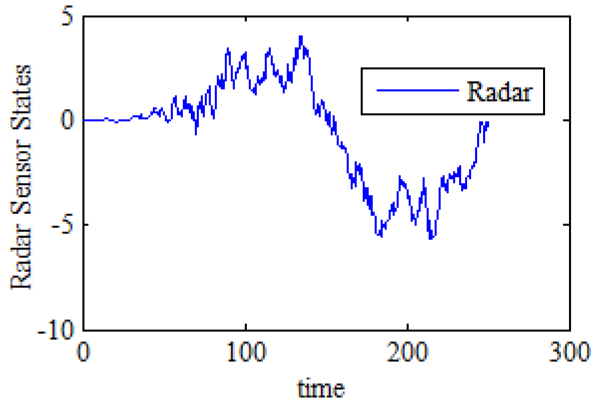

Figure 8. Graphical output of the states of RADAR Sensor

B Performance Evaluation

The performance measures [8] like Percentage Fit Error (PFE), Mean Square Error (MSE) and Mean Absolute Error (MAE) of three algorithms (SVF, MF, and GF) are shown in Table I, Table II and Table III.

TABLE I

PERCENTAGE FIT ERROR

State	MF	SVF	GF	IR	RADAR
PFEx	0.78	0.78	1.57	11.60	7.90
PFEy	0.16	0.16	1.78	10.48	2.04
PFEz	0.70	0.70	8.77	9.54	9.68
PFExd	2.19	2.20	7.61	12.67	8.73
PFEyd	2.85	2.80	8.48	28.68	9.11
PFEzd	29.10	28.01	129.14	49.48	131.18
PFExdd	111.84	108.87	150.23	118.81	151.29
PFEydd	80.14	75.77	85.515	132.22	86.28
PFEzdd	97.33	92.98	133.23	102.47	134.32

TABLE II

MEAN SQUARE ERROR

State	MF	SVF	GF	IR	RADAR
MSEx	2024.9	2027.4	8446.68	445223.8	205546.45
MSEy	59.63	63.02	7295.6	277288.3	9391.91
MSEz	70.39	69.84	11427.1	13324.67	13681.99
MSExd	20.63	20.79	259.34	690.52	334.28
MSEyd	16.72	16.13	152.00	1814.05	174.34
MSEzd	16.32	15.12	336.13	47.19	346.9535
MSExdd	3.156	2.98	5.77	3.62	5.8647
MSEydd	2.39	2.14	2.73	6.59	2.7866
MSEzdd	2.76	2.52	5.27	3.06	5.3645

TABLE III

MEAN ABSOLUTE ERROR

State	MF	SVF	GF	IR	RADAR
MAEx	6.2477	6.4446	60.6082	392.5319	77.4481
MAEy	4.8967	5.1984	63.8345	335.3438	66.1245
MAEz	5.7331	5.6979	87.0213	90.4763	89.8327
MAExd	3.3231	3.3089	12.7671	21.8512	12.8205
MAEyd	3.1456	3.1188	9.7290	27.9598	9.9797
MAEzd	3.1497	3.0113	13.3416	5.4447	13.5286
MAExdd	1.4131	1.3668	1.9379	1.5148	1.9587
MAEydd	1.2006	1.1387	1.3225	1.9965	1.3350
MAEzdd	1.2893	1.2300	1.7608	1.3313	1.7755

V. 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 State Vector Fusion (SVF), Measurement Fusion (MF) and Gain Fusion (GF) algorithms have been implemented in a tracking system. From the performance measure it is observed that the Kalman Filter based State Vector Fusion algorithm performs well comparatively, for the system taken. This work can be further extended by implementing sensors with nonlinear characteristics in more systems and different fusion algorithms can be developed and implemented in many other systems.

REFERENCES

[1] 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.

[2] Chen Yukun, Si Xicai, Li Zhigang, “Research on Kalman-filter based multisensor data fusion,” *Journal of Systems Engineering and Electronics* vol. 18, no. 3, pp. 497-502, 2007.

[3] Bahador Khaleghi, Alaa Khamis, Fakhreddine O. Karray, Saiedeh N. Razavi, “Multisensor data fusion: A review of the state-of-the-art,” *Information Fusion* 14 (2013) 28–44.

[4] 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.

[5] 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.

[6] Jiang Dong, Dafang Zhuang,Yaohuan Huang and Jingying Fu, “Advances in Multi-Sensor Data Fusion: Algorithms and Applications,” *Sensors 2009,* 9, 7771- 7784.

[7] 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.

[8] VPS Naidu, “Architectures for 3d Target Tracking using IRST and RADAR Measurements,” *Journal of Aerospace Sciences&Technologies,* vol. 62, no.3, pp. 183-195.

[9] Jitendra R. Raol, “Multi-Sensor Data Fusion with Matlab,”*CRC Press, Taylor & Francis Group,* ISBN 978-1-4398-0003-4, 2010.