OCP Based Online Multisensor Data Fusion for Autonomous Ground Vehicle

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Abstract

In this paper, online multisensor data fusion algorithm using CORBA event channel is proposed, in order to deal with simplifying problem in sensor registration and fusion for vehicle's state estimation. The networked based navigation concept for Autonomous Ground Vehicle (AGV) using several sensors is presented. A simulation of various application scenarios are considered by choosing several parameters of UKF, i.e. weighting constant for sigma points α and β, and square root matrix κ. Normalized mean square error (MSE) of Monte Carlo simulations are computed and reported in the simulation results. Furthermore, the middleware infrastructure based on Open Control Platform (OCP) to support the interconnection between the whole filter structures also reported.

Keywords: *Autonomous Vehicle, OCP, CORBA, UKF*

1. Introduction

The software based controls for robotic and autonomous vehicle have been dominated in recent years. An OCP is an object-oriented software infrastructure implemented that allows seamless integration of cross-platform software and hardware components in any control system architecture. An OCP is a middleware that is based on the real-time common object request broker architecture (RT-CORBA). Middleware is connectivity software that consists of a set of services, allowing multiple processes running on one or more machines to interact across a network [1].

The multisensor data fusion using Kalman filter (KF) has been widely applied in integrated navigation system for many applications [2-3]. Estimation of navigation system in nonlinear system approach to use the extended Kalman filter (EKF) which simply linearizes all nonlinear models are reported in [4-5], so that the traditional KF can be used. An alternative approach, the unscented Kalman filter (UKF) where the random variable, Gaussian distributions is linearized while the nonlinear model equations are directly used in the calculations [6]. The centralized filter where all measured sensor data are communicated to the central site for processing [7], and distributed filter [8] where the local estimators from all sensor can yield the global optimal or sub optimal state estimator according to certain information fusion criterion.

In this paper, an online decentralized multisensor data fusion of two stage federated UKF algorithms connected by RT-CORBA middleware network is proposed. We assumed that the problem solution of fault detection and isolation in the Autonomous Ground Vehicle (AGV) will made easily.

2. System Models

When the vehicle negotiates a turn, this motion can be described as a rotation about Instantaneous Centre of Rotation (ICR) with the same angular speed, we assumed that there is no slip between the tires and the ground. In the figure1, a degree of freedom that appear are the steer angle ϕ and drive speed γ of the front wheel can be expressed as function of the control inputs which act on each wheel. B is the distance between the front and rear axles, and the width of front axle is H.

The filters state space x consists of the position of the body (x_1 and x_2), its velocity (x_3 and x_4), and a parameter of its aerodynamic property (x_5). The vehicle state dynamics in a simple form are:

$$
\begin{aligned}
\dot{x}_1(k) &= x_3(k) \\
\dot{x}_2(k) &= x_4(k) \\
\dot{x}_3(k) &= A(k)x_3(k) + D(k)x_1(k) + \vartheta_1(k) \\
\dot{x}_4(k) &= A(k)x_4(k) + D(k)x_2(k) + \vartheta_2(k) \\
\dot{x}_5(k) &= \vartheta_3(k) \\
A(k) &= -\beta(k)\exp\left\{R_0 - R(k)\right\}V(k) \\
D(k) &= \frac{D_{m_0}}{r^2(k)} \\
\beta(k) &= \beta_0(k)\exp x_5(k)
\end{aligned}
\tag{1}
$$

where $A(k)$ is acceleration-related force, $D(k)$ is breaking-related force, ϑ_1, ϑ_2, and ϑ_3 is measurement noise, β is vehicle characteristic uncertainly, $R(k)$ is distance from central $=\sqrt{x_1^2(k)+x_2^2}$, and $V(k)$ is absolute vehicle speed $=\sqrt{x_3^2(k)+x_4^2}$. In summary, the state space is:

$$X_{t+1} = \begin{bmatrix} X_1 & X_2 & \gamma & R & \omega & \dot{\omega} \end{bmatrix}^T \tag{2}$$

where ω is the angular speed of the front wheel, and its expressed as $\begin{bmatrix} \dfrac{\omega_{fr} \sin\gamma_{fr}}{\sin\gamma} & \dfrac{\omega_{fl} \sin\gamma_{fl}}{\sin\gamma} \end{bmatrix}^T$.

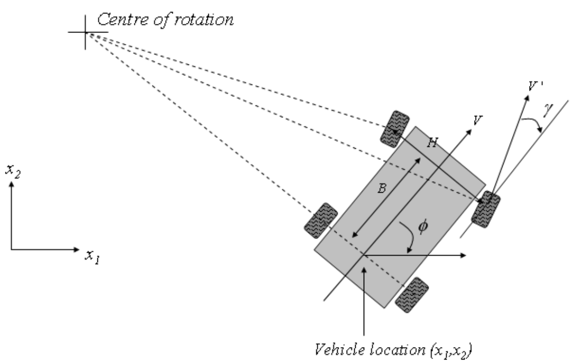

Figure 1. Vehicle Motion Model

A sensor system assembled from low cost solid state components, which are ultrasonic range finder and rotary odometer sensor. A high noise and low accuracy of low cost sensors can be overcome by careful filter design which is based on appropriate dynamic modeling.

2.1. Range Sensor Model

By approximation, the model of ultrasonic range sensor can be illustrated in the figure 2, where Z_{t+1} sensor position from moving object, d_i is distance, θ is measurement direction. In summary, a sensor model is:

$$Z_{t+1}^{US} = \left[x_{1_o} + kd_i \sin\theta, x_{2_o} + kd_i \cos\theta \right]^T \qquad (3)$$

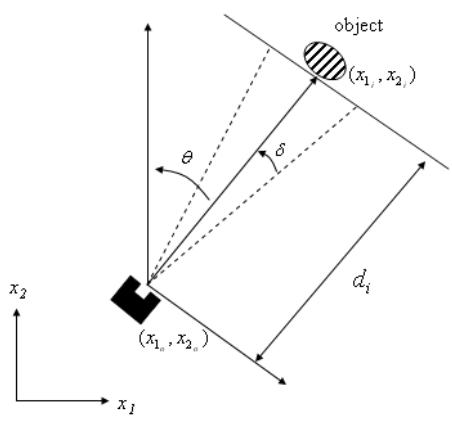

Figure 2. Ultrasonic Range Sensor Model

II.2. Rotary Sensor Model

To estimate the motion and the location parameters, the dead-reckoning sensor is utilize using rotary odometer sensor to measure the wheels quantified displacement is expressed by:

$$Z_{t+1}^{ODO} = \left[\Delta x_{t+1}^{ODO_R} \quad \Delta x_{t+1}^{ODO_L} \right]^T = h^{ODO}(X_{t+1}) + W_{t+1}^{ODO} \qquad (4)$$

where $\left[\Delta x_{t+1}^{ODO_R} \quad \Delta x_{t+1}^{ODO_L} \right]$ denote the right and left wheel distance measurement, h^{ODO} is the nonlinear measurement function, X_{t+1}^{ODO} is the location of vehicle, and W_{t+1}^{ODO} is an additional white Gaussion noise with zero mean and R_{t+1}^{ODO} covariance matrix.

2.3. GPS Model

When the GPS measure is available, the filter estimate the location and the motion of the vehicle using predicted GPS measure is:

$$Z_{t+1}^{GPS} = \left[x_{1t+1}^{GPS} \quad x_{2t+1}^{GPS} \right]^T = h^{GPS}(X_{t+1}) + W_{t+1}^{GPS} \qquad (5)$$

where h^{GPS} is the measurement function, X_{t+1}^{GPS} is the location of vehicle, and W_{t+1}^{GPS} is an additional white Gaussion noise with zero mean and R_{t+1}^{GPS} covariance matrix, than it became: $\hat{Z}_{t+1}^{GPS} = h^{GPS}(\hat{X}_{t+1|t})$.

3. Filtering Model

Sensor fusion is the combining of sensory data such that the resulting information is in some sense better than when these sources were used individually. The term better in that case can mean more accurate, more complete, or more dependable. The data sources for a fusion process are not specified to originate from identical sensors. One can distinguish direct fusion, indirect fusion and fusion, direct fusion is the fusion of sensor data from a set of heterogeneous or homogeneous sensors, soft sensors, and history values of sensor data, while indirect fusion uses information sources like a priori knowledge about the environment and interupt input.

A sensor fusion technique should be able to estimates a state of AGV through time due to its dynamics, which experiences a set of complicated and highly nonlinear forces. In this chapter, the design and implementation of online decentralized multisensor data fusion is discussed.

The time evolution is describe using general continuous-time model:

$$x_T(t) = f_T\left[x_T(t), u_T(t), v_T(t), t \right] \qquad (6)$$

Subscript T denotes the fact that this is the state of true system, in practice the structure and form of true system is unknown and approximations must be used. The current position and velocity of the AGV as well as on certain characteristics are not precisely known.

In general, the nonlinear system dynamics and observation equations of AGV actuator j in discrete form are given as:

$$x_{j,k} = f(x_{j,k-1}, u_{j,k-1}, v_{j,k-1}, k-1) + G_{k-1} w_{k-1} \\ z_{j,k} = h_{j,k}(x_{j,k}) + \vartheta_{j,k} \tag{7}$$

where $f_k(\cdot) \in \mathbb{R}^{n \times n}$ is the process model, $x_k \in \mathbb{R}^n$ is the state vector, $u_k \in \mathbb{R}^n$ is the control input, $v_k \in \mathbb{R}^n$ is the process noise, G_k is the system noise matrix, $w_k \in \mathbb{R}^n$ is the system noise, $z_k \in \mathbb{R}^p$ is the measurement vector, $h_k(\cdot) \in \mathbb{R}^{p \times n}$ is the measurement model, and $\vartheta_k \in \mathbb{R}^p$ is the measurement noise.

3.1. Initialization

$$\chi_{k,k-1} = f(\chi_{k-1,} k-1) \\ Z_{k,k-1} = h(\chi_{k-1}) \tag{8}$$

We assume that noise is uncorrelated Gaussian white noise sequences with mean and covariance as follows: $E\{w_i\} = 0$, $E\{w_i w_j\} = Q\delta_{ij}$, $E\{\vartheta_i\} = 0$, $E\{\vartheta_i \vartheta_j\} = R\delta_{ij}$, $E\{w_i \vartheta_j\} = 0$, for all i, j . Where $E\{\cdot\}$ denotes the expectation, and δ_{ij} is the Kronecker delta function. Q and R are bound positive definitive matrices ($Q>0, R>0$). Initial state x_0 is normally distributed with zero mean and covariance P_0 .

3.2. Updating

II.2.a. Computing Sigma Point

$$\chi_{0,k-1} = \hat{x}_{k-1} \\ \chi_{i,k-1} = \hat{x}_{k-1} + (\sqrt{(n_s + \lambda) P_{k-1}})i, i = 1, ..., n_s \\ \chi_{i,k-1} = \hat{x}_{k-1} - (\sqrt{(n_s + \lambda) P_{k-1}})i, i = n_s + 1, ..., 2n_s \tag{9}$$

where χ is a sigma points of the augmented vector, n_s is a number of the states in the augmented state vector, λ is a scaling parameter $= \alpha^2 (n_s + \kappa) - n_s$, α is to determines how the sigma point are spread, typical value is 10^{-3}, and κ is a scaling parameter which can be used to incorporate up to fourth order precision in the transformation, usually set to zero.

The prediction of the state and measurement vector as well covariance of the state vector is:

$$\hat{x}_k^- = \sum_{i=0}^{2n_s} W_i^s \chi_{i,k|k-1} \\ \hat{z}_k^- = \sum_{i=0}^{2n_s} W_i^m Z_{i,k|k-1} \\ P_k^- = \sum_{i=0}^{2n_s} W_i^c (\chi_{i,k|k-1} - \hat{x}_k^-)(\chi_{i,k|k-1} - \hat{x}_k^-)^T + Q \tag{10}$$

and weights for the states and covariance matrices is:

$$W_0^s = \lambda / (n_s + \lambda) \\ W_0^c = (1 - \alpha^2 + \beta) + 0.5\lambda / (n_s + \lambda) \\ W_i^s = W_i^c = 0.5\lambda / (n_s + \lambda), i = 1, ..., 2n_s \tag{11}$$

where β is used to incorporate knowledge of the distribution of state, optimal value for Gaussian distribution is 2, ans s, m, and c is a state, measurement and covariance respectively.

3.2.b. Time Update

$$\hat{x}_{j,k}^- = \left(\sum_{i=0}^{2n_s} W_i^s X_{i,k|k-1} \right)_j \\ p_{j,k}^- = \left(\sum_{i=0}^{2n_s} W_i^c \left(X_{i,k|k-1} - \hat{x}_k^- \right) \left(X_{i,k|k-1} - \hat{x}_k^- \right)^T + Q \right)_j \\ \hat{z}_{j,k} = \left(\sum_{i=0}^{2n_s} W_i^m Z_{i,k|k-1} \right)_j \tag{12}$$

where: $j = 1, 2, ..., L, M$

3.2.c. Measurement Update

Update the measurement prediction covariance, the cross covariance between the state and measurement, the Kalman gain, the state estimate and the state covariance as:

$$P_{\hat{z}_k \hat{z}_k} = \sum_{i=0}^{2n_s} W_i^c (Z_{i,k|k-1} - \hat{z}_k)(Z_{i,k|k-1} - \hat{z}_k)^T + R \\ P_{\hat{z}_k^- \hat{z}_k}^- = \sum_{i=0}^{2n_s} W_i^c (Z_{i,k|k-1} - \hat{z}_k)(Z_{i,k|k-1} - \hat{z}_k)^T \\ K_k = P_{\hat{z}_k^- \hat{z}_k} P_{\hat{z}_k \hat{z}_k}^{-1} \\ \hat{x}_k = \hat{x}_k^- + K_k (z_k - \hat{z}_k) \\ \hat{P}_k = P_k^- - K_k P_{\hat{z}_k \hat{z}_k} K_k^T \tag{13}$$

When the several identical sensors are used, combining the observations will result an improved estimation. (A statistical advantage is gained by adding the N independent observations is improved by a factor proportional to $N^{1/2}$). To improve the observation process, two sensors that measure angular directions on AGV can be coordinated to determine the position using two sensors, one moving in a known way with respect to another; it can be used to measure instantaneously a position and velocity, with respect to the observing sensors.

In the decentralized form of UKF scheme as in [8], local filters are generally based on the models as:

$$\begin{aligned} x_k &= f(x_{k-1},u_{k-1},v_{k-1},k-1)+G_{k-1}w_{k-1} \\ z_k &= h_k(x_k)+\vartheta_k \end{aligned} \tag{14}$$

As all the local UKFs estimate same state variables, these models that have the same dynamics are appropriate.

The decentralized UKF can obtain the globally optimal estimate by using the information strategy to each local filter and than fusing the estimates of the local filter. For the system with local UKF, equation for the time and measurement update is mentioned as:

Time update equations:

$$\hat{x}^-_{j,k} = \left(\sum_{i=0}^{2n_s} W_i^s X_{i,k|k-1}\right)_j \tag{15}$$

$$p^-_{j,k} = \left(\sum_{i=0}^{2n_s} W_i^c \left(X_{i,k|k-1}-\hat{x}^-_k\right)\left(X_{i,k|k-1}-\hat{x}^-_k\right)^T + Q\right)_j \tag{16}$$

where $j=1,2\ldots,L,M$

$$\hat{z}_{j,k} = \left(\sum_{i=0}^{2n_s} W_i^m Z_{i,k|k-1}\right)_j \quad ,j=1,2\ldots,L$$

Measurement update:

$$p_{j,\hat{z}_k\hat{z}_k} = \left(\sum_{i=0}^{2n_s} W_i^c \left(Z_{i,k|k-1}-\hat{z}_k\right)\left(Z_{i,k|k-1}-\hat{z}_k\right)^T + R\right)_j \tag{17}$$

$$p^-_{j,x^-_k k\hat{z}_k} = \left(\sum_{i=0}^{2n_s} W_i^c \left(X_{i,k|k-1}-\hat{x}_k\right)\left(Z_{i,k|k-1}-\hat{z}_k\right)^T\right)_j \tag{18}$$

where $j=1,2,\ldots,L$

$$K_{j,k} = \left(P_{\hat{x}^-_k\hat{z}_k} P^-_{\hat{x}^-_k\hat{z}_k}\right)_j$$

$$\hat{x}_{j,k} = \left(\hat{x}^-_k + K_k\left(z_k-\hat{z}_k\right)\right)_j$$

$$\hat{P}_{j,k} = \left(P^-_k - K_k P_{\hat{z}_k\hat{z}_k} K_k^T\right)_j$$

where $\hat{x}^-_k \in \mathbb{R}^{nj}$ is the priori estimate of x_k , $Q \in \mathbb{R}^{nj\times nj}$ is the covariance matrix of system noise, $\hat{x}_k \in \mathbb{R}^{nj}$ is the posteriori estimate of x_k , $P^-_k \in \mathbb{R}^{nj\times nj}$ is the priori covariance matrix of estimation error, $\hat{P}_k \in \mathbb{R}^{nj\times nj}$ is the posteriori covariance matrix of estimation errors. In the [8], master filter are generally modeled as:

$$P^{-1}_{f,k} = P^{-1}_{M,k} + \sum_{j=1}^{N} P^{-1}_{j,k} \tag{19}$$

where $P^{-1}_{M,k} = \beta_{M,k} P^{-1}_{f,k|k-1}$.

$$P^{-1}_{f,k}\hat{x}_{f,k} = P^{-1}_{M,k}\hat{x}_{M,k} + \sum_{j=1}^{N} P^{-1}_{j,k}\hat{x}_{j,k} \tag{20}$$

where $\hat{x}_{M,k} = \hat{x}_{f,k|k-1}$

$P^{-1}_{f,k} \in \Re^{nf}$ is the inverse of the fused covariance, $\hat{x}_{f,k} \in \Re^{nf}$ is the fused state estimate.

Once the global solution is obtained, it can be feedback to the local UKF, this operation called the reset operation, by the following algorithm:

$$\left.\begin{aligned} P_{j,k} &= \beta_j^{-1} P_{f,k}, \\ \hat{x}_{j,k} &= \hat{x}_{f,k} \end{aligned}\right\},j=1,2,\ldots,M \tag{21}$$

where β_j is the information sharing coefficient and must satisfy the following conservation of information principle:

$$\beta_M + \sum_{j=1}^{N} \beta_j = 1 \tag{22}$$

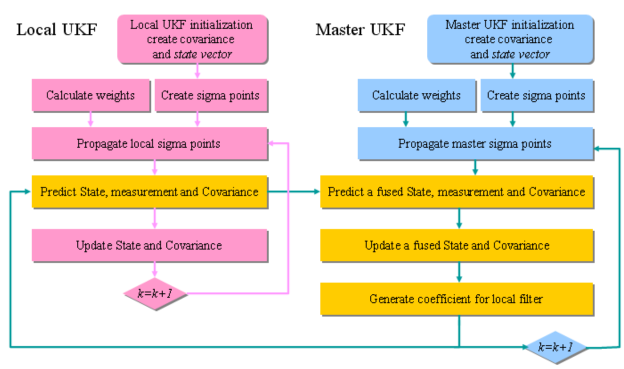

Figure 3. The Decentralized UKF implementation

In the decentralized implementation illustrated in figure 3, the state vectors of the local and master filters are same. If the fusion and reset operation are performed after every measurement cycle, the decentralized UKF solution is the same as centralized UKF. To remain optimal, the filter must combine the local estimates into a single every cycle. After the combination step, at the start of the next cycle, the estimates can feedback to the local information. Furthermore, the total process information, represented by the matrix Q shared among the local filters, must sum up to the true net process information.

For the application of the proposed, there is no sensor acts as a fundamental sensor in the system, and its data is the measurement input for the local filter. The data from sensors are dedicated to corresponding local filter, after calculation was completed than supply their resulting solutions to the main filter for the master update, yielding a global solution.

4. System Development

In figure 4, OCP can accommodate rapidly changing application requirements, easily incorporate hardware platforms or sensors interoperate in heterogeneous, unpredictable, and changing environments. Using OCP structure will enable to accommodate changing application requirements and maintain viability in changing environments, which is suitable to integrate a high number of sensors and actuators.

To develop a code that estimate the position, attitude, speed and other parameters of vehicle is one of the most safety-critical parts of software. Automatic code generator or program fusion techniques have reported in [9], to develop KF code from high-level declaration specification of state estimation problem can help to solve this predicament by completely automating the coding phase.

The algorithms and software code generation are designed to deliver an online robust and accurate state estimates, predictive model (control, trajectory planning, fault detection, and recovery), uncertainty bounds (control, trajectory planning, and fault detection), but it not presented in this paper.

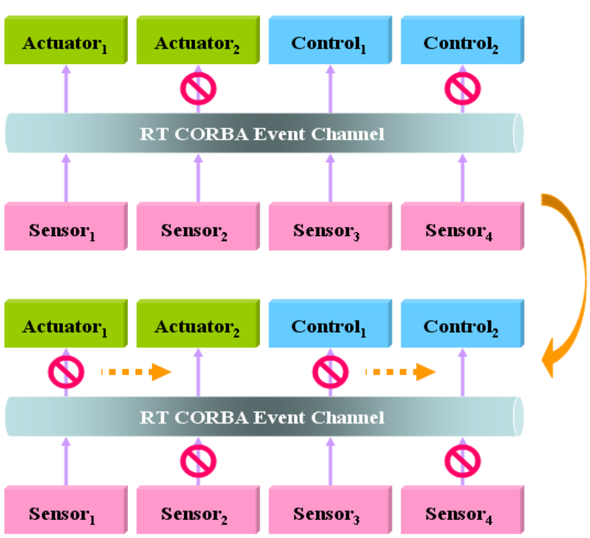

Figure 4. Open Control Platform Rapid Changing

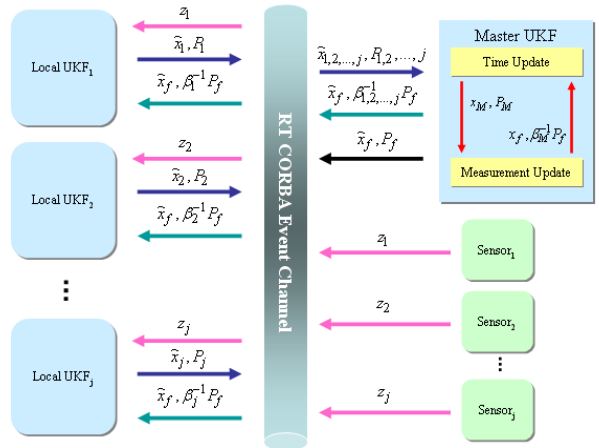

Figure 5. Sensor Fusion Implementation

5. Simulation Results

A simulation environment that contains many of the complexities is required to validate the algorithm development. To solve this problem, we have a several steps: 1) developing a system dynamic model more detail, instead of Autonomous Vehicle, 2) to create some simulation scenarios that reflects the important situations, especially to test an algorithm and model in critical condition of implementation (e.g. when mean and covariance of Gaussian white noise sequences are bias).

The entire local UKF have a same state variables and same dynamics. To obtain a global optimal estimation of decentralized UKF, information from each local filter will be used, and than fuse the global estimation of the master filter.

For simulations, we have a simple scenario, that a sensor fusion technique should be able to track an Autonomous Vehicle that experiences a set of complicated and highly nonlinear forces. The current position and velocity of the vehicle, as well as on certain characteristics are not precisely known.

All the simulations for local filter and master filter have been carried out using Matlab. A random measurement noise from GPS is included in the simulations. Here, we assume that range sensor computations are sampled in 1ms, rotary sensor is provided at 1 Hz, and GPS updates are available at 30 Hz. In the simulations, all sensor are alignment in 1 Hz, and will be running for 400 iteration periods. The initial values $x_1(0)$ and $x_2(0)$ of the state vector x_1 and x_2 is chosen as zero and the initial alignment error are also assumed to be zero. $P_1(0), P_2(0), Q_1, Q_2, R_1$, and R_2 are chosen for a medium accuracy. Normalized mean-square error (MSE) of Monte Carlo simulations are computed as depicted in figure 6, while estimated of the state vector x_1 and x_2 depicted in figure7.

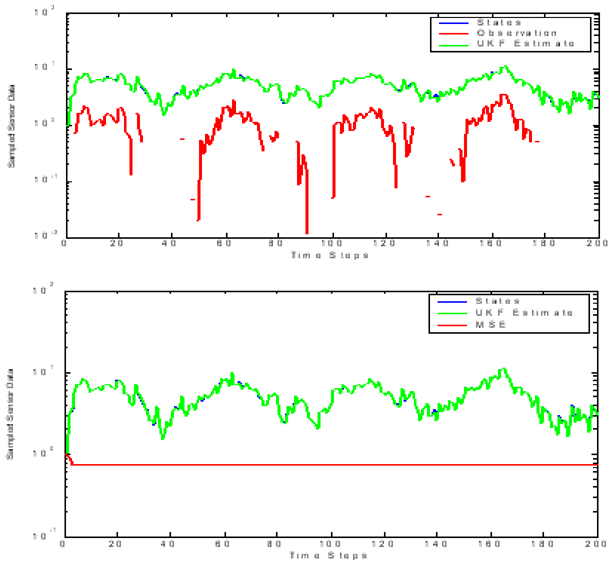

Figure 6. Local Filter Estimation and Its MSE

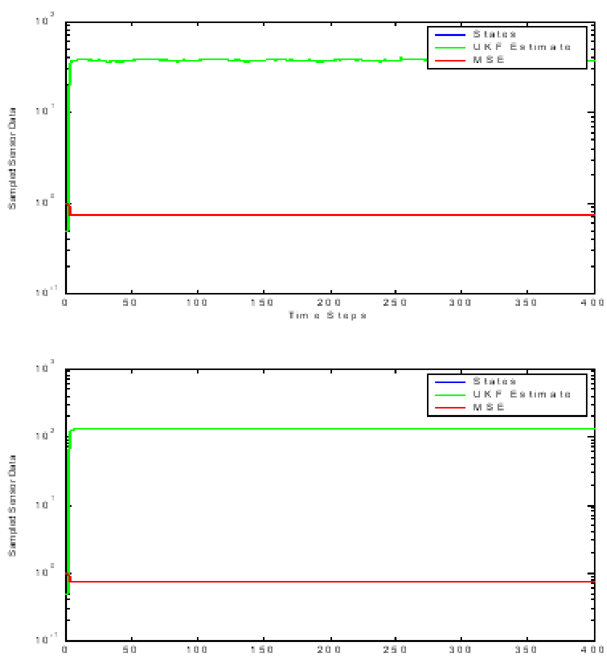

Figure 7. Master Filter Estimation for X_1 and X_2

6. Conclussions

An UKF based multisensor data fusion algorithm in decentralized application is computationally intensive, but it is promising to perform fault detection and isolation technique easier. An OCP is practical, that contains the same process model and makes their available for control designer, to draw from concepts to implementations.

The simulation results in this paper not capture the whole system representation. In the future work, we will utilize the true sensor data from the testbed which will be constructed to validate the algorithm have been proposed in this paper. A tesbed consist of several sensors and actuators system. Which are attached to the two PCs connected by wireless networked. A sensor system using 4 unit's rotary sensor AUTONICS ENB-500-3-1 act as odometer and its data is the measurement input for the local filter. Data from 8 units ultrasonic range sensor SHARP GP2Y0A02YK is dedicated to corresponding local filter. A GPS and all sensors dedicated to supply the local solutions to the main filter for yielding a global solution. Otherwise, an actuator using 4 unit DC motor drive to actuate the control command of steering, braking, accelerating and IR camera direction.

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