Fusion Kalman Filter Estimation (FKFE) for Resource Constrained Wireless Sensor Network

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***Abstract*-Fusion kalman filter estimation is proposed for energy and bandwidth constrained wireless sensor network. It is achieved by combining the transmission frequency and dimensionality reduction method. Bandwidth is effectively utilized by transmitting only some components of each sensor kalman estimate to the fusion center. To reduce the energy consumption only one sensor is allowed to transmit at a time. In the fusion center, the proposed fusion estimation based on kalman filter is recursively computed. Performance of the proposed algorithm is evaluated. Finally, an object tracking application is used to see the effectiveness of proposed estimation.**

***Keywords*-Wireless sensor network, kalman filter, bandwidth limitation, fusion schemes.**

I. INTRODUCTION

Wireless sensor network is the set of densely distributed sensor nodes and the processing center. Each sensor has enough ability to sensing, processing and transmitting its observed data [1]. Generally, WSN is formed in a various disturbing environment that might be interfere with its measurement. Thus, the measurement of sensor may be inaccurate. Measurement from various sensors is combined to get more accurate observation than a single one. This is said to be Multi sensor measurement fusion (MSMF). This fusion overcomes node failure, resource limitation and coverage problems. The centralized and decentralized estimation are two types of fusion estimation. In centralized estimation, sensor's measurement is directly transmits to the processing center. It leads to heavy communication traffic and computation burden. In decentralized/ distributed fusion, each sensor preprocesses its measurement and transmits only the compressed data to the processing center where the measured parameter is to be estimated [2]-[3]. When the number of sensors increases, it needs more wires to connect them. Wireless channel is introduced between sensor and processing center in order to reduce the wiring cost and its complexity. Two following issues are arises while transmitting through wireless channel. 1) Due to transmission delay, packet may be delayed or lost [4] - [5]. 2) Since sensors have limited power and communication capabilities, they consume more energy. The main focus is to develop estimation with efficient bandwidth and energy utilization.

II. RELATED WORK

The paper [6]-[9] discussed the fusion estimation problem in constrained network where each sensor minimizes the number of bits that can send to the processing center at each step. Andong [10] proposed the moving horizon estimation for a class of networked systems with quantized measurement, packet dropouts and bounded noise. The moving horizon estimator has been designed by minimizing a stochastic cost function, which deals with estimation and prediction problems in the case of errors and packet dropouts. Hong bin [11] has been proposed the joint dimension and compression techniques to meet the bandwidth and power constraint in wireless sensor network. They developed an effective algorithm that jointly determines the assignment and its corresponding compression matrix associated with each sensor. In paper [12] – [13], they achieved the energy efficient estimation through transmission frequency method. The maximum likelihood estimation was proposed in [14], where energy consumption was reduced by reducing the number of sensor's transmission at a time. By motivation from above method, this present a novel approach based on transmission frequency and dimensionality reduction that satisfy the bandwidth and energy constraints. Different from above analysis, this paper propose a novel idea of selecting some part of sensor estimate directly to transmit to the processing center and no need to compute compression matrix.

III. SYSTEM FORMULATION

Consider a dynamic system in which fusion center is connected with N distributed sensors. Each sensor makes an observation about the nature of environment where it is placed. To overcome the noise involved in measurement and system itself, each sensor computes the kalman estimate of system parameter using its measurement. Sensor's estimate is transmitted into fusion center where proposed estimation is computed. The dynamic system is represented by state space model,

$$x(m+1) = A(m)x(m) + w(m) \quad (1)$$

Similarly, the sensor measurement is represented as

$$y(m) = Cx(m) + v(m) \quad (2)$$

where $x(m)$ is the state of dynamic system, $y(m)$ is the measured value from the sensor . $A(m)$ and C are time varying matrices. $w(m)$ and $v(m)$ are system and measurement noise. They are uncorrelated zero mean noise with following normal distribution $w \sim N(0, Q_w)$ and $v \sim N(0, R)$. Here Q_w and R are covariance of system and measurement noise.

IV. FKFE ALGORITHM

Equations (1) and (2) describing the sensor network with constrained bandwidth and energy. In fig.1, each sensor output is given into kalman filter (KF) to estimate the state of the system under noisy environment. To satisfy a limited bandwidth, only some components of sensor's estimate are allowed to transmit into the processing center. Received state is obtained at the fusion center. It has some zero components that indicate the untransmitted component of sensor's estimate. But, the final fusion estimation is depending on the received state (RS). So, the accuracy of the estimation is improved by computing the compensate estimate (CE).From that, the final fusion kalman filter is derived along with its error covariance matrix.

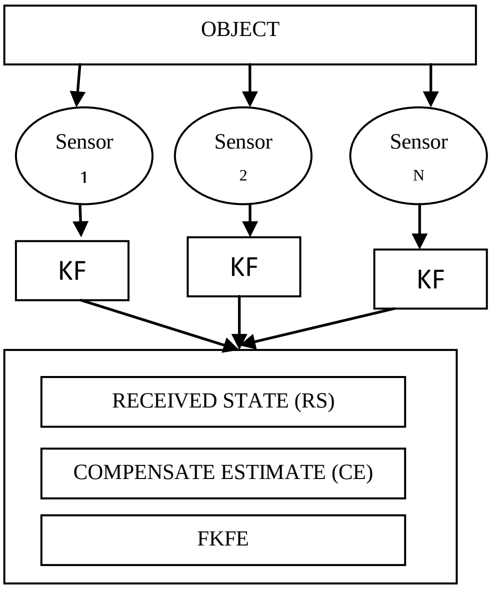

Fig.1. Block diagram of proposed algorithm

This proposed algorithm is used in object tracking applications with the modules such as sensor, trisensor pattern, kalman filter, RS, CE and FKFE.

A. *Sensor*

Sensors are randomly placed in the predefined monitored area. It provides the various attributes of the object which is allowed to move in the monitored area. Assume that each sensor location is known to the fusion center. Based on the sensor location, object is tracked.

B. *Trisensor Pattern*

The sequential pattern of sensor that detects the object movement is obtained. Information from all sensors is not able to transmit because of bandwidth constrained. So, trisensor pattern is computed that finds the sensor with more information about object. It is obtained by considering the occurrence of the object in a particular sensor. Trisensor pattern is used as initial state for kalman estimate.

C. *Kalman Filter*

It is the set of mathematical equations that estimates the state of dynamic parameter observed in noise by minimizing the mean square error. It has two steps predict/time update and correct/Measurement update.

TABLE-I:

Summary of Kalman equations

Initial state of estimate: $\hat{x}(0|-1)=0$

Priori estimate:

$$\hat{x}^{-}(m|m-1)=A(m-1)\hat{x}(m-1)$$

Error covariance matrix:

$$p^{-}(m|m-1)=A(m-1)p(m|m-1)A(m-1)^{T}+Q$$

Posteriori estimate :

$$\hat{x}^{+}(m|m)=[1-G(m)C]A(m-1)x(m-1)+G(m)y(m)$$

Gain matrix:

$$G(m)=p^{-}(m|m-1)C^{T}(m)[C(m)p^{-}(m|m-1)C^{T}(m)+R]$$

Error covariance matrix:

$$p^{+}(m|m)=[I-G(m)C(m)]p^{-}(m|m-1)$$

D. *Received State*

Consider that sensor k send its kalman filter estimate to the fusion center. In order to satisfy the limited bandwidth, only some components of kalman estimate are allowed to transmit it. Thus RS at the fusion center is obtained as

$$\hat{x}_k^{r}(m)=H_k(m)\hat{x}_k(m) \qquad (3)$$

where H (m) is the diagonal matrix with the elements 0 and 1.

E. *Compensate Estimate (CE)*

The performance of the fusion estimation is depending only on the received information from sensor. Since some component in RS are zero, compensate estimate (CE) is computed to overcome zero components and to achieve high precision. It is the linear combination of received state and forward prediction. Thus the CE for received state from sensor k is

$$\hat{x}_k^{c}(m)=\hat{x}_k^{r}(m)+\left[1-H_k(m)\right]A(m-1)\hat{x}(m-1) \qquad (4)$$

F. *Fusion Kalman Filter Estimate (FKFE)*

Once the compensate estimate for each sensor is obtained, then final fusion estimation is given by

$$\hat{x}(m)=\sum_{k=1}^{N} Omega_k(m)\,\hat{x}_k^{\,c}(m) \qquad (5)$$

Where, $Omega_k(m)$ is the optimal weighting matrix.

V. SIMULATION

Our simulation is carried out in GUI (MATLAB) for object tracking network. The simulation setting is listed in the following table 2

Table-II:

Simulation settings

Number of sensors	Up to 100 sensor nodes
Number of tracking object	1
Monitored region	150× 150 meter2
Sensor coverage area	5-15m
Network topology	2D- Grid topology
Simulation duration	10sec/object
Number of trails	1

The GUI for object tracking network is developed. It is the process of tracking the mobile object in the predefined monitored area and reports its latest location. The object tracking network have six push buttons No. of sensors, No. of tracking object, trisensor pattern, FKFE, Proposed constrains and exit. The fig.2 shows the snapshot of network with 66 nodes and object obj1.Here, object movement is indicated by red triangle icon. Assume that each sensor is static in nature and its location is well known to the processing center. As the object moves in the network, the sensor nodes have capable of observing the various attributes of object such as position, velocity and acceleration.

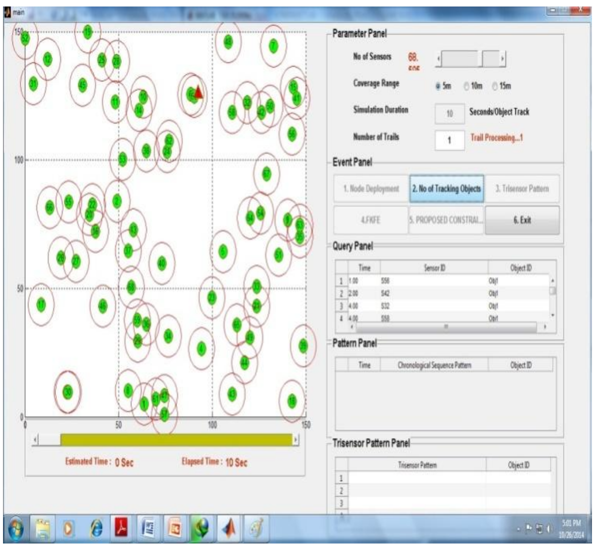

Fig.2. Snapshot of object movement in the network of 66 nodes.

The object movement is detected by trisensor pattern. The sensor that detects the object is recorded in the query panel. Finally the sensor that detects the object during the time of simulation is shown in the pattern panel. From that, trisensor pattern is obtained in the trisensor pattern panel. Instead of transmitting all sensors measurement, sensor with high confidence of information is transmitted to the fusion center. At fusion center, noisy information is obtained. Finally Fusion Kalman Filter Estimation (FKFE) is recursively computed. The fig.3 and 4 show the estimation of object parameters through FKFE.

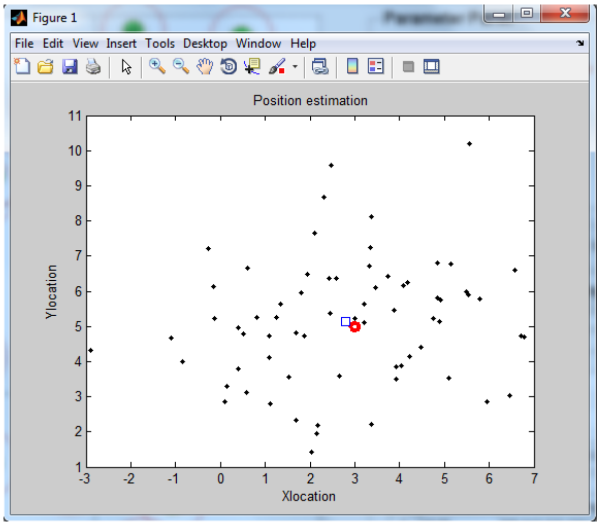

Fig.3. Position estimation

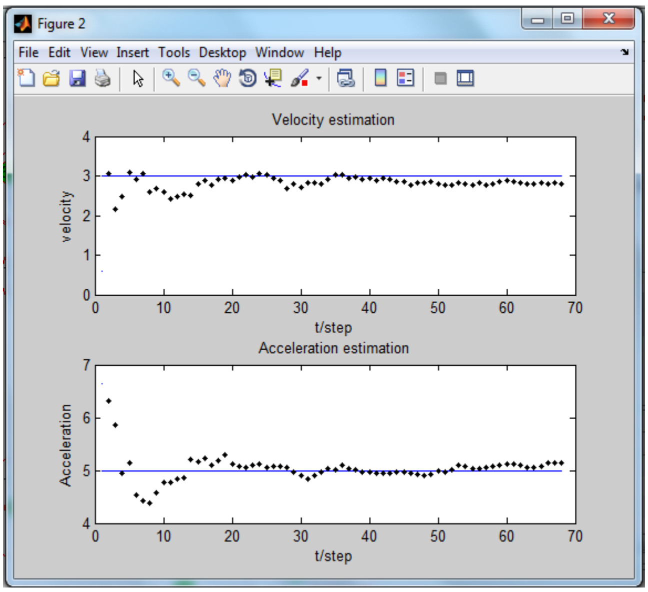

Fig.4. Velocity and acceleration

The performance of the estimation is analyzed through the error covariance matrix. The error covariance matrix of kalman filter, compensate estimate and FHKF are compared in the fig.5. It shows that FKFE has low error covariance compared to KF and CE. It reveals that our fusion kalman filter estimation (FKFE) has accurate estimator compared to Kalman filter.

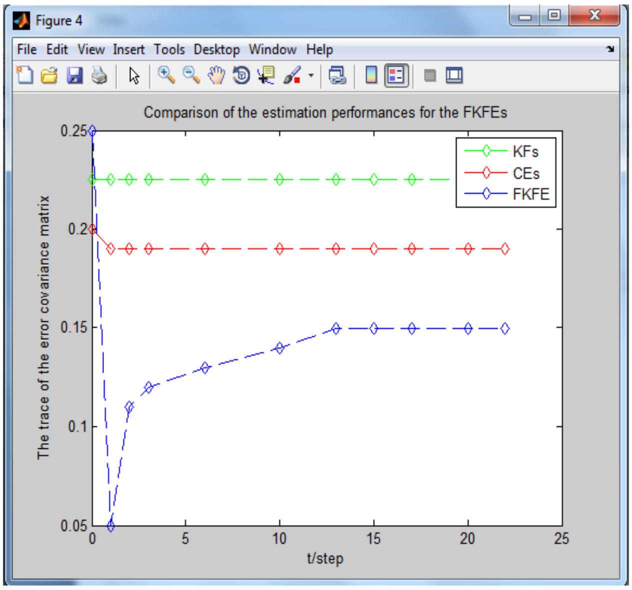

Fig.5. Comparison of estimation for FKFE, KF and CE

The Mean square error for position, velocity and acceleration estimation is individually computed and it is plotted in the fig.6. It shows that how far the estimated value is differs from the original values.

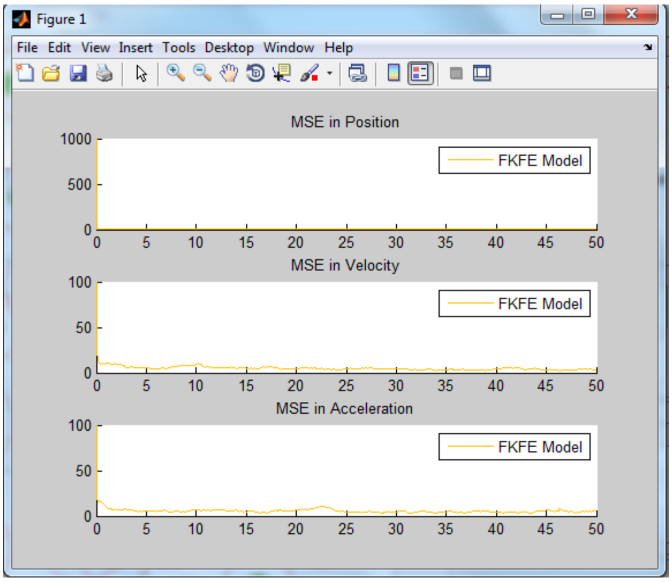

Fig.6. MSE in position, velocity and acceleration estimation

Energy saving rate (ESR) of the object tracking network is calculated by dividing the energy consumed by sensor with total energy given in the network and is plotted as

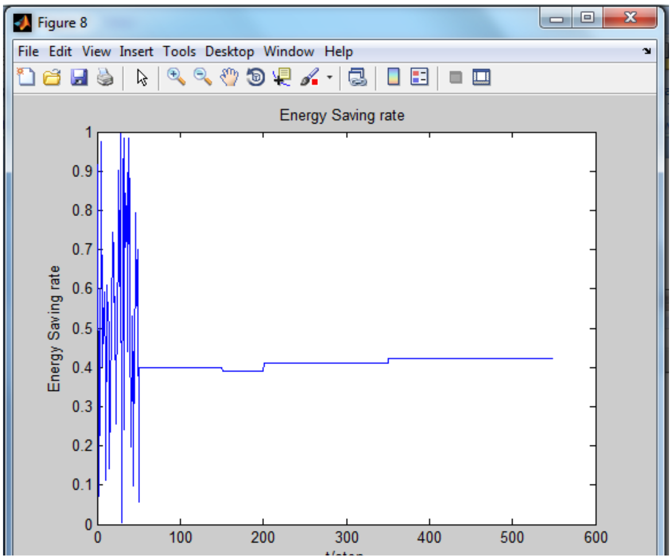

Fig.7. ESR in wireless sensor network

VI.CONCLUSION

Thus the fusion kalman filter estimation has been proposed for wireless sensor network with constrained resources. It uses dimensionality reduction and transmission period methods to satisfy both bandwidth and energy constraints. This proposed approach has been used in object tracking applications. Position, velocity and acceleration of object have been estimated through FKFE. Finally, performance of the estimation has been evaluated through MSE and ESR. Our future work is to design the distributed fusion estimator for non linear measurement.

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