A Localization System of a Mobile Robot by Fusing Dead-Reckoning and Ultrasonic Measurements

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***Abstract*— This paper introduces a novel hardware system structure and systematic digital signal processing algorithms for the automatic localization of an autonomous mobile robot by merging dead-reckoning and ultrasonic measurements. The multisensorial dead-reckoning (DR) subsystem is based on optimal filtering that merges heading readings from a magnetic compass, a rate-gyroscope, and two encoders mounted on the robot wheels to compute the dead-reckoned location estimate. The novel ultrasonic localization subsystem consists of one ultrasonic transmitter and one radio-frequency (RF) controlled switch mounted at a known location fixed to an inertial frame of reference, four ultrasonic receivers, and one RF controlled switch installed on the mobile robot. Four ultrasonic time-of-flight (TOF) measurements together with the dead-reckoned location information are used to update the vehicle's position by utilizing the extended Kalman filtering (EKF) algorithm. The proposed algorithms are implemented using a host PC 586 computer and standard C++ programming techniques. The system prototype together with the experimental results were used to confirm that the system not only retains high accuracy and magnetic interference immunity, but also provides a simple and practical structure for use and installation/calibration.**

***Index Terms*—Extended Kalman filtering, localization, mobile robot, multisensorial dead-reckoning, sensor fusion, ultrasonics.**

I. Introduction

THE POSITIONING capability of an autonomous mobile robot is extremely important for free range path tracking as well as reactive navigation in any given environment. The dead-reckoning method has been widely used for most wheeled mobile robots to calculate their current locations with respect to an inertial frame of reference. Since this method, based on the encoded or odometric information from the wheels, is subject to major accumulation errors caused by wheel slippage, or by mechanical tolerances and surface roughness, the robot may fail to keep track of its true location over long distances. To compensate for the inaccuracy of dead-reckoning, Kim and Seong [1] devised a highly cost-effective location system which used an encoded magnetic compass to account for abnormal orientation drift due to wheel slippage, thereby resulting in robot position recovery. However, a magnetic compass does not function well at a place where the magnetic fields vary from position to position. Using the Kalman filtering, Song and Suen [2] investigated how a low-cost rate-gyro can be applied to adjust dead-reckoning estimates to overcome the wheel slippage problem. Unfortunately, the low-cost rate-gyro usually suffers from high drift rate. These two techniques [1], [2] cannot eliminate the cumulative errors caused by surface roughness.

Ultrasonic ranging sensors with their dedicated location methods have been proved to be very useful, economical external sensing systems for mobile robot location. Among the numerous technical papers concerned with ultrasonic location methods, they can be divided into two groups of technical methodologies. The first is that, given any known or partially recognized known structured environment, the robot measures time-of-flight (TOF) temporal data from itself to its surroundings by using several ultrasonic sensors mounted on itself and then processes this temporal information to obtain its spatial location by means of barrier tests [3], extended Kalman filtering with environment models [4]–[7], fuzzy fusion logic [8], and neural networks [9]. The other methodology is based on active beacon positioning, called 3-D location technique [10], which has a transmitter, as a beacon, mounted on the robot and several receivers installed at the prespecified locations with respect to a reference coordinate system. This approach requires the least-squares algorithm or the EKF-based algorithm for converting the TOF temporal data between the beacon and those receivers to the robot location. Generally speaking, robot location techniques based on the first methodology lack accuracy and flexibility and the 3-D location technique is not easy to implement or use.

To improve the confidence in and accuracy of mobile robot location without the aforementioned difficulties, a novel location system was developed which consists of an improved multisensorial dead-reckoning subsystem and a modified ultrasonic location subsystem. The novelty of the multisensorial dead-reckoning lies in the statistical treatment of the robot's heading readings from a rate-gyro, a magnetic compass, and encoded information from the driving wheels. The features for the ultrasonic system hinge on its strengths which not only encompass all of the inherent advantages declared by Figueroa and Mahajan [10] but also provide a simpler, more economical structure for implementation, installation, and use. Another keynote of this paper is the investigation of how the extended Kalman filter can be applied to combine dead-reckoning and ultrasonic data for obtaining a more accurate and precise position estimate over long distances. This location system is expected to be most suitable for mobile robot navigation in structured environments, such as factories, hospitals, offices, warehouses, and other hazardous areas.

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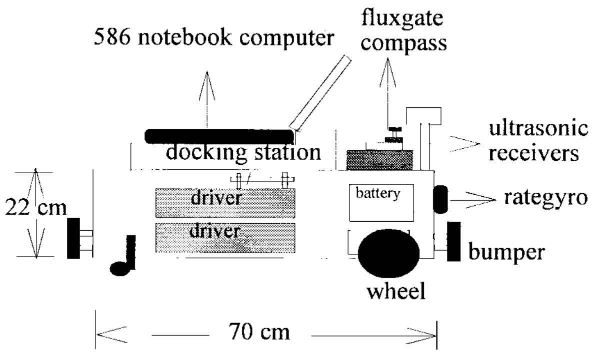

Fig. 1. Physical configuration of the multisensorial dead-reckoning subsystem mounted on a laboratory-based autonomous mobile robot.

The remaining sections of this paper are organized as follows. Section II briefly describes the hardware configuration of the location system and kinematics of a mobile robot. The multisensorial dead-reckoning subsystem is developed in Section III. Section IV explores how to use the extended Kalman filtering to fuse the dead-reckoning and ultrasonic temporal data. Two experiments are described which were performed in Section V to confirm the accuracy and performance of the proposed system. Section VI concludes the paper.

II. System Configuration and Vehicle Kinematics

A. Brief Description of the Location System

The location system is composed of a multisensorial dead-reckoning subsystem and a modified ultrasonic location subsystem. The multisensorial dead-reckoning subsystem consists of a flux gate compass with one-degree resolution and two-degree accuracy, a low-cost rate-gyro with a high drift rate, and two high-resolution optical incremental shaft encoders mounted on the robot wheels. Fig. 1 describes the physical configuration of the multisensorial dead-reckoning subsystem mounted on a laboratory-based autonomous mobile robot which has two independently driven front wheels and two freely rotating back wheels. The flux gate compass provides a measure of absolute robot heading by sensing and processing the averaged strength of the earth's magnetic field. In contrast to the flux gate compass, the rate-gyro periodically produces nonjammable, relative robot heading measurements by integrating its instantaneous angular velocity over a period. The notebook computer system with an analog and digital signal interfacing board is responsible for performing all of the reading procedures, executing multisensorial dead-reckoning and sensor fusion algorithms, and recording the final outcomes.

Fig. 2 depicts the physical configuration of the modified ultrasonic location system which consists of only one RF controlled ultrasonic transmitter mounted on the known location fixed to an inertial frame of reference, and four ultrasonic receivers and one RF controlled switch placed on the mobile robot. The scenario for measuring the TOF data between the ultrasonic transmitter/receiver modules is stated as follows. First, the ultrasonic transmitter immediately sends out a modulated signal after receiving a starting signal via the RF switch controlled by the computer. Second, each 16-bit counter with 2 MHz counting rate accumulates the TOF data until the corresponding receiver confirms that the ultrasonic modulated signal has been received. The method used for the TOF measurements is based on simple threshold detection with a time-varying gain-scheduled amplifier and a capacitive charge-up circuit. Finally, the computer reads all the TOF data via designed digital interfacing circuits and starts to execute the location updating algorithm. The whole measurement process is periodically repeated and the sampling rate depends upon the vehicle's linear speed. Worthy of mention is that the system may fail to receive TOF data when the robot moves out of the effective coverage of the ultrasonic wave propagation.

B. Vehicle Kinematics

For the robot configuration presented in this paper, a time-domain kinematic model of the robot is governed by the following nonlinear state equation [11]:

$$\begin{bmatrix} \dot{x}(t) \\ \dot{y}(t) \\ \dot{\theta}(t) \end{bmatrix} = \begin{bmatrix} v_d(t)\cos\theta(t) \\ v_d(t)\sin\theta(t) \\ \dfrac{R(\omega_r(t)-\omega_l(t))}{2br} \end{bmatrix} \tag{1}$$

where $x(t)$ and $y(t)$ are the location of the robot in the reference coordinate system, $\theta(t)$ is the robot heading, $\dot{x}(t)$ and $\dot{y}(t)$ are robot velocities, $\dot{\theta}(t)$ is the angular velocity of the robot, $\omega_r(t)$ and $\omega_l(t)$ are the angular velocity outputs of the right and left motors, r denotes the gear ratio, R represents the radius of the drive wheels, and b represents half the distance between the driven wheels. Thus, the linear velocity of the robot is given using

$$v_d(t) = \frac{R}{2r}(\omega_r(t)+\omega_l(t)). \tag{2}$$

III. Multisensorial Dead Reckoning

As the ultrasonic TOF temporal readings are unavailable, the proposed location system operates in a dead-reckoning mode. This section presents a highly cost-effective robot location measurement using the information from the flux gate compass, the rate-gyro, and the two encoders. The basic idea in doing so is to develop a multisensorial fusion scheme to obtain a robust robot orientation estimate at the outset and then to compute a robot location estimate by dead reckoning.

The robot heading estimate based on the encoded information from the wheels can be calculated by numerically integrating (1) and then expressed by

$$\theta_e(k) = \theta_e(k-1) + (d\theta_r(k) - d\theta_l(k)) \bullet \frac{R}{2br} + v_e(k) \tag{3}$$

where $d\theta_r(k)$ and $d\theta_l(k)$ denote the differential forward angles of the right and left encoders between time $k-1$ and time k, $\theta_e(k)$ and $\theta_e(k-1)$ represent the dead-reckoned orientation estimates of the robot using the two encoders' measurements at time k and $k-1$, respectively. In (3), measurement noise $v_e(k)$ denotes the error caused by the resolution of the encoders. Practically, the noise process $v_e(k)$ is assumed to be a discrete-time, zero-mean white Gaussian process with variance σ_e^2. Major cumulative error in (3) is often caused by wheel slippage

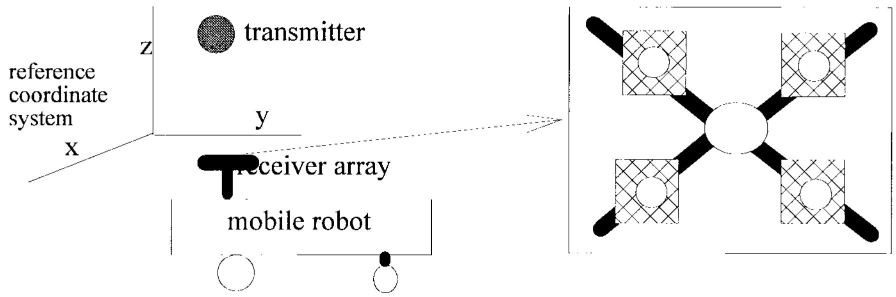

Fig. 2. Physical configuration of the modified ultrasonic location subsystem.

or surface roughness which generates noisy measurements of $d\theta_r(k)$ and $d\theta_l(k)$. This type of error is, however, not easy to model as a discrete-time stochastic process like $v_e(k)$, but it can be detected by utilizing the compass or the rate-gyro.

Next, the robot orientation measurement using the rate-gyro is expressed by

$$\theta_g(k) = \theta_g(k-1) + \int_{(k-1)T}^{kT} \dot{\theta}(t)\, dt + v_g(k). \tag{4}$$

The high drift rate of the rate-gyro will cause errors in the integration term of (4) to grow with time. To model such an error, it is definitely reasonable to assume the measurement noise $v_g(k)$ to be a discrete-time, zero-mean white Gaussian process with variance σ_g^2 over a sampling period.

Finally, the robot orientation measurement obtained from the flux gate compass is given using

$$\theta_c(k) = \theta(k) + v_c(k) \tag{5}$$

where the noise $v_c(k)$ is also assumed to be a discrete-time, zero-mean white Gaussian process with variance σ_c^2.

To simplify the derivation of the multisensorial dead-reckoning subsystem, we assume that all three measurement noise processes $v_e(k)$, $v_g(k)$, and $v_c(k)$ are mutually independent. We further assume that the initial robot orientation θ_0 is a Gaussian random variable with mean $\hat{\theta}_0$ and variance σ_0^2. By letting $\hat{\theta}(k-1)$ denote the optimal orientation estimate of the robot using the three types of measurements at time $k-1$, it is definitely reasonable to set

$$\theta_e(k-1) = \theta_g(k-1) = \theta_c(k-1) = \hat{\theta}(k-1). \tag{6}$$

Before merging the measurements at time k, a simple voting scheme has to be taken into account in order to delete any abnormal reading resulting from wheel slippage, surface roughness, or magnetic interference. The voting logic is based on how close the three types of measurements are and is depicted as follows. If the absolute difference of any two readings is less than a selected threshold value, namely that there is no wheel slippage and no magnetic interference, then the optimal orientation estimate $\hat{\theta}(k)$ of the robot is obtained from

$$\theta(k) = \frac{\theta_e(k)\delta_c^2\delta_g^2 + \theta_g(k)\delta_c^2\delta_e^2 + \theta_c(k)\delta_e^2\delta_g^2}{\delta_c^2\delta_g^2 + \delta_c^2\delta_e^2 + \delta_e^2\delta_g^2}. \tag{7}$$

Any reading deviating from the cluster of the other two readings will be removed and the two remaining readings are used to compute $\hat{\theta}(k)$ utilizing the following formula:

$$\theta(k) = \frac{\theta_1(k)\delta_2^2 + \theta_2(k)\delta_1^2}{\delta_1^2 + \delta_2^2} \tag{8}$$

where $\theta_1(k)$ and $\theta_2(k)$ represent the two acceptable measurements, and their variances are denoted by σ_1^2 and σ_2^2, respectively. The physical interpretation of this situation is given as follows. If the very measurement from the encoders is confirmed to be abnormal, then wheel slippage or surface roughness has taken place. If only the compass reading is not correct, then the robot maneuvers in a place with space-varying magnetic fields.

Last but not least, if all three measurements are far apart from each other, then the optimal orientation estimate $\hat{\theta}(k)$ is set to be $\theta_g(k)$. This is because the rate-gyro is not affected by wheel slippage, surface roughness, or magnetic interference, and its heading output is rather precise and accurate as the robot moves over short distances.

Having obtained a reliable, optimal robot orientation estimate, the robot location can be dead reckoned by numerically integrating (1) over a sampling period. For most computer-controlled mobile robots, the angular velocities of the right and left drive motors are usually known and constant over any sampling period T. Using (2), the integration of the location increments in (1) can be approximated using the trapezoidal rule and is given by (9) and (10), shown at the bottom of the next page.

As can be seen in (9) and (10), the cumulative error due to truncation operations, wheel slippage, or surface roughness is unavoidable.

IV. EKF-Based Sensor Fusion

As the robot moves into any area where the ultrasonic data becomes available, the location system is changed into the sensor fusion operating mode. The system measures TOF data and then uses these temporal readings to update the dead-reckoned location estimate of the robot utilizing the extended Kalman filtering approach. This includes the speed of sound as a variable and recursively determines it at each operation in order to increase the accuracy of the system.

Let the transmitter location in Fig. 3 be given by (x_5, y_5, z_5) and each receiver location be denoted by (x_i, y_i, z_i), $i = 1, \cdots, 4$, respectively, and $(x_1, y_1, z_1) = (x(k) + d\cos\hat{\theta}(k), y(k) + d\sin\hat{\theta}(k), z(k))$, $(x_2, y_2, z_2) = (x(k) + d\sin\hat{\theta}(k), y(k) - d\cos\hat{\theta}(k), z(k))$, $(x_3, y_3, z_3) =$

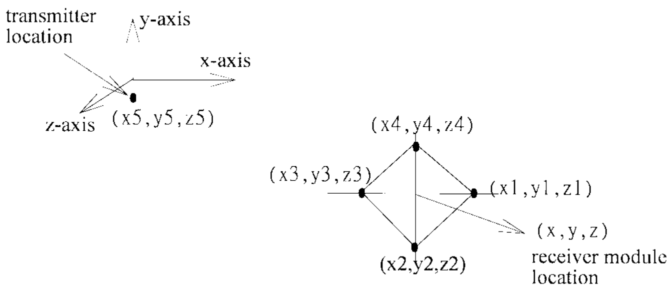

Fig. 3. Modified ultrasonic location subsystem schematic.

$(x(k) - d\cos\hat{\theta}(k), y(k) - d\sin\hat{\theta}(k), z(k))$, $(x_4, y_4, z_4) = (x(k) - d\sin\hat{\theta}(k), y(k) + d\cos\hat{\theta}(k), z(k))$ where d denotes the distance from the module center to each receiver. If the robot moves slowly, then the TOF measurements are given using the following matrix equation:

$$\begin{bmatrix} t_1(k) - t_{di} \\ t_2(k) - t_{d2} \\ t_3(k) - t_{d3} \\ t_4(k) - t_{d4} \end{bmatrix} = \begin{bmatrix} \dfrac{D_1}{c} \\ \dfrac{D_2}{c} \\ \dfrac{D_3}{c} \\ \dfrac{D_4}{c} \end{bmatrix} + \begin{bmatrix} n_1(k) \\ n_2(k) \\ n_3(k) \\ n_4(k) \end{bmatrix} \tag{11}$$

where

$$\begin{aligned} D_1 &= \sqrt{(x_1 - x_5)^2 + (y_1 - y_5)^2 + (z_1 - z_5)^2} \\ D_2 &= \sqrt{(x_2 - x_5)^2 + (y_2 - y_5)^2 + (z_2 - z_5)^2} \\ D_3 &= \sqrt{(x_3 - x_5)^2 + (y_3 - y_5)^2 + (z_3 - z_5)^2} \\ D_4 &= \sqrt{(x_4 - x_5)^2 + (y_4 - y_5)^2 + (z_4 - z_5)^2}. \end{aligned}$$

In (11), $t_i(k)$ and t_{di} are the TOF and the constant system time delay of the pulse emitted by the transmitter and sensed by the ith receiver at time k, respectively. Measurement noises $n_1(k)$, $n_2(k)$, $n_3(k)$, and $n_4(k)$ are mutually independent, zero-mean white Gaussian processes with covariance $R(k) = \text{diag}\{r_1(k), r_2(k), r_3(k), r_4(k)\}$.

The time delay term t_{di} incorporates the delay from the electronic circuitry adopted for conditioning the signal at the ith receiver, the delay which is inherent to the signal detection method to acknowledge reception of the pulse at the ith receiver, and the acousto-electro-mechanical delay associated with the transducers. This can be determined by calibrating the ultrasonic subsystem. Once the calibration process has been achieved, the time delay t_{di} can be estimated by subtracting the corresponding computed TOF from the calibrated reading. By defining

$$\begin{aligned} Z(k) &= [t_1(k) - t_{d1} \;\; t_2(k) - t_{d2} \;\; t_3(k) - t_{d3} \;\; t_4(k) - t_{d4}]^T, \\ V(k) &= [n_1(k), n_2(k), n_3(k), n_4(k)]^T, \\ X(k) &= [x(k), y(k), z(k), c(k)]^T \end{aligned}$$

(11) can be rewritten in a vector-matrix form:

$$Z(k) = h(X(k)) + V(k). \tag{12}$$

In applying the extended Kalman filter to correct the cumulative location estimate error for the robot, a state equation describing the dynamics of the state must be known and expressed using

$$\begin{bmatrix} x(k) \\ y(k) \\ z(k) \\ c(k) \end{bmatrix} = \begin{bmatrix} x(k-1) + \Delta x(k) \\ y(k-1) + \Delta y(k) \\ z(k-1) \\ c(k-1) \end{bmatrix} + \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \\ \xi_4 \end{bmatrix} \tag{13}$$

where ξ_1 and ξ_2 denote the errors of the dead-reckoned position estimates, ξ_3 represents the randomness of the surface roughness, and ξ_4 means the speed variations in the sound due to temperature fluctuations ΔT_a (in degrees Celsius). Moreover, the process noises are supposed to be discrete-time, zero-mean white Gaussian sequences with diagonal covariance matrix $Q(k)$. The process noises and the measurement noises are mutually independent. To obtain the best location estimate of the robot, a discrete-time Kalman filter is proposed as follows.

Step 1: At the time $k = 0$, select a good estimate $\hat{X}(0|0)$ and an initial error covariance matrix $\tilde{P}(0|0)$.

$$\begin{aligned} \Delta x(k) &\equiv x(k) - x(k-1) = \int_{(k-1)T}^{kT} v_d(t)\cos\theta(t)\,dt \\ &= \begin{cases} \dfrac{R}{2r}(d\theta_r(k) + d\theta_l(k))\cos\hat{\theta}(k), & \text{if } \hat{\theta}(k) = \hat{\theta}(k-1) \\ \dfrac{R(d\theta_r(k) + d\theta_l(k))}{2r(\hat{\theta}(k) - \hat{\theta}(k-1))}(\sin\hat{\theta}(k) - \sin\hat{\theta}(k-1)), & \text{if } \hat{\theta}(k) \neq \hat{\theta}(k-1) \end{cases} \end{aligned} \tag{9}$$

and

$$\begin{aligned} \Delta y(k) &\equiv y(k) - y(k-1) = \int_{(k-1)T}^{kT} v_d(t)\sin\theta(t)\,dt \\ &= \begin{cases} \dfrac{R}{2r}(d\theta_r(k) + d\theta_l(k))\sin\hat{\theta}(k), & \text{if } \hat{\theta}(k) = \hat{\theta}(k-1) \\ \dfrac{R(d\theta_r(k) + d\theta_l(k))}{2r(\hat{\theta}(k) - \hat{\theta}(k-1))}(\cos\hat{\theta}(k-1) - \cos\hat{\theta}(k)), & \text{if } \hat{\theta}(k) \neq \hat{\theta}(k-1) \end{cases} \end{aligned} \tag{10}$$

Step 2: Let the optimal estimate of $X(k-1)$ at time $k-1$ be $\hat{X}(k-1|k-1)$ and its error covariance matrix be $\tilde{P}(k-1|k-1)$. Use (9), (10), (14), and (15) to calculate the best prediction, $\hat{X}(k/k-1)$, and its propagation error covariance matrix $\tilde{P}(k|k-1)$

$$\hat{X}(k/k-1) = \hat{X}(k-1/k-1) + \begin{bmatrix} \Delta x(k) \\ \Delta y(k) \\ 0 \\ 0 \end{bmatrix} \quad (14)$$

$$\tilde{P}(k|k-1) = \tilde{P}(k-1|k-1) + Q(k-1). \quad (15)$$

Step 3: At time k, the location system reads four TOF temporal data $Z(k)$ and then uses (16) and (17) to obtain the updating estimate $\hat{X}(k/k)$ and the error covariance matrix $\tilde{P}(k/k)$

$$\hat{X}(k|k) = \hat{X}(k|k-1) + K(k)[Z(k) - h(\hat{X}(k/k-1))] \quad (16)$$

$$\tilde{P}(k|k) = [I - K(k)H(\hat{X}(k/k-1))]\tilde{P}(k|k-1) \quad (17)$$

where the Kalman filter gain matrix is given by

$$K(k) = \tilde{P}(k|k-1)H(\hat{X}(k|k-1))^T \cdot [H(\hat{X}(k|k-1))\tilde{P}(k|k-1) \cdot H(\hat{X}(k|k-1))^T + R(k)]^{-1} \quad (18)$$

$$H(X(k|k-1)) = \begin{bmatrix} \frac{x+d}{cD_1} & \frac{y}{cD_1} & \frac{z}{cD_1} & \frac{-1}{c^2D_1} \\ \frac{x}{cD_2} & \frac{y-d}{cD_2} & \frac{z}{cD_2} & \frac{-1}{c^2D_2} \\ \frac{x-d}{cD_3} & \frac{y}{cD_3} & \frac{z}{cD_3} & \frac{-1}{c^2D_3} \\ \frac{x}{cD_4} & \frac{y+d}{cD_4} & \frac{z}{cD_4} & \frac{-1}{c^2D_4} \end{bmatrix}.$$

Step 4: Repeat Step 2.

V. Experimental Results and Discussions

Two experimental studies are performed in this section to investigate the feasibility, accuracy, and performance of the proposed location system. The first experiment aims at studying what accuracy and precision the experimental system achieves when the robot stops inside the effective coverage area of ultrasonic wave propagation. The second one focuses on investigating how the system overcomes the slippage and magnetic interference problems while the robot moves along a line path.

For these two experiments, the transmitter was located at the position (−167.6, −237.0, 253.0) (unit: cm) with respect to the world coordinate reference system. While the experiments were being performed, the mean ambient temperature was fixed to be almost constant ($T_a = 23.1$°C) with small temperature fluctuations allowed ($\Delta T_a = \pm 0.3$°C). Therefore the correct speed of the sound was 34 503.5 cm/s [7]. Thus, the standard deviations of the TOF measurements were computed as $r_1(k) = 6.2$ μs, $r_2(k) = 6.6$ μs, $r_3(k) = 6.5$ μs, and $r_4(k) = 6.5$ μs.

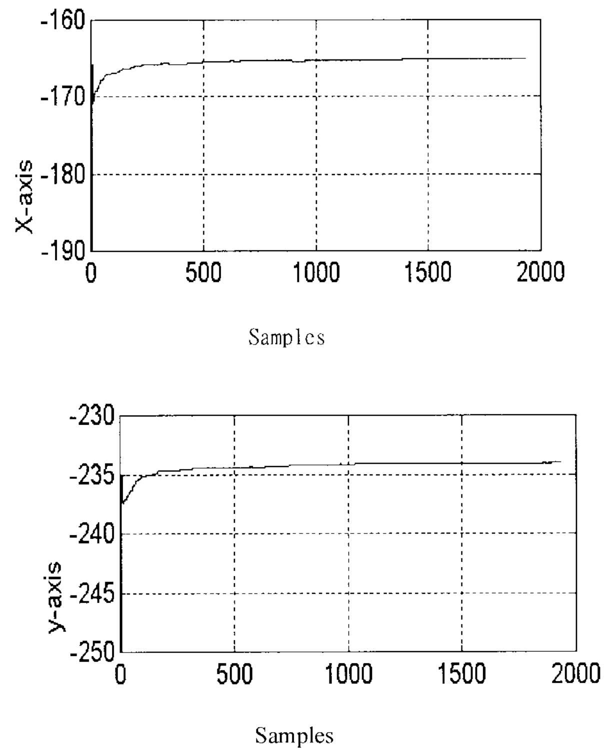

Fig. 4. Time history of the robot location estimate.

Before proceeding with the experiments, all important components, such as the flux gate compass, the rate-gyro, the encoders, and the ultrasonic transmitter/receiver module, were correctly calibrated, thereby allowing us to compute the statistical parameters of their noise models ($\sigma_e = 1°$, $\sigma_g = 1°$, and $\sigma_c = 2°$) and the time delay terms of the ultrasonic transmitter/receiver modules ($t_{d1} = 0.449$ ms, $t_{d2} = 0.455$ ms, $t_{d3} = 0.425$ ms, and $t_{d4} = 0.443$ ms). In addition, all of the required parameters were measured and listed as below: spaced distance $d = 19$ cm, the sampling period $T = 0.5$ s, the radius of the drive wheel $R = 10.75$ cm, the half distance between the two drive wheels $b = 22.5$ cm, and the gear ratio $r = 27$.

The first experiment was performed to investigate the behavior of the proposed location system while the robot was stopped at a prespecified position (−165, −234.5, 109.8). The multisensorial dead-reckoning algorithm and the EKF-based sensor fusion algorithm were implemented using the host PC586 computer. The matrix $\tilde{P}(0/0) = \text{diag}\{10, 10, 10, 100\}$ was considered for initializing the error covariance matrix. Fig. 4 depicts the time history of the robot location estimate, assuming the initial estimate to be $\hat{X}(0/0) = [-190, -260, 109.8, 34503.5]^T$. The initial location estimate error could be regarded as an accumulation error caused by wheel slippage or surface roughness. As can be seen in Fig. 4, the location estimate quickly converges to the prespecified position with little steady-state position estimate error (−0.2, −0.5), which can be eliminated by precisely measuring the four constant time delay terms. In this experiment, if the initial conditions of $\hat{X}(0/0)$ are far from the position, then the Kalman filter may fail to converge to the desired values.

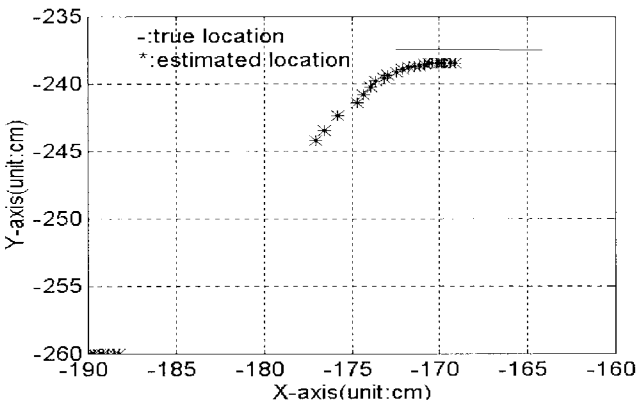

Fig. 5. Robot location estimate and its actual measurement.

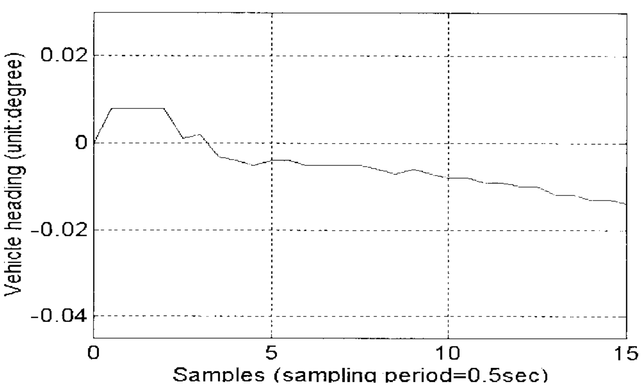

Fig. 6. Robot heading estimate.

This experiment also implies that the proposed location system can be used not only to find the location coordinates of the robot, but also to find the position of the transmitter.

The second experiment was used for evaluating the dynamic performance of the proposed location system while the robot moved along a line path in a structured environment with sandy, partly smooth surfaces and a magnetic interference source. To simulate the magnetic interference source, a working induction motor was put into the experimental environment. All of the initial parameter settings were identical to the previous experiment. The constant linear velocity of the robot was $V_d = 1.0$ cm/s ($\omega_r(t) = \omega_l(t) = 0.1$ rad/s) and the vehicle heading was zero degrees.

Figs. 5 and 6 show the location and heading estimates and the actual measurements for the robot with linear motion parallel to the x-axis. Fig. 6 shows that the proposed multisensorial dead-reckoning technique overcomes the magnetic interference problem and the orientation estimate is preserved while the robot passed over the area. To find the accuracy and precision, the actual values of the robot location were carefully measured by hand and then compared to the corresponding estimates, thus computing a steady-state accuracy (+4.9, −1.0) for the system.

VI. Conclusions

The paper has developed a novel location system for an autonomous mobile robot designed to perform missions in any given structured environment. Its hardware consists of a multisensorial dead-reckoning subsystem, a modified ultrasonic location subsystem, and a host PC 586 computer. The voting scheme was presented for detecting the occurrence of wheel slippage or for determining the position at which magnetic interference takes place. With this voting scheme, the multisensorial dead-reckoning subsystem deletes unwanted reading(s) and fuses the remaining measurements to obtain the optimal orientation and location estimates of the robot, thereby providing a highly robust and reliable orientation estimate. The modified ultrasonic location subsystem with known position for the transmitter was used based on an EKF algorithm to completely eliminate the cumulative location error caused by wheel slippage or surface roughness. In order to precisely carry out the proposed algorithm, the mean ambient temperature must be correctly measured. Experimental results confirm that the proposed location system not only achieves the strengths declared by Figueroa and Mahajan [10] but also provides a much simpler and more practical hardware structure for use and installation/calibration.

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