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Sensor fusion based ambulatory system for indoor localization

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Abstract

Indoor localization for pedestrian is the key technology for caring the elderly, the visually impaired and the handicapped in health care districts. It also becomes essential for the emergency responders where the GPS signal is not available. This paper presents newly developed pedestrian localization system using the gyro sensors, the magnetic compass and pressure sensors. Instead of using the accelerometer, the pedestrian gait is estimated from the gyro sensor measurements and the travel distance is estimated based on the gait kinematics. Fusing the gyro information and the magnetic compass information for heading angle estimation is presented with the error covariance analysis. A pressure sensor is used to identify the floor the pedestrian is walking on. A complete ambulatory system is implemented which estimates the pedestrian's 3D position and the heading.

Key Words : indoor localization, ambulatory system, sensor fusion

1. Introduction

In mobile robot application, localization is one of the essential functions. A lot of work has been done in the last decades to get precise estimation of location. One of the common localization methods is using the internal encoder sensors and extra sensors such as the camera, the accelerometer, etc. However, it can not be applied to the localization of the pedestrian because the pedestrians do not have the dead reckoning sensors and may move differently from the mobile robot.

The augmented reality technique, which merges the real and the virtual worlds, has received a great deal of attention for displaying location-based information in the real world. To realize an augmented reality system, the exact position and orientation of a user are required. Indoor environments, where a GPS can not be used, many localization methods have been proposed.

Using several sensors, including the inertial sensors, RFID tags, IrDA markers provided measurement of user location[1]. The gyroscopes and the accelerometers are commonly used inertial sensors for estimating the movement. Sensor fusion techniques are proposed for human motion capture by integrating the gyroscopes and the accelerometers[2]. Personal dead-reckoning navigation system for walking persons is introduced[3]. It used a six-axis inertial measurement unit attached to the user's boot and a technique known as "Zero Velocity Update" that virtually eliminates the ill-effects of drift in the accelerometers. Mezentsev[4] presented an analysis of the performance of medium-accuracy pedestrian dead reckoning systems. An inertial navigation system for pedestrian position tracking is proposed by Suh[5]. The position is computed using inertial and magnetic sensors on shoes. The gait states are modeled as a Markov process and gait state is estimated using the hidden Markov model filter. A digital gait analyzer using the triaxial accelerometer was developed[6]. Based on the decay slope peak detection algorithm, the pedestrian gait was detected. However, only the detection of the gait was considered but not the movement nor the position of the pedestrian. A real-time monitoring of posture and activity using a 3-axis accelerometer was introduced[7]. It is mainly focused on detection of the emergency such as falling. Lee[8] presented gyro based localization system for 2-D. Simple sensor fusion algorithm to select either the magnetic compass output or the gyro output for orientation is used.

In this paper, we developed the localization system based on the estimated gait of the pedestrian. By analyzing the gait of the pedestrian, Kinematic model of

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human gait is developed and the movement of the pedestrian is estimated from this model with sensor information. Rather than sensing the movement of both legs, the heading angle is measured from the extra gyro sensor, so that only one leg sensing is necessary. In order to reduce the effect of the drift error of the gyro, sensor fusion algorithm for magnetic compass information and gyro value is developed. A pressure sensor is used to differentiate the floors in a building. A complete 3-D position and heading angle are estimated using this sensor system. The error analysis is performed based on the error propagation law.

In the following section, the model of the gait and the estimation of the forward velocity are presented. Sensor fusion with the magnetic compass for heading angle estimation is discussed and the localization results with the pressure sensor are described in Section 3, followed by the conclusion.

2. Gait Model and Estimation

The Inertial Measurement Unit(IMU) is commonly used as a supplementary device to estimate the velocity and the position. It is supplementary because the IMU alone has the intrinsic drift error, and the position calculated from the double integration with respect to time has the accumulated error. Over last several decades, overcoming this error has been studied extensively. In aerospace application, very accurate and sophisticated IMUs are developed and being used widely. However, most of them are very expensive and need auxiliary devices such as GPS.

We are developing a simple and low-price localization system, which is for pedestrians(indoor use). The system is presented in Fig. 1, which shows the sensors and the corresponding estimation modules. Two gyros provide the thigh and the calf angles to the gate estimator, which estimates the forward velocity. Heading is estimated from the gyro and the compass information. Together with the altitude measurements using the pressure sensor, the localization system estimates complete 3D position and the heading of the pedestrian.

Instead of relying on the accelerometer information, we are measuring the movement of pedestrian's leg. Like a humanoid robot, by measuring the angular velocities of the thigh and the calf, simple Kinematic model provides the estimated movement of the hip. Those two angles are estimated from two gyro sensor information. Our proposed method is limited and this applies to normal walking only; no rolling, no side-walk.

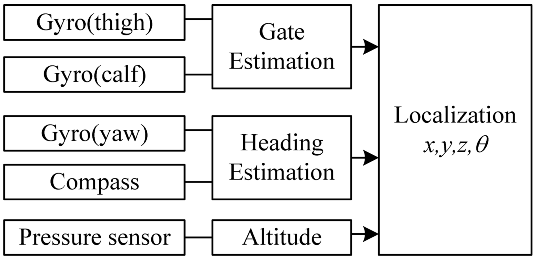

Fig. 1. Localization system.

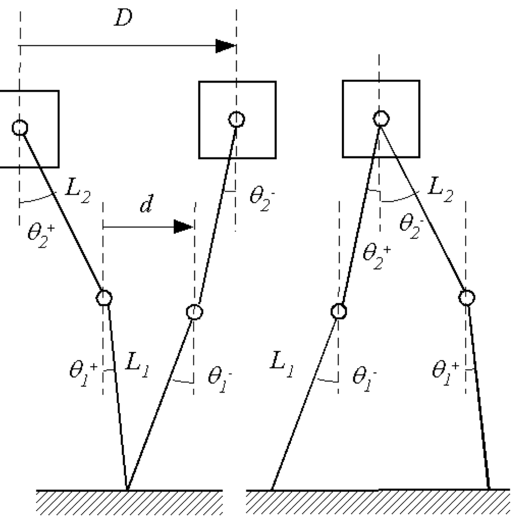

Fig. 2. Gait model.

Fig. 2 shows the model of the gait; d is the travel distance of the knee joint and D is the travel distance of the hip.

The following equations are derived from the gate model.

$$d = L_1 \sin(\theta_1^+) + L_1 \sin(\theta_1^-) \tag{1}$$

$$D = d + L_2 \sin(\theta_2^+) + L_2 \sin(\theta_2^-) \tag{2}$$

In our experiments, the parameters of the user's leg are $L_1 = 0.48$ m, $L_2 = 0.56$ m. ADIS16100 gyro is used which can measure up to ±300 °/sec of angular velocity. Fig. 3 shows the experimental setup with two gyro sensors attached.

By differentiating eq. (2), the velocity of the pedestrian is derived as

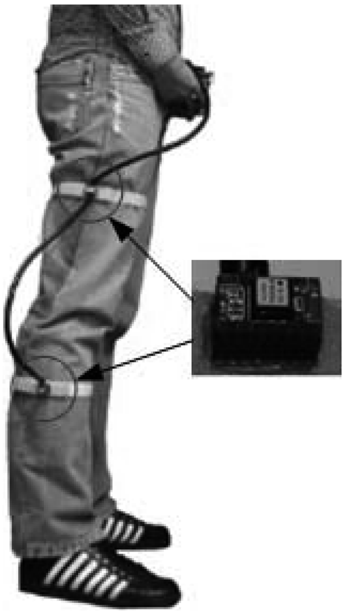

Fig. 3. Experimental setup and the gyro.

$$V=\dot{D}=L_1\cos(\theta_1^+)\omega_1+L_1\cos(\theta_1^-)\omega_1 \tag{3}$$

$$+L_2\cos(\theta_2^+)\omega_2+L_2\cos(\theta_2^-)\omega_2$$

$$=L_1\omega_1(\cos(\theta_1^+)+\cos(\theta_1^-))$$

$$+L_2\omega_2(\cos(\theta_2^+)+\cos(\theta_2^-))$$

For error covariance analysis, we assume that the magnitudes of θ_1^+ and θ_1^- are almost the same and so are θ_2^+ and θ_2^-. The nominal values of the angles are defined as

$$\theta_1^n=\frac{\theta_1^+ + \theta_1^-}{2} \tag{4}$$

$$\theta_2^n=\frac{\theta_2^+ + \theta_2^-}{2} \tag{5}$$

and the changes of the angles are

$$\Delta\theta_1=\frac{\theta_1^+ - \theta_1^-}{2} \tag{6}$$

$$\Delta\theta_2=\frac{\theta_2^+ - \theta_2^-}{2} \tag{7}$$

In other words, we assume $\theta_1^n \cong 0$ and $\theta_2^n \cong 0$ but we leave them for analysis. Eqs. (1) and (2) are rewritten as

$$D=L_1\sin(\theta_1^n-\Delta\theta_1)+L_1\sin(\theta_1^n+\Delta\theta_1) \tag{8}$$

$$+L_2\sin(\theta_2^n-\Delta\theta_2)+L_2\sin(\theta_2^n+\Delta\theta_2)$$

Using the first order Taylor expansion, the covariance of the estimated D is given by the error propagation law[9] as

$$C_D=F_\theta C_\theta F_\theta^T \tag{9}$$

and F_θ is the Jacobian matrix defined as

$$F_\theta=\begin{bmatrix}\frac{\partial D}{\partial\theta_1^n} & \frac{\partial D}{\partial\Delta\theta_1} & \frac{\partial D}{\partial\theta_2^n} & \frac{\partial D}{\partial\Delta\theta_2}\end{bmatrix} \tag{10}$$

where

$$\frac{\partial D}{\partial\theta_1^n}=L_1\cos(\theta_1^n-\Delta\theta_1)+L_1\cos(\theta_1^n+\Delta\theta_1)$$

$$\frac{\partial D}{\partial\Delta\theta_1}=-L_1\cos(\theta_1^n-\Delta\theta_1)+L_1\cos(\theta_1^n+\Delta\theta_1)$$

$$\frac{\partial D}{\partial\theta_2^n}=L_2\cos(\theta_2^n-\Delta\theta_2)+L_2\cos(\theta_2^n+\Delta\theta_2)$$

$$\frac{\partial D}{\partial\Delta\theta_2}=-L_2\cos(\theta_2^n-\Delta\theta_2)+L_2\cos(\theta_2^n+\Delta\theta_2)$$

Generally, the thigh and the calf angles are independent to each other and we assume the covariance matrix θ of has zero off-diagonal elements as

$$C_\theta=\begin{bmatrix}\sigma_{\theta_1}^2 & 0\\ 0 & \sigma_{\theta_2}^2\end{bmatrix} \tag{11}$$

Using eqs. (9)~(11), we can estimate the error covariance of D at specific condition.

The gyro sensor has the intrinsic drift error, which makes the estimated angle from the measured angular velocity diverge. Still we can reset the drift error of the gyro based on the fact that the neutral position of the leg should be upright and it can't diverge to positive nor negative direction.

Fig. 4 shows how the proposed algorithm works. Due to the intrinsic drift error, movements of the leg are being shifted to the positive direction as in Fig. 4(a). After one period of movement(oscillation), the neutral position is reset to the initial value as in Fig. 4(b).

For verification of the gait model, the angular veloc-

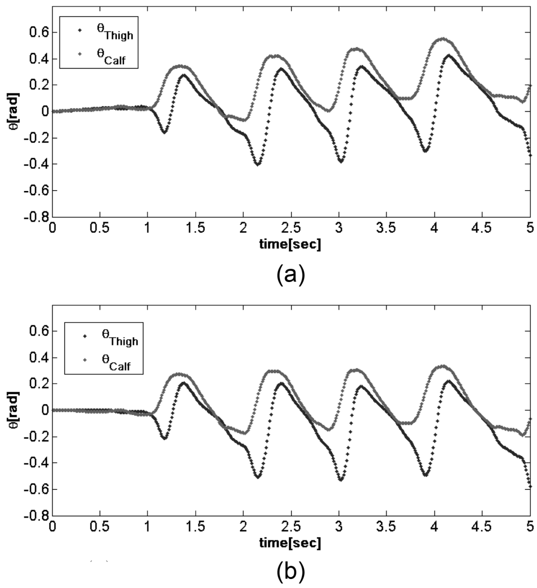

Fig. 4. (a) Integrated gyro sensor output (b) Compensated estimation.

ities of the thigh and the calf are measured and those are integrated with respect to time which are used as the angle values for the model. Note that only the travel distance is estimated from one leg model, but not the direction of the walk.

3. Gait Estimation based Localization

For getting complete knowledge of the location including the orientation, there are two solutions. The first one is, measuring both legs' travel distances and the second one is measuring the heading angle of the human body with the measurement of one leg.

In this paper, the results of the second solution are presented. There are three gyro sensors used. One for the thigh, one for the calf and the third one is to measure the rate of the heading angle which is fixed at the belt. As described in previous section, the drift errors from the gyros for thigh and calf are successfully removed assuming that the neutral position of the leg is upright. However, there is no similar way available for the heading angle. Hence, we developed a fusing algorithm to use the magnetic compass information in order to get the correct heading angle.

Sensor fusion is based on the variance analysis. The gyro sensor is very accurate and has very small variance but it has the drift error. The compass has large variance, but no drift error. Therefore, we get the optimal estimates based on the following weighted least-sqaures technique[9]. Let θ_c represent the output of the compass and θ_g do the integrated value of the gyro output with respect to time. For optimal estimate of θ, let's define $\hat{\theta}_1 = \theta_c$ with variance of $\sigma_1^2 = \sigma_c^2$ and similarly $\hat{\theta}_2 = \theta_g$ with variance of $\sigma_2^2 = \sigma_g^2$. The optimal solution minimizes the weighted sum of errors defined as

$$S = \sum_{i=1}^{n} w_i(\hat{\theta} - \theta_i)^2 \tag{12}$$

where w_i is the weight of the measurement i. To find the minimum error, let

$$\frac{\partial S}{\partial \hat{\theta}} = 2\sum_{i=1}^{n} w_i(\hat{\theta} - \theta_i) = 0 \tag{13}$$

$$\sum_{i=1}^{n} w_i\hat{\theta} - \sum_{i=1}^{n} w_i\theta_i = 0 \tag{14}$$

then,

$$\hat{\theta} = \frac{\sum_{i=1}^{n} w_i\theta_i}{\sum_{i=1}^{n} w_i} \tag{15}$$

if we take the weight w_i as

$$w_i = \frac{1}{\sigma_i^2} \tag{16}$$

then the value of $\hat{\theta}$ in terms of two measurements is defined as

$$\hat{\theta} = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2}\theta_1 + \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2}\theta_2 \tag{17}$$

and the resulting variance is

$$\sigma^2 = \frac{\sigma_1^2\sigma_2^2}{\sigma_2^2 + \sigma_1^2} \tag{18}$$

Thus the uncertainty of the angle is decreased by combining the two measurements.

The configuration of the pedestrian is modeled as 3 degrees of freedom(x,y,θ), a planar rigid body motion. We estimate the forward velocity, V and the rate of heading angle change w are defined as shown in Fig. 5. The forward velocity is calculated from eq. (3) with two measurements using gyro sensors.

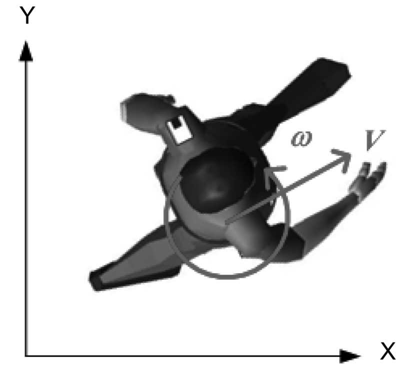

Fig. 5. Forward velocity and heading rate of pedestrian.

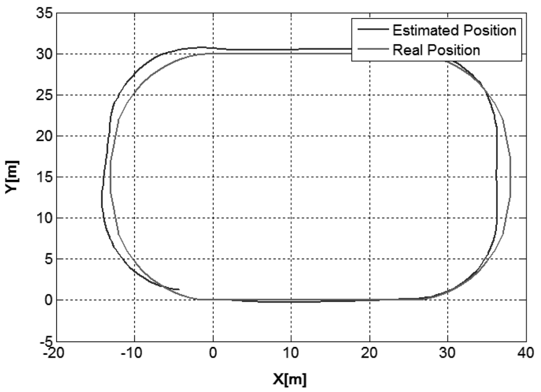

Fig. 6. Estimated position of the pedestrian(40 m × 30 m track).

The heading angle, θ is estimated from eq. (17). The position of the sensor unit is represented as following equations.

$$x = \int V\cos\theta dt \tag{19}$$

$$y = \int V\sin\theta dt \tag{20}$$

All the sensors are interfaced with a AVR ATmega128 microcontroller via SPI or I^2C. The localization results are updated with the sampling frequency of 10 Hz.

Fig. 6 shows the results of the experiment of walking 40 m × 30 m track. The red line is the actual trajectory the pedestrian followed and the blue line is the estimated trajectory. The estimated final position shows about 8 m deviation from the actual one. We expect the deviation error is proportional to the travel distance. Still, the orientation estimation is fairly accurate.

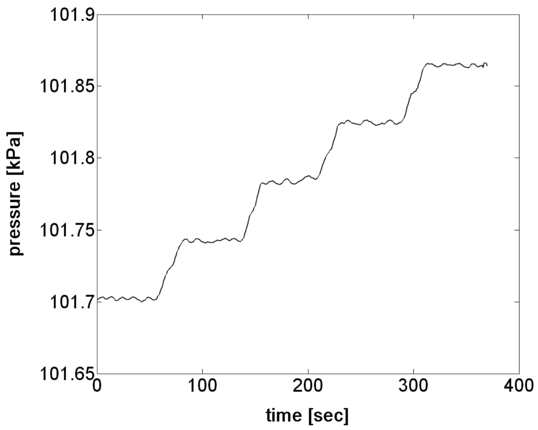

Fig. 7. Pressure sensor output change while walking from the 5th floor of the building down to the 1st floor.

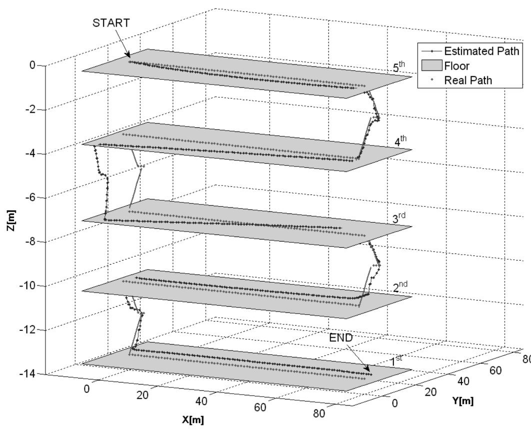

Fig. 8. 3D localization results.

The proposed localization scheme in this paper is for indoor use. “Indoor” is the environment where GPS signal is not available. This also restricts planar 2-D motion where the altitude doesn't change(no hill climbing, no mountain hiking, for instance). The gait model based localization still provides the correct travel distance for non-planar movement. Even only for the indoor use, it would be much more useful to identify the floor the pedestrian is on. We tested the SCP1000-D01 pressure sensor for this application. Fig. 7 shows the pressure sensor outputs while the pedestrian walks on the 5th floor corridor(about 80 m long), then walks down to the 4th floor, walks on the 4th floor corridor and repeats till he finished walking on the 1st floor.

Even though the pressure sensor output does not remain as constant on a floor, it is stationary enough that we can differentiate which floor the pedestrian is on. By integrating the floor information with the 2D gait based localization results, we get 3D localization(x,y,z,θ) results as shown in Fig. 8.

Note that values in Fig. 8 are not converted from the pressure sensor readings. Instead, the heights of the floors, defined with respect to the 5th floor, are used once the floor is identified.

4. Conclusion

A new pedestrian localization system based on the gait estimation is presented. Measurements of the thigh and the calf angular velocities are done with the gyros and the forward velocity of the hip is estimated from the gait model. The yaw angle is estimated from the fusion algorithm for the yaw rate gyro and the magnetic compass sensor. With the forward velocity and the yaw angle, the localization of a pedestrian is performed. By combining the pressure sensor information, it is possible to estimate the indoor altitude(to identify the floor), hence a 3D localization is implemented for indoor pedestrian localization. The proposed localization system shows less drift error and is very effective for indoor use.

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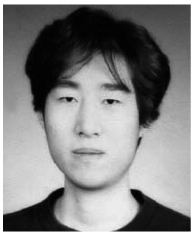

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