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ADAPTIVE FUZZY LOGIC SYSTEM FOR SENSOR FUSION IN DEAD-RECKONING MOBILE ROBOT NAVIGATION

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Abstract: This paper presents the sensor fusion for dead-reckoning mobile robot navigation. Odometry and sonar measurement signals are fused together using Extended Kalman Filter (EKF) and Adaptive Fuzzy Logic System (AFLS). Two methods of adaptation scheme are used, the first one uses $\mathbf{Q}$ and $\mathbf{R}$, the second one only uses $\mathbf{Q}$. The first method gives faster result than the second one. The fused signal is more accurate than any of the original signals considered separately. The enhanced, more accurate signal is used to guide and navigate the robot. *Copyright Ó 2002 IFAC*

Keywords: Autonomous Robots, Guidance, Navigation and Control, Sensor fusion, Kalman Filter, Adaptive Fuzzy Logic System

1 INTRODUCTION

To follow the designed path, an autonomous vehicle has to be equipped with three systems: navigation, guidance, and control system, see Gai (1996), Kaminer, *et. al.* (1998). Navigation system provides estimation of position and velocity (path), guidance system determines the optimal trajectory to drive the vehicle to desire path, and control system commands the vehicle's actuators to drive the vehicle to the value determined by the guidance system.

For navigation system, there are two basic position-estimation methods commonly applied: relative and absolute positioning, see Borenstein and Feng (1996), Shoval, *et al*. (1998), Jetto, *et al*. (1999), Jetto, *et al*. (1999), and Roumeliotis, *et al*. (1999). Relative positioning, sometimes called dead reckoning, is usually based on inertial sensors or odometry sensors. In this method, the calculated distance from initial position determines current position estimation. In absolute positioning system, the positioning sensors interact with dynamic environment, such as navigation beacons, landmark, map matching, or satellite-based navigation signal, to find the position estimation.

To solve the positioning problems, there are two types of sensors available: internal and external sensors, as explained by McKerrow (1991). Internal sensors measure physical variables on the vehicle itself; external sensors measure relationships between the vehicle and its environment, which can be natural or artificial objects.

When the above sensors are implemented to solve positioning problems, both have advantages and disadvantages. The self-containing characteristic of the internal sensors make the measurement results of these sensors are almost always available to solve positioning problems, whereas, many situation, such as the shortage of signal caused by high building, tunnel, etc, make the external sensors are not viable to be used in that problems. For short period, measurements using internal sensors are quite accurate. However, for long-term estimation, the measurements usually produce a drift. On the contrary, because it measures absolute quantity, external sensors do not produce the drift, however, their measurements are usually not always available, Santini (1997).

This problem raises the idea of using multi sensors in the system. Measurement results from many sensors are fused to find an optimal estimation of position or velocity of the vehicle.

The common estimation method used is by applying the Extended Kalman Filter (EKF), such as shown in the work by Jetto, *et al*., (1997, 1999), Tham, *et al*., (1999), Sasiadek and Wang (1999), Sasiadek and Hartana (2000).

Odometry is one internal sensor that is widely used in navigation. It is mounted on the vehicle's driving wheels and register angular movements of the wheels, which are then translated into linear movements. Because of the translation process, it has limited accuracy. For example, if slip has occurred on the wheel, the movement will be registered by the odometry, where in fact, the vehicle may stay on its position. Although the measurement signals are always available, in the long period, the incremental motion of odometry will cause the accumulative error in positioning process.

When using odometry sensor, a systematic error can occur, which causes the bias in one direction of the movement of the vehicle. Unequal in the radius of the wheel where the odometry sensors are attached is one example of the systematic error. One method used to reduce this error is by conducting a benchmark experiment prior to regular operation of the vehicle (Borenstein). Using this benchmark, after the error is identified, the correction is applied in the control system parameters. If the systematic errors occur frequently, this method may not be sufficient. Therefore, it is beneficial if the error correction can be done in real time operation.

The most common combination of sensors used in positioning and localization problems is combination of odometry and sonar sensor. Odometry sensor is mounted on the robot's driving wheels and register angular movements of the wheels, which are then translated into linear movements. Beside the drawback that the translation introduces the error, see Sasiadek and Hartana (2000), this implementation makes the odometry signal always available. The sonar sensor, which measures absolute position of the robot, is used to update the position measured by odometry.

It is widely known that poorly designed mathematical model for the EKF will lead to the divergence. Clearly, if the plant parameters are subject to perturbations and dynamics of the system are too complex to be characterized by an explicit mathematical model, an adaptive scheme is needed. Jetto, *et al*., (1999) used Fuzzy Logic Adapted Kalman Filter (FLAKF) to prevent the filter from divergence when fusing measurement from odometry and sonar sensors. In this method, the ratio of innovation and covariance of innovation is used as input to the fuzzy logic, and the output is used to weight the process noise covariance in EKF. Sasiadek and Wang (1999) used exponential data weighting to prevent the divergence. Mean value and covariance of innovation are used as the input of the Fuzzy Logic Adaptive Controller (FLAC). The output is then used to weight process noise and measurement noise covariance in EKF. This FLAC is implemented on the flying vehicle navigating in three-dimensional space. Both those methods have shown improvement in the estimation of the vehicle position in comparison with the EKF only.

In this paper, the systematic error in odometry sensor is corrected during real-time operation of the vehicle by using measurements result from the sonar sensor. EKF is applied to fuse those two signals to find the best estimation of position. To prevent the filter from divergence, an adaptation scheme using fuzzy logic id used. Two methods are implemented as fuzzy controller. The first method is using exponential data weighting, and the second method is using comparison between calculated covariance and estimated covariance. Those two methods are explained later.

2 MODEL

The model of the vehicle used in the simulation is based on a differential-drive. In this model, the vehicle can be steered by differentiating the wheels angular velocity. The kinematic model of this vehicle is described by the following equations, see Wang (1988):

$$\dot{x}(t) = v(t)\sin q(t) \tag{1}$$

$$\dot{y}(t) = v(t)\sin q(t) \tag{2}$$

$$\dot{q}(t) = w(t) \tag{3}$$

where $v(t)$ and $w(t)$ are, respectively, the linear and angular velocities of the robot, and are expressed by:

$$v(t) = \frac{w_r(t) + w_l(t)}{4} D \qquad (4)$$

$$w(t) = \frac{w_r(t) - w_l(t)}{2d} D \qquad (5)$$

where D and d are the wheel diameter and the distance between the odometry encoder respectively.

If we denote the state variable of the vehicle as $\mathbf{x}(t) = [x(t) \quad y(t) \quad q(t)]^T$, and the vehicle control input as $\mathbf{u}(t) = [v(t) \quad w(t)]^T$, the kinematic model in equations (1) - (3) can be written in the form of stochastic differential equation as:

$$\dot{\mathbf{x}}(t) = f(\mathbf{x}(t), \mathbf{u}(t)) + \mathbf{w}(t) \qquad (6)$$

where $\mathbf{w}(t)$ is a zero-mean Gaussian white noise with covariance matrix $\mathbf{Q}(t)$, which represents the model inaccuracies. This time-equation is linearized and sampled in a small period $T = t_{k+1} - t_k$. Assuming that during this time interval, the linear and angular velocities are constant, and that the vehicle is following an arc path (see Wang (1988)), then, the equations for Extended Kalman Filter can be expressed by:

$$\mathbf{x}_{k+1}^- = \mathbf{x}_k + \mathbf{B}_k \mathbf{u}_k \qquad (7)$$

$$\mathbf{P}_{k+1}^- = \mathbf{A}_k \mathbf{P}_k \mathbf{A}_k^T + \mathbf{Q}_k \qquad (8)$$

$$\mathbf{K}_{k+1} = \mathbf{P}_{k+1}^- \mathbf{C}_{k+1}^T [\mathbf{C}_{k+1} \mathbf{P}_{k+1}^- \mathbf{C}_{k+1}^T + \mathbf{R}_{k+1}]^{-1} \qquad (9)$$

$$\mathbf{x}_{k+1} = \mathbf{x}_{k+1}^- + \mathbf{K}_{k+1} [\mathbf{y}_{k+1} - \mathbf{C}_{k+1} \mathbf{x}_{k+1}^-] \qquad (10)$$

$$\mathbf{P}_{k+1} = [\mathbf{I} - \mathbf{K}_{k+1} \mathbf{C}_{k+1}] \mathbf{P}_{k+1}^- \qquad (11)$$

where:

$$\mathbf{x}_k = [x_k \quad y_k \quad q_k]^T \qquad (12)$$

$$\mathbf{B}_k = \begin{bmatrix} T \cos\left(q_k + \frac{\Delta q_k}{2}\right) & 0 \\ T \sin\left(q_k + \frac{\Delta q_k}{2}\right) & 0 \\ 0 & 1 \end{bmatrix} \qquad (13)$$

$$\mathbf{A}_k = \begin{bmatrix} 1 & 0 & -v_k T \sin q_k \\ 0 & 1 & v_k T \cos q_k \\ 0 & 0 & 1 \end{bmatrix} \qquad (14)$$

$$\mathbf{Q}_k = [\mathbf{Q}_1 \quad \mathbf{Q}_2 \quad \mathbf{Q}_3] \qquad (15)$$

$$\mathbf{Q}_1 = \begin{bmatrix} Q_{11} T + Q_{33} (T^3/3) v_k^2 \sin^2 q_k \\ -Q_{33} (T^3/3) v_k^2 \sin q_k \cos q_k \\ -Q_{33} (T^2/2) v_k \sin q_k \end{bmatrix} \qquad (16)$$

$$\mathbf{Q}_2 = \begin{bmatrix} -Q_{33} (T^3/3) v_k^2 \sin q_k \cos q_k \\ Q_{22} T + Q_{33} (T^3/3) v_k^2 \cos^2 q_k \\ Q_{33} (T^2/2) v_k \cos q_k \end{bmatrix} \qquad (17)$$

$$\mathbf{Q}_3 = \begin{bmatrix} -Q_{33} (T^2/2) v_k \sin q_k \\ Q_{33} (T^2/2) v_k \cos q_k \\ Q_{33} T \end{bmatrix} \qquad (18)$$

and, $Q_{11} = s_x^2$, $Q_{22} = s_y^2$, and $Q_{33} = s_q^2$ are diagonal elements of covariance matrix $\mathbf{Q}(t)$ of $\mathbf{w}(t)$ in Eq. (6).

The measurement, in this case, will consist of the measurement from odometry sensor and sonar sensor. The size of the measurement vector depends on the number of active sonar sensor. In general, this vector can be expressed as (See Jetto et. al. (1999)):

$$\mathbf{y}(\mathbf{x}_k, \Pi) = [x_k \quad y_k \quad q_k \quad d_{1k} \quad d_{2k} \quad \mathbf{K} \quad d_{nk}]^T \qquad (19)$$

where d_{nk} is the measurement of sonar *n*th at time *k*.

3 ADAPTIVE FUZZY LOGIC SYSTEM

In Kalman filter model, both process noise $\mathbf{w}_k$ and measurement noise $\mathbf{v}_k$ are assumed zero-mean white noise sequence with covariance $\mathbf{Q}_k$ and $\mathbf{R}_k$. If the model of EKF is tuned perfectly, the residual between actual and predicted measurement should be a zero-mean white noise process.

In real application, we do not know all parameters of the model, therefore, the exact values of $\mathbf{Q}_k$ and $\mathbf{R}_k$ are not known. If the actual process and measurement noises are not a zero-mean white noise, the residual in Kalman filter will also not be a white noise. If this is happened, the Kalman filter would diverge or at best converge to a large bound.

Jetto, *et al*. (1999) used fuzzy logic adapted Kalman filter to prevent the filter from divergence. The fuzzy logic controller uses one input and one output. The ratio between innovation and covariance of innovation process is used as an input. The output is a constant, which is used to weight the process noise covariance. The controller uses five fuzzy rules, and it is implemented in a wheeled mobile robot equipped with odometry and sonar sensors.

Sasiadek and Wang (1999) used fuzzy logic adapted controller (FLAC) to prevent the filter from divergence when fusing signals coming from INS and GPS on flying vehicle. Nine rules were used. There were two inputs, which are the mean value and covariance of innovation, and the output is a constant that is used to weight exponentially the model and measurement noise covariance.

In the case of fusing signals that come from odometry and sonar sensors, sometime only odometry measurements are available. The innovation will be a white noise as long as the process and measurement noises are assumed as a white noise. However, when the sonar measurements become available, and combined with the odometry measurement, the innovation might be not a white noise anymore. This will cause the filter to diverge.

When systematic error occurs in the vehicle, the process and measurement noise actually are not a gaussian white noise, which causes divergence in EKF. AFLS can be used to adapt the filter gain so that the divergence can be avoided. The scheme of the adaptation process is shown in Fig. 1.

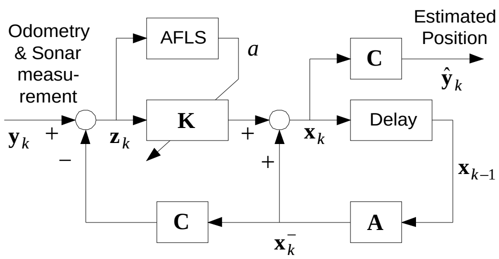

Fig. 1. Adaptive Fuzzy Logic System (AFLS) scheme

3.1 METHOD 1

The first method used to adapt the Kalman filter is by using exponential data weighting. In this method, the weighted process and measurement noise covariance can be written as:

$$\mathbf{R}_k = \mathbf{R}a^{-2(k+1)} \tag{20}$$

$$\mathbf{Q}_k = \mathbf{Q}a^{-2(k+1)} \tag{21}$$

where $a \geq 1$. $\mathbf{Q}$ and $\mathbf{R}$ are constant matrices of process and measurement noise covariance. For $a > 1$, as time k increases, $\mathbf{Q}_k$ and $\mathbf{R}_k$ will decrease, which means that the most recent measurement is given higher weighting.

If the weighted estimation covariance is defined as:

$$\mathbf{P}_k^{a-} = \mathbf{P}_k^- a^{2k} \tag{22}$$

then the EKF equations become:

$$\mathbf{x}_{k+1}^- = \mathbf{x}_k + \mathbf{B}_k \mathbf{u}_k \tag{23}$$

$$\mathbf{P}_{k+1}^{a-} = a^2 \mathbf{A}_k \mathbf{P}_k^a \mathbf{A}_k^T + \mathbf{Q}_k \tag{24}$$

$$\mathbf{K}_{k+1} = \mathbf{P}_{k+1}^{a-} \mathbf{C}_{k+1}^T [\mathbf{C}_{k+1} \mathbf{P}_{k+1}^{a-} \mathbf{C}_{k+1}^T + \frac{\mathbf{R}_{k+1}}{a^2}]^{-1} \tag{25}$$

$$\mathbf{x}_{k+1} = \mathbf{x}_{k+1}^- + \mathbf{K}_{k+1}[\mathbf{y}_{k+1} - \mathbf{C}_{k+1}\mathbf{x}_{k+1}^-] \tag{26}$$

$$\mathbf{P}_{k+1}^a = [\mathbf{I} - \mathbf{K}_{k+1}\mathbf{C}_{k+1}]\mathbf{P}_{k+1}^{a-} \tag{27}$$

The membership function used in this method and the rule table can be found in Sasiadek and Hartana (2000).

3.2 METHOD 2

In the first method, both $\mathbf{Q}$ and $\mathbf{R}$ are used to adapt the Kalman filter. In the second method, only $\mathbf{Q}$ is used.

If we assume $s_x = s_y = s$, and $s_z = \frac{s_q}{s}$, then equation (15) can be written as:

$$\mathbf{Q}_k = s_k^2 \overline{\mathbf{Q}}_k \tag{28}$$

where

$$\overline{\mathbf{Q}}_k = [\overline{\mathbf{Q}}_1 \quad \overline{\mathbf{Q}}_2 \quad \overline{\mathbf{Q}}_3] \tag{29}$$

$$\overline{\mathbf{Q}}_1 = \begin{bmatrix} T + s_z^2 (T^3/3) v_k^2 \sin^2 q_k \\ - s_z^2 (T^3/3) v_k^2 \sin q_k \cos q_k \\ - s_z^2 (T^2/2) v_k \sin q_k \end{bmatrix} \tag{30}$$

$$\overline{\mathbf{Q}}_2 = \begin{bmatrix} - s_z^2 (T^3/3) v_k^2 \sin q_k \cos q_k \\ T + s_z^2 (T^3/3) v_k^2 \cos^2 q_k \\ s_z^2 (T^2/2) v_k \cos q_k \end{bmatrix} \tag{31}$$

$$\overline{\mathbf{Q}}_3 = \begin{bmatrix} - s_z^2 (T^2/2) v_k \sin q_k \\ s_z^2 (T^2/2) v_k \cos q_k \\ s_z^2 T \end{bmatrix} \tag{32}$$

If $[\mathbf{y}_{k+1} - \mathbf{C}_{k+1}\mathbf{x}_{k+1}^-]$ is the error between the measurement and the estimation, which is modeled as a zero-mean, white Gaussian sequence with covariance matrix as in Eq. (11), we can create a variable g as:

$$g = \frac{\text{Calculated error covariance}}{\mathbf{P}_{k+1}} \qquad (33)$$

This variable indicates the comparison between the actual covariance and its theoretically assumed value. If g is near one, this means that the value of $\mathbf{Q}_k$ is appropriate. If g is very near to zero, the assumed covariance is too large and we need to reduce the value of $\mathbf{Q}_k$. If g is larger than one, that means we need to increase the value of $\mathbf{Q}_k$.

The change in the value of $\mathbf{Q}_k$ can be achieved by using the Eq. (28), where:

$$a = \frac{s_k^2}{s_{k-1}^2} \qquad (34)$$

There are 5 rules are used. The linguistic variables used for g are: NZ (near zero), S (small), M (medium), ML (moderately large), and L (large). The linguistic variable used for a are: NZ (near zero), N1 (near to 1), LL1 (little larger that 1), ML1 (moderately larger than 1), L (large).

The membership function (MF) for g and a are displayed in Fig. 2 and Fig. 3.

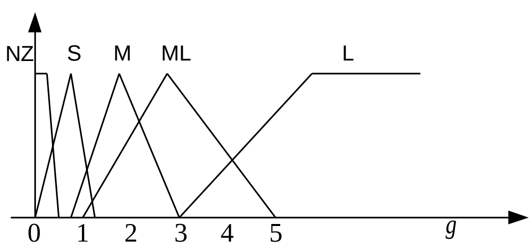

Fig. 2. MF of g

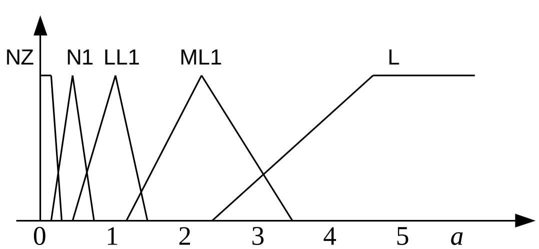

Fig. 3. MF of a

4 EXPERIMENTS AND RESULTS

Simulation experiments have been conducted to show the implementation of AFLS when fusing the signals that come from odometry and sonar sensor. Systematic error in odometry measurement, which comes from unequal in wheel's diameter, is also considered. The vehicle is planned to follow sinus path in in-door environment. The map of the in-door environment along with the movement of the mobile vehicle that has systematic error is shown in Fig. 4.

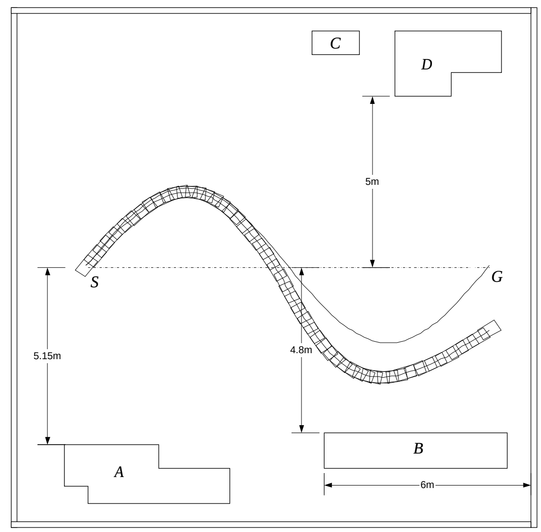

Fig. 4. Map of in-door environment

The implementation of the AFLS using method 1 and method 2 are simulated. The simulation result for method 1 is displayed in Fig. 5. In this experiment, the present of sonar sensor, which measures the relation of the mobile vehicle and its environment, reduces the systematic error, and the mobile vehicle can follow the designed path. The implementation of AFLS into the EKF allows the vehicle to follow the designed path smoothly.

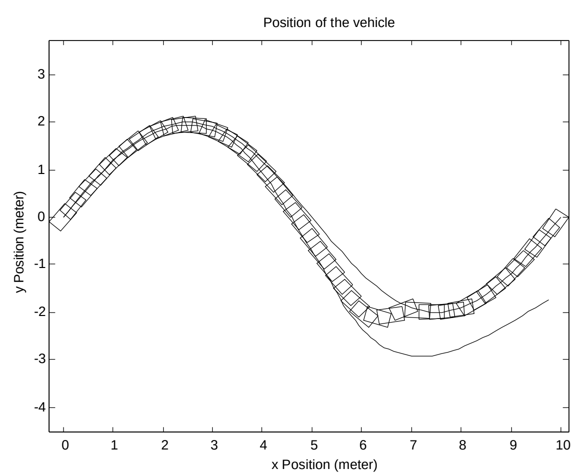

Fig. 5. Simulation result of AFLS using method 1.

The simulation result for method 2 is displayed in Fig. 6. In this experiment, the result is almost the same as in the method 1, except that there is one overshoot occurs when the signals from sonar sensors become available.

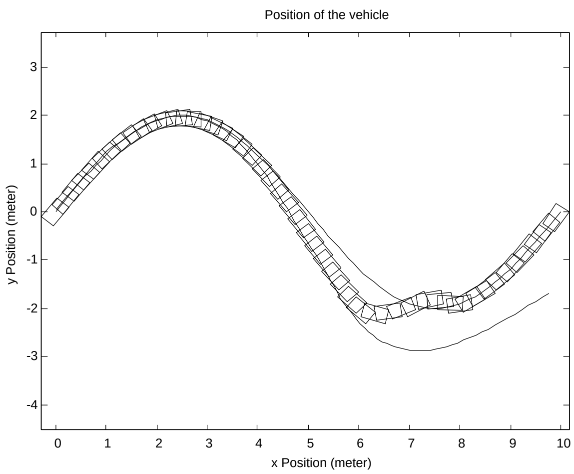

Fig. 6. Simulation result of AFLS using method 2.

Two variables adapted in method 1, $\mathbf{Q}$ and $\mathbf{R}$, makes the method 1 gives faster result than method 2, which is only one variable is adapted.

4.1 CONCLUSIONS

In this paper, Extended Kalman Filter (EKF) has been used to estimate the position of the mobile vehicle. To prevent the filter from divergence, the adaptation scheme using fuzzy logic system (Adaptive Fuzzy Logic System - AFLS) was implemented. Two methods were used in the adaptation process, the first one uses $\mathbf{Q}$ and $\mathbf{R}$, the second one only uses $\mathbf{Q}$.

Odometry and sonar sensors have been used to simulate the method. From the simulation experiment, it shows that method 1 gives faster result than method 2. The method can also be used to correct the systematic error. Using this method, real-time operation of the vehicle can be reduced.

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