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A Decentralized Data Fusion Algorithm for Local Kalman Estimates in Multisensor Environment

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Abstract—**A novel suboptimal fusion algorithm for decentralized architecture is proposed. The proposed method is based on the optimal mean-square combination of an arbitrary number of local estimates. The proposed algorithm is well suited for real-time computation of global estimate with parallel processing of individual sensor measurements. Low communication bandwidth is required for proposed method as only local estimates are transmitted among network nodes instead of higher dimensional raw sensor measurements or feature vectors.**

Index Terms - **Dynamic systems, Kalman filter, Decentralized network architecture, Data fusion, Multisensor environment**

I. INTRODUCTION

In recent years, here has been increased interest in multisensor data fusion to improve the accuracy of estimation parameters and system states [1-2]. Combining local estimates and/or measurements on different times/types of sensors is common problem in multisensor environment. The Bar-Shalom-Campo formula (BSCF) for two estimates is commonly used in data fusion for tracking and filtering [4]. Some applications of Kalman filtering (KF) to various network topologies of decentralized systems are discussed in [3-4]. During early 1960's number of technical paper were published describing sequential approaches to estimation. Kalman and Bucy published paper [6] describing linearized sequential technique to update an estimate of state vector. An informal history of the development of Kalman filter and its application to space flight is provided by McGee A et al. [7]. Since then much work has been performed on discrete estimation to use digital computers for related problems.

Several approaches may be used to derive sequential estimation equations. This paper deals with estimation problem with restricted computation and communication resources. The centralized signal processing architecture requires high computation power and communication bandwidth whereas sensors perform as data collectors only. Centralized network can collapse down due to discontinuation in communication channel or central fusion centre failure.

A new fusion algorithm for multisensor environment is proposed which is equally suited for different network architectures with reduced-order and robust functionality. The proposed algorithm is generalization of BSCF for an arbitrary number of local estimates.

The proposed algorithm is applied to linear dynamic systems with multisensor environment to compute global estimate using local sensor estimates. The proposed Fusion Formula (FF) represents an optimal mean square linear combination of local Kalman estimates generated by individual sensors. Weights of fused local Kalman estimates depend on cross covariance between filtering errors. Sensors are assumed to have processing capabilities i.e. a certain amount of computation is performed at each sensor and compressed version of sensor measurements transmitted to be fused for global inference. The FF has parallel processing architecture for sensors observations. Fusion centre may or may not be dedicated node in accordance with network architecture, resources available. The proposed algorithm reduces the computational cost, communication bandwidth requirements and suitable for real-time applications with robust behavior.

Remaining portion of this paper explains problem statement, derivation of proposed scheme, experimental results and conclusion.

II. DECENTRALIZED DATA FUSION ALGORITHM

Problem Formulation: For simplicity, consider a discrete-time linear dynamic system with additive white Gaussian noise,

$$x_{k+1} = F_k x_k + G_k v_k, \quad k = 0,1,\ldots \tag{1}$$

where $x_k \in \mathbf{R}^n$ is state vector, and $v_k \in \mathbf{R}^r$ is a Gaussian random noise $v_k \sim N(0, Q_k)$. Suppose that overall observation vector $Y_k \in \mathbf{R}^m$ is composed of N different types of observation sub-vectors (local sensor measurements) i.e. $y_k^{(1)},\ldots,y_k^{(N)}$,

$$Y_k = \left[y_k^{(1)} \cdots y_k^{(N)}\right]^T, \tag{2}$$

where $y_k^{(i)}, \quad i = 1,\ldots,N$ are determined by

$$\begin{aligned} y_k^{(1)} &= H_k^{(1)} x_k + w_k^{(1)}, \quad y_k^{(1)} \in \mathbf{R}^{m_1}, \\ &\vdots \\ y_k^{(N)} &= H_k^{(N)} x_k + w_k^{(N)}, \quad y_k^{(N)} \in \mathbf{R}^{m_N}, \end{aligned} \tag{3}$$

with observation noise $\{w_k^{(1)}\},\ldots,\{w_k^{(N)}\}$ being zero-mean white Gaussian i.e. $w_k^{(i)} \sim \mathbf{N}(0, R_k^{(i)})$, $i = 1,\ldots,N$, $m_1 + \cdots + m_N = m$. The initial state is modeled as a Gaussian random vector $x_0 \sim N(\bar{x}_0, P_0)$. The process noise $\{v_k\}$, observation noise $\{w_k^{(i)}\}$, and initial state x_0 are mutually independent. It is required to estimate the state x_k of dynamic system using overall observation vector Y_k. Rewriting the observation model (2), (3) in equivalent form

$$Y_k = \begin{bmatrix} H_k^{(1)} \\ \vdots \\ H_k^{(N)} \end{bmatrix} x_k + \begin{bmatrix} w_k^{(1)} \\ \vdots \\ w_k^{(N)} \end{bmatrix} \quad (4)$$

Applying conventional Kalman filter (KF) to the model (1), (4) - We get optimal estimate $\hat{x}_k^{opt}$ of the state x_k using overall observations $Y_k \in \mathbf{R}^{\mathbf{m}}$. However implementation of KF has several limitations like computational cost, bandwidth requirements for data transmission to central location and increased numerical errors in conjunction with data size. KF is impractical for its centralized network architecture, numerical errors and resource requirements. Reduced-order, parallel architecture filters are preferable with no obligation to use entire sensor measurements Y_k at central location.

The remaining portion of paper deals with formulation of computing local sensor estimates and fusion to determine global estimate.

The new proposed algorithm is based on assumption that the overall measurement vector Y_k consists of observation sub-vectors $y_k^{(1)},\ldots,y_k^{(N)}$ to be processed in parallel fashion. According to (1) and (3), we have unconnected dynamic subsystems $(i = 1,\ldots,N)$ with state vector $x_k \in \mathbf{R}^{\mathbf{n}}$ and observation sub-vectors (local sensor measurements) $y_k^{(i)} \in \mathbf{R}^{\mathbf{m}_i}$:

$$\begin{aligned} x_{k+1} &= F_k x_k + G_k v_k, \\ y_k^{(i)} &= H_k^{(i)} x_k + w_k^{(i)} \end{aligned} \quad (5)$$

Where **i** represent fixed-number of subsystems. Let us denote the local estimate of the state x_k based on the local observation $y_k^{(i)}$ by $\hat{x}_{k|k}^{(i)}$. To find $\hat{x}_{k|k}^{(i)}$ we apply the KF to the subsystem. **N** local estimates are computed by applying KF on individual sensor observations i.e. processing all measurements in parallel mode. KF equations to determine local estimates are as follows:

$$\begin{aligned} \hat{x}_k^{(i)} &= F_{k-1}\hat{x}_{k-1}^{(i)} + K_k^{(i)}\left[y_k^{(i)} - H_k^{(i)}F_{k-1}\hat{x}_{k-1}^{(i)}\right], \\ M_k^{(ii)} &= F_{k-1}P_{k-1}^{(ii)}F_{k-1}^T + G_{k-1}Q_{k-1}G_{k-1}^T, \\ K_k^{(i)} &= M_k^{(ii)}\left(H_k^{(i)}\right)^T\left[H_k^{(i)}M_k^{(ii)}\left(H_k^{(i)}\right)^T + R_k^{(i)}\right]^{-1}, \\ P_k^{(ii)} &= \left[I_n - K_k^{(i)}H_k^{(i)}\right]M_k^{(ii)}, \end{aligned} \quad (6)$$

where $i = 1,\ldots,N$, and $P_k^{(ii)}$ is the filtering error covariance, i.e.

$$P_k^{(ii)} = \mathrm{cov}\{\tilde{x}_k^{(i)}, \tilde{x}_k^{(i)}\}, \quad \tilde{x}_k^{(i)} = x_k - \hat{x}_k^{(i)}; \quad (7)$$

$i = 1,\ldots,N$

Using KF on model represented by equation (5), we have N local Kalman estimates

$$\hat{x}_k^{(1)}, \quad \ldots, \quad \hat{x}_k^{(N)} \quad (8)$$

based on observations $y_k^{(1)}, \ldots, y_k^{(N)}$ respectively with corresponding local Kalman error covariance

$$P_k^{(11)}, \quad \ldots, \quad P_k^{(NN)}. \quad (9)$$

In the next step, all the local Kalman estimates are fused together to compute global estimate. While applying the same problem statement for different kind of dynamic systems, we assumed that process and measurement noise is constant for simplicity otherwise these are varying with time in real life. The new global estimate $\hat{x}_k^{ge}$ of the state vector x_k based on the overall local estimates (8) by using the FF:

$$\hat{x}_k^{ge} = \sum_{i=1}^{N} c_k^{(i)}\hat{x}_k^{(i)}, \quad \sum_{i=1}^{N} c_k^{(i)} = I_n, \quad (10)$$

where I_n is the $n \times n$ unit matrix, and $c_k^{(1)},\ldots,c_k^{(N)}$ are $n \times n$ the time-varying weighting matrices determined by mean-square criterion,

$$J_k = E\left(\left\| x_k - \sum_{i=1}^{N} c_k^{(i)}\hat{x}_k^{(i)} \right\|^2\right) \to \min_{c_k^{(i)}}. \quad (11)$$

Following theorem describes global estimate $\hat{x}_k^{ge}$ and error covariance

$$P_k^{ge} = \mathrm{cov}\left(\tilde{x}_k^{ge}, \tilde{x}_k^{ge}\right), \ \tilde{x}_k^{ge} = x_k - \hat{x}_k^{ge}. \quad (12)$$

Theorem 1 (Fusion Formula): Let $\hat{x}_k^{(1)},\ldots, \hat{x}_k^{(N)}$ are the local Kalman estimates (8) of an unknown state vector x_k. The weighting matrices $c_k^{(1)},\ldots,c_k^{(N)}$ are given by

$$\sum_{i=1}^{N} c_k^{(i)}\left[P_k^{(ij)} - P_k^{(iN)}\right] = 0, \quad \sum_{i=1}^{N} c_k^{(i)} = I_n, \quad (13)$$

where $P_k^{(ii)}$, the local Kalman error covariance (9) is determined using KF (6), and $P_k^{(ij)} = \left(P_k^{(ji)}\right)^T$, $i \neq j$ is cross-covariance,

$$P_k^{(ij)} = \mathrm{cov}\left\{\tilde{x}_k^{(i)}, \tilde{x}_k^{(j)}\right\}, \quad i \neq j. \tag{14}$$

Theorem 2: The cross-covariance $P_k^{(ij)}$ satisfies the following recursion:

$$P_k^{(ij)} = \left[I_n - K_k^{(i)} H_k^{(i)}\right]\left[F_{k-1} P_{k-1}^{(ij)} F_{k-1}^T + G_{k-1} Q_{k-1} G_{k-1}^T\right] \times \left[I_n - K_k^{(j)} H_k^{(j)}\right]^T, \quad P_0^{(ij)} = P_0, \quad i, j = 1, \ldots, N, \tag{15}$$

where the gain $K_k^{(i)}$ is determined by means of KF (6).

Corollary 1: If $\hat{x}_k^{(1)}$, …, $\hat{x}_k^{(N)}$ are unbiased local Kalman estimates then the global estimate $\hat{x}_k^{ge}$ in (10) is unbiased too.

Corollary 2: The overall error covariance P_k^{ge} is given by

$$P_k^{ge} = \sum_{i,j=1}^{N} c_k^{(i)} P_k^{(ij)} \left(c_k^{(j)}\right)^T. \tag{16}$$

The local Kalman estimates (6), FF (10) and recursive equation (15) completely define new fusion algorithm for multisensor environment. If $N = 2$, the FF (10) and (13) reduces to the Bar-Shalom-Campo formula [9]:

$$\hat{x}_k^{ge} = c_k^{(1)} \hat{x}_k^{(1)} + c_k^{(2)} \hat{x}_k^{(2)},$$

$$c_k^{(1)} = \left[P_k^{(22)} - P_k^{(21)}\right]\left[P_k^{(11)} + P_k^{(22)} - P_k^{(12)} - P_k^{(12)}\right]^{-1}, \tag{17}$$

$$c_k^{(1)} = \left[P_k^{(11)} - P_k^{(12)}\right]\left[P_k^{(11)} + P_k^{(22)} - P_k^{(12)} - P_k^{(12)}\right]^{-1}.$$

if the two estimates $\hat{x}_k^{(1)}$ and $\hat{x}_k^{(2)}$ are uncorrelated, i.e. $P_k^{(12)} = P_k^{(21)} = 0$ in Equation (17), then we have the Millman's formulae for weights [8], [11]:

$$c_k^{(1)} = P_k^{(22)}\left[P_k^{(11)} + P_k^{(22)}\right]^{-1} \tag{18}$$

$$c_k^{(2)} = P_k^{(11)}\left[P_k^{(11)} + P_k^{(22)}\right]^{-1},$$

The local Kalman estimates $\hat{x}_k^{(1)}, \ldots, \hat{x}_k^{(N)}$ are computed in parallel fashion to facilitate real time processing. The proposed fusion algorithm exhibits following properties:

$$P_k^{ij} = \left(P_k^{ji}\right)^T, P_k^{ii} = \left(P_k^{ii}\right)^T \tag{19}$$

$$\frac{\partial}{\partial C_k^{(i)}}\left[\mathrm{tr}\left(C_k^{(i)} P_k^{(ij)}\right)\right] = \left(P_k^{(ij)}\right)^T; \tag{20}$$

$$\frac{\partial}{\partial C_k^{(i)}}\left[\mathrm{tr}\left(P_k^{(ij)} C_k^{(i)}\right)\right] = \left(P_k^{(ij)}\right) \tag{21}$$

$$\frac{\partial}{\partial C_k^{(i)}}\left[\mathrm{tr}\left(C_k^{(i)} P_k^{(ij)} C_k^{(i)T}\right)\right] = C_k^{(i)}\left[P_k^{(ij)} + P_k^{(ij)T}\right] \tag{22}$$

The proposed filter renders robust behavior with automatic correction incase of diverging local estimate $\hat{x}_k^{(i)}$. Diverging local estimate $\hat{x}_k^{(i)}$ will have zero or less contribution in the weighted sum of local estimates i.e. weight matrix $c_k^{(i)}$ for diverging local estimates approaches zero in FF.

III. EXPERIMENTAL AND RESULTS

Experiment 1: Fusion of Multisensor Estimates

Consider a discrete-time scalar system described by

$$x_{k+1} = a x_k + v_k, \quad k = 0, 1, \ldots, T, \tag{23}$$

$$y_k^{(i)} = x_k + w_k^{(i)}, \quad i = 1, 2, \ldots, N, \tag{24}$$

where $v_k \sim \mathbf{N}(0, q)$, $x_0 \sim \mathbf{N}(\bar{\theta}, \sigma_\theta^2)$, $w_k^{(i)} \sim \mathbf{N}(0, r_i)$, $i = 1, \ldots, N$. Equations (23)-(24) represent dynamic system consisting of N sensors. The parameters are subject to a = 0.9, $T = 20$, q = 0.01, $\bar{\theta} = 0.5$, $\sigma_\theta^2 = 1$, and $N = 1,2,3,4$. $\hat{x}_k^{opt}$ represents the optimal/conventional Kalman filter estimate whereas global estimate $\hat{x}_k^{ge}$ determined using N local estimates i.e. $\hat{x}_k^{(1)}$, …, $\hat{x}_k^{(N)}$. The observation noise variances of different sensors are assumed to be r1 = 0.2, r2 = 0.1, r3 = 0.06 and r4 = 0.04; for simplicity. Fig. 1 shows comparison of mean square error (MSE) of optimal KF estimate - P_k^{opt} and global estimate - P_k^{ge}. MSEs of optimal KF estimate and global estimate coincide in the presence of single sensor. MSE for P_k^{opt} and P_k^{ge} are decrementing with increasing number of sensors. Number/type of sensors' selection is dependent on required accuracy, resources available and dynamic system behavior.

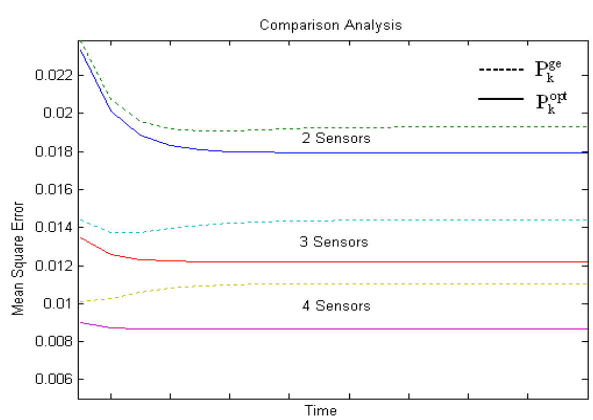

Fig. 1: MSE Analysis of Optimal KF and Global Estimate

The difference between P_k^{opt} and P_k^{ge} is small for different number of sensors especially in steady state. P_k^{opt} suffers from inherent problem of numerical errors with increasing number of sensors. Computation of P_k^{opt} requires higher communication bandwidth to transmit raw sensor measurements i.e. high dimension data. Whereas P_k^{ge} computation is possible on lower communication bandwidth as local estimates are transmitted instead of raw sensor measurements.

Experiment 2: Damper Harmonic Oscillator with Multisensor Environment

Consider a two dimensional model of the harmonic oscillator [11]

$$\dot{x}_t = \begin{bmatrix} 0 & 1 \\ -\omega_n^2 & -2\alpha \end{bmatrix} x_t + \begin{bmatrix} 0 \\ 1 \end{bmatrix} v_t, \quad t \geq 0, \tag{25}$$

where $x_t = \begin{bmatrix} x_{1,t} & x_{2,t} \end{bmatrix}^T$ and $x_{1,t}$ is position, and $x_{2,t}$ is velocity, $v_t \sim (0, q)$ represent normally distributed system noise and initial state $x_0 \sim N(\bar{x}_0, P_0)$. The measurement model consists of two sensors

$$\begin{aligned} y_t^{(1)} &= H^{(1)} x_t + w_t^{(1)}, \\ y_t^{(2)} &= H^{(2)} x_t + w_t^{(2)}, \end{aligned} \tag{26}$$

where $H^{(1)}$ and $H^{(2)}$ are 1×2 measurement matrices, $w_t^{(1)} \sim (0, r_1)$ and $w_t^{(2)} \sim (0, r_2)$ represent white measurement noises. System noise, measurement noise and initial states are assumed to be uncorrelated. The optimal KF is applied to measurement model for state estimation

$$Y_t = H x_t + w_t, \tag{27}$$

where

$$Y_t = \begin{bmatrix} y_t^{(1)} \\ y_t^{(2)} \end{bmatrix}, \quad H = \begin{bmatrix} H^{(1)} \\ H^{(2)} \end{bmatrix}, \quad w_t = \begin{bmatrix} w_t^{(1)} \\ w_t^{(2)} \end{bmatrix} \tag{28}$$

The global estimate using local sensor estimates is computed as follows:

$$\hat{x}_t^{ge} = c_t^{(1)} \hat{x}_t^{(1)} + c_t^{(2)} \hat{x}_t^{(2)}, \tag{29}$$

where $\hat{x}_t^{(1)}$ and $\hat{x}_t^{(2)}$ are local Kalman estimates based on the individual measurement models:

$$y_t^{(1)} = H^{(1)} x_t + w_t^{(1)}, \tag{30}$$

$$y_t^{(2)} = H^{(2)} x_t + w_t^{(2)}. \tag{31}$$

This experiment consists of three programs of measurement: Program 1. Position $x_{1,t}$ is estimated by two sensors i.e.

$$H^{(1)} = \begin{bmatrix} 1 & 0 \end{bmatrix}, \quad H^{(2)} = \begin{bmatrix} 1 & 0 \end{bmatrix}; \tag{32}$$

Program 2. Velocity $x_{2,t}$ is estimated by two sensors i.e.

$$H^{(1)} = \begin{bmatrix} 0 & 1 \end{bmatrix}, \quad H^{(2)} = \begin{bmatrix} 0 & 1 \end{bmatrix}; \tag{33}$$

Program 3. Position and velocity estimated by sensor-1 and sensor-2 respectively i.e.

$$H^{(1)} = \begin{bmatrix} 1 & 0 \end{bmatrix}, \quad H^{(2)} = \begin{bmatrix} 0 & 1 \end{bmatrix}; \tag{34}$$

let $\omega_n^2 = 0.64$, $\alpha = 0.16$, $q = 1$, $r_1 = 0.02$, $r_2 = 0.01$, and $P_0 = \mathrm{diag}\begin{bmatrix} 2 & 1 \end{bmatrix}$. Mean square error (MSE) of optimal KF and global estimation filter is represented as,

$$P_t^{KF} = E\left[e_t^{KF} \left(e_t^{KF}\right)^T\right] = \begin{bmatrix} P_{11}^{KF} & P_{12}^{KF} \\ P_{12}^{KF} & P_{22}^{KF} \end{bmatrix} \tag{35}$$

where $e_t^{KF} = x_t - \hat{x}_t^{KF}$

$$P_t^{ge} = E\left[e_t^{ge} \left(e_t^{ge}\right)^T\right] = \begin{bmatrix} P_{11}^{ge} & P_{12}^{ge} \\ P_{12}^{ge} & P_{22}^{ge} \end{bmatrix} \tag{36}$$

where $e_t^{ge} = x_t - \hat{x}_t^{ge}$

Following figs. show automatic correction and robust nature of proposed algorithm. Fig First sensor observes position while second dedicated for velocity. Estimation results for program measurement – 3 (34) are displayed in fig. 2-4.

In measurement program – 3, each sensor is observing different dynamic system component, accuracy of local estimate depends on what sensor actually observes. Sensor – 1 observing position of damper harmonic oscillator, can better estimate position than velocity as depicted in fig. 2. The global estimate computed does not deviate from ideal position due to robust nature of proposed filter i.e. weight of diverging estimate tends to zero having minimal effect on global estimate. Individual local estimates are not reliable due to diverging behavior, spatial and temporal coverage limitation.

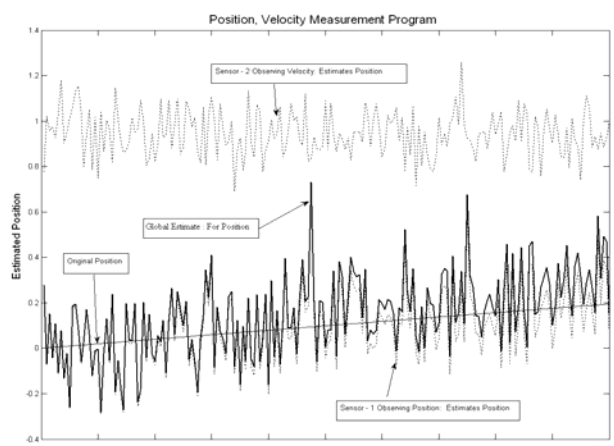

Fig. 2: Comparison of Local, Global Position Estimation

Fig. 3. compares local estimates and global estimates for velocity. Sensor – 2 observing velocity produces precise local estimate while sensor -1 estimates diverging behavior. Global estimate stays closer to ideal velocity by discarding diverging estimate in fusion process.

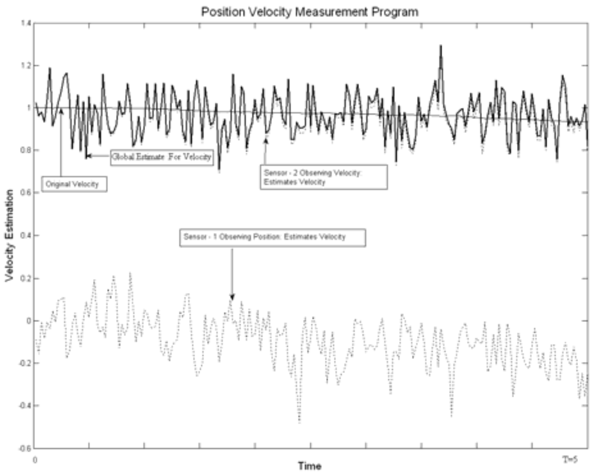

Fig. 3: Comparison of Local, Global Velocity Estimation

Fig. 4. represents MSE analysis of optimal KF and global estimate, differences between P_t^{KF} and P_t^{ge} are negligible especially for steady-state. It is apparent that proposed algorithm exhibits efficiency property i.e. quality of estimator increasing with number of measurements.

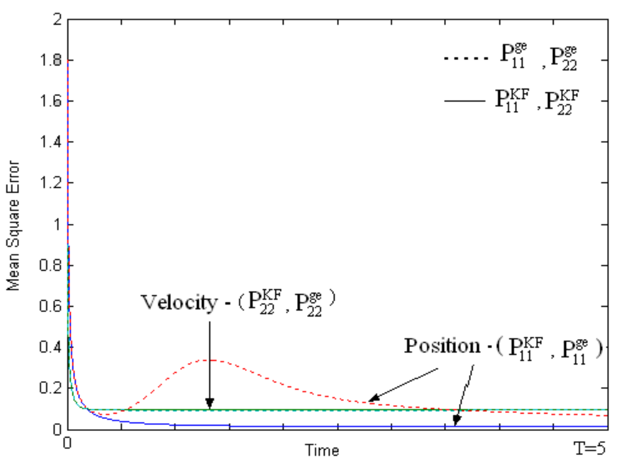

Fig. 4: MSE Analysis of KF and GE Filter

IV. CONCLUSION

In this paper, we designed novel fusion algorithm for linear dynamic systems in multisensor environment. The proposed filter presents linear combinations of local Kalman estimates. Each local estimate is fused according to the minimum mean-square criterion. Simulation results prove good accuracy of proposed filter. The parallel structure of the proposed algorithm can be supportive to produce estimate for real-time applications. The proposed filter is well suited for real-time applications in multisensor environment with decentralized network architecture. Proposed decentralized fusion filter eliminates many of the inherent disadvantages of centralized and hierarchical architecture and can be used in various applications: industrial, military, space, communications, target tracking, inertial navigation, to name a few.

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