International Journal of Sensor and Its Applications for Control Systems
Vol.4, No.2 (2016), pp.9-20
http://dx.doi.org/10.14257/ijsacs.2016.4.2.02

The Impact of Hybrid Data Fusion Based on Probabilistic Detection Identification Model for Intelligent Rail Communication Highway

Tanuja P. Patgar[1] and Shankaraiah[2]

[1]Research Scholar, SJCE Research Center, Mysore, India
[2]Professor, Dept. of ECE, SJCE, Mysore, India
[1]tanuja_patgar@yahoo.com, [2]shankarsjce@gmail.com

Abstract

Data fusion has an emerging technology that received core attraction for maneuvering and non-maneuvering application. The multiple sources in the data fusion process are distributed accuracy based systems that differ from traditional single source in many ways; these have suppressed the irrelevant data and noise, better numerical precision, reliable, stable and accurate. The end-to-end basic probabilistic models have been proposed for different architectures in data fusion to manage sensor information. This paper proposes probabilistic detection identification model based on Bayes theorem and compare its performance with traditional single source network. Subsequently, it is cross validated using various data folds of kinematics measurements available from Differential GPS, Wireless Sensor and Radio Frequency Identification. This study proves the probabilistic model offers significant detection performance accuracy level of 95% for moving locomotives across wide range of operational scenarios.

Key words: *Data fusion, Bayes theorem, Probability identification model*

1. Introduction

Data fusion technology is of highly special significance in multiple real time application where group of data are combined, fused and modify to generate data information of appropriate quality. It is the process of combing information from multiple similar or dissimilar sources to provide robust and complete description of an environment or process of interest [1]. It finds many applications in military systems, in civilian surveillance and monitoring targets, in autonomous and process control system etc. 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 [2]. There are many constraints that need to be coined in order to achieve re-implementation of certain technological enhancement of the current system. The maximum extent to get better result numerical precision, reliable, stable and accuracy are to be considered. For such reason the data fusion methods are preferably considered in the drive toward autonomous systems. In principle, automated data fusion processes allow required measurements and information are to be combined to give knowledge of sufficient precision and integrity that problem may be formulated and executed autonomously [3].

The most important problem in data fusion technology is the development of sensor models associated with both the state and observation process. The focus is highlight on the use of probabilistic and information-theoretic methods for sensor modeling and for data fusion. Probability theory provides an extensive and unified set of methods for describing and manipulating uncertainty. It explains clearly how basic probability models can be used to fuse information, to describe different architectures for data fusion and to

ISSN: 2287-8467 IJSACS

manage sensors and its information. Bayes theorem is one of the best methods to deal with multi-source data fusion problems [4]. The value of Bayes theorem is to provide direct means of combining observed information with prior observation about the state of the probabilistic matrix. It has special advantage in supplying direct interpretation of multi sources observation with loads of information.

The combination of multi sensors may differ from sensor to sensor depending on real time application. This paper proposes multi-source system with three dissimilar sources such as Differential GPS (DGPS), Wireless Sensor (WS) and Radio Frequency Identification (RFID) whose sensor data are fused at decision level. Innovations are done so far in wireless communication and networking technology applied to railway. This challenge drastically changes the vision that transportation system of rail and its supporting system the way we mould the technology in the future. To identify the rail transportation safety issues in some notable cases such as accidents due to collision, at level crossing, derailment due to over speed, track and signaling fault, frequent train delay due to landslides are minimized only when we strictly monitor continuously the position and speed of the moving locomotive [6].

Accurate estimation of locomotive position and speed is the basis for the safety of the automatic operation. None of the solution is possible unless the existing tracking and controlling system is replaced by more informative feasible system that showcases accurate locomotive position and speed of the entire network [7]. This opens significant platform for the research on development of an automated system which based on Differential Global Positioning System (DGPS), Wireless Sensor (WS) and Radio Frequency Identification (RFID) technologies with data fusion.

The organization of the paper is as follows. Section (2) explains the surveillance integration model of DGPS, WSN and RFID in which how data are communicate and processed to central office. This section also explains how the integration model is helpful for tracking locomotive in satellite visible and low satellite visibility areas. The data fusion methodology using dissimilar sources such as DGPS, WSN and RFID designing are explained in section (3). Section (3.1) explains the **p**roposed algorithm for fusion of different sources based on Bayes theorem. Section (3.2) describes the proposed Sensor model using Probability detection density function. Three sensors integration model analysis is done for different cases are explained in section (4). Section (5) explains simulation set up and results analysis using Mat lab and Lab View. It also explains the results and analysis of the moving locomotive's position and velocity parameter concern graph with related prior and posterior probability density function. Section (6) depicts concluding remarks.

2. Ground Based Real Time Wireless Rail Surveillance Integration Model

Figure 1 depicts the real time Wireless Surveillance Integration model for continuous monitoring of locomotives in satellite visible and low satellite visible environment.

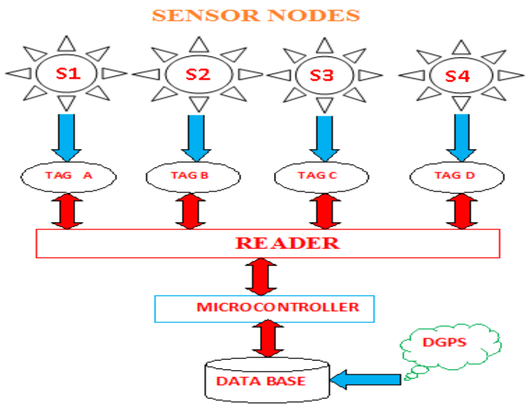

Figure 1. Block Diagram Representation of Wireless Surveillance Integration Model

It consists of Differential GPS, Wireless Sensor and Radio Frequency Identification model. The Differential GPS gives meter level accuracy which measures the locomotive position, velocity and other current state values. It uses multiple receivers to increase measurement accuracy. With the help of both roving receivers and stationary receivers it measures satellite position. Wireless Sensor is predominant technology for autonomous sensor data collection process [10]. It is possible only when group of heterogeneous sensor nodes capable of sensing, identifying, positioning the objects to monitor and control in distributed manners. But correct detection and identifying the rail is also very important that are not easily done by WSN. On the other hand Radio Frequency Identification (RFID) detects and identifies the locomotives that are not easily detectable by WSN. A tag has an identification information and memory that stores additional data. The reader is able to read and write the data from tags [12][14]. Each tag is equipped with wireless module which can transmit data to the reader. In fact the reader is acts as sensor node which reads the identification of moving locomotive.

3. Selection of Data Fusion Methodology

A single source cannot provide complete information but multi- source data fusion would provide robust and optimized information about the problem. The fused data observation has improved reliability and it preserve all relevant information contained in the primary source data. Data fusion is the combination of data from different similar or dissimilar sources, and can be implemented in number of ways.

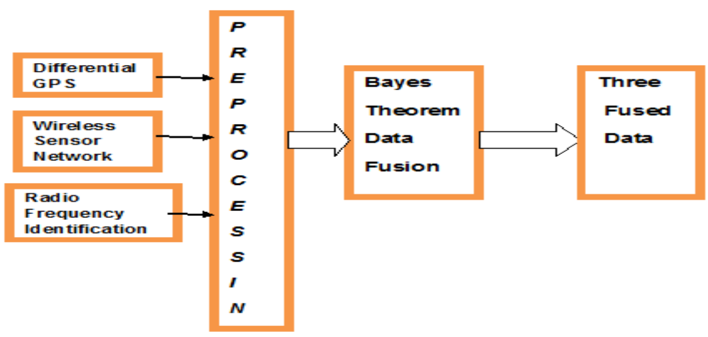

Figure 3. Block Diagram of Data Fusion System

For our modeling purposes we design simplest data fusion model as shown in Figure 3 where DGPS, WSN and RFID models are considered as three dissimilar sources sending same data with multiple inputs. Differential GPS is using multiple receivers to increase measurement accuracy. The mobile receivers calculate their absolute positions with increased accuracy by altering their received satellite measurements in co-ordination with base station. WSN are mainly used for sensing, identifying, positioning, monitoring the locomotive and its surrounding environment. Radio Frequency Identification (RFID) integrating with WSN provide more accurate and higher precise results. RFID detects and identify the object that is not easily detectable by WSN. In Pre-Processing, the different input data convert in to a format that is usable by the developed frame work. Then combine these data using data fusion process in order to increase the accuracy and stability. The data fusion technique is used to combining data available from multiple sources and converts in to one representational form. The process is supposed to achieve improved accuracy [17].

There are several methods that works on data fusion technology irrelevant to number and type of source data. There are number of Sensor fusion algorithms can be classified into three different groups:

(a) Fusion based on Least Squares Techniques---Kalman Filtering

(b) Fusion based onprobabilistic models ---- Bayes theorem, Particle Filtering

(c) Intelligent fusion---fuzzy logic

We focus our attention on probabilistic model with single network flow that is assumed to consist of single data path attempting to gather information from number of data sources. Bayes theorem provides most general Probability model used for fusing data information.

3.1. Proposed Algorithm for Fusion of Different Sources Based on Bayes Theorem

It is required to determine target (locomotive), where detection probabilities are obtained from three independent sources **y**1 (DGPS), **y**2(WSN) and y3(RFID). The source bases target reporting on three sensor sources **x**1,**x**2,x3. The first source is employing a pair of dependent observations **z**1, **z**2, and the second from observation z2, z3 and third source is employing dependent observation z3,z1.

Consider three independent sources such as DGPS, WSN and RFID models with corresponding random variables x, y, z on which joint probability density function can be represented as P(x, y, z). Then with the help of chain–rule of conditional probabilities, the density function is expanded as,

$$P(x, y, z) = P(x, y/ z)\, P(z) \quad (1)$$

$$P(x, y, z) = P(x/y, z)\, P(y/z)\, P(z) \quad (2)$$

$$P(x, y/z) = P(x/z)\, P(y/z) \quad (3)$$

Rearranging the conditional densities,

$$P(x/z) = P(z/x)\, P(x) \div P(z) \quad (4)$$

$$P(y/z) = P(z/y)\, p(y) \div P(z) \quad (5)$$

Where P (x), P (y) --- Prior Probability detection density function

P (x/z), P (y/z) ---- Posterior distribution function

P (z/x), P (z/y) ------ Conditional Probabilities detection density function

The Bayes theorem highlight on by combining observed information with prior and posterior distribution state of the variable. The conditional Probability P(z/x) and P (z/y) are act as sensor model.

3.2. Proposed Sensor Model Using Probability Detection Density Function

While we are building sensor model using Probability detection density function, the following assumptions are to be consider;

(1) By fixing the value of X=x and then asking what Probability detection density function in the variable z results.

(2) By fixing the value of Y=y and then asking what Probability detection density Function in the variable z results.

(3) Then consider sensor model in which observations not distributions are results in the form of Z=z. Finally ask what the Probability detection density Function on X and Y.

Practically P (z/x) and P (z/y) are constructed as function of both the variables. For fixed values of X and Y, the distribution in Z is defined. As X and Y vary family of distribution in Z is formed. Hence Bayes theorem is directly apply to the multi sources for data fusion process.

Consider the set of observations corresponding to the multi sources such as DGPS, WSN and RFID.

$$\mathbf{Z}^n = \{\mathbf{z}1 \in Z1, \ldots, \mathbf{z}_n \in Zn\} \quad \ldots(6)$$

Based on this information it is easy to construct a posterior distribution $P(\mathbf{x} \mid \mathbf{Z}n)$ and $P(y/Z_n)$. These are describing the relative likelihoods of the various values of the state of interest $\mathbf{x} \in X$ and $y \in Y$. In principle, Bayes theorem can be directly apply to compute this distribution function from

$$P(\mathbf{x} \mid \mathbf{Z}^n) = P(\mathbf{Z}^n \mid \mathbf{x})\, P(\mathbf{x}) \div P(\mathbf{Z}^n)$$
$$= P(\mathbf{z}_1 \ldots \mathbf{z}_n \mid \mathbf{x})\, P(\mathbf{x}) \div P(\mathbf{z}_1, \ldots, \mathbf{z}_n) \quad \ldots(7)$$
$$P(y \mid \mathbf{Z}^n) = P(\mathbf{Z}^n \mid y)\, P(y) \div P(\mathbf{Z}^n)$$
$$= P(\mathbf{z}_1 \ldots \mathbf{Z}_n \mid y)\, P(y) \div P(\mathbf{z}_1, \ldots, \mathbf{z}_n) \quad \ldots(8)$$

The joint distribution [P (x/z) and P(y/z)] of all possible combinations of observations P (z/x) and P (z/y) are conditioned the true state $x \in X$ *and* $y \in Y$. *T*he information obtained from the i^{th} information source is independent of the information obtained from other sources.

With this assumption, applying the chain rule to the joint probability detection density function on three random variable x, y, z

$$P(x/y, z) = P(x/z), \quad P(y/x, z) = P(y/z) \quad \text{which implies that}$$
$$P(\mathbf{z} \mid \mathbf{x}, \mathbf{z}1, \cdots, \mathbf{z}i-1, \mathbf{z}i+1, \cdots, \mathbf{z}\, n) = P(\mathbf{z}_i \mid \mathbf{x}) \quad \ldots(9)$$
$$P(z/y, z_1 \ldots z_{i-1}, z_{i+1} \ldots z_n) = P(z_I/y) \quad \ldots(10)$$

With conditional independence of the Probability detection density Function,

$$P(x, y/z) = P(x/z)\, P(y/z)$$
$$P(\mathbf{z}1, \cdots, \mathbf{z}\, n \mid \mathbf{x}) = P(\mathbf{z}1 \mid \mathbf{x}) \cdots P(\mathbf{z}\, n \mid \mathbf{x}) = \textstyle\sum_{i=1} P(z_I / x) \quad \ldots(11)$$
$$P(\mathbf{z}1, \cdot \ldots, \mathbf{z}\, n \mid y) = P(\mathbf{z}1 \mid y) \cdot \ldots \cdot P(\mathbf{z}\, n \mid y) = \textstyle\sum_{i=1} P(z_I / y) \quad \ldots(12)$$

Substituting equation (11) in eq. (7)

$P(x/z^n) = [P(z^n)]^{-1} P(x) \sum_{i=1} P(z_I/x)$……………………………………………..(13)

Substituting equation (12) in eq. (8)

$P(y/z^n) = [P(z^n)]^{-1} P(y) \sum_{i=1} P(z_I/y)$……………………………………….(14)

Hence the updated likelihoods in the final state depend on the posterior distribution on **x and y** is proportional to the product of prior likelihood and individual likelihoods from each information source. The conditional distribution $P(\mathbf{Z}n)$ is considered to be normalizing constant. Equation (13) and (14) highlights on direct computation methods for relative likelihood in different values of state from multiple numbers of observations. The conditional probabilities $P(\mathbf{z}_i | \mathbf{x})$ and $P(z_i/y)$ are collect priori as functions of x, y and $\mathbf{z}\, i$.

When sequence of observation $\mathbf{Z}n = \{z1, z2, \cdots, z_n\}$ is consider, then probability distribution and likelihood functions are depends only on unknown state **x and y.** For specific observation sequence $\{z1, z2 \ldots\ldots z_n\}$, posterior distribution $P(x/z_n)$ and $P(y/z_n)$ which is function of x and y is product of likelihood functions with the prior information $P(\mathbf{x})$ and P(y).

The results obtained from multiple sources are independent when conditioned on the true state.

$P(\mathbf{z}1, \cdots, \mathbf{z}_n) \neq P(\mathbf{z}1) \cdots P(\mathbf{z}_n)$,……………………………………………...(15)

As each source of information depend on common state $\mathbf{x} \in X$ *and* $y \in Y$. It is proved that the underlying state is the only thing in common among information sources. In this way once the state has been specified it is apparently assume that the information collected is conditionally independent of the state.

The integration of information is combined with all past and present information $P(\mathbf{z}\, k | \mathbf{x})$ and $P(z\, k/y)$.

$P(\mathbf{x}, \mathbf{Z}\, \mathbf{k}) = P(\mathbf{x} | \mathbf{Z}\, k) P(\mathbf{Z}\, k)$
$= P(\mathbf{z}k, \mathbf{Z}k-1 | \mathbf{x}) P(\mathbf{x})$
$= P(\mathbf{z}\, k | \mathbf{x})\, P(\mathbf{Z}k-1 | \mathbf{x})\, P(\mathbf{x})$……………………………………………..(16)

And $P(y, Z\, k) = P(z\, k/y)\, P(Zk\text{-}1/y)\, P(y)$ …………..………………………………(17)

Equating both sides of this expansion gives

$P(\mathbf{x} | \mathbf{Z}\, k)\, P(\mathbf{Z}\, k) = P(\mathbf{z}\, k | \mathbf{x})\, P(\mathbf{Z}k-1 | \mathbf{x})\, P(\mathbf{x})$…..…………………………(18)

$= P(\mathbf{z}\, k | \mathbf{x})\, P(\mathbf{x} | \mathbf{Z}k-1)\, P(\mathbf{Z}k-1)$…...……………………………..(19)

$P(\mathbf{Z}\, k) / P(\mathbf{Z}k-1) = P(\mathbf{z}\, k | \mathbf{Z}k-1)$

$P(\mathbf{x} | \mathbf{Z}\, k) = P(\mathbf{z}\, k | \mathbf{x})\, P(\mathbf{x} | \mathbf{Z}k-1)\, P(\mathbf{z}\, k | \mathbf{Z}k-1)$ …………….…………..(20)

Similarly $P(y/Z\, k) = P(z\, k/y)\, P(x/Zk\text{-}1)\, P(z\, k/Zk\text{-}1)$…………………...…………(21)

The significance of above equation is said to be improvement in computational and memory requirement and it contains complete history of past information.

4. Three Sensors Integration Model Analysis

Consider multi-source model described by the likelihood matrix which estimating discrete parameters on the basis of observations and some prior information. The subject of interest is modeled by single state **x** which can take on one of three values:

[A] x1: x is type 1 target (locomotive) where it tracks in satellite visible environment.
[B] x2: x is type 2 target (locomotive) where it tracks in satellite low visible environment
[C] x3: No visible target (locomotive)

Consider sensor observation based on **x** and returns three possible values such as

[a] z1: Observation of a type 1 target (locomotive) when train is in satellite visible area
[b] z2: Observation of a type 2 target (locomotive) when train is in low satellite area.
[c] z3: No target (locomotive) observed.

	P (z1/DGPS)	P (z2/WSN)	P (z3/RFID)
DGPS	0.45	0.1	0.45
WSN	0.1	0.45	0.45
RFID	0.45	0.45	0.1

Then the posterior likelihood in DGPSis given by

P (DGPS| z1, z1) = Q P12 (z1, z1 | DGPS)
= Q P1 (z1 | DGPS) P2 (z1 | DGPS)
= Q× (0.45, 0.45, 0.1) *(0.45, 0.1, 0.45)
= (0.6924, 0.1538, 0.1538)

Comparing this with two observations z1 of DGPS measurements in which the resulting Posterior was (0.488, 0.488, 0.024). It can be seen that WSN measurements adds substantial target discrimination power slight loss of detection performance for the same number of observations. Repeating this calculation for each **z**1, **z**2 observation pair, results in the combined likelihood matrix for different observation such as,

[A].Case1. z1 = z1 and z2 = z1 z2 z3

	P (z1/DGPS)	P (z2/WSN)	P (z3/RFID)
DGPS	0.6924	0.1538	0.4880
WSN	0.1538	0.6924	0.4880
RFID	0.1538	0.1538	0.0240

[B]. Case2.z1 = z2 and z2 = z1 z2 z3

	P (z1/DGPS)	P (z2/WSN)	P (z3/RFID)
DGPS	0.6924	0.1538	0.4880
WSN	0.1538	0.6924	0.4880
RFID	0.1538	0.1538	0.0240

[C]. Case3z1 = z3 and z2 = z1 z2 z3

	P (z1/DGPS)	P (z2/WSN)	P (z3/RFID)
DGPS	0.1084	0.0241	0.2647
WSN	0.0241	0.1084	0.2647
RFID	0.8675	0.8675	0.4706

From the above three cases, we notice that the result of the integration process is to increase the probability in both type 1 target (locomotive in satellite visible) and type 2 targets (locomotive in low satellite visible) at the expense of the no-target (locomotive) theory. Clearly, DGPS, WSN and RFID integration model is good at detecting locomotive in both areas. The fused data emerging out of various sources provides substantial improvements in overall system performance.

5. Simulation Results with Result Analysis

Our experimental results shows that, the comparisons between measurement of kinematic parameters of moving locomotive by single source as well as fusion result using DGPS, WSN and RFID. The experimental setup is as follows: the DGPS model, WSN model, RFID model and data fusion models are scaled of 5 evenly spaced values of the sensing ranging from 1 to 50 are tested, while for the observation model the number of sources is varied from +20 to-20. For three models the communication radius duration is varied from 10 to 45msec in increments of 5. For each combination 10 experiments were run. In some cases a particular experiment is results in unconnected graphs or no inputs. The measurement calculations from these cases are not considered while computing the averages. Figure 4 depicts the prior probability detection density functions when the locomotive is moving in satellite visible areas.

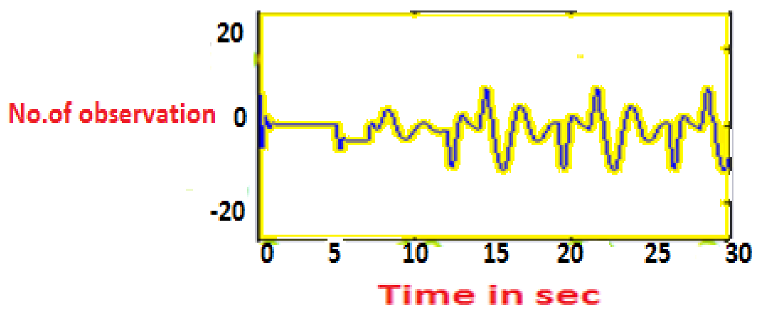

Figure 4. Prior Probability Detection Density Function Observation

Figure 5 represents the posterior probability detection density functions when the locomotive is moving in low satellite visible areas. The sensing range selected for both the cases is same.

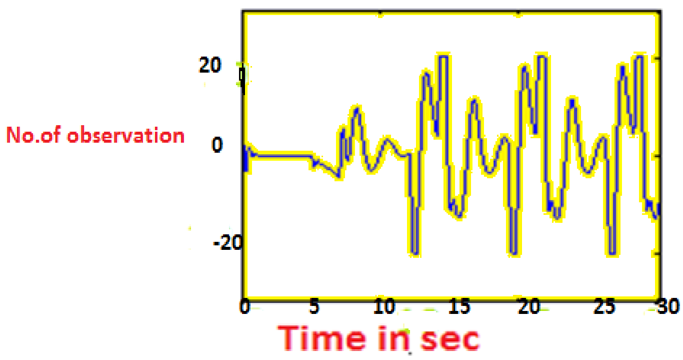

Figure 5. Posterior Probability Detection Density Function

Figure 6 shows the comparison of continuous position monitoring of locomotives using various sensor modes. As the communication range is varied, keeping the sensing range constant at time period up to 50ms. The position of the locomotive is continuously tracked and monitored individually by DGPS, WSN and RFID model. At the very bottom is the lower bound on WSN shown in Figure 6. In this figure it is seen that the WSN and DGPS sensor measurements are seems to coincide with one another in the lower bound all throughout. This is because when detection range is even of moderate length, with high probability results in high detection performance accuracy.

The performance of the RFID approaches optimal as sensing time period increases. For the time interval t=0 to 50 as is seen from the graph, the detection performance of DGPS is more deviated in positive prior probability detection density function. The detection performance of Wireless sensor is more deviated towards negative prior probability detection density function and result of RFID is neither more positive nor more negative prior probability detection density function. For t=0 to 20ms, the detection performance accuracy graph of WSN, RFID and DGPS is almost closely related to each other. For the time interval t=20ms to 50ms, the accuracy of the detection performance of these sensor data are constant. But the fused data show very good detection performance for the t=20 to 50ms.

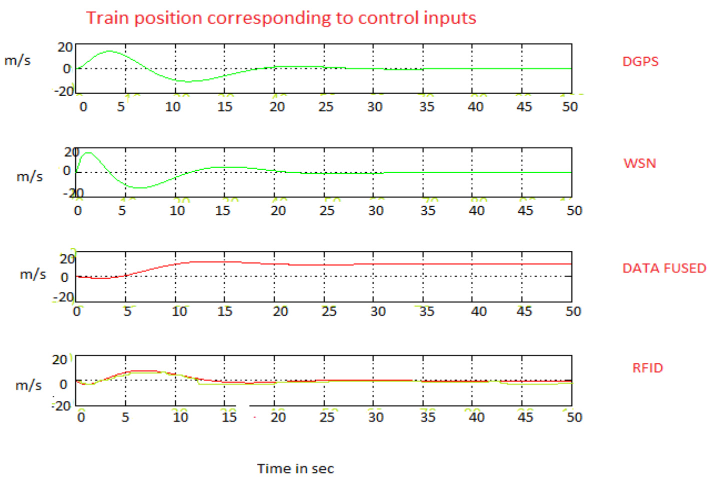

Figure 6. Position Measurement of Moving Locomotive

Figure 7 Shows the velocity measurement performance by various sensors when the locomotive is moving in satellite visible and low satellite visible areas. For the sensing time period t=0 to 35ms, the velocity detection performance of DGPS, WSN are almost shows the result based on posterior density function but RFID performs poorly when the sensing range is really large least performance. At t=45ms, the fused data graph depict more accurate and stable result well all through. In other words, the outputs of DGPS, WSN and RFID models shows same quality and mathematically equivalent results in this test. The priori and posterior error Variance of fused data outputs computed on the basis of comparability with all sources with 80% - 95% detection accuracy.

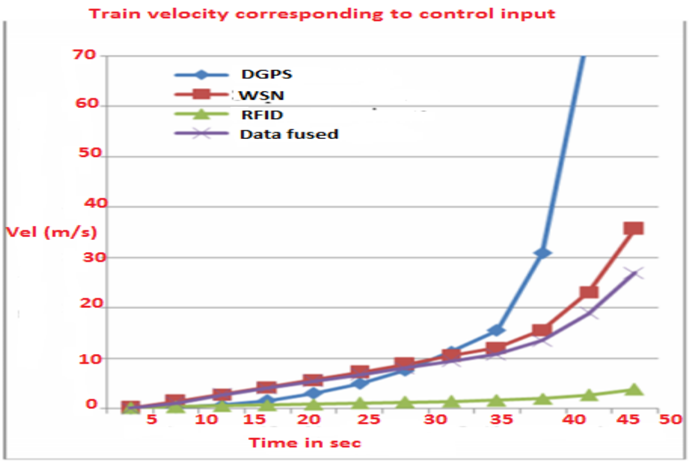

Figure 7. Velocity Measurement of Moving Locomotives

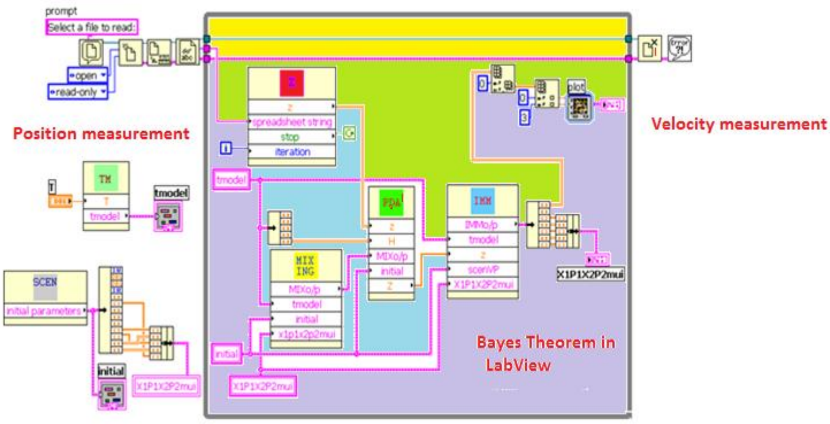

Figure 8. Simulation of Data Fusion using Lab View

From the simulation results it is noticed that the data fusion has improved performance comparing to measurement of individual sensor and that it results in better detection of the locomotive. To summarize, our experiments shows the detection accuracy due to data fusion can be quite significant with DGPS, WSN and RFID particularly when there are lot of sources are consider.

6. Conclusion

Data fusion process is done using multi-source such as DGPS, WSN and RFID models. It provides better numerical precision, reliable and accurate complete information than performance of single sensor. The fused data observation is utilized for kinematics measurement of moving locomotives in satellite visible as well as low satellite visible areas. Bayes theorem is proposed here and the implementation is done with the help of prior probability detection density and posterior probability detection density model. Two set of reading are verified for position and velocity parameters. It is conclude that the computation time for each sensor and fused sensor is estimated with respect to the distribution observation. The probabilistic detection model design based on Bayes theorem have been tested for detection of moving locomotive through the fusion of position and velocity measurements coming from DGPS, WSN and RFID sensors. Our paper has summarized the basics of the Bayes theorem, which is the most popular approach to implement sensor data fusion in probabilistic systems and its related application in real time continuous tracking and monitoring of locomotives. This research proves the probabilistic model offers significant detection performance accuracy level of 95% for moving locomotives across wide range of operational scenarios.

References

[1] A hand book on ‘’Multi-Sensor Data Fusion: An Introduction”, H.B. Mitchell, Springer, **(2007)**.
[2] J. R. Raol, “Multi-Sensor Data Fusion with MATLAB”, CRC Press, Taylor & Francis Group, **(2010)**.
[3] A. Kurian, “Data fusion in an intelligent transportation systems: Progress and challenges a survey”, Journal of Information Fusion, vol. 12, **(2011)**.
[4] S. N. Razavi, “Multi-sensor data fusion: A review of the state-of-the-art”, Journal of Information Fusion, vol. 14, **(2013)**.
[5] L. Aguado, “A low Cost Low Power GPS Positioning system for monitoring Landslide”, NAVI Tech., **(2007)**.
[6] Zhang and Z. Wang, “Integration of RFID into Wireless Sensor Networks: Architectures, Opportunities and Challenging Problems”, Proceedings of the Fifth International Conference on Grid and Cooperative Computing Workshops (GCCW'06), 2006.et work.
[7] J. Stephen and G. Lachapelle, “Development and testing of a GPS-augmented multi- sensor vehicle navigation system”, Journal of Navigation, vol. 54, no. 2, **(2001)**, pp. 297-319.
[8] Oka and L. Lampe, “Distributed Target Tracking signal Strength Measurement by a Wireless Sensor Network”, IEEE Journal on selected areas in Communications, vol. 28, no. 7, **(2010)**, pp. 1006-101.
[9] A. Goldsmith, “Wireless Communication Tradeoff in distributed Control”, Proceedings of the 42nd IEEE Conference on Decision and Control, **(2009)** December, pp. 682-694.
[10] L. Lampe, “Distributed Target Tracking signal Strength Measurement by a Wireless Sensor”, N L. IEEE Journal on selected areas in Communications, vol. 28, no. 7, **(2010)**, pp. 1006-101.
[11] W. Zou and W. Sun, “A multi-dimensional data association algorithm for multi-sensor fusion”, Intelligent Science and Intelligent Data Engineering. Springer Berlin Heidelberg, **(2013)**, pp. 280-288.
[12] T. Cho, C. Lee and S. Choi, “Multi-sensor fusion with interacting multiple model filter for improved aircraft position accuracy”, Sensors, vol. 13, no. 4, **(2013)**, pp. 4122-4137.
[13] Y. Hou, “Multiple-sensor fusion tracking based on square-root cubature Kalman filtering”, Journal of Network, vol. 9, no. 7, **(2014)**.
[14] S. S. Wang, “Multi-feature Fusion Tracking Based on A New Particle Filter”, Journal of Computers, vol. 7, **(2012)**.
[15] S. Chhokar, “An Intelligent System Based on Sensor Integration and Sensor Fusion”, Inter-national Journal of Advanced Research in Computer Science and Software Engineering, vol. 2, **(2012)**.
[16] C. Luo, “Multi sensor Fusion and Integration: Approaches, Applications and Future Research Directions”, **(2001)**.
[17] S. Win berg, “Multi sensor Data Fusion: Target Tracking with a Doppler Radar and an Electro Optic Camera”, IEEE International Conference on Control System, Computing and Engineering, **(2011)**.
[18] S. Amir Hoseini, “Computational complexity comparison of multi sensor single target data fusion method by mat lab”, International Journal of Chaos, Control, Modeling and Simulation (IJCCMS), DOI: 10.5121/ijccms.2013.22011, vol. 2, no. 2, **(2013)** June.
[19] P. Patgar Tanuja and Dr. Shankaraiah, “A kinematics Update State Hypotheses Information Surveillance Model for a Moving Train”, International Journal of Electronics and Electrical (IJEE), vol. 7, **(2015)** June, pp. 30-36.
[20] P. Patgar Tanuja and Dr. Shankaraiah “A Heterogeneous Access Remote Integrating Surveillance Heuristic Model for a Moving Train in Tunnel”, International Journal of Intelligent System and Application (IJISA), vol. 8, no. 3, **(2016)**, pp. 59-65.

Authors

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, Mysore, Karnataka, India under Visvesvaraya Technological University (VTU) Belgaum, India. Her research field is Wireless Sensor Network. Her research is under patent.

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, Mysore, and Karnataka, India

