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Sensor Fusion Based on Fuzzy Kalman Filtering for Autonomous Robot Vehicle

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Abstract

This paper presents the method of sensor fusion based on the Adaptive Fuzzy Kalman Filtering. This method has been applied to fuse position signals from the Global Positioning System (GPS) and Inertial Navigation System (INS) for the autonomous mobile vehicles. The presented method has been validated in 3-D environment and is of particular importance for guidance, navigation, and control of flying vehicles. The Extended Kalman Filter (EKF) and the noise characteristic has been modified using the Fuzzy Logic Adaptive System and compared with the performance of regular EKF.
It has been demonstrated that the Fuzzy Adaptive Kalman Filter gives better results (more accurate) than the EKF.

Introduction

When navigating and guiding an autonomous vehicle, the position and velocity of the vehicle must be determined. The Global Positioning System (GPS) is a satellite-based navigation system that provides a user with the proper equipment access to useful and accurate positioning information anywhere on the globe [1]. However, several errors are associated with the GPS measurement. It has superior long-term error performance, but poor short-term accuracy. For many vehicle navigation systems, GPS is insufficient as a stand-alone position system. The integration of GPS and Inertial Navigation System (INS) is ideal for vehicle navigation systems. In generally, the short-term accuracy of INS is good; the long-term accuracy is poor. The disadvantages of GPS/INS are ideally cancelled. If the signal of GPS is interrupted, the INS enables the navigation system to coast along until GPS signal is reestablished [1]. The requirements for accuracy, availability and robustness are therefore achieved.

Kalman filtering is a form of optimal estimation characterized by recursive evaluation, and an internal model of the dynamics of the system being estimated. The dynamic weighting of incoming evidence with ongoing expectation produces estimates of the state of the observed system [2]. An extended Kalman filter (EKF) can be used to fuse measurements from GPS and INS. In this EKF, the INS data are used as a reference trajectory, and GPS data are applied to update and estimate the error states of this trajectory. The Kalman filter requires that all the plant dynamics and noise processes are exactly known and the noise processes are zero mean white noise. If the theoretical behavior of a filter and its actual behavior do not agree, divergence problems will occur. There are two kinds of divergence: Apparent divergence and True divergence [3][4]. In the apparent divergence, the actual estimate error covariance remains bounded, but it approaches a larger bound than does predicted error covariance. In true divergence, the actual estimation covariance eventually becomes infinite. The divergence due to modeling errors is critical in Kalman filter application. If, the Kalman filter is fed information that the process behaved one way, whereas, in fact, it behaves another way, the filter will try to continually fit a wrong process. When the measurement situation does not provide enough information to estimate all the state variables of the system, in other words, the computed estimation error matrix becomes unrealistically small, and the filter disregards the measurement, then the problem is particularly severe. Thus, in order to solve the divergence due to modeling errors, we can estimate unmodeled states, but it add complexity to the filter and one can never be sure that all of the suspected unstable states are indeed model states[3]. Another possibility is to add process noise. It makes sure that the Kalman filter is driven by white noise, and prevents the filter from disregarding new measurement. In this paper, a fuzzy logic adaptive system (FLAS) is used to prevent the Kalman filter from divergence. The fuzzy logic adaptive controller (FLAC) will continually adjust the noise strengths in the filter's internal model, and tune the filter as well as possible. The FLAC performance is evaluated by simulation of the fuzzy adaptive extended Kalman filtering scheme of Fig.1.

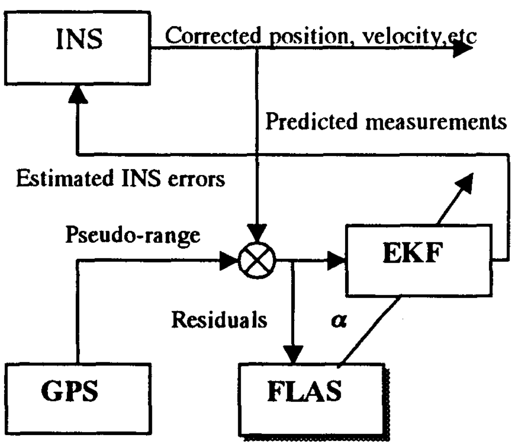

Fig.1. Fuzzy adaptive extended Kalman filter

Weighted EKF

Because the processes of both GPS and INS are nonlinear, a linearization is necessary. An extended Kalman filter is used to fuse the measurements from the GPS and INS. To prevent divergence by keeping the filter from discounting measurements for large k, the exponential data weighting [4] is used.

The models and implementation equations for the weighted extended Kalman filter are:

Nonlinear dynamic model

$$\mathbf{x}_{k+1} = f(\mathbf{x}_k, k) + \mathbf{w}_k \qquad (1)$$

$\mathbf{w}_k \sim N(0,\mathrm{Q})$;

Nonlinear measurement model

$$\mathbf{z}_k = h(\mathbf{x}_k, k) + \mathbf{v}_k \qquad (2)$$

$\mathbf{v}_k \sim N(0, \mathbf{R})$;

Let us set the model covariance matrices equal to

$$\mathbf{R}_k = \mathbf{R}\alpha^{-2(k+1)} \qquad (3)$$

$$\mathbf{Q}_k = \mathbf{Q}\alpha^{-2(k+1)} \qquad (4)$$

where, $\alpha \geq 1$, and constant matrices **Q** and **R**. For $\alpha > 1$, as time k increases, the **R** and **Q** decrease, so that the most recent measurement is given higher weighting. If $\alpha = 1$, it is a regular EKF.

By defining the weighted covariance

$$\mathbf{P}_k^{\alpha-} = \mathbf{P}_k^- \alpha^{2k} \qquad (5)$$

The Kalman gain can be computed:

$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{H}_k^T (\mathbf{H}_k \mathbf{P}_k^- \mathbf{H}_k^T + \mathbf{R}\alpha^{-2(k+1)})^{-1}$$

$$= \mathbf{P}_k^{\alpha-} \mathbf{H}_k^T \left(\mathbf{H}_k \mathbf{P}_k^{\alpha-} \mathbf{H}_k^T + \frac{\mathbf{R}}{\alpha^2} \right)^{-1} \qquad (6)$$

The predicted state estimate is:

$$\hat{\mathbf{x}}_{k+1}^- = f(\hat{\mathbf{x}}_k, k) \qquad (7)$$

The predicted measurement is:

$$\hat{\mathbf{z}}_k = h(\hat{\mathbf{x}}_k^-, k) \qquad (8)$$

The linear approximation equations can be presented in form:

$$\Phi_k \approx \left. \frac{\partial f(x,k)}{\partial x} \right|_{x = \hat{x}_k^-} \qquad (9)$$

The predicted estimate on the measurement can be computed:

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}_k (\mathbf{z}_k - \hat{\mathbf{z}}_k) \qquad (10)$$

$$\mathbf{H}_k \approx \left. \frac{\partial h(x,k)}{\partial x} \right|_{x = x_k^-} \qquad (11)$$

Computing the *a priori* covariance matrix:

$$\mathbf{P}_{k+1}^- = \Phi_k \mathbf{P}_k \Phi_k^T + \mathbf{Q}\alpha^{-2(k+1)} \qquad (12)$$

Re-writing (12) gives:

$$\mathbf{P}_{k+1}^{\alpha-} = \alpha^2 \Phi_k \mathbf{P}_k^{\alpha} \Phi^T + \mathbf{Q} \tag{13}$$

Computing the *a posteriori* covariance matrix gives:

$$\mathbf{P}_k^{\alpha} = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \mathbf{P}_k^{\alpha-} \tag{14}$$

The initial condition is:

$$\mathbf{P}_0^{\alpha-} = \mathbf{P}_0$$

In equation (10), the term $\mathbf{z}_k - \hat{\mathbf{z}}_k$ is called residuals or innovations. It reflects the degree to which the model fits the data.

INS and GPS

The inertial navigation system (INS) consists of a sensor package, which includes accelerometers and gyros to measure accelerations and angular rates. By using these signals as input, the attitude angle and three-dimensional vectors of velocity and position are computed [5]. The errors in the measurements of force made by the accelerometers and the errors in the measurement of angular change in orientation with respect to inertial space made by gyroscopes are two fundamental error sources, which affect the error behavior of an inertial system. The inertial system error response, related to position, velocity, and orientation is divergent with time due to noise input [6]. There are biases associated with the accelerometers and gyros. In order to correct the errors of INS, the GPS measurements are used to estimate the inertial system errors, subtract them from the INS outputs, and then obtain the corrected INS outputs. There is number of errors in GPS, such as ephemeris errors, propagation errors, selective availability, multi-path, and receiver noise, etc. By using differential GPS (DGPS), most of the errors can be corrected, but the multi-path and receiver noise cannot be eliminated.

Fuzzy Logic Adaptive System

It is assumed that both, the process noise $\mathbf{w}_k$ and the measurement noise $\mathbf{v}_k$ are zero-mean white sequences with known covariance Q and **R** in the Kalman filter. If the Kalman filter is based on a complete and perfectly tuned model, the residuals should be a zero-mean white noise process. If the residuals are not white noise, there is something wrong with the design and the filter is not performing optimally [4]. The Kalman filters will diverge or coverage to a large bound. In practice, it is difficult to know the exact value for **Q** and **R**. In order to reduce computation, we have to ignore some errors, but sometimes those unmodeled errors will become significant. These are the instrument bias errors of INS. Generally the $\mathbf{w}_k$ does not always have zero mean. In those cases, the residuals can be used to adapt the filter. In fact, the residuals are the differences between actual measurements and best measurement predictions based on the filter's internal model. A well-tuned filter is that where the 95% of the autocorrelation function of innovation series should fall within the $\pm 2\sigma$ boundary [7]. If the filter diverges, the residuals will not be zero mean and become larger.

There are very few papers on application of fuzzy logic to adapt the Kalman filter. In [8], fuzzy logic is used to the on-line detection and correction of divergence in a single state Kalman filter. There were three inputs and two outputs to fuzzy logic controller (FLC), and 24 rules were used. The purpose of our fuzzy logic adaptive system (FLAS) is to detect the bias of measurements and prevent divergence of the extended Kalman filter. It has been applied in three axes — East (x), North (y), and Altitude (z). The covariance of the residuals and the mean of residuals are used as the inputs to FLAS for all three fuzzy inference engines. The exponential weighting α for three axes are the outputs. As an input to FLAS, the covariance of the residuals and mean values of residuals are used to decide the degree of divergence. The value of covariances relates to **R**. The equation for covariance of the residual is:

$$\mathbf{P}_z = \mathbf{H}_k \mathbf{P}_k^- \mathbf{H}_k^T + \mathbf{R} \tag{15}$$

When the Kalman filter is performing optimally, the mean values of residuals are near zero. Generally, when the covariance is becoming large, and mean value is moving away from zero, the Kalman filter is becoming unstable. In this case, a large α will be applied. A large α means that process noises are added. It can ensure that in the model all states are sufficiently excited by the process noise. When the covariance is extremely large, there are some problems with the GPS measurements, so the filter cannot depend on these measurements anymore, and a small α will be used. The perfect measurements are given more weighting. By selecting appropriate α, the FLAS will adapt the Kalman filter optimally and try to keep the innovation sequence acting as zero-mean white noise.

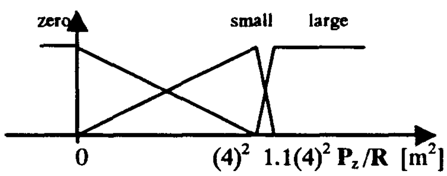

Fig.2. Covariance Membership Functions

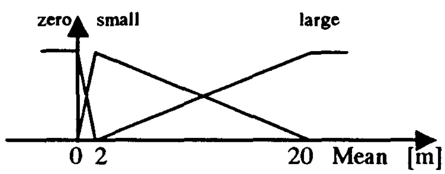

Fig.3. Mean Value Membership Functions

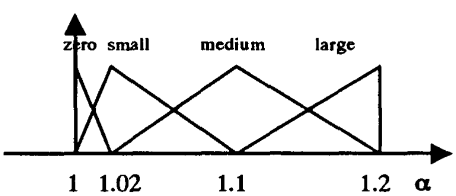

Fig.4. α Membership Functions

The FLAS uses 9 rules, such as:

If the covariance of residuals is large ***and*** *the mean values are zero* ***Then*** α *is large.*

If the covariance of residuals is zero ***and*** *the mean values are large* ***Then*** α *is zero.*

The fuzzy adaptive Kalman filtering has been used for guidance and navigation of mobile robots, especially for 3-D environment. The navigation of flying robots requires fast, on-line control algorithms. The "regular" Extended Kalman Filter requires high number of states for accurate navigation and positioning. The FLAC requires smaller number of states for the same accuracy and therefore it would need less computational effort. Alternatively, the same number of states (as in "regular" filter) would allow for more accurate navigation.

Table. 1. Rule Table for FLAS

α		Mean Value		
		Z	S	L
P	Z	S	Z	Z
	S	Z	L	M
	L	L	M	Z

S --- Small; M --- Medium;
L --- Large; Z --- Zero;

Simulation

MATLAB codes developed by authors has been used to simulate and test the proposed method.

The state variables used in simulation are:

$$\mathbf{x}_k = [x_k, \dot{x}_k, y_k, \dot{y}_k, z_k, \dot{z}_k, c\Delta t, c\dot{\Delta t}] \quad (16)$$

The states are position, and velocity errors of the INS East, North, Altitude, GPS range bias and range drift. The covariance of GPS measurement $\mathbf{R}$ is 5 [m^2]. It is assumed that the measurements of INS have some biases. In the first simulation (Fig. 5), the mean values of INS are 0.0014 meter, 0.00035 meter, and 0.0007 meter for the East (x), North (y), and Altitude (z) respectively. A white noise with a standard deviation of 3 meter is added to GPS measurements. The sample period is 1 second. The first row in Fig. 5 is the innovations of fuzzy adaptive EKF and EKF in East (x). The innovation of EKF had a large drift, and was stable at a high mean value. The fuzzy adaptive EKF clearly improved the performance of EKF, and the mean value was much smaller than that of EKF. Other figures present the corrected position (first column) and velocity (second column) errors. The corrected error is the current INS error minus estimated INS error. The dashed lines are the corrected errors of EKF, and the solid lines are the corrected errors of fuzzy adaptive EKF. The fuzzy adaptive EKF significantly reduced the corrected position and velocity errors. In the second simulation (Fig. 6), the same measurements as in the first simulation for INS were used. A white noise with a standard deviation of 2 meter from 0 s to 1000 s and 1500 s to 2000s was applied to GPS measurements. From 1000 s to 1500 s, the standard deviation of 6 meter with mean value of 6 meter was added to GPS measurements. Although, the GPS measurement noises features were changed, the fuzzy adaptive EKF still worked well. Those simulations also showed that the corrected errors of EKF were proportional to the mean values of INS measurements. In other word, the more errors are not modeled, the worse the EKF performs.

Conclusions

In this paper, a fuzzy adaptive extended Kalman filter has been developed to detect and prevent the EKF from divergence. By monitoring the innovations sequence, the FLAS can evaluate the performance of an EKF. If the filter does not perform well, it would apply an appropriate weighting factor α to improve the accuracy of an EKF.

The simulation results show that the FLAS significantly reduces the corrected position and velocity errors when the EKF results diverge. In FLAS, there are 9 rules and therefore, little computational time is needed. It can be used to navigate and guide autonomous vehicles or robots [9] and achieved a relatively accurate performance. Also, the FLAS can use lower order state-model without compromising accuracy significantly. Another words, for any given accuracy, the fuzzy adaptive Kalman filter may be able to use a lower order state model. The FLAS makes the necessary trade-off between accuracy and computational burden due to the increased dimension of the error state vector and associated matrices.

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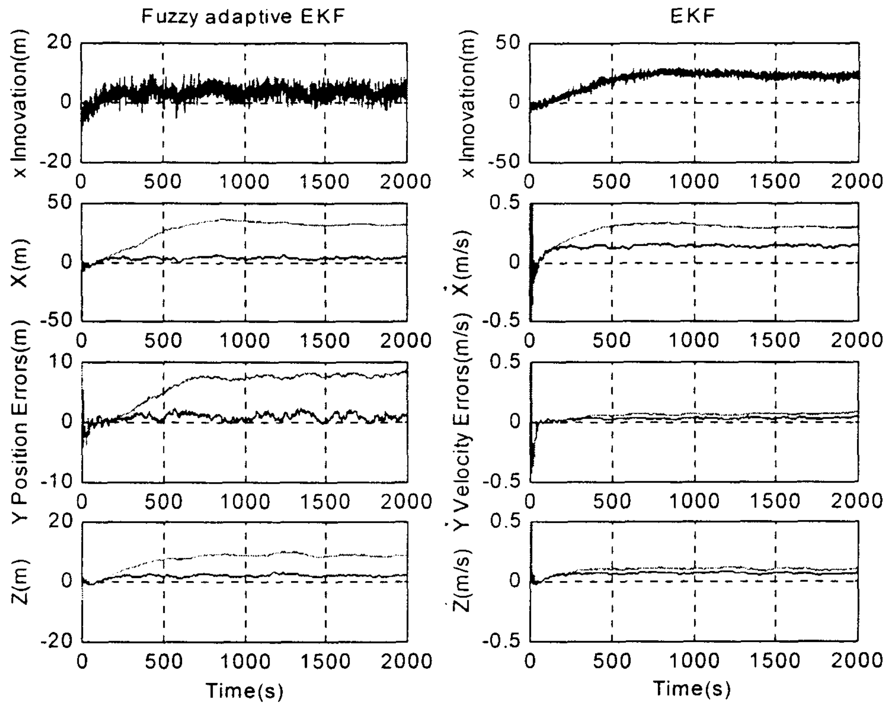

Fig.5. Simulation 1

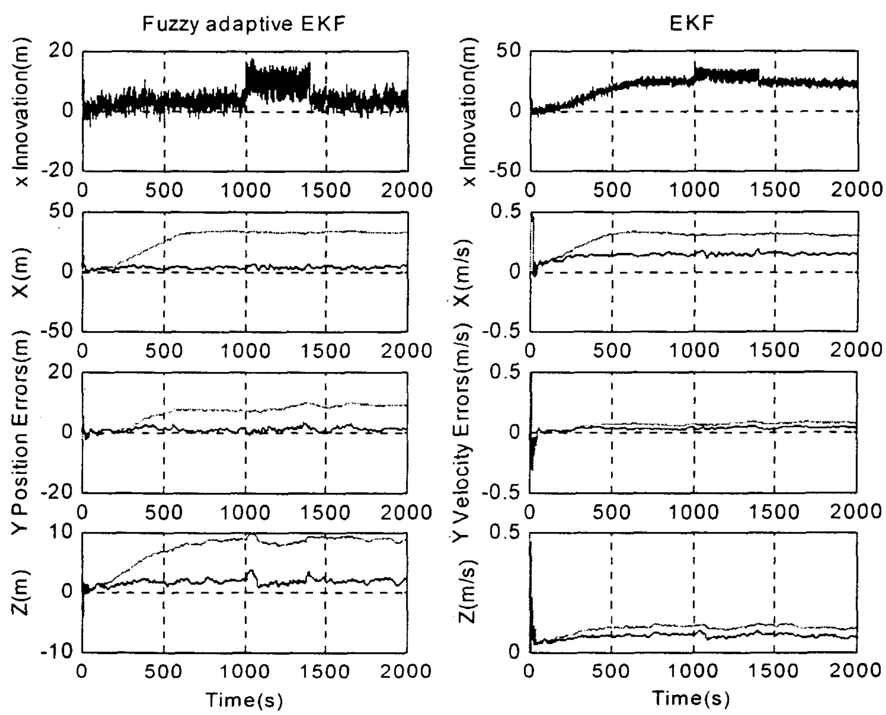

Fig.6. Simulation 2