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Double-Fuzzy Kalman Filter Based on GPS/IMU/MV Sensor Fusion for Tractor Autonomous Guidance

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***Abstract* - Sensor fusion technique has been commonly used for improving the navigation of autonomous agricultural vehicles by means of combining sensors mounted on such vehicles for the position and attitude angle measurements. In this research, a real-time tractor position estimation system, which is consisted with the global positioning system (GPS), the six-axis inertial measurement unit (IMU) and the machine vision (MV) was discussed. A double-fuzzy Kalman filter (DFKF) was used to fuse the information from these sensors so that the noise in the GPS and the machine vision signals was filtered, the redundant information was fused and a higher update rate of output signals was obtained. The drift error of the IMU was also compensated. One of the double-fuzzy logic controller was designed to modify the filter gain matrix *K* and the measurement noise covariance *R* on line based on Dead Reckoning algorithm, and the other fuzzy logic controller was designed to modify the process noise covariance *Q* on line based on the variety of the innovation vector. Through trials with simulated data the procedure's effectiveness is shown to be quite robust at a variety of noise levels and relative sample rates for this practical problem.**

Index Terms - Fuzzy logic; Fusion; Kalman filter; Machine vision; Autonomous guidance

Ⅰ. INTRODUCTION

The concept of sensor fusion was firstly proposed in 1970s, and the technology was gradually used in the military affairs since 1980. In the past two decades, sensor fusion technology has attracted considerable attention from Chinese government in the precision agricultural area. To work in a complicated agricultural environment, a tractor needs to get two basic parameters, which are the heading angle and the lateral deviation. The global positioning system (GPS), machine vision (MV) and the inertial measurement unit (IMU) promise to serve as an appropriate and universal sensor, however, to achieve the goal of great reliability and high measurement precision a single sensor is not enough, for signal frequency of the GPS is low, and the accuracy of the GPS is affected by the satellite orientation, interference from trees and obstructions and the other factors; the reliability of the MV is affected by weed infestation, soil color and changing light levels; and the drifting error is always involved in the IMU output. So in this research, the GPS, the MV and the IMU are used together to decrease the impact of the sensor error.

The Kalman filter is one of the most popular optimal technology in the sensors fusion. However, some parameters in the traditional Kalman filter are set to be constant, such as the filter gain *K,* the process noise covariance *Q* and the measurement noise covariance *R,* which may lead the working status to be unstable. In fact, the signal quality obtained from each sensor is varied with the change of the complicated working environment. So it is not feasible to have constant noise values for each sensor and have constant filter gain *K* for the Kalman filter. This paper designed the Double-Fuzzy logic controller to modify the parameters of *K*, *Q* and *R* according to the variety of signal quality. The guidance precision of the tractor can be greatly improved by using the proposed algorithm.

Ⅱ. THE MATHEMATIC MODEL OF THE DOUBLE-FUZZY KALMAN FILTER

The Kalman filter based on the vehicle kinematics model was used to fuse the information from the GPS, the MV and the IMU. The vehicle modeling relies upon celebrated Ackermann's model, also named bicycle model, as shown in Fig. 1.

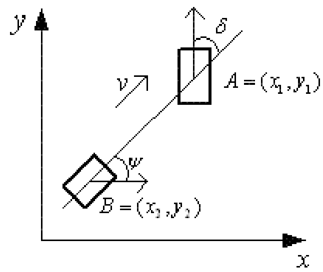


Fig. 1 Geometry of automatic motion for tractor

Vehicle kinematics state space model is:

$$\begin{cases} \dot{\varphi}(\mathrm{t}) = \dfrac{v}{l}\tan\delta(t) \\ \dot{x}(t) = v\cos\varphi(t) \\ \dot{y}(t) = v\sin\varphi(t) \\ \dot{\delta}(t) = -\dfrac{1}{\tau}\delta(t) \end{cases} \tag{1}$$

where *φ(t), x(t), y(t), δ(t)* are heading angle, longitudinal deviation, lateral deviation and front wheel steering angle from the DFKF, v is vehicle speed, l is vehicle wheelbase, and τ is time constant.

Based on this design, the vehicle state vector X is defined as:

$$X = [y \quad \varphi \quad \delta]^{\mathrm{T}} \tag{2}$$

where y, φ and δ are lateral deviation, heading angle and front wheel steering angle from the DFKF.

The system observations are defined as:

$$Z = [y_g \quad y_v \quad \varphi_v \quad \varphi_{imu} \quad \delta]^{\mathrm{T}} \tag{3}$$

where y_g is lateral deviation from the GPS, y_v and φ_v are lateral deviation and heading angle from the MV, φ_{imu} is heading angle from the IMU, and δ is front wheel steering angle from the Steering angle sensor.

The information from the GPS is absolute value, and the information from the MV and the IMU is relative value, so a coordinate transformation is needed, in this paper, all the values are transformed to relative value.

The state equation and the measurement equation of Kalman filter are defined as:

$$X_k = \Phi_{k,k-1} X_{k-1} + W_{k-1} \tag{4}$$

$$Z_k = H X_k + V_k \tag{5}$$

where the state transition matrix $\Phi_{k,k-1}$ is obtained by using (1) and the Extended Kalman filter (EKF) theory.

$$\phi_{k,k-1} = \begin{bmatrix} 1 & T*V*\cos\theta_k & 0 \\ 0 & 1 & T*V*\sec^2(\alpha_k)/L \\ 0 & 0 & 1-\dfrac{T}{\tau} \end{bmatrix} \tag{6}$$

The observation matrix is:

$$H = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}^{\mathrm{T}} \tag{7}$$

The measurements carried out in the estimation process are directly the readings of the sensors. The electronic noise at the output of the sensors is assumed to be zero-mean Gaussian noise with known covariance. The elements of the measurement noise covariance matrix R are the estimated covariance of the sensor noise. Usually, the parameters of R can be determined prior to the implementation of the filter, based on previous experience with the sensor or technical specifications provided by the sensor's manufacturer, however, with the variety of the signal quality, the parameters of R do not keep constant, so an initial value (shown in (8)) with a coefficient from the DFKF was adopted.

$$R = \begin{bmatrix} 0.4 & 0 & 0 & 0 & 0 \\ 0 & 0.4 & 0 & 0 & 0 \\ 0 & 0 & 0.1 & 0 & 0 \\ 0 & 0 & 0 & 0.1 & 0 \\ 0 & 0 & 0 & 0 & 0.1 \end{bmatrix} \tag{8}$$

The filter gain K is used to minimize the posteriori error covariance P which is impacted with the measurement noise, however, it is difficult to directly observe the measurement noise. In the traditional Kalman filter, the parameters are set to be constant, which is in an optimum state, however, with color noise involved it is hard to keep the system in optimum state. So filter gain K needs to update too.

The process noise covariance matrix Q provides a model for estimating uncertainty in the process. In the random processes used in Kalman filtering, the noise introduced in the model is considered a zero-mean white Gaussian noise with the finite covariance. Generally speaking, Q is difficult to determine since the process cannot be observed. However, acceptable results can be typically obtained if parameters are properly tuned. In this implementation of the filter, an initial value (shown in (9)) with a coefficient from the DFKF was adopted.

$$Q = \begin{bmatrix} 0.4 & 0 & 0 \\ 0 & 0.01 & 0 \\ 0 & 0 & 0.01 \end{bmatrix} \tag{9}$$

The flow chart of the DFKF is shown in Fig. 2.

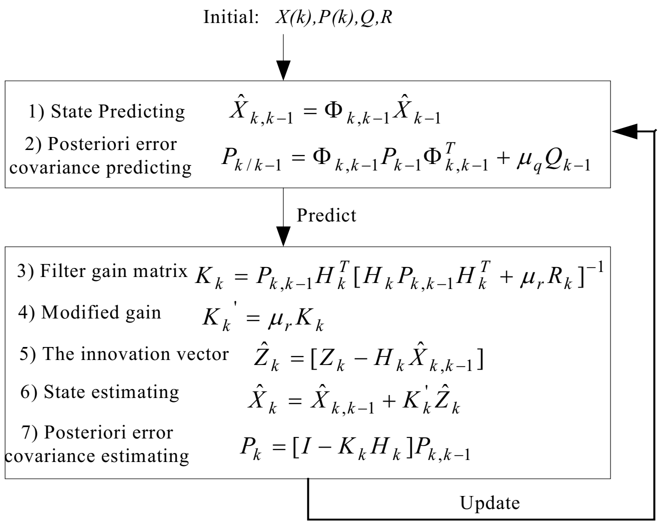


Fig. 2 Double-fuzzy Kalman filter model

III. DOUBLE FUZZY LOGICAL CONTROLLER

A. *Fuzzy Logic Controller Based on DR*

Dead reckoning (DR) is the process of estimating vehicle's current position based upon a previously determined position, and advancing that position based upon known speed, elapsed time, and heading angle. The principle of DR is:

$$y_n = y_{n-1} + T v_n \sin\theta_n \quad (10)$$

$$\theta_n = \theta_{n-1} + T\omega_n \quad (11)$$

As mentioned before, R and K do not keep constant. It can be controlled by the same way since the two parameters are both influenced by the measurement noise. In this paper, a fuzzy logic controller is designed to modify R and K by multiplying a coefficient μ_r with the variety of signal quality judged by dead reckoning algorithm.

The IMU is a high accuracy sensor which is rarely influenced by the environment factors, however, drifting error is always involved and accumulative error is caused by the transformation from angular velocity values to angular values. For the variety of the IMU signal is regular, a modified coefficient μ_{imu} can be estimated from the simulated and experimental result. The IMU was mounted on the tractor, and then turned on with the tractor's engine on, and the information from the IMU was collected for 30 minutes. It was estimated that the coefficient μ_{imu} is 0.56. The IMU error experimental result is shown in Fig.3. After mounted on the right place on the tractor, it is not necessary to align the IMU when the navigation system is initialized.

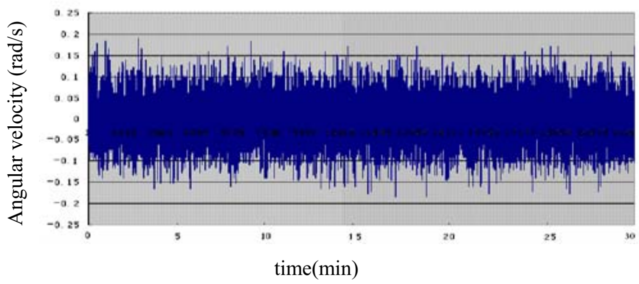


Fig. 3 The IMU error experimental result

With the variety of signal quality, a multi-sensor fusion strategy based on GPS/MV/IMU is shown in Fig. 4.

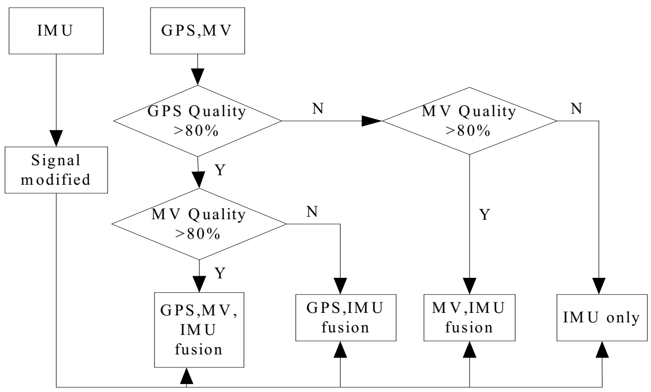


Fig. 4 GPS, MV and IMU fusion strategy

The input values to the fuzzy logic supervisor are the lateral deviation errors between the dead reckoning signal to the GPS and the MV signal. The output values are the signal qualities of the GPS and the MV, the modified coefficient obtained from experiment and fuzzy logic controller is shown in (12). The membership functions between the input and the output are shown in Fig. 5.

$$\mu_r = \begin{bmatrix} \mu_g & 0 & 0 & 0 & 0 \\ 0 & \mu_v & 0 & 0 & 0 \\ 0 & 0 & \mu_v & 0 & 0 \\ 0 & 0 & 0 & \mu_{imu} & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (12)$$

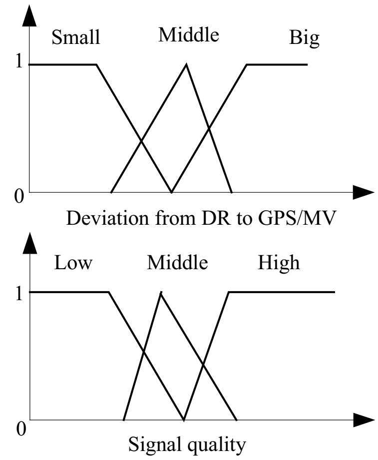


Fig. 5 Membership functions for sensor supervisor

Based on the above theory the rule set for the supervisor is shown in Table I. Defuzzification was done using the center of gravity method.

TABLE I

FUZZY LOGIC RULE SET FOR SENSOR SUPERVISOR

Deviation form GPS	Deviation form MV	Output values
Small	Small	μ_g Big, μ_v Big
	Middle	μ_g Big, μ_v Middle
	Big	μ_g Big, μ_v Small
Middle	Small	μ_g Middle, μ_v Big
	Middle	μ_g Middle, μ_v Middle
	Big	μ_g Middle, μ_v Small
Big	Small	μ_g Small, μ_v Big
	Middle	μ_g Small, μ_v Middle
	Big	μ_g Small, μ_v Small

B. Fuzzy Logic Controller Based on the Variation of the Innovation Vector Z'(k)

As in (2) shown in Fig. 2, the measurement error covariance matrix P gives a measure of the estimated accuracy of the state estimate, and the covariance matrix Q for process noise plays an important role in it. As mentioned before, Q is not constant, the process noise is affected by the innovation vector $Z'(k)$ which is defined as the difference between the measured vector and the estimation of the measurement vector. In an optimum Kalman filter, $Z'(k)$ is a zero mean Gaussian white noise, but the working condition of the tractor is so complicated that the filter is hard to keep optimum. Color noise is caused by the deviation between the mathematic model and the real system, the variety of signal quality, soil condition and so on. With these affects *Z'(k)* may not keep as a zero-mean Gaussian white noise. And the larger the value of *Z'(k)* is, the larger the difference between the measured vector and the estimation of the measurement vector is. To keep the filter in optimum state, *Q* is needed to update depending on the innovation sequence. This update is performed using fuzzy logic. The input to the fuzzy logic controller is the innovation vector *Z'(y)* and *Z'(φ)* which is obtained by (13) and (14).

$$\hat{Z}(y) = \frac{\mu_g \cdot \hat{Z}(y_g) + \mu_v \hat{Z}(y_v)}{\mu_g + \mu_v} \tag{13}$$

$$\hat{Z}(\varphi) = \frac{\mu_v \cdot \hat{Z}(\varphi_v) + \mu_{imu} \cdot \hat{Z}(\varphi_{imu})}{\mu_v + \mu_{imu}} \tag{14}$$

The output values from the fuzzy logic system are the modified coefficients *Q(y)* and *Q(φ)*. The coefficient μ_q is consisted with *Q(y)* and *Q(φ)* to modify *Q*, as in (15). With this updating design, the Kalman filter can be adjusted in optimum state.

$$\mu_q = \begin{bmatrix} Q(y) & 0 & 0 \\ 0 & Q(\varphi) & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{15}$$

The membership functions are shown in Fig. 6. Normalization is done using triangle function with scale 0 to 1.

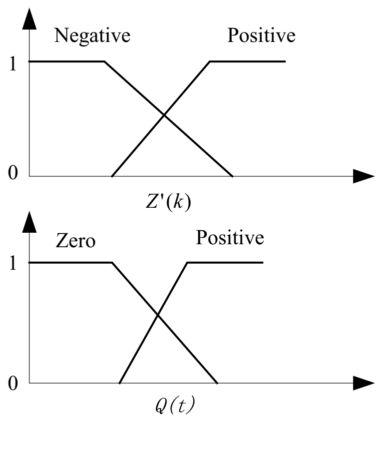


Fig. 6 Membership function for updating *Q*

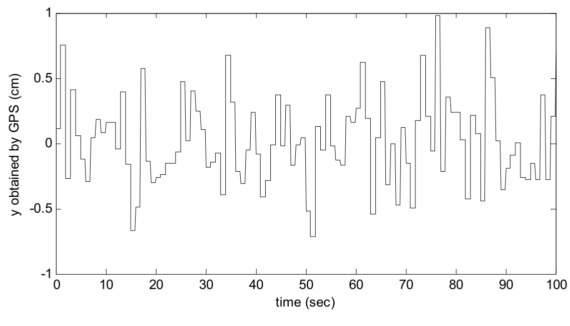
Based on the above argument for updating *Q*, a set of if-then rules were developed by experiment. The rule set is shown in table Ⅱ. For example, considering the first case where *Z'(y)* and *Z'(φ)* are both negative, this indicates that the error in position has reduced compared to the previous time step and the vehicle heading in the right direction, then the process noise for position and heading are both zero. The fourth case is totally in a differently situation.

TABLE Ⅱ.
FUZZY LOGIC RULE SET FOR DIVERGENCE CORRECTION

Z'(y)	*Z'(φ)*	*Q(y)*	*Q(φ)*
Negative	Negative	Zero	Zero
Negative	Positive	Positive	Positive
Positive	Negative	Positive	Zero
Positive	Positive	Positive	Positive

Ⅳ. Results and Discussion

To validate the designed DFKF algorithm, a Matlab program was developed to perform the processing of the sensor fusion. In this processing, the absolute positioning data obtained from the GPS was updated at 1Hz, the relative positioning data obtained from the IMU and the MV was updated at 10 Hz. The sampling time of the fusion algorithm was 0.1s. The tractor wheelbase *l* is 2.46m, the time constant τ is 1 s. The lateral deviations obtained from the GPS and the MV are shown in Fig. 7. And the fusion results of lateral deviation by the EKF and the DFKF at a relatively low vehicle speed (0.6m/s) are shown in Fig. 8. The results showed that by using the DFKF the maximum error is reduced from 1.5031 cm to 0.5887 cm, and the mean error is reduced from 0.0098 cm to –0.0024 cm, compared with the EKF. It is obvious that the signal fused by the DFKF was more smooth than the EKF. The fusion results of lateral deviation by the EKF and the DFKF and at a relatively high vehicle speed (3m/s) are shown in Fig. 9. The results showed that the influence of speed on the DFKF algorithm is not distinct. The specific parameters of the lateral deviation fused by the DFKF and the EKF at the speed of 0.6m/s and 3m/s are compared in Table Ⅲ, such as the maximal value, the minimal value, the mean value and the variance value. The results showed that by using the DFKF the redundant error was effectively removed, the drift error was compensated and the accuracy was improved, compared with the EKF.



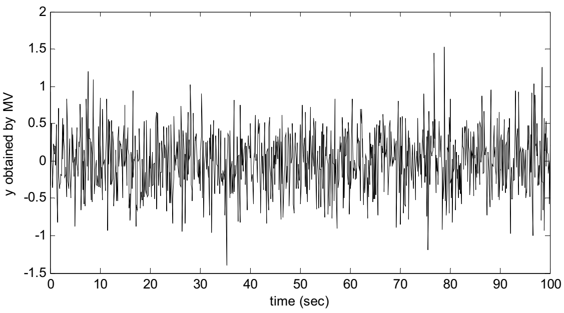


Fig. 7 Lateral deviation obtained from GPS and MV

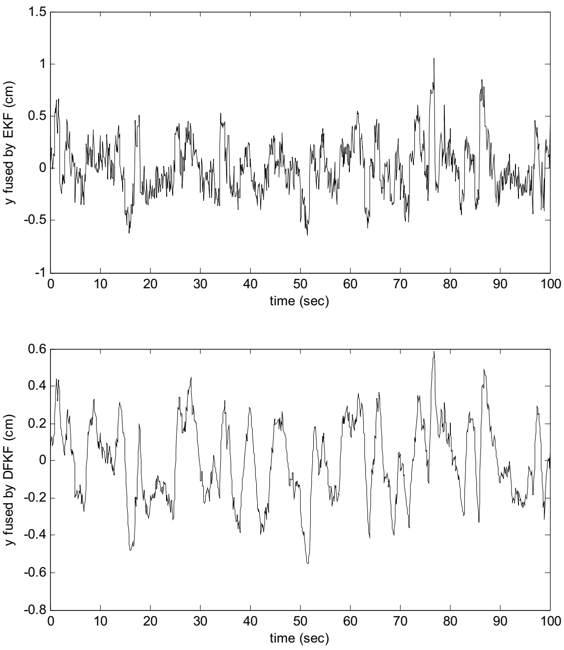


Fig. 8 Position errors of EKF and DFKF at speeds of 0.6m/s

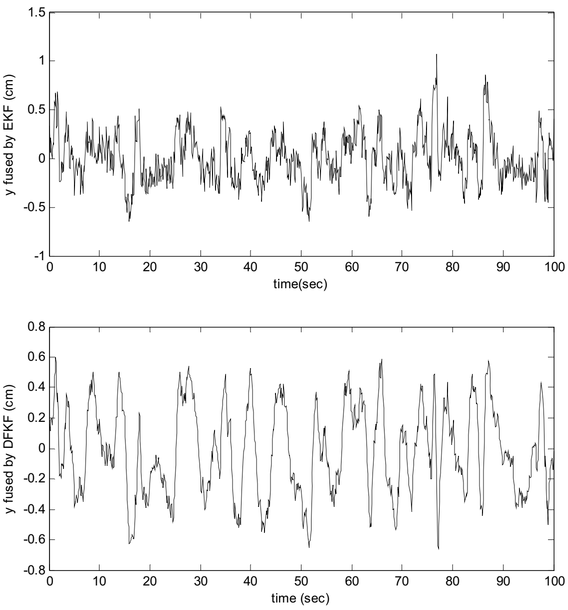


Fig. 9 Position errors of EKF and DFKF at speeds of 3m/s

TABLE Ⅲ.

LATERAL DEVIATION ERRORS OF DFKF AND KF

Parameters	DFKF		EKF	
	0.6m/s	3m/s	0.6m/s	3m/s
Max	0. 5887	0.6012	1.0531	1. 0760
Min	-0.5512	-0.6595	-0. 6428	-0.6505
Mean	-0. 0024	-0.0092	0.0098	0.0099
Variance	0. 0454	0.0697	0.0641	0.0855

V. CONCLUSION

The real-time tractor position estimation system was developed in this paper. This system could improve the positioning accuracy, smooth the GPS noise, reduce signal error from the MV and compensate drift for the IMU. A double-fuzzy Kalman filter algorithm was designed to integrate the information from the GPS, the MV and the IMU for providing accurate dynamic positioning for a tractor. The algorithm could significantly improve the attitude measurement both in terms of noise level and drifting even when some sensor attitude estimates were not available for certain period. The algorithm was also capable of removing the high frequency noise associated with the MV and the GPS sensor measurement. By using this algorithm, the Kalman filter can be kept in optimum state and the tractor position estimation signals can be more reliable and accuracy.

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