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Application of Data Fusion Algorithm Based on Kalman filter in Mobile Robot Position Measuring System

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***Abstract*-A data fusion scheme for mobile robots with multiple sensors is proposed in this work. The task is to reduce and eliminate the pose error of robot produced by restriction uncertainty between robot wheels and the ground. Kalman filter (KF) is used to fuse several kinds of data from encoders, gyroscope and ultrasonic sensors. The program of one dimension KF is brief, it can be complicated in each servo cycle. With the proposed data fusion scheme, the path tracking and point positioning was accomplished under the industrial conditions. By data fusion of sensor signals, random error of path tracking was reduced, moreover, final position precision of the mobile robot was improved through ultrasonic sensors.**

***Index Terms*-Kalman filter, data fusion, position measurement, mobile robot.**

I. INTRODUCTION

The navigation of wheeled mobile robots is still a problem, mainly because of the restriction between the wheels and the ground[1]-[2]. There exists elastic deforms and slippages between wheels and ground when the robot moves, so does produce the pose error, and it will accumulates along with motion so as to degrade the precision. At present, the most position sensors often used are mainly classified into two kinds: (1) encoders, gyroscopes, accelerometers, and speedometers are used to measure the movement state of the robot. It has the advantages, such as the high reliability and lower requirements of surroundings with respect to the others, but the errors will accumulate while the robot moves. (2) The surroundings of the robot is apperceived using the ultrasonic, infrared, laser, and vision sensors[2]-[3]. This requires the pre-set flags in the robots working area, and the lower speed of real-time data feedback is the main disadvantage. But it can avoid the error accumulating. In this paper we combine the two methods together and use the data fusion to estimate the position angle by encoders and gyroscope respectively. The common algorithm of data fusion are as fellows: weighted average, Kalman Filter, Bayes , fuzzy logic and NN method etc[4]-[7]. Among them, the KF is a effective method, so it was used to deal with the data fuse in this system.

II. ROB OT SYSTEM

The system is the wheeled mobile robot XAUT.AGV100 developed by our institute, which is a vehicle driven by two wheels, and each wheel driven by a step motor (BERGER LAHR, Germany). The motor parameters are as follows: model (VRDM360/LHA), rated torque (0.9Nm), driver (D921). The principle of the feedback and fusion system is shown in Fig.1. The controller is PMAC2 manufactured by DELTAU Co. USA, which has the capacity of 8-axis. The angles of the step motors (φ_1, φ_2) are counted by encoders, which can be used to calculate the orientation angle (θ_w), and fused with the orientation angle (θ_g) fed back by gyroscope, so as to obtain the vehicle estimate orientation angle ($\hat{\theta}$), then we can forecast and rectify the next pose of the robot using the dead reckoning algorithm. The ultrasonic sensors are only used to ensure the position precision near the target points, and they don't work in the path of moving.

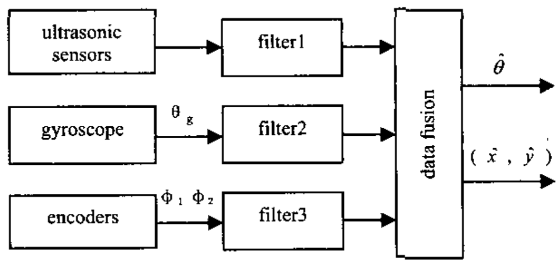

Fig.1 System composition

III. DATA FUSION ALGORITHM

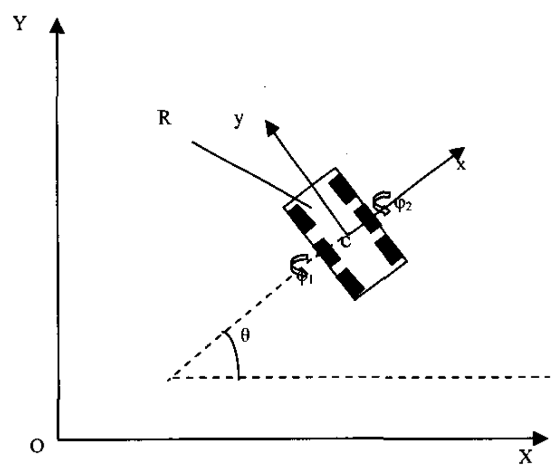

Fig.2 . Coordinates of the mobile robot

A. System Equation

In order to accomplish the data fusion algorithm, the equation of the system must be figured out first. Shown in Fig. 2, the parameter R stands for mobile robot itself, coordinates Σ o is fixed on the ground, and Σ c on the robot. Hypothesis: the positive direction of the orientation-angle θ is anticlockwise; the direction of φ_1 and φ_2 is positive when the AGV moves along the y axis, so we can get the robot kinematics equations(1), in which $\delta\varphi_1(n+1)$ and $\delta\varphi_2(n+1)$ stand for the incensement value of the two driving-wheels angle from the moment n to n+1 respectively , r for the radius of the driving-wheel, and d for the distance between the two driving-wheels center, (x,y) for the origin distance between Σ c and Σ o, and θ for the angle between Σ o and Σ c

$$\begin{bmatrix} x(n+1) \\ y(n+1) \\ \theta(n+1) \end{bmatrix} = \begin{bmatrix} -\sin\theta in+1)r/2 & -\sin\theta in+1)r/2 \\ \cos\theta os+1)r/2 & \cos\theta os+1)r/2 \\ r/d & -r/d \end{bmatrix} \cdot \begin{bmatrix} \delta\varphi_1(n+1) \\ \delta\varphi_2(n+1) \end{bmatrix} + \begin{bmatrix} x(n) \\ y(n) \\ \theta(n) \end{bmatrix} \quad (1)$$

B. KF Formulations

KF algorithm can optimizes the state estimate, aiming at the random dynamic system, its model can be represented by the equation(2):

$$\begin{cases} x(k+1) = \Phi(k+1,k)x(k) + \Gamma(k+1,k)w(k) \\ y(k+1) = H(k+1)x(k+1) + v(k+1) \end{cases} \quad (2)$$

Where x stands for the system status, y for the observation value, w for the noise value, v for the observation noise, Φ for the state transform matrix, Γ for the noise matrix, and H for the survey matrix. Aiming at the system model above, the iterative algorithm of KF is presented by the following formulations from (3) to (6):

Filter Equation:

$$\hat{x}(k+1) = \hat{x}(k+1/k) + K(k+1)[y(k+1) - \hat{y}(k+1/k)] \quad (3)$$

Forecast Equation:

$$\begin{aligned} \hat{x}(k+1/k) &= \hat{\Phi}(k+1,k)\hat{x}(k) \\ \hat{y}(k+1/k) &= H(k+1)\hat{x}(k+1/k) \end{aligned} \quad (4)$$

Gain Equation:

$$K(k+1) = P(k+1/k)H^T(k+1)[H(k+1)P(k+1/k)H^T(k+1) + R(k+1)]^{-1} \quad (5)$$

Error-foresee Equation:

$$P(k+1/k) = \Phi(k+1,k)P(k)\Phi^T(k+1,k) + \Gamma(k+1,k)Q(k)\Gamma^T(k+1,k) \quad (6)$$

Filter error Variance Equation:

$$P(k+1) = (I - K(k+1)H(k+1))P(k+1/k) \quad (7)$$

Where the initial value are: $\hat{x}(0) = E[x(0)]$, $P(0) = var[x(0)]$, and the K(k+1) is a weight matrix, which plays a role of rectifying the new information in the course of state estimating. If the value of $w(k)$ is smaller and $v(k+1)$ is bigger, the foreseen value $\hat{x}(k+1/k)$ should be much more accepted, so $K(k+1)$ should be close to zero, on the contrary, close to 1. How much the optimum estimate value meets with the real value at the moment of k+1 depends on the following two factors: one is that whether the former is close to the latter, and then affect the approach between the foreseen value of observation $\hat{z}(k+1/k)$ and the ideal value y(k+1); and the other is that how much the value K(k+1) correct the value $\hat{z}(k+1/k)$ .The Kalman Filter algorithm adopted in this paper is only one-dimension , so that the operation work is much more smaller with respect to others. The controller PMAC2 is designed using DSP(Motolola56000). So the total update operation can be completed in each servo cycle.

C. Filter Equation of the System

From equation (1), to accomplish the dead-reckoning of robot, we have to know $\delta\varphi_1(n+1)$, $\delta\varphi_2(n+1)$ and $\hat{\theta}(n+1)$, that is the estimated value for $\theta(n+1)$. It is to say that the no-bias estimated value $\theta(n+1)$ is calculated by data fusion using KF that is introduced in chapter B. θ_w is orientation of robot obtained by encoders and θ_g is orientation obtained by gyroscope. First, we must make certain the error distributing state of θ_w and θ_g. The error includes systemic error and random error. The former can be corrected by control program, but the later must be calculated through by experiments, a large number of samples are needed to analysis and statistical rule must be obtained, then no-bias estimate value under the least variance can be calculated through KF. According to formula (1): $\delta\hat{\theta}_w = (\delta\hat{\varphi}_1 - \delta\hat{\varphi}_2)r/d$, where $\delta\hat{\theta}_w$ is the no-bias estimate value of $\delta\theta_w$,.In terms of reference [7], measuring error variance can be expressed as: $\sigma^2 = (\varepsilon\delta\hat{\varphi})^2$, where constant ε can be obtained through experiments. The measurement values obtained by two encoders are irrelevant, the covariance of them is zero. Measurement value of gyroscope is angle speed, the orientation θ of the mobile can be obtained by accumulation of ω, as in equation (8). ω stands for angle speed of AGV, ΔT stands for time of servo cycle.

Integral equation of gyroscope angle:

$$\theta_g = \int_0 \omega dt \approx \sum_{i=1}^{k} \Delta T\omega_i \quad (8)$$

The state predict equation of wheel angles:

$$\begin{bmatrix} \hat{\theta}_{w1}(k+1) \\ \hat{\theta}_{w2}(k+1) \end{bmatrix} = \begin{bmatrix} \hat{\theta}_{w1}(n) \\ \hat{\theta}_{w2}(n) \end{bmatrix} + \begin{bmatrix} \delta\theta_{w1} \\ \delta\theta_{w2} \end{bmatrix} \quad (9)$$

Filter equation of the AGV:

$$\begin{bmatrix}\hat{\theta}_g(k+1)\\ \hat{\theta}_w(k+1)\end{bmatrix}=\begin{bmatrix}\hat{\theta}_g(k+1/k)\\ \hat{\theta}_w(k+1/k)\end{bmatrix}+\begin{bmatrix}k_g(k+1)\\ k_w(k+1)\end{bmatrix}\cdot\begin{bmatrix}\theta_g(k+1)-\hat{\theta}_g(k+1/k)\\ \theta_w(k+1)-\hat{\theta}_w(k+1/k)\end{bmatrix} \tag{10}$$

The estimated value of $\theta(n+1)-\hat{\theta}(n+1)$ can be calculated through by iterating equation(10). The gain (K), error value (P) and variance [P(k+1)] can be calculated through (5-7) .Then the position and pose of mobile robot are obtained through (1), as follows:

$$\hat{x}(n+1)=[-\sin\hat{\theta}(n+1)\cdot\delta\hat{\varphi}_1(n+1) - \sin\hat{\theta}(n+1)\cdot\delta\hat{\varphi}_2(n+1)]r/2+\hat{x}(n) \tag{11}$$

$$\hat{y}(n+1)=[\cos\hat{\theta}(n+1)\cdot\delta\hat{\varphi}_1(n+1) + \cos\hat{\theta}(n+1)\cdot\delta\hat{\varphi}_2(n+1)]r/2+\hat{y}(n) \tag{12}$$

IV. EXPERIMENTS

To verify the availability of the filter algorithm above, the experiment is carried out on XAUT. AGV100. The photo of XAUT. AGV100 is shown in Fig.3, its parameters are listed in table 1. The sensors and the landmarks are shown in Fig. 4. The sensors used in the system are as follows:

TABLE1
PARAMETERS OF THE AGV

length (m)	width (m)	hight (m)	weight (Kg)	load (kg)	Max v (m/s)	Max a (m/s^2)
1.2	0.86	0.4	210	150	0.7	0.4

gyroscope: type(CS61B-3, the 26th electronics institute, CHN), scale (±180°/s) , resolution (0.05°/s) ,the frequency(≥ 60Hz.).ultrasonic-sensor:type(UB500-18GM75-U-V15)measuring precision(≤0.5%), scale(10.:.500mm); the delay time(50ms); output signal(0-10V).encoders: 2500 pulse per revolution. The path tracking and working stations positioning

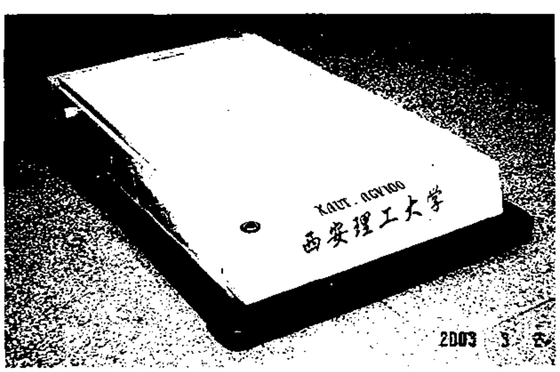

Fig. 3. XAUT. AGV100

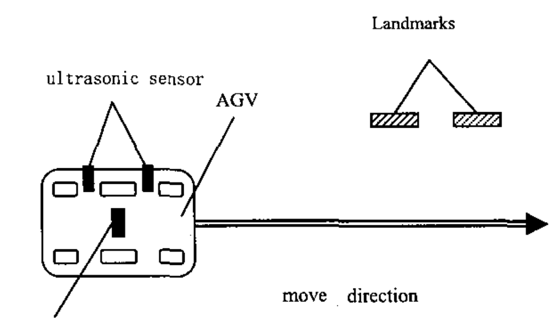

Fig.4 Landmarks and sensors positions

are carried out in the experiment according to the real working conditions. The path consists of two straight lines and two arcs, shown in the Fig 5. The robot moves in anti-clockwise at the average speed of 20m/min. There are four workstations along the path and two ultrasonic reflectors are set at each workstation. AGV autonomous navigation depends on the information get from gyroscope and encoders between two workstations. When it arrives in the detective range of ultrasonic sensor, the pose of the AGV is corrected accurately by ultrasonic sensor information. AGV have a short time pause at each workstation. Because of the accumulating error of the gyroscope, the pose error is inevitable: The max position error is 50mm, the max orientation error is 2.5° when AGV completes the line path (the distance is: L=18m), but it is still in the detective range of the ultrasonic sensors (10-500mm). corrected by ultrasonic sensors, the orientation precision is ±0.5° , the position precision is ±5mm. Position and pose precision has been improved greatly. It is more accurate than former precision.

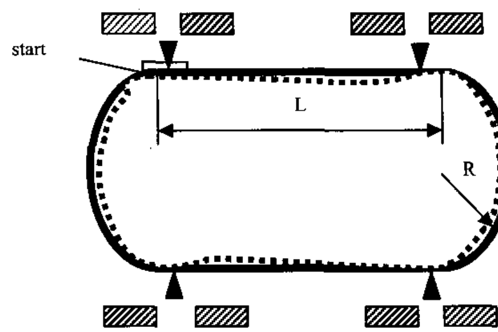

Fig.5 .AGV tracking and positioning path

— reflector
— work station
— ideal path
— real path
(L=18m R=5m)

V. CONCLUSION

Because wheeled mobile robots have restriction uncertainty between the wheels and the ground, it is very difficult for AGV navigation, especially for longer distance. The accumulating errors are eliminated via setting position point, and to fuse the measurement values of gyroscope and encoders can accomplish autonomous navigation for AGV assuring accurate pose of the AGV. KF can ensure the AGV's no-bias estimated value of orientation θ. The fusion measuring precision is higher than that using single sensor.The results of the experiment show that the pose precision can meet industry need. The navigation method proposed in this paper has some practical value.

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