Performance Evaluation of Kalman Filter Sensor Fusion Based Algorithm and Gain Fusion Based Algorithm

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Abstract---- The aim of this paper is to analyze the different schemes of data fusion techniques. The data will be generated for different sensors and fused together to generate or deduce an output. The different schemes for data fusion technologies are mentioned in the text. For our analysis we will consider KFA, XXX YYY techniques. The output will be shown with the help of graphs. These schemes are applicable for multi sensor data fusion where the data is generated or collected via different sensors.

DF (Data fusion) or multisensory data fusion (MSDF) is the process of combining or integrating measured or pre-processed data or information originating from different active or passive sensors or sources to produce a more specific, comprehensive, and unified dataset or world model about an entity or event of interest that has been observed. Sensor data fusion has wide number of applications from telecommunications, radar, satellite communication to data networks.

The tracking of moving objects includes targets, mobile robots, and other vehicles which uses measurements from sensors is of considerable interest in many military and civil applications that use radar, sonar systems, and electro-optical tracking systems (EOTs) for tracking flight testing of aircrafts, such as missiles, unmanned aerial vehicles, micro- or mini-air vehicles, and rotorcrafts. It is also useful in nonmilitary applications such as robotics, air traffi c control and management, air surveillance, and ground vehicle tracking. In practice, scenarios for target tracking could include manoeuvring, crossing, and splitting (meeting and separating) targets. Various algorithms are available to achieve target tracking for such scenarios. The selection of the algorithms is generally application dependent and is also based on the merits of the algorithm, complexity of the problem (data corrupted by ground clutter, noise processes, and so on), and computational burden. Target tracking comprises estimation of the current state of a target, usually based on noisy measurements. The problem is complex even for single target tracking because of uncertainties in the target's mathematical model, especially for manoeuvring targets (which need more than one model and one transition model, and so on), and process/state and measurement noises. The complexity of the tracking problem increases for multiple-targets using measurements from multiple sensors.

I. INTRODUCTION

The procedure of using pre-processed data and information, which is coming from different types of sensors or sources, in order to fuse it to give more specific output or result about an object that is being observed is called DF or Data fusion or multi sensor data fusion (MSDF).

If a Data Fusion series is assumed, where the fusion process is indicated by the fusion symbol like addition, multiplication through operations which involves probabilities and logical explanation, then if it's a success, with improved accuracy, fusion can be achieved, which means it helps in the reduction of the uncertainty, it also helps in state prediction and identification of the object under observation and more specific conclusions can be generated which cannot be achieved by using a single sensor.

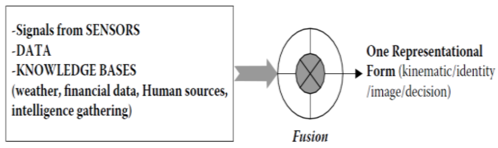

FIGURE 2.1
The conceptual chain of data fusion from data to the fusion result.

Fig. 1:

Configuration and arrangement of various sensors should be such that, that it is able to achieve the desired result. Occasionally, the arrangement is mostly entertained by the geometry or geography of multiple available sensors. The configuration of sensors is very important portion in order to gain desired result. For example, If Arrangement of radar is not correct for the desired output, then the incoming result can be a disaster.

II. LITERATURE SURVEY ON SENSOR FUSION

A. Sensor Topologies:

Topologies for sensor fusion should be very specific, it should have definite architecture and it should be divided into categories depending upon the type of sensors used and their arrangement

B. Complementary Configuration: Sensors don't have direct dependency on each other. Sensors are divided specifically to govern their each region, like one sensor handles one region, while the other overlooks the other regions, thus no interfering in each other areas and by collecting all the figures, we can get overall picture under observation. for example, while using multiple cameras fitted in a room viewing the different section of the room under observation, a complete view of the room can be obtained

C. Competitive Configuration: Sensors deliver different faces or in other words different measurements of an object under observation. Sensor fusion of different data coming from different sensors regarding the same object can be fused. data from a single sensor delivered at different time frames can also be fused under competitive configuration. Such structure is robust and fault tolerant. It can also help in fault detection when compared with other structures and and such topologies can be useful in more fault prone areas. Sensors of different types can also be used in this topology which is an advantage.

D. Cooperative Configuration: Incoming data from different sensors is fused to get an output that was not available via a single sensor. e.g. a 3d image obtained by fusing the data coming from two 2D cameras. Such configuration in sensor fusion is very difficult to make, as the resultant data is very sensitive to all kind of small errors occurred by each and every individual sensors.

Apart from these configurations, other types of hybrid structure can also be created depending upon the requirements of fusion.

III. .Fusion Architectures

The Multi sensor data Fusion process, involves various arrangements and procedures which involve sensors integration, pre data processing, data estimation, post data processing and decision making. Most commonly architecture has been described into three types.

A. Centralized Fusion

This architecture involves mainly similar sensors or homogeneous sensors, such that they are all time synced and keep auto correcting the sensory data. It also acts as a translator for sensor data processing. Data is originally in distributed form in this fusion architecture and optimal decision is taken based on measurements achieved from all the sensors.

B. Distributed Fusion

Sensors can be homogeneous or non homogeneous. Data is processed and collected by an individual Kalman filter from each sensor involved.It then involves the state vector fusion process to gain the output which has been discussed in the appendix. This fusion method can be used in large sensor networks where lots of data is to be processed.

C. Hybrid Fusion

This method involves fused version of centralised and distributed fusion methodologies based on sensor fusion requirements. To reduce the communicational errors distributed fusion method can be used and when target tracking is required in a dense area than centralised fusion can be considered. Based on sensor availability combination of the other two fusion schemes can be used for a better fused state of the target. It's widely used for flight range testing and digital signal processing.

D. Kalman Filter

The Kalman filter is an algorithm that, observed over time, uses a series of measurements which can contain noise or random variations and other accuracies and produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone[36]. It is also known as linear quadratic estimation (LQE). Kalman filter mainly works on the streaming noisy input data to produce an optimal estimate of the underlying state of the system. The filter is named for Rudolf (Rudy) E. Kalman, one of the primary developers of its theory [36].

The Kalman filter has n number of applications in the communication, digital signal processing and navigation technologies, like control and navigations of aircraft and spacecraft or time series analysis [36].

It is a two step procedure. First is the prediction step, in which the Kalman filter produces estimates of the current state variables, along with their uncertainties. Once the next measurement outcome (almost corrupted with small amount of error, including random noise) is observed, updating of these estimates is done using a weighted average, with more weight being given to estimates with higher certainty. Kalman filter best advantage is that it doesn't depends on past information, i.e. it can run in real time using only the present input measurements and the previously calculated state and its uncertainty matrix. Unlike the prejudiced thinking all error terms and measurements that are used in Kalman filter are not Gaussian distributed.

Extensions and generalizations to the KF method have also been developed, such as the extended Kalman filter and the unscented Kalman filter which work on nonlinear systems.

IV. Disadvantages

- Mostly Kalman filters are used for linear state transitions, for non linear transitions one, we can use advance filters like particle filters.
- Sensor measurements of Gaussian form can only be used.

A. Data Fusion Algorithms

Sensor data is used to track the moving objects; this is very useful in military applications. Various vehicles like aircrafts make use of these technologies. various sensors like radar, sonar are used in various civil apps which help in day to day life of a human being. Many algorithms have been derived to provide target tracking of a moving object. Algorithms are selected based on application, its complexity and its computation ability.

In this chapter, we discuss some algorithms which help in data fusion of sensory data.

B. State-Vector And Measurement-Level Fusion

Data fusion is of two types:

1. measurement fusion
2. State-vector fusion.

Measurement Fusion is considered better as the data is fused without being processed However in practical situations data volume is much larger than expected and sending it without processing can cause chaos and delays and inaccurate data, and can harm transmission capacity of channel too, it is where state vector fusion comes in.

In state vector fusion firstly data is estimated by each sensor and covariance matrix is generated, which is collected by Kalman filter. the vectors are then transmitted and thus help in reducing overheads and overloads. However at fusion centre noise appears which is later corrected but this is a drawback of the system.

C. Fusion Algorithms

There are two types of algorithms on which we are working here.

1. Kalman filter Algorithm
2. Gain Fusion Algorithm

D. Kalman Filter based Algorithm

It is based on state vector fusion method,Firstly the data is estimated by Kalman filter

$\bar{x}^{m}(k+1) = F\,\hat{x}^{m}(k)$

State and covariance matrix is:

$\bar{x}^{m}(k+1) = F\hat{x}^{m}(k)$

$\bar{p}^{m} = F\hat{p}^{m}F^{1}+GQG^{1}$

Dynamically both sensors in each filter are same, however the sensor measurement and noisy statistics in the measurement could be different. The fusion algorithm is then becomes

$\hat{x}^f = \hat{x}^1 + \hat{p}^1 (\hat{p}1 + \hat{p}^2)^{-1} (\hat{x}^2 - \hat{x}^1)$

E. Gain Fusion–Based Algorithm

From the equations of the KF-based fusion algorithm, we observe that it requires calculations of inverse covariance to obtain the global results, but the recent fusion algorithms do not require calculations of covariance inverses and has parallel processing capability. The dynamic system equations are same as used in Kalman filter equations. The gain fusion algorithm for multi-sensor integration involves information feedback from the global filter to the local filters.

We see that there is information feedback from the global filter to the local filters. The Gain Fusion algo inorder to calculate global estimates, does not need the measurement update of the local covariances. Because the global *a priori* estimates are fed back to the local filter, there is implicit measurement data sharing between the local filters. This feature is evaluated when there is data loss in either of the two sensors.

F. Simulation And Results

The following graphs show the results in sensor 1 and sensor 2. We have three things:

- Original data
- Data for sensor 1(with no error)
- Data for sensor 2(with error)

If we notice the graphs, for the estimated and measured position in terms of sensor 1, its curve overlaps the original curve as there is no error and hence the residue of sensor 1 is approx 0 all over the range. However in case of sensor 2, we can see that the curve for the measured data does not properly follow the curve for the original data because of the error which results in high residue as shown in the figure.

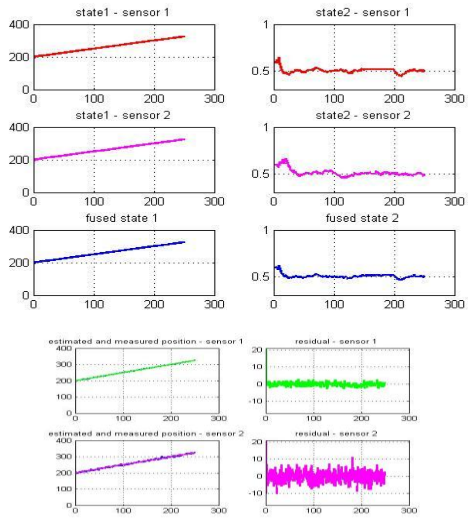

Fig 2:

The covariance's of the functions and the fusion filter is shown in the graph. It can be seen that the covariance of the fusion filter as the lower line seems better than the covariance's of f1(sensor 1) and f2(sensor 2). Covariance of f1 is the middle curve, covariance of the f2 is the topmost curve and covariance of the fused data is the lowermost curve.

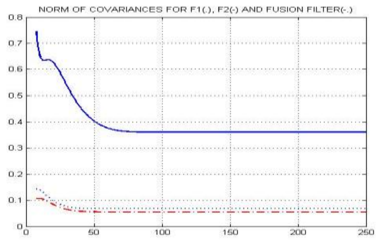

Fig.3: the norm of the fused covariance is lower than both the norms.

Here in this graphs, the position and the velocity states are compared and analyzed. There are total 6 graphs. We can see the curve for position state error and velocity state error for sensor 1 and sensor 2. Here we are plotting the errors in the measurement. As we can see the error is very much high in case of sensor 2 and is approximately ok in case of sensor 1, we fused both the datas using our algo, GFBA in this case and if we see the third row of fused data graphs, we can see a better performance of position and velocity state errors.

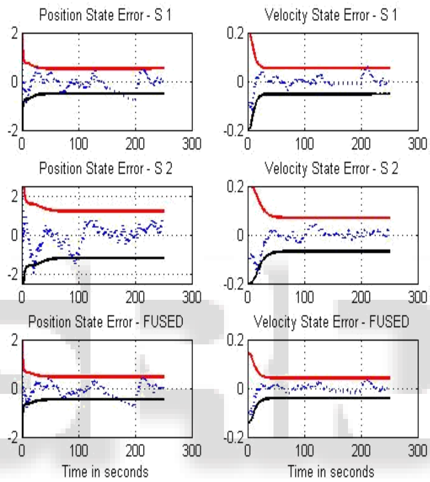

Fig. 4: Graph Of Kalman Fusion Algorithm With Respect To Position And Velocity

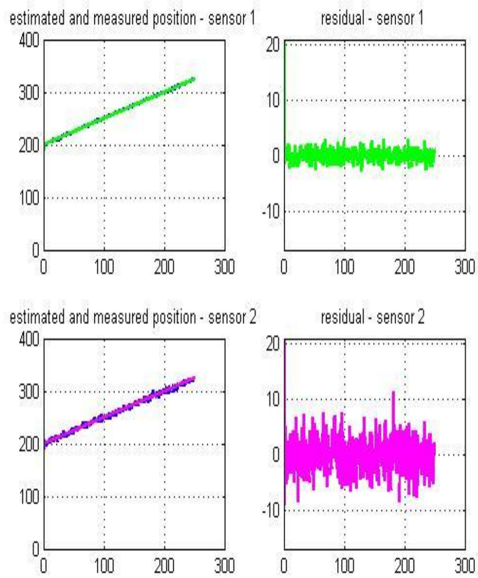

Fig. 5:

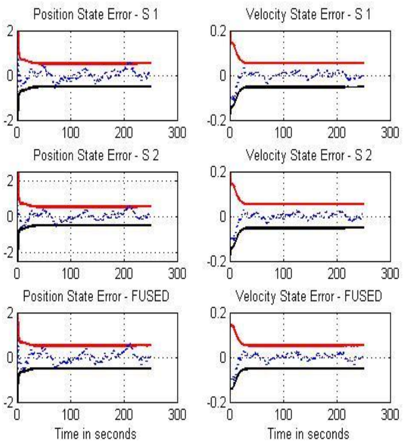

Fig. 6:

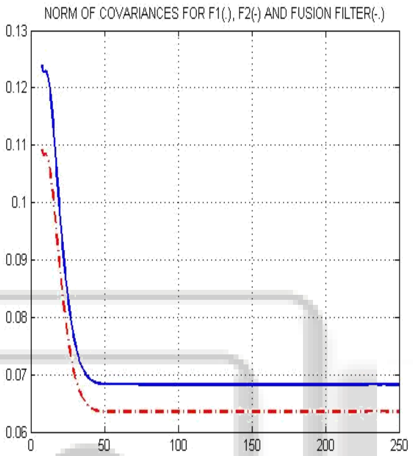

Fig. 7: Graph Of GFA

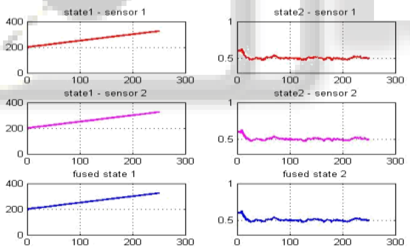

Fig. 8:

V. Results

GFA is better than Kalman Filter:

- No need to calculate the local covariance for the global estimates
- Parallel Processing capabilities and hence works fast
- Feedbacks information from global filter to the local filter.

GFA works better when there is loss of data because of the feedback of info from global to local filter. But when there is no error in the data, this feature won't work and in that condition Kalman Filter will work better**.**

VI. Conclusion

This paper on sensor data fusion explains the concepts and the various algorithms there are for fusion of the data coming from different sensors. We explained Kalman filter based approach and Gain fusion based approach in details and simulated them. The various simulations are shown in the text. The two main aims were achieved, one is the fusion of data through these algorithms and other is their analysis. KFBA performs little poorer and slower as compared to GFBA algorithm when there is a loss in data in any of the two sensors defined. The main reason for GFBA to work better is that it does not need to calculate the local covariances like KFBA for the global estimates. Also it feedbacks the information from the global filter to the local filter and allows parallel processing which make it work faster than the KFBA based approach. However in the presence of Gaussian noise, KFBA is the better approach to be used. Still there is lot more work to do in this field. Sensor data fusion technique has a wide variety of applications from navigation systems to the satellite systems, radar communication, wireless sensor networks etc with different algorithm to be used in different conditions, still there is no fix standardization which we can consider for our future work.

References

[1] Raol, J. R., G. Girija, and J. Singh. 2004. Modelling and parameter estimation of dynamic systems (IEE control engg,) Vol. 65. London: IEE.

[2] Rong Li, X., Y. M. Zhu, and C. Z. Han. Unifi ed optimal linear estimation fusion Part I: Unifi ed models and fusion rules. In Proceedings of 2000 International Conference on Information Fusion, MoC2.10−MoC2.17, Paris, France.

[3] Rong Li, X., and J. Wang. 2000. Unifi ed optimal linear estimation fusion Part II: Discussions and examples. In Proceedings of 2000 International conference on information fusion, MoC2.10−MoC2.17, Paris, France.

[4] Rong Li, X., and P. Zhang. Optimal linear estimation fusion—Part III: Crosscorrelation of local estimation errors. In Proceedings of 2000 International Conference on Information Fusion, WeB1.11–WeB1.18, Montreal, QC, Canada .

[5] Rong Li, X., K. Zhang, J. Zhao, and Y. M. Zhu. 2002. Optimal linear estimation fusion Part V: Relationships. Proceedings of 5th International Conf. Information Fusion , 497−504, Annapolis, MD, USA.

[6] Dempster, A. P. 1967. Upper and lower probabilities induced by a multivalued mapping. Annu Math Stat 38:325−39.

[7] Challa, S., and D. Koks. 2004. Bayesian and Dempster–Shafer fusion. Sadhana 29(2):145−76.

[8] Leung, L. W., B. King, and V. Vohora. 2001. Comparison of image data fusion techniques using entropy and INI. In Proceedings of the 22nd Asian conference on remote sensing, Singapore, November 5–9.

[9] Iyengar, S. S., and R. R. Brooks, eds. 2005. Distributed sensor networks. Boca Raton, FL: Chapman & Hall/CRC Press.

[10] Hu, H., and J. Q. Gan. 2005. Sensors and data fusion algorithms in mobile robotics. TR CSM-422, Dept. of Comp. Science, University of Essex, UK.

[11] Vaghi, A. 2003–2004. Sensor management by a graphical model approach. Thesis, Politecnico di Milano.

[12] Kashyap, S. K., and J. R. Raol. 2006. Evaluation of derivative free Kalman filter and fusion in non-linear

estimation . Ottawa, ON, Canada: IEEE Canadian Conference on Electrical and Computer Engineering.
[13] Kashyap, S. K., and J. R. Raol. 2008. Evaluation of derivative free Kalman filter for non-linear state-parameter estimation and fusion. J Aeronaut Soc India 60(2):101−14.
[14] Naidu, V. P. S., G. Girija, and J. R. Raol. 2005. Data association and fusion algorithms for tracking in presence of measurement loss. J Inst Eng I AS 86:17−28.
[15] Mori, S., W. H. Barker, C.-Y. Chong, and K.-C. Chang. 2002. Track association and track fusion with nondeterministic target dynamics. IEEE Trans Aerosp Electron Syst 38(2):659–668.
[16] Shanthakumar, N., and G. Girija. 2007. Measurement level and state-vector data fusion implementations. Personal communications and personal notes. Flight Mechanics and Control Division, National Aerospace Laboratories, Bangalore.
[17] Kashyap, S. K., N. Shanthakumar, G. Girija, and J. R. Raol. 2003. Sensor data characterization and fusion for target tracking applications. International Radar Symposium India (IRSI), 3–5 December. Bangalore.
[18] Raol, J. R., and G. Girija. 2002. Sensor data fusion algorithms using squareroot information fi ltering. IEE Proc Radar Sonar Navig 149(2):89−96.
[19] Naidu, V. P. S., G. Girija, and N. Santhakumar. 2007. Three model IMM-EKF for tracking targets executing evasive maneuvers. AIAA-66928, 45th AIAA conference on Aerospace Sciences, Reno, USA.
[20] Simeonova, L., and T. Semerdjiev. 2002. Specifi c features of IMM tracking filter design. Inf Secur Int J 9:154−65.
[21] Challa, S., R. J. Evans, and X. Wang. 2003. A Bayesian solution and its approximations to out-of-sequence measurement problems. Inf Fusion 4(3):185−99.
[22] Shanthakumar, N., G. Girija, and J. R. Raol. 2001. Performance of Kalman and gain fusion algorithms for sensor data fusion with measurement loss. International Radar Symposium India (IRSI), Bangalore.
[23] Jin, S. H., J. B. Park, K. K. Kim, and T. S. Yoon. 2001. Krein space approach to decentralized H ∞ state estimation. IEE Proc Control Theor App 148(6):502−8.
[24] Lee, T. H., W. S. Ra, T. S. Yoon, and J. B. Park. 2004. Robust Kalman filtering via Krein space estimation. IEE Proc Control Theor App 151(1):59−63.
[25] Raol, J. R., and F. Ionescu. 2002. Performance of H-Infinity filter-based data fusion algorithm with outliers. 40th AIAA Aerospace Sciences Meeting & Exhibit, 14–17 January 2002, Reno, NV, USA, A02-13598.
[26] Ananthasayanam, M. R., A. K. Sarkar, A. Bhattacharya, P. Tiwari, and P. Vorha. 2005. Nonlinear observer state estimation from seeker measurements and seeker-radar measurements fusion, Paper No AIAA-2005-6066-CP.
[27] Kashyap , S. K., N. Shanthakumar, V. P. S. Naidu, G. Girija, and J. R. Raol. 2007. State estimation for Pursuer guidance using interacting multiple model based augmented extended Kalman fi lter . International Radar Symposium, India, (IRSI) Bangalore.
[28] Kashyap, S. K., V. P. S. Naidu, J. Singh, G. Girija, and J. R. Raol. 2006. Tracking of multiple targets using interactive multiple model and data association filter. J Aerosp Sci Technol Aeronaut Soc India 58(1):65−74.
[29] Park, S.-T., and J. Gyu Lee. 2001. Improved Kalman filter design for three dimension radar tracking. IEEE Trans Aerosp Electron Syst 37(2):727–739.
[30] Kashyap, S. K., G. Girija, and J. R. Raol. 2003. Evaluation of converted measurement- and modifi ed extended-Kalman fi lters for target tracking. AIAA Conference and Exhibit, Guidance, Navigation and Control, Texas, US, 11–17th August.
[31] Kashyap, S. K., G. Girija, and J. R. Raol. 2006. Converted measurement- and modifi ed extended-Kalman fi lter for target tracking. Def Sci J 56(5):679−92. Shantha kumar, N., and T. Jann. 2004. Estimation of attitudes from a low cost