# Extended Kalman Filter based Fusion of Reliable Sensors using Fuzzy Logic

Tanmoy Kumar Das, P. A. Diluka Harischandra, A. M. Harsha S. Abeykoon
Department of Industrial Systems Engineering
Asian Institute of Technology
Pathumthani, Thailand
das.tanmoykr@gmail.com, diluka.harischandra@gmail.com, harsha@ait.asia

***Abstract*—Precise localization for autonomous robots is necessary for advancement in the world of unmanned robotics. Probabilistic algorithms are used to fuse multiple position sensors in order to locate a robot. But failure of any sensor in this process drastically lowers the performance of these algorithms. Here comes the need to facilitate these probabilistic models with intelligence. This paper presents an intelligent localization technique for autonomous maneuvering of robots. Localization of the robot is done by fusing three different types of position sensors using an Extended Kalman Filter (EKF) and a Kalman Filter (KF). The fusing method is made intelligent by keeping track of the relative error among the sensors and deciding a reliability factor on each sensor accordingly. A Fuzzy inference model has been adopted to predict the reliability factor for each sensor. According to the predicted reliability of each sensor, an error covariance matrix is set up, which is fed into the traditional KF and EKF algorithms. This helps the fusion algorithms to fuse the sensors intelligently and the final output is more accurate. A high precision localization is achieved by this intelligent method of fusing. A simulation is carried out in MATLAB considering three position sensors. The simulation is validated by making one of the sensors erroneous and comparing the output results of the new fusion algorithm with the traditional algorithm.**

***Keywords*— Kalman Filter, Extended Kalman Filter, Fuzzy Inference Model, Sensor Reliability, Localization.***

## I. Introduction

Intelligent robots have gained a lot of popularity in the recent years. These robots are used in various tasks. Agricultural sectors use mobile robots to survey the aggregated land and also use automatic tractors for farming. Military on the other hand, have started implementing intelligent ground vehicles and flying machines for survey, mapping and even for combat. Disaster management teams have also switched to intelligent robots for gathering information related to affected areas before sending actual human assistance. In this way, intelligent robots are ensuring human safety and easing many toilsome tasks previously handled by humans. Navigation of the mobile robots without human assistance is a prime objective in this area. To navigate these robots, a very precise localization technique is required. In autonomous navigation, there is always a question to be answered is, "Where am I?". Research over years have proved that, a single sensor is not capable of providing a perfect answer to the above question. Thus, multiple position sensors in conjunction are used to find the exact location of a robot, which is known as sensor fusion in the technical world. Sensors which are generally used in calculating position of a robot are Global Positioning Systems (GPS), encoders, accelerometers, gyroscopes, magnetometers or compasses, laser sensors, cameras, optical flow meters, ultrasonic sensors, radars, etc. Most of these sensors are being fused to calculate the position of an intelligent vehicle. The sensors mentioned above are subjected to external noise and in addition to that they have limitations of their own. These limitations of the sensors gave rise to the need of probabilistic algorithms to fuse the sensors together. Researchers have come up with different techniques to fuse sensors. Fusing algorithms are based mostly on KF [1], EKF [2], Bayesian Filter [3] and Particle Filter (PF) [4]. These probabilistic algorithms are capable of minimizing the noise and provide almost accurate results. Apart from the fusing algorithms, some researchers have used feature matching algorithms that works in parallel with the fusing algorithms. They use FAST [5], that detects feature points and then PTAM [5] is implemented. Vision SLAM [6], a similar algorithm like PTAM is also used for mapping and localization. But these algorithms can be used at an expense of high computational power. These algorithms are vastly used in UAVs. But the processing is usually done off board due to the high computation required and high power requirements. In all the techniques used for sensor fusion, it is always considered that the sensors approximately provide us with nearly accurate position information in addition with some noise. Under this assumption, the algorithms like KF and in case of non-linear systems, the EKF works in a fairly accurate manner.

Localization of a mobile robot under outdoor environments is done by using [7] a KF to fuse the data from a wheel encoder, GPS and IMU. A similar approach has been adopted by another researcher, who has fused data from GPS, inertial navigation system (INS) and optical flow meter [8]. The linear and non-linear equality state constrains are taken into the EKF framework to fuse GPS and odometry data for more accurate results [9]. All these approaches are dependent on the GPS data which updates the noisy odometry data received from the other sensors. GPS is fairly accurate at outdoor conditions but becomes unreliable under indoor conditions.

EKF is used to fuse the data from a radar, ultrasonic and odometry sensor to localize a mobile robot [10]. EKF is used as the sensor fusion technique for localization of a wheeled robot [11]. Here, the traditional navigational sensors are used for

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navigation along with visual odometry. This eradicates the drawbacks of GPS but at an expense of high computational cost. This also compels to use off board computation. Therefore, the robot no longer operates as a stand-alone system.

Further, neural network and fuzzy logic has also been applied for mobile robot navigation ([12], [13], [14]). The outputs obtained from these algorithms even showed better results than the conventional navigation techniques. But neural fuzzy theory is an intelligent approach of navigation and it requires prior training sets to make the network practically workable in the real environment.

All the above mentioned navigation algorithms rely on the information provided by the on-board sensors that continuously provide information about the vicinity of the mobile robot. Though the error of the sensors is taken into account while modelling the navigation algorithm, but these sensors can never be predicted based on their error models. The behavior of the sensors changes dynamically. One shortcoming of the navigation algorithms is that whenever one or more sensor starts working erroneously, the probabilistic model still takes the faulty sensor data into account. This makes the fused output highly erroneous. Therefore, researchers have come up with fault detection techniques to bypass the faulty sensor. Fault Detection and Isolation (FDI) techniques have been applied to overcome the faulty sensor problem. FDI technique has been used along with a particle filter for fault detection in sensors [15]. Particle filter to be at its best, needs a pre-defined map, which in itself brings about uncertainties with a dynamic environment.

In this paper, we introduce a fusion algorithm, which uses the traditional EKF and KF for fusing the non-linear and linearly behaving sensors respectively. Analytical methods have a greater chance of failure in detecting faults in sensors. Therefore, a Fuzzy model has been adopted based on the relative real time errors among the sensors and to decide reliability factors for each sensor. This reliability factor, then helps to decide on the error covariance of each sensor. This error covariance is applied to the KF and EKF algorithms, which makes the fusing process intelligent by fusing only the least erroneous sensors.

The remainder of the paper is organized as follows. Section II introduces the conventional KF and EKF algorithms. Section III describes the fusion method and introduces the fuzzy logic into our proposed fusion algorithm. Section IV shows the simulation results of the Kalman Intelligent Filtering (KIF). Finally, in section V we conclude our paper.

## II. Kalman Filter And Extended Kalman Filter

KF [2] consist of two steps namely the prediction step (6), (7) and the update or correction step (8), (9), (10). In the prediction step, the state of the robot (1) i.e. the position coordinates and orientation, from the previous filtered output is taken to estimate the new state of the robot (6). In the update step, the new estimated state is corrected or updated with the upcoming data from the sensors (9).

In KF, we should have a system model (2) and a measurement model (3). Each model is added with dynamic zero mean white Gaussian noise (4), (5).

TABLE I. Nomenclature

| Parameters | Descriptions |
|---|---|
| $A_k$ | State transition matrix |
| $B_k$ | Control input model |
| $C_k$ | Measurement Matrix |
| $dt$ | Sampling time |
| $f(X_{k-1,}u_k)$ | Non-linear function of state transition and control model |
| $F_k$ | Jacobian of function of state transition model |
| $h(X_k)$ | Non-linear function of measurement model |
| $H_k$ | Jacobian of function of measurement model |
| $I$ | Identity matrix |
| $k$ | Time step |
| $K_k$ | Kalman gain |
| $N$ | Multivariate normal distribution |
| $\hat{P}_k^-$ | Predicted estimated covariance |
| $\hat{P}$ | Updated estimated covariance |
| $Q_k$ | Process noise covariance |
| $R_k$ | Sensor noise covariance |
| $S_1, S_2, S_3$ | Sensor-1, Sensor-2, Sensor-3, respectively |
| $u_k$ | Control vector |
| $v_k$ | Measurement noise |
| $V_k$ | Linear velocity of the robot |
| $w_k$ | Process noise |
| $x$ | Position in x-coordinate |
| $X_k$ | State of the robot |
| $\hat{X}_k^-$ | Predicted state estimate |
| $\hat{X}_k$ | Updated state estimate |
| $y$ | Position in y-coordinate |
| $z_k$ | Measurement |
| $\theta$ | Orientation of the robot |
| $\omega_k$ | Angular velocity of the robot |

State:

$$X = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} \quad (1)$$

System Model:

$$X_k = A_k X_{k-1} + B_k u_k + w_k \quad (2)$$

Measurement model:

$$z_k = C_k X_k + v_k \quad (3)$$

Here, $w_k$ and $v_k$ are the dynamic zero mean white Gaussian noise of the state model and the measurement model respectively.

$$w_k \sim N(0, Q_k) \quad (4)$$

$$v_k \sim N(0, R_k) \quad (5)$$

Kalman Filter equations:

Prediction step:

$$\hat{X}_k^- = A_k \hat{X}_{k-1} + B_k u_k \quad (6)$$

$$\hat{P}_k^- = A_k \hat{P}_{k-1} A_k^T + Q_k \quad (7)$$

Update step:

$$K_k = \hat{P}_k^- C_k^T \left( C_k \hat{P}_k^- C_k^T + R_k \right)^{-1} \quad (8)$$

$$\hat{X}_k = \hat{X}_k^- + K_k \left( z_k - C_k \hat{X}_k^- \right) \quad (9)$$

$$\hat{P}_k = (I - K_k C_k) \hat{P}_k^- \quad (10)$$

Real systems in the world are never linear in nature, therefore, the KF fails under real environments. To make the KF valid in real systems, the non-linear function governing the robot state is linearized by taking the Jacobian of the same. This KF is named as Extended Kalman filter (EKF).

The modified system model (11) and measurement model (12) are shown below respectively:

$$X_k = f(X_{k-1,}u_k) + w_k \tag{11}$$
$$z_k = h(X_k) + v_k \tag{12}$$

Extended Kalman Filter Equations:

Prediction step:

$$\hat{X}_k^- = f(\hat{X}_{k-1}, u_k) \tag{13}$$
$$\hat{P}_k^- = F_k \hat{P}_{k-1} F_k^T + Q_k \tag{14}$$

Update step:

$$K_k = \hat{P}_k^- H_k^T \left(H_k \hat{P}_k^- H_k^T + R_k\right)^{-1} \tag{15}$$
$$\hat{X}_k = \hat{X}_k^- + K_k\left(z_k - h(\hat{X}_k^-)\right) \tag{16}$$
$$\hat{P}_k = (I - K_k H_k)\hat{P}_k^- \tag{17}$$

Here,

$$F_k = \frac{\partial(f(X_{k-1,}u_k))}{\partial X} |\hat{X}_k^- \tag{18}$$

$$H_k = \frac{\partial(h(X_k)}{\partial X} |\hat{X}_k^- \tag{19}$$

## III. Proposed Fusion Algorithm

A discrete KF is used to fuse the linearly behaving sensors and an EKF is used to fuse the non-linear sensors. KF and EKF, both are used in order to prove the validity of the proposed fusion algorithm under both linear and non-linear ranges. As we know, sensors behave dynamically under different real time conditions, and no noise model (4), (5) can be in sync with the real sensor noises over the time. Thus, our algorithm relies on a fuzzy model as shown in Fig. 4, created on the basis of the relative differences among the sensory outputs as shown in Fig. 3. This fuzzy model sets a reliability factor on each sensor. According to the fuzzy rule set as presented in Table II, process covariance, $Q_{k|S_1}$ for sensor-1 and error covariance, $R_{k|S_2}$and $R_{k|S_3}$for sensor-2 and sensor-3 respectively, are modelled at each time step k. These covariance matrices are replaced by the conventional covariance matrices in (28), (29) and (34). This allows the KF algorithm to fuse the sensors intelligently. The Kalman Intelligent Filtering (KIF) algorithm shown in Fig. 2, gets rid of the analytical noise modelling which has a higher possibility of failure with time. Under different simulation conditions, it has been proved that KIF skips the most erroneous sensor in the fusing process and again takes it into consideration under a considerable reliability factor.

### *A. Architecture of sensor fusion algorithm*

For executing the simulation, one of the sensors, $S_1$ is considered non-linear and the other two sensors, $S_2$ and $S_3$ are expected to give a position coordinate as shown.

$$z_{S_2} = \begin{bmatrix} x_1 \\ y_1 \end{bmatrix} \tag{20}$$

$$z_{S_3} = \begin{bmatrix} x_2 \\ y_2 \end{bmatrix} \tag{21}$$

$S_1$ follows a velocity based function, which is the state transition model (22) in our case.

State Transition Model:

$$f(X_{k-1,}u_k) = \begin{bmatrix} x_{k-1} - \frac{V_k}{\omega_k} sin\theta_k + \frac{V_k}{\omega_k}\sin(\theta_k + \omega_k dt) \\ y_{k-1} + \frac{V_k}{\omega_k} cos\theta_k - \frac{V_k}{\omega_k}\cos(\theta_k + \omega_k dt) \\ \theta_{k-1} + \omega_k dt \end{bmatrix} \tag{22}$$

As it is a non-linear function, it has to be linearized by taking the Jacobian (18) of the state function as shown in (22), w.r.t. the state of the robot (1).

$$F_k = \begin{bmatrix} 1 & 0 & \frac{V_k}{\omega_k}\cos(\theta_k + \omega_k dt) - \frac{V_k}{\omega_k} cos\theta_k \\ 0 & 1 & \frac{V_k}{\omega_k}\sin(\theta_k + \omega_k dt) - \frac{V_k}{\omega_k} sin\theta_k \\ 0 & 0 & 1 \end{bmatrix} \tag{23}$$

Measurement model for $S_2$ and $S_3$ respectively:

$$z_{S_2} = C_{k|S_2} X_k + v_{k|S_2} \tag{24}$$
$$z_{S_3} = C_{k|S_3} X_k + v_{k|S_3} \tag{25}$$

The measurement matrices for (24) and (25) are as shown below:

$$C_{S_2} = C_{S_3} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \tag{26}$$

Therefore, in the fusing algorithm, the $S_1$ and $S_2$ are fused using EKF and the estimated output is again fused with $S_3$ using KF for precise positioning as shown in Fig. 1.

Equations Governing the fusion algorithm:

**STAGE 1:**

Prediction step:

$$\hat{X}_{k|S_1}^- = f(\hat{X}_{k-1}, u_{k|S_1}) \tag{27}$$
$$\hat{P}_{k|S_1}^- = F_{k|S_1} \hat{P}_{k-1} F_{k|S_1}^T + Q_{k|S_1} \tag{28}$$

Update step:

$$K_{k|(S_1+S_2)} = \hat{P}_{k|S_1}^- C_{k|S_2}^T \left(C_{k|S_2} \hat{P}_{k|S_1}^- C_{k|S_2}^T + R_{k|S_2}\right)^{-1} \tag{29}$$
$$\hat{X}_{k|(S_1+S_2)} = \hat{X}_{k|S_1}^- + K_{k|(S_1+S_2)}\left(z_{k|S_2} - C_{k|S_2}\hat{X}_{k|S_1}^-\right) \tag{30}$$
$$\hat{P}_{k|(S_1+S_2)} = \left(I - K_{k|(S_1+S_2)} C_{k|S_2}\right)\hat{P}_{k|S_1}^- \tag{31}$$

**STAGE 2:**

Prediction step:

$$\hat{X}_{k|(S_1+S_2)}^- = A_{k|(S_1+S_2)} \hat{X}_{k|(S_1+S_2)} \tag{32}$$

$$\hat{P}_{k|(S_1+S_2)}^- = A_{k|(S_1+S_2)} \hat{P}_{k|(S_1+S_2)} A_{k|(S_1+S_2)}^T + Q_{k|(S_1+S_2)} \tag{33}$$

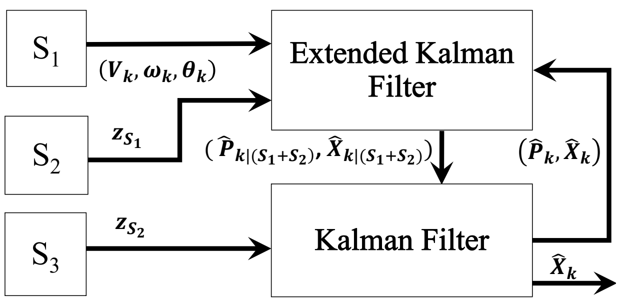



Fig. 1. Proposed Fusion Process

Update step:

$$K_{k|(S_1+S_2+S_3)} = \hat{P}^{-}_{k|(S_1+S_2)} C^{T}_{k|S_3} \left( C_{k|S_3} \hat{P}^{-}_{k|(S_1+S_2)} C^{T}_{k|S_3} + R_{k|S_3} \right)^{-1} \tag{34}$$

$$\hat{X}_{k|(S_1+S_2+S_3)} = \hat{X}^{-}_{k|(S_1+S_2)} + K_{k|(S_1+S_2+S_3)} \left( z_{k|S_3} - C_{k|S_3} \hat{X}^{-}_{k|(S_1+S_2)} \right) \tag{35}$$

$$\hat{P}_{k|(S_1+S_2+S_3)} = \left( I - K_{k|(S_1+S_2+S_3)} C_{k|S_3} \right) \hat{P}^{-}_{k|(S_1+S_2)} \tag{36}$$

As, it is a recursive process, therefore the updated state estimate (35) and updated estimate covariance (36), are fed back to (27) and (28) as $\hat{X}_k$ and $\hat{P}_k$ respectively, as shown in Fig. 1 and Fig. 2, for the next iteration.

### B. *Deciding on the Error Covariance matrix using Fuzzy inference model*

The aim here, is to model an error covariance matrix with zero mean for each sensor. A fuzzy inference model as shown in Fig. 4 is used on the basis of the relative difference among the sensory outputs Fig. 3. The reliability factor on a sensor is set to low when two connecting error branches to that sensor, is much higher than the third branch. According to the rule set as presented in Table II, the error covariance matrix for the least reliable sensor is multiplied by a high factor. This makes the influence of the erroneous sensor over the estimated covariance (36) and Kalman Filter Gain (34) very less. Therefore, the Updated state estimate (35) is much more oriented towards the state estimated by the reliable sensors. The Fuzzy inference model has three inputs and three outputs. The absolute difference between two particular sensory outputs is taken as the input. If the first sensor gives $(x_1, y_1)$ as the position co-ordinates and the second sensor gives $(x_2, y_2)$ , then the absolute error between them is:

$$\Delta E = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{37}$$

Likewise, $\Delta E_1$, $\Delta E_2$ and $\Delta E_3$ are the inputs to the fuzzy inference model as shown in Fig. 4. The output of the Fuzzy model is the process covariance matrix $Q_{k|S_1}$ and the error covariance matrices $R_{k|S_2}$ and $R_{k|S_3}$.

## IV. Results And Discussions

Simulation of the Fuzzy based EKF sensor fusion technique has been simulated using MATLAB. We validated our algorithm using two trajectories similar to an R-shaped

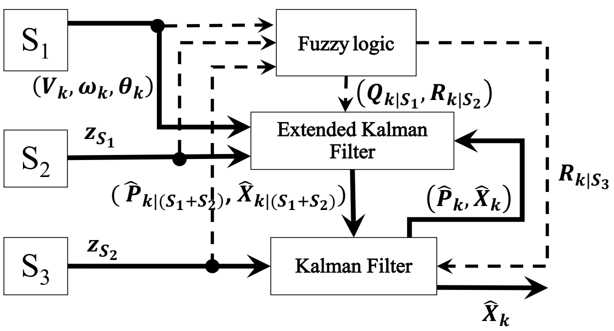



Fig. 2. Kalman Intelligent Filtering Algorithm

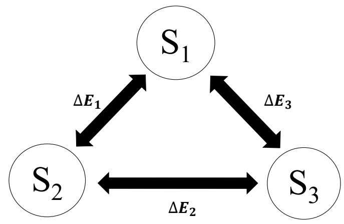



Fig. 3. Relative error among the sensory output

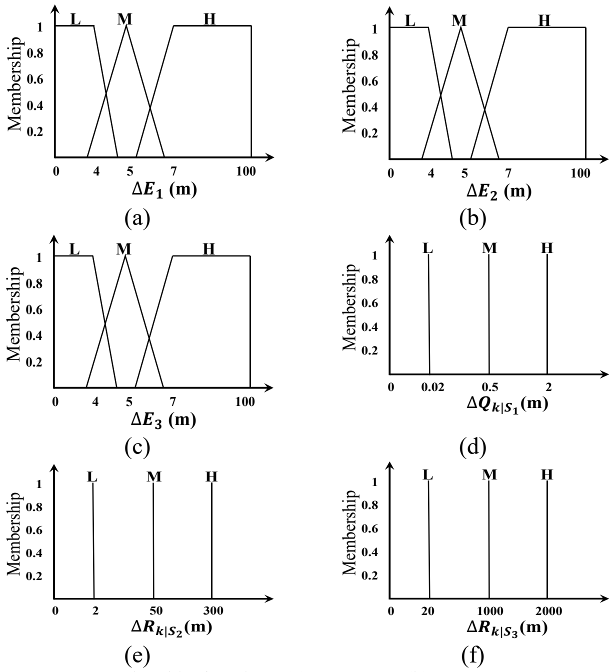


Fig. 4. Fuzzy membership functions (a) Input $\Delta E_1$ (b) Input $\Delta E_2$ (c) Input $\Delta E_3$ (d) Output $Q_{k|S_1}$ (e) Output $R_{k|S_2}$ (f) Output $R_{k|S_3}$

TABLE II. Rule Set For The Fuzzy Inference Model

| $\Delta E_1$ | $\Delta E_2$ | $\Delta E_3$ | $Q_{k\|S_1}$ | $R_{k\|S_2}$ | $R_{k\|S_3}$ |
|---|---|---|---|---|---|
| L | L | L | L | L | L |
| L | L | M | L | L | L |
| L | L | H | L | L | M |
| L | M | L | L | L | L |
| L | M | M | L | L | M |
| L | M | H | L | L | H |
| L | H | L | L | L | L |
| L | H | M | L | L | H |
| L | H | H | L | L | H |
| M | L | L | L | L | L |
| M | L | M | M | L | L |
| M | L | H | H | L | L |
| M | M | L | L | M | L |
| M | M | M | L | M | M |
| M | M | H | L | L | H |
| M | H | L | L | H | L |
| M | H | M | L | M | M |
| M | H | H | L | L | H |
| H | L | L | L | M | L |
| H | L | M | M | L | L |
| H | L | H | H | L | L |
| H | M | L | L | H | L |
| H | M | M | L | M | L |
| H | M | H | H | L | L |
| H | H | L | L | H | L |
| H | H | M | L | H | L |
| H | H | H | L | M | H |

path and a circle. These paths are created using a velocity based model (22), added with random white Gaussian noise, in an iterative process for 360 iterations. Three different error scenarios are also considered for the validity of the proposed algorithm. The three sensor error scenarios are as follows:

**Scenario 1:** When $S_3$ drifts away totally as shown in Fig. 5.
**Scenario 2:** When $S_2$ mal functions and shows repeatedly same data for an elongated period of time as shown in Fig. 6. Same scenario considering $S_3$ erroneous, is shown in Fig. 8.
**Scenario 3:** When $S_1$ is affected by a bias value as shown in Fig. 7.

Note: For all the figures shown below, $S_1$ is represented in magenta, $S_2$ in green, $S_3$ in indigo and fused outputs in red.

For the first scenario conventional EKF has been applied and it can be clearly seen in Fig. 5(a), that the fused output, gets distorted and tries to follow an optimum path considering all the available sensory data. Under the same applied conditions, the simulation is repeated but using our new intelligent technique of fusing. This time, the algorithm takes a decision between the accurate and the erroneous sensors, and the filtered output follows the more accurate sensors. It can be seen in Fig. 5(b) that the KIF technique completely skips the erroneous sensor from the fusion process.

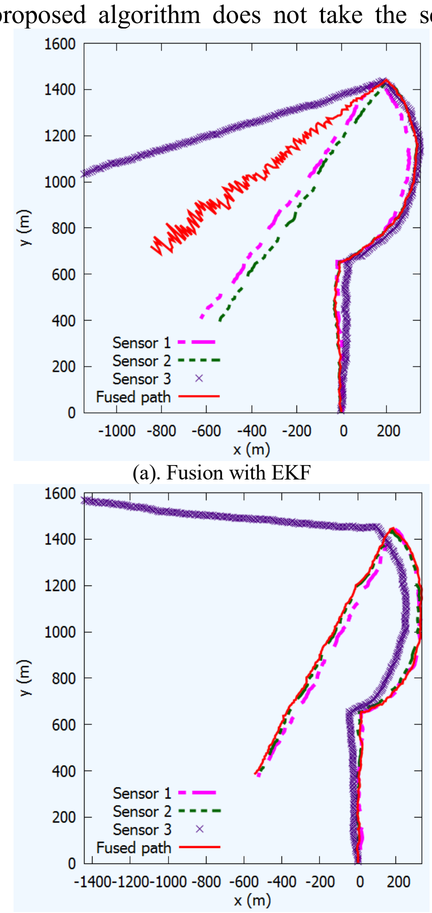
In the second scenario Fig. 6(b) and Fig. 8(b) shows better results as compared to Fig. 6(a) and Fig. 8(a) respectively. Our proposed algorithm does not take the sensor into the fusion process when it loses signal but again takes it into consideration when sensible data is received from that sensor.

In the third scenario as $S_1$ is an aiding sensor to the system model, therefore the EKF model has corrected the state of the robot, considering the measurement models as shown in Fig. 7(a). But compared to the result shown in Fig. 7(b), it can be seen that our proposed algorithm shows better results.

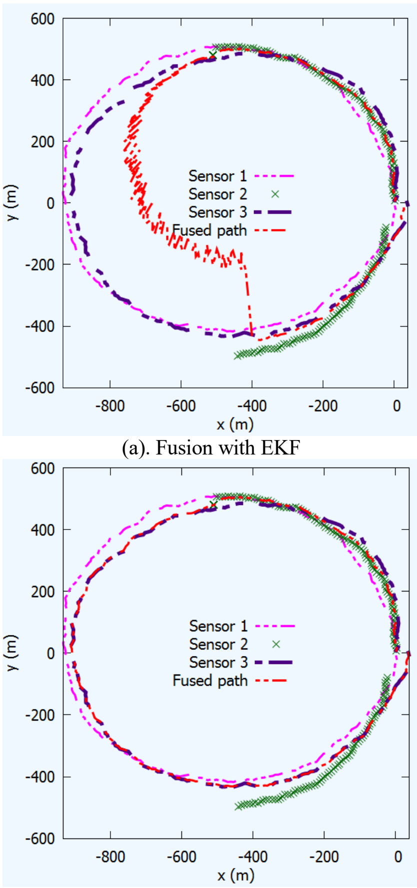
In Table III, the standard deviation of the most accurate sensors and the fused output under different scenarios has been compared. The maximum standard deviation along x-coordinate and y-coordinate has been recorded for both the algorithms. It is clear from Table III, that under the above cited scenarios, the standard deviation of the position coordinates under proposed algorithm is much less than that of the traditional EKF algorithm.

TABLE III. STANDARD DEVIATION FOR DIFFERENT SCENARIOS

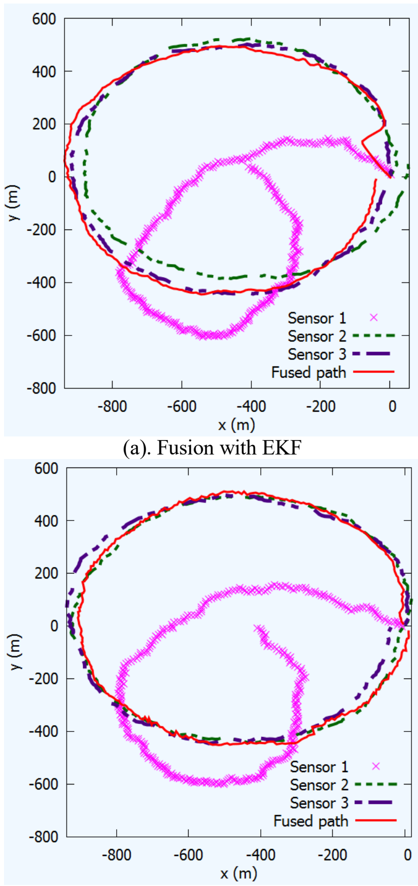
| **Scenario** | **Erroneous Sensor** | **Trajectory** | **Standard deviation along x-coordinate (max)** | | **Standard deviation along y-coordinate (max)** | |
|---|---|---|---|---|---|---|
| | | | ***EKF (m)*** | ***KIF (m)*** | ***EKF (m)*** | ***KIF (m)*** |
| 1 | $S_3$ | R-shaped | 165.02 | 26.81 | 186.07 | 11.91 |
| 2 | $S_2$ | Circle | 126.73 | 30.06 | 165.56 | 22.82 |
| | $S_3$ | R-shaped | 85.94 | 17.18 | 243.93 | 17.28 |
| 3 | $S_1$ | Circle | 51.13 | 27.82 | 39.69 | 15.64 |



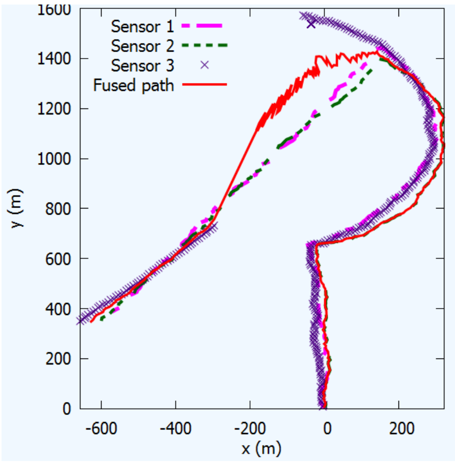
(a). Fusion with EKF
(b). Fusion with proposed method
Fig. 5. Scenario 1 with drift in sensor 3.



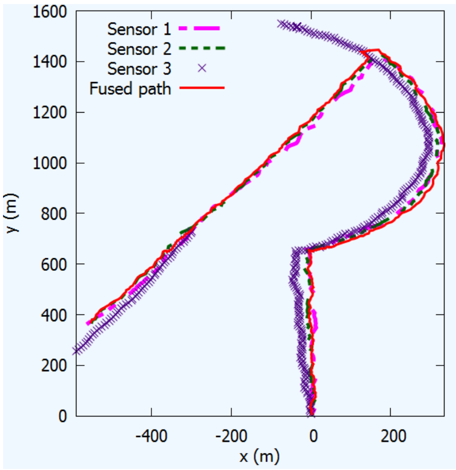
(a). Fusion with EKF
(b). Fusion with proposed method
Fig. 6. Scenario 2 with signal lost by sensor 2.



(a). Fusion with EKF
(b). Fusion with proposed method
Fig. 7. Scenario 3 with sensor 3 biased by a factor.




(a). Fusion with EKF




(b). Fusion with proposed method

Fig. 8. Scenario 2 with lost in signal by sensor 3.

From the simulation results between the standard EKF technique and our proposed technique, it is clear that our technique works better than the traditional one under the condition that one of the sensors in the fusion process is erroneous.

## V. CONCLUSION

In this paper, an intelligent way of sensor fusion using EKF has been proposed for localization of autonomous robots. In the sensor fusion techniques for robot localization, sensory error models are taken into consideration while fusing. But in dynamic environments the sensors might behave differently than the analytical error models. It can be seen from the simulations that EKF fails under such conditions. We came up with a solution to this problem by integrating the fuzzy inference theory to the EKF. Position sensors usually suffer from problems like signal lose, drift and permanent shift. These three scenarios are considered in our simulation and our proposed algorithm tackles all these three types of errors better than the standard EKF model. Our proposed algorithm opens up, one more dimension to the Kalman Filter family. Our concept of Kalman Intelligent Filtering has been validated via simulations in MATLAB. This model eradicates the necessity of modelling sensor noise. Computing the error covariance of a particular sensor in dynamic environments is perfectly carried out by the fuzzy model irrespective of the path maneuvered. This method proposed as Kalman Intelligent Filtering (KIF) can be applied to the real world mobile robots and UAVs where a reliable localization estimation is necessary.

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