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Performance Analysis of Multi-Source Data Fusion Tracking Algorithm for Ground Based Surveillance Model to Monitor the Moving Locomotive

[1]Tanuja. P. Patgar, [2]Dr. Shankaraiah
[1]Research Scholar, Department of Electronics and Communication Engineering,
SJCE research center, Mysore, India
[2]Professor, Department of Electronics and Communication Engineering,
SJCE research center, Mysore, India
[1]tanuja_patgar@yahoo.com, [2]shankarsjce@gmail.com

Abstract: *Multi source data fusion has an emerging technology that received core attraction for maneuvering and non-maneuvering application. Data fusion observation has improved reliability and it could be easy for the user to detect, recognize and identify the targets and increase user's situational awareness. The fused data should preserve all relevant information contained in the source data .Based on current trend of data fusion process, this paper presents a novel methodology to increase tracking accuracy of locomotive using Square Root Information Filter Algorithm (SRIFA).The tracking algorithm at decision level fusion, merges the information of Differential Global Positioning System (DGPS) and Wireless Sensors. The simulation results clearly shows the tracking accuracy that provide by multi-source data fusion process better than could be provide by single source alone.*

Keyword: *Ground based surveillance mod; DGPS; WSN; Data fusion; Information Filter; SRIFA;*

1. INTRODUCTION

In an intelligent vehicle system, the development of sensor technology and signal processing methodology plays major role in modern technology. The multi-source data fusion system is combining data from multiple sources to achieve significant accuracies results than using single source alone [1]. By using more advanced signal processing technique and data fusion process gives contribution towards multi sensor data fusion concept. The main application of multi sensor data fusion are automated target tracking, remote sensing, battlefield surveillance, guidance and control of autonomous vehicles, smart building, robotics and medical application [2]. The principle process of data fusion involves Identity fusion, data level fusion, and decision level fusion. The decision level fusion follows the merging information from multiple algorithms performed by multiple sources to yield resultant fused decision [4].

The current paper explains the fusion tracking algorithm for moving locomotives. The locomotive tracking is observed by Differential Global Positioning System (DGPS) measurements. The DGPS provides the ability to determine accurately the locomotive's location in the satellite visible area, but has limited ability to determine the location of the moving locomotive in the tunnel. By contrast, the Wireless Sensor can accurately determine the location even in tunnel, but is unable to measure the range. If these two calculations are correctly matched, then the combination of these data supplies more improved version for determination of location than could be obtained by single source alone [7]. We will focus on two types of situations for the fusion. (a) Fusion of location data to determine the position and velocity of moving train in satellite visible areas; Kalman filter based algorithm is applied. (b) Fusion of location data to determine the kinematics of moving train in tunnel, Quadratic Optimal Control algorithm is used for analysis.

In filtering the modified processing of measurements values, the computation of coefficients smoothing, the accumulation of the results are taking place. The Information Filter is advanced version of the discrete-time Kalman filter. The state estimates and the estimation covariance in Kalman filter are replaced by the information matrices and information vector [8]. Information filter is one of the best methods to deal with multi-source data fusion problems. It has special advantage in supplying direct

International Journal of Advances in Computer and Electronics Engineering
Volume: 01 Issue: 03, July 2016, pp. 23 – 30

interpretation of multi-sources observation with loads of information. Based on current result of data fusion tracking algorithm, this paper presents novel technology using Square Root Information Filter Algorithm (SRIFA) for possible application to data fusion process [12]. The implementation by Square Root Information Filter Algorithm (SRIFA) suppressed the irrelevant data and noise in the fused results to maximum extent to get better numerical precision, reliable, stable and accurate.

The organization of the paper is as follows. Section 2 explains the ground based surveillance model which defines the principle of multi-source data fusion technology. The two sources which are considered are Differential Global Positioning System (DGPS) and Wireless Sensor Network (WSN).

The architecture for multi-source data fusion and its modeling assumption are explained in section 3. Section.3.1 describes the problem formulation for DGPS using Kalman filter. The modeling assumption for WSN using Quadratic Optimal Control algorithm is explained in Section 3.2. Section 3.3 explained the basic modeling assumption of Information Filter. The algorithm used to fused the data from two sources are done using Square Root Information Filter is clearly explained in Section 4. Section 5 explains the decision level data fusion using Information Filter. The simulation set up using Matlab, and the results, analysis of the moving locomotive's position and velocity graph with related control inputs are explained in Section 6. Finally Section.7depicts concluding remarks.

2. GROUND BASED SURVEILLANCE MULTI-SOURCE FUSION MODEL

The major objective of ground based surveillance model is to track, detect and recognize the moving train in the allocated track. For continuous tracking and monitoring of locomotive surveillance model is required. Fig.1describes the block diagram of ground based surveillance model based on Differential GPS and Wireless Sensor technology. Differential GPS (DGPS) and Wireless Sensors are considering as two dissimilar sources and their data are to be fused at decision level.

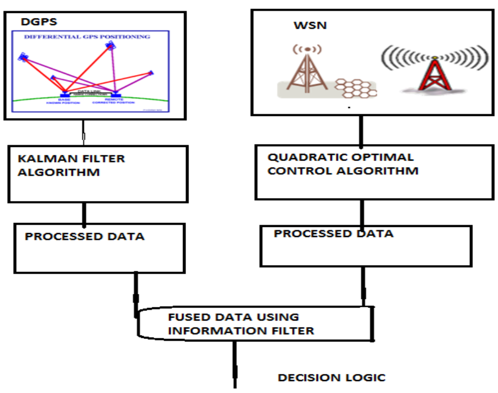

Figure1Block diagram of Ground Based Surveillance Model

The data from DGPS measurements are analyzed using Discrete Kalman Filter Algorithm. The prediction and estimation state vector model is considered separately. The data from WS are analyzed using Quadratic Optimal Control algorithm the fused information from each source is expected to improve the train detection and tracking accuracy [21].

In our research it is employed to monitor the rail and its surrounding environment with more sensing and increase accuracy. In this research work, Information Filter is proposed at the data fusion level. It is consider being one of advance version of Kalman Filter and is best suited for multi sensor data fusion.

3. PROPOSED ARCHITECTURE FOR MULTI-SOURCE DATA FUSION AND ITS MODELING ASSUMPTIONS

The architecture selection method is trade-off between the numerical accuracy, computation time and complexity. Fig.2 describes the decentralized architecture of Multi-Sources Data Fusion (MSDF) for dissimilar sources.

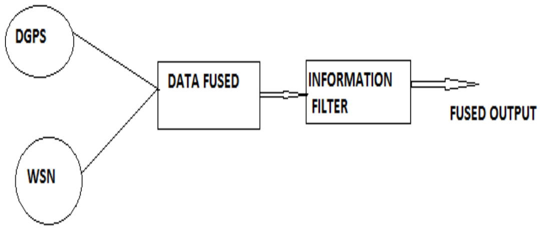

Figure 2 Decentralized architecture of Multi-Sensor Data Fusion

Let us consider multi-source system with two dissimilar sources S_1 (DGPS) and S_2 (WSN) whose sensor data are fused at decision level. For tracking analysis, we maintain Differential GPS measurements for satellite visible environments and Wireless Sensor measurements for tunnel. Both the data are calculate separately as single sources and then finally fused data from information pair and the orthogonal transformation provide enhanced numerical solution.

3.1 Problem Formulation for DGPS Measurements Using Kalman Filter

Consider locomotive constrained to move in straight line with constant velocity. Let **X (n)** and **X' (n)** are the locomotive position and velocity respectively. Let **F (n)** be the measurement noise which observe the position of train. The train is moving with constant speed **X''(n) =0**.The system states are position, velocity and acceleration. The State vector are represented as X = [Position, Velocity, Acc] ^{T} x, y, z. The implementation of Kalman filter requires the prior knowledge of both the process and measurement model.

3.1.1 Tracking State Model

Let us consider the state model for locomotive position and velocity only. The tracking kinematic

International Journal of Advances in Computer and Electronics Engineering
Volume: 01 Issue: 03, July 2016, pp. 23 – 30

parameter are along X and Y co-ordinates with the time interval from n to n+1. Let us consider XP(n), YP(n) are locomotive position tracking values in two direction and XV(n), YV(n) are locomotive velocity tracking parameters respectively.

X (n+1) = A X (n) + Q u (n)…………………..(a_1)

WhereA = system transition matrix, Q= process noise gain matrix

$$\boldsymbol{A}=\begin{bmatrix}1 & \delta t & \delta t^2/2 & \delta t^3/3\\ 0 & 1 & \delta t & \delta t^2/2\\ 0 & 0 & 1 & \delta t\\ 0 & 0 & 0 & 1\end{bmatrix} \qquad \mathbf{Q}=\begin{bmatrix}\delta t^3/3\\ \delta t^2/2\\ \delta t\\ 1\end{bmatrix}$$

Where δt is the sampling interval = 1sec

X (n+1) = A X (n) + Q u (n)

$$\begin{bmatrix}XP(n+1)\\ XV(n+1)\\ YP(n+1)\\ YV(n+1)\end{bmatrix}=\begin{bmatrix}XP(n)\\ XV(n)\\ YP(n)\\ YV\ (n)\end{bmatrix}+\begin{bmatrix}\delta t^3/3\\ \delta t^2/2\\ \delta t\\ 1\end{bmatrix}\begin{bmatrix}u_{XP}(n)\\ u_{XV}(n)\\ u_{YP}(n)\\ u_{YV}(n)\end{bmatrix}$$

If the time interval is from n to n-1, then the tracking state model equation becomes

X (n) = A X (n-1) + Q u (n-1)……….……..(a_2)

A, Q matrices remains same. Where E {u (n)} = 0 and Variance {u (n)} = T

Where T= Target model noise co-variance matrix.

3.1.2 Measurement Model

M (n) = R X (n) + F (n)………………………(a_3)

$$\text{Where R is sensor output }=\begin{bmatrix}1 & \delta t & \delta t^2/2 & \delta t^3/3\\ 0 & 1 & \delta t & \delta t^2/2\\ 0 & 0 & 1 & \delta t\\ 0 & 0 & 0 & 1\end{bmatrix}$$

$$\text{If } \delta t=0\text{, then, } R=\begin{bmatrix}1 & 0 & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 1 & 0\\ 0 & 0 & 0 & 1\end{bmatrix}$$

$$\begin{bmatrix}MXP\ (n)\\ MXV(n)\\ MYP(n)\\ MYV\ \ (n)\end{bmatrix}=\begin{bmatrix}1 & 0 & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 1 & 0\\ 0 & 0 & 0 & 1\end{bmatrix}\begin{bmatrix}XP(n)\\ XV(n)\\ YP(n)\\ YV(n)\end{bmatrix}+\begin{bmatrix}v_{XP}(n)\\ v_{XV}(n)\\ v_{YP}(n)\\ v_{YV}(n)\end{bmatrix}\ \ldots\ldots\ldots\ldots(a_4)$$

E {F (n)}= 0, and Variance {F (n) } = N

The adopted algorithm to predict and estimates the locomotive kinematic parameters.

Function Value [X $_{prediction}$, P $_{prediction}$] = Predict (X,P,A,T)

X $_{prediction}$ = A* X ;

P $_{prediction}$ = A*P*A^1 + T ;

Function Value [Difference, S] = Dynamic (X $_{prediction}$, P $_{prediction}$, M,R,N)

Difference = M-R* X $_{prediction}$;

S = N+R * P $_{prediction}$ *R^1

Function Value [X $_{KUSHI}$, P$_{KUSHI}$] = Dynamic @ update (X $_{prediction}$,P $_{prediction}$,Diff, S,R)

K= P $_{prediction}$ *F^1*S^1

X $_{KUSHI}$ = X $_{prediction}$ +K*Difference

P $_{KUSHI}$ = P $_{prediction}$ – K*S*K^1

3.2 Problem Formulation for Wireless Sensor Measurements Using Quadratic Optimal Control Algorithm

The state model and its tracking control performance are obtained with the help of quadratic optimal control theory. The advantage of using this theory is that the system designed is stable. The wireless tracking controller based on quadratic optimal control theory is considering for analysis. Overall performance of the control design is based on Liapunov approach, where quadratic performance index is directly related to Liapunov functions [20].

By minimizing and maximizing the performance index value corresponding to control inputs will trace the tracking error inaccuracies. Consider step input as control input in all cases. Let us now design the quadratic optimal control problem where the process is continues without bound N=∞ the plant equation is

X (K+1) = H X (K) + I U (K)…………………(b_1)

Y (K) = T X (K)……………………………(b_2)

V (K) = V (K-1) + S (K) - YK)…………..…(b_3)

V (K+1) = V (k) + S (K+1) – Y (K+1)

= V (K) + S (K+1) – T [H X (K) + IU(K)]

= V (K) + S (K+1) – THX (K) – T U(K)………..(b_4)

U (K) = K_I V (K) – KX (K)………………(b_5)

Where, K_I = Gain constant and K= Feedback gain matrix By considering equations (b_1) and (b_4), the state model is written as

$$\begin{bmatrix}X(K+1)\\ V(K+1)\end{bmatrix}=\begin{bmatrix}H & 0\\ -TH & 1\end{bmatrix}\begin{bmatrix}X(K)\\ V(K)\end{bmatrix}+\begin{bmatrix}I\\ -TI\end{bmatrix}U(K)+\begin{bmatrix}0\\ 1\end{bmatrix}S(K+1)\ \ldots\ldots\ldots\ldots (b_6)$$

By defining,

$$H^\wedge=\begin{bmatrix}H & 0\\ -TH & 1\end{bmatrix}\quad I^\wedge=\begin{bmatrix}I\\ -TI\end{bmatrix}\quad K^\wedge=[\,K, -K_I]$$

International Journal of Advances in Computer and Electronics Engineering
Volume: 01 Issue: 03, July 2016, pp. 23 – 30

Now consider the quadratic optimal control problem where the process is continuous with K=∞.

$$\begin{bmatrix} X(\infty) \\ V(\infty) \end{bmatrix} = \begin{bmatrix} H\ 0 \\ TH\ 1 \end{bmatrix} \begin{bmatrix} X(\infty) \\ V(\infty) \end{bmatrix} + \begin{bmatrix} I \\ -TI \end{bmatrix} U(\infty) + \begin{bmatrix} 0 \\ 1 \end{bmatrix} S(\infty) \ldots\ldots\ldots\ldots (b_7)$$

The error can be calculated by considering equation (b_6)

$$\begin{bmatrix} \mathrm{Xe}(K+1) \\ \mathrm{Ve}(K+1) \end{bmatrix} = \begin{bmatrix} H\ 0 \\ -TH\ \ 1 \end{bmatrix} \begin{bmatrix} \mathrm{Xe}(K) \\ \mathrm{Ve}(K) \end{bmatrix} + I \begin{bmatrix} U(K) \\ -TI \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} S(K+1)$$

Assuming that the input S (K) is step function.

S (K) = S (K+1) = S

By defining, $X_e(K) = X(K)\ X(\infty)$

$V_e(K) = V(K) - V(\infty)$,

$U_e(K)=K\ X_e(K)+K_e(K)$

$$= -[K\ -\ KI] \begin{bmatrix} \mathrm{X\ e}(K+1) \\ \mathrm{Ve}(K+1) \end{bmatrix} \ldots\ldots\ldots\ldots (b_8)$$

The performance index directly depends on tracking value of control input.

3.3 Proposed Modeling Assumption of Information Filter

Based on the multi sensor observations, the Information Filter state is updated continuously. Consider a linear system, the observations are modeled in terms of its information observed from different sources. Let A (p,q) is the observation model where 'M' is an p-vector observation and 'X' is an q-vector of variables to be estimated. Let 'B' is a p-vector of measurement noise.

$$M= AX+B \ldots\ldots\ldots\ldots (c_1)$$

By minimizing the mean square observation error, the least square solution of 'X' in terms of performance index is given as

$$J(X) = (M-AX)^T (M-AX) \ldots\ldots\ldots\ldots (c_2)$$

For the designing of estimation model of a linear system, information matrix is design in such a way that it should contain priori state information of the states update. Let us consider a priori state information matrix pair,

$$IMP =(X^{\wedge},Y^{\wedge}) \ldots\ldots\ldots\ldots (c_3)$$

Then the modified performance index based on priori state information is given by substituting equation (3) in to equation (2).

$$J(X)=(M-AX)^T(M-AX)+(X-X^{\wedge})^T Y(X-X) \ldots\ldots\ldots (c4)$$

The algorithm to implement Information Filter is Square Root filter algorithm. This algorithm increases numerical computation accuracy and concise as well as fast and efficient computation. Square Root Filter (SRF) gives the square root of the co-variance matrix [10]. The filter is calculating the sensitivity, covariance and final solution of the parameter.

4. DECISION LOGIC FOR SQUARE ROOT INFORMATION FILTER (SRF) ALGORITHM

The algorithm avoids the inverting of small matrices sequentially formed at each time interval by substituting inverse of one big matrix one time. The information matrix is factored and orthogonal transformation matrix is consider in equation (c_3), then

$$J(X)=(M-AX)^T(M-AX)+(X-X^{\wedge})^T Y^{\wedge T} Y^{\wedge}(X-X^{\wedge}) \ldots .(c_5)$$
$$[\ Y=Y^{\wedge T}Y^{\wedge}]$$

The equation (c_1) can be written as

$$M^{\wedge}= Y^{\wedge}X+B^{\wedge} \ldots\ldots\ldots\ldots (c_6)$$

We observe that the performance function of the equation (4) shows

$$J(X)=(M-AX)^T(M-AX)+(M^{\wedge}-Y^{\wedge}X)^T(M^{\wedge}-{}^{\wedge}X) \ldots\ ..(c_7)$$

The composite system for equation (1) is,

$$M^{\wedge} = Y^{\wedge}X+B^{\wedge}$$

$$\begin{pmatrix} M^{\wedge} \\ M \end{pmatrix} = \begin{pmatrix} Y^{\wedge}X \\ A \end{pmatrix} + \begin{pmatrix} B^{\wedge} \\ B \end{pmatrix} \ldots\ldots\ldots\ldots (c_8)$$

If the priori and post state information data is added with the fundamental observation model then the solution of the equation becomes,

$$T\begin{pmatrix} Y^{\wedge}_{K-1} & M^{\wedge}_{K-1} \\ A_K & M_K \end{pmatrix} = \begin{pmatrix} Y^{\wedge}_K & M^{\wedge}_K \\ 0 & E_K \end{pmatrix} \ldots\ldots\ldots\ldots (c_9)$$

$$T\begin{pmatrix} Y^{\wedge}_{K+1} & M^{\wedge}_{K+1} \\ A_K & M_K \end{pmatrix} = \begin{pmatrix} Y^{\wedge}_K & M^{\wedge}_K \\ 0 & E_K \end{pmatrix}$$

The process is repeated for different measurement to get recursive information filter.

5. DECISION LEVEL DATA FUSION USING INFORMATION FILTER

The data fused equation are drawn from equation (c_9),

$$T\begin{pmatrix} Y^{\wedge}_{K+1} & M^{\wedge}_{K+1} \\ A_{1K} & M_{1K} \\ A_{2K} & M_{2K} \end{pmatrix} = \begin{pmatrix} Y^{\wedge}_K & M^{\wedge}_K \\ 0 & E_K \end{pmatrix}$$

International Journal of Advances in Computer and Electronics Engineering
Volume: 01 Issue: 03, July 2016, pp. 23 – 30

The fusion process can be obtained in form of equation as,

$$M^{\wedge}_{FUSION} = M^{\wedge}_{1} + M^{\wedge}_{2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(d_1)$$

$$Y^{\wedge}_{FUSION} = Y^{\wedge}_{1} + Y^{\wedge}_{2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(d_2)$$

The data fused state is obtained by using

$$X^{\wedge}_{FUSION} = M^{\wedge}_{FUSION} Y^{\wedge -1}_{FUSION} \ldots\ldots\ldots\ldots\ldots(d_3)$$

From the above data equation of the information filter and orthogonal transformation gives enhanced numerical picture. We impose conclusion on the fusion result as;

1. A single sensor cannot provide complete information but multi- source data sensor fusion would provide better information about the problem.
2. Data fused observation has improved reliability and it could be easy for the user to detect, recognize and identify the targets and increase user's situational awareness.
3. The fused data should preserve all relevant information contained in the source data.
4. Irrelevant data and noise should be suppressed in the fused results to a maximum extent.

6. SIMULATION RESULTS AND DISCUSSION

The tracking is analyzed by the movement of locomotive in straight line with constant velocity. Simulation is done using Matlab algorithm and Visual Kalman Filter Window. It provides visual method to estimate the state of process or removes noise from data.

Case1. Position identification of moving locomotive with DGPS using Kalman Filter algorithm

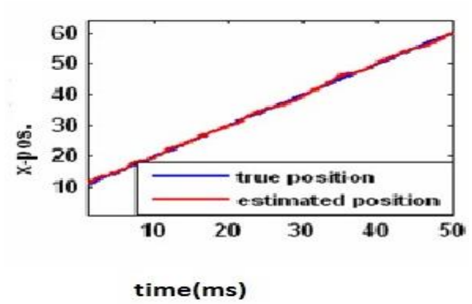

Figure 3 Position along X—direction

Figure 3 and Figure 4 shows the position track of locomotive achieved by the Kalman filter. The initial potion track is observed for straight run of 60 samples. If we design model based on the true situation, our estimated data are very close to the true value. The state errors in X and Y position are inverse to each other. When the locomotive travelled along X direction then position state error is +0.5 at t=30 and -1 at t=35. Similarly along Y direction position state error is +0.5 at t=3, 40. From these graphs we conclude that the data loss is less when the train travelled along X direction and produce only 0.005% inaccuracy.

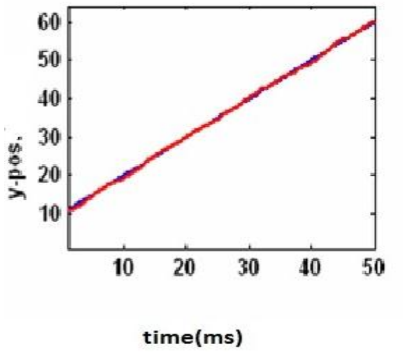

Figure 4 Position along Y-direction

Case2. Velocity of moving locomotive with DGPS using Kalman Filter Algorithm

Figure 5 and Figure 6 shows the velocity measurement of locomotives. From the graph we observe that the estimated velocity is getting close to the true velocity value and has less error than measurement noise. There is no much variation along X direction but is very noticeable along the Y direction as expected.

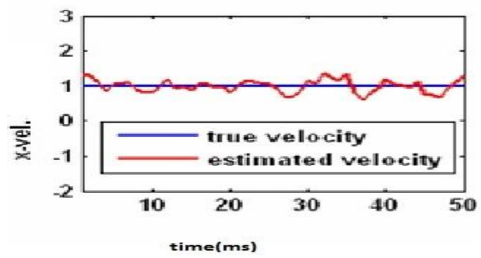

Figure 5 Velocity measurement along X-direction

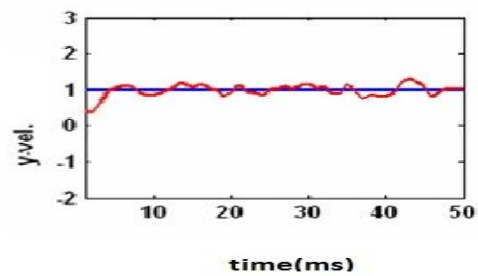

Figure 6 Velocity measurement along Y-direction

Case3. Position of moving locomotive with WSN using Quadratic Optimal Control Algorithm

By considering optimal control input U (K) = -0.7913, Performance Index J = 0.5. Fig.7 and Fig.8 shows the simulation results of position measurements of locomotive moving in X-direction and Y-direction and its corresponding state error. By maximizing the performance index to some extent we could improve the response even better. It concludes that the data loss is less and produces 0.006% inaccuracy. The

International Journal of Advances in Computer and Electronics Engineering
Volume: 01 Issue: 03, July 2016, pp. 23 – 30

locomotive's final position is also not close to the desired location but has in fact travelled in opposite direction.

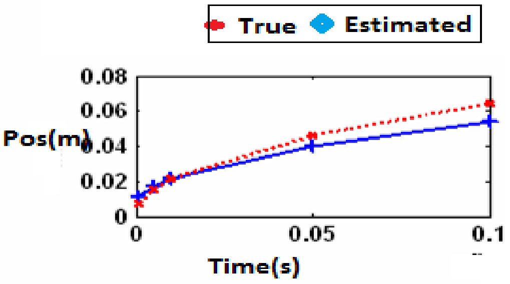

Figure 7 Position along X-direction

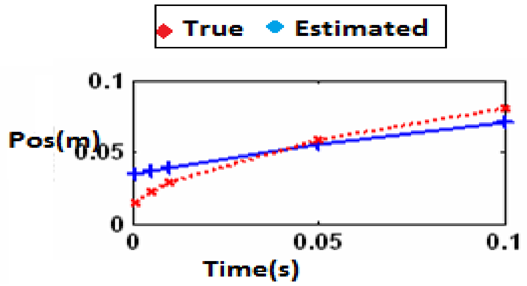

Figure 8 Position along Y-direction

Case4. Velocity of moving locomotive with WSN using Quadratic Optimal Control Algorithm

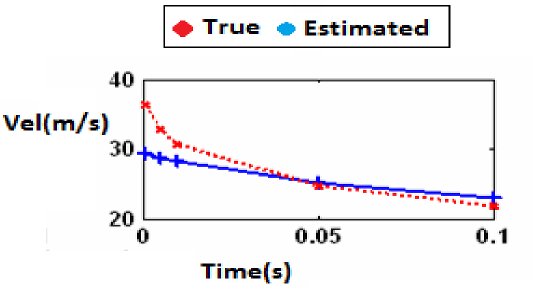

Figure 9 Velocity measurement along X-direction

By considering optimal control input U (K) = -0.2087, Performance Index J = 1.8 Figure.9 and Fig.10 indicates the velocity measurement graph with control input history to provide acceptable tracking performance. It is evident that the calculated state velocity is almost closer to the reference state value.

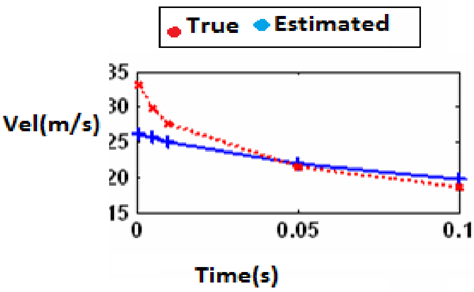

Figure 10 Velocity measurement along Y-direction

Case5. Data fusion using Square Root Information Filter

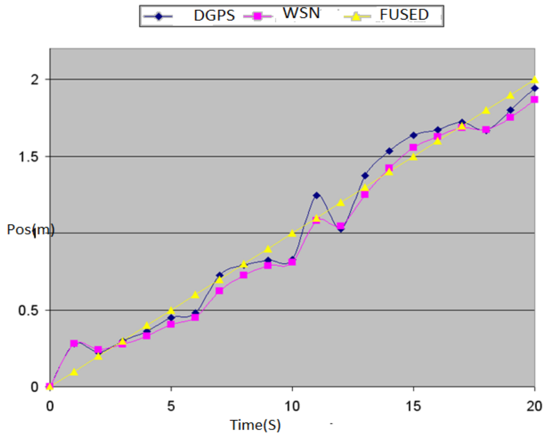

Figure 11 Position measurement of locomotive along X-direction with data Fusion

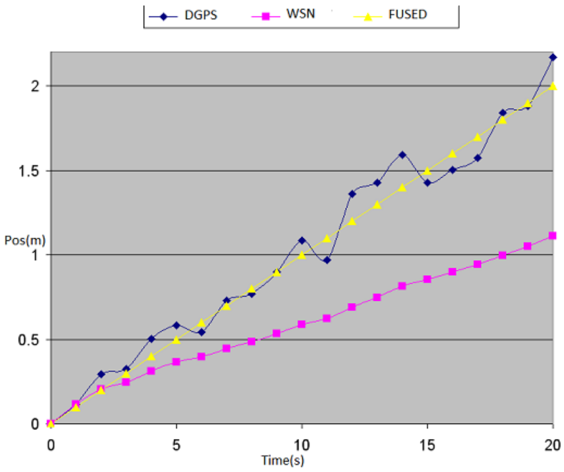

Figure 12 Position measurement of locomotive along Y-direction with data Fusion

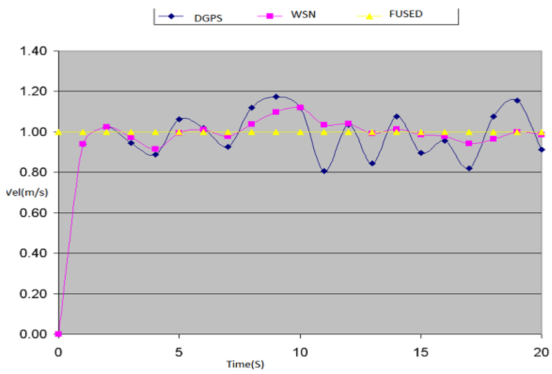

Figure 13 Velocity measurement of locomotive along X-direction with data Fusion

Figuer 11 and Figure 12 shows the position measurement of locomotive along X and Y direction using Square Root Information Filter Algorithm (SRIFA). The data is simulated for two dissimilar sources.

International Journal of Advances in Computer and Electronics Engineering
Volume: 01 Issue: 03, July 2016, pp. 23 – 30

TABLE I STATE ERROR OF DGPS, WSN AND ITS FUSED DATA

No. of trial	Kinematics Parameter	DGPS	WSN	Fused Estimation	Fused measurement	Fused at estimation	Fused at measurements
Observation I	Position (m)	0.2039	0.2113	0.2076	0.5321	0.2076	0.5321
	Velocity (m/S)	0.0164	0.0284	0.0224	0.0174	0.0224	0.0174
Observation II	Position (m)	0.2039	0.1736	0.1887	0.5310	0.18875	0.5310
	Velocity (m/S)	0.0164	0.0427	0.02955	0.0351	0.02955	0.0351

Similarly Figure 13 and Figure 14 shows the velocity measurement of locomotive along X and Y direction using SRIFA. It conclude that these results show the applicability of the SRIFA to the problem of sensor fusion either at data level or at the state vector estimate level and is found to be perform satisfactorily. Table 1 shows the state error for two cases. The state errors are compared both at estimation and fusion level.

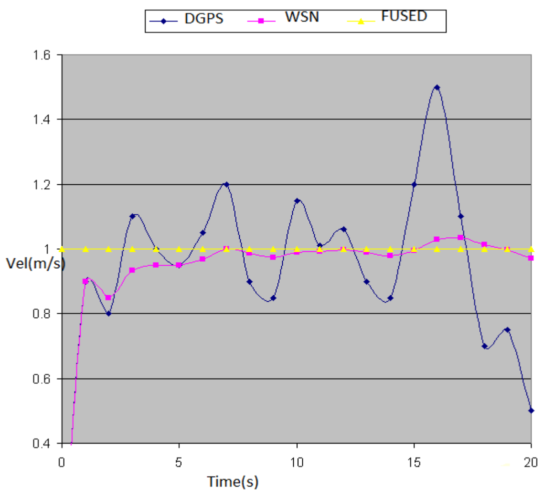

Fig.14 Velocity measurement of locomotive along Y-direction with data Fusion.

7. CONCLUSION

A single sensor cannot provide complete information but multi- source such as DGPS and WSN data fusion is provide better information about the problem. The fused observation is utilized for to detect, recognize and identify the locomotives. The advanced version of Kalman filter is Information Filter is proposed here and the implementation is done by Square Root Information Filter Algorithm (SRIFA).Two set of reading are verified for Position and velocity parameters. It is conclude that the state error of position at estimation level is less than at measurement level. But the state error of velocity measurement at estimation level is more than at measurement level.

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Authors Biography

Tanuja. P. Patgar received B.E degree in Electronics and Communication from Kuvempu university, Karnataka, India in 1996. In 2010, she received M.E in Control and Instrumentation from University Vishweshraya Collage of Engineering, Bangalore, India. She is currently a research scholar in the department of Electronics and Communication at Sri Jayachamarajendra College of Engineering, Mysuru, and Karnataka, India under Visvesvaraya Technological University, Belgaum, India. Her research field is Wireless Sensor Network.

Dr. Shankaraiah received his B.E. degree in Electronics and Communication Engineering from Mysore University, Mysore, India, in 1994, M.Tech. Degree in Digital Electronics and Communication Systems from Mysore University in 1997. He completed Ph.D. under the guidance of Prof. P. Venkataram, Dept. of ECE**, IISc. , Bangalore**. He has Investigated a transactions based QoS, Resource management schemes for mobile communications environment. He has more than 18 years of teaching experience in Engineering. He has published more than 30 papers in national and international journals and conferences. He is a reviewer and chair for many conferences. His research interest includes bandwidth management, Quality of Service (QoS) management, topology management, and Energy management for hybrid wireless superstore environments. He is a student member of IEEE and life member of India Society for Technical Education (LMISTE). He is presently working as Professor in the Department of E&C of Sri Jayachamarajendra College of Engineering, Mysuru, and Karnataka, India.