Adaptive Step Length Method of Dead Reckoning

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Abstract. Aimed at the demand of positioning in complicated environments such as indoor and built-up areas, the method of autonomous navigation positioning and orientation based on an adaptive step length model was proposed in this paper. Using an accelerometer placed on the human waist, stride was recognized and the relationship between the step length, stride factor, and walking speed was established. The stride factor was calibrated by least squares, which adaptively adjusted the calculation of the step length in situations of different walking speeds and manners, thus enhancing the accuracy of the step length. Additionally, information of the magnetometers, gyroscopes, and other sensors were fused to estimate heading with an extended Kalman filter. Personal dead reckoning was achieved based on the results of the moving distance and heading. The experimental results showed that positioning errors of the method were less than 3.5% of the travel distance, and it was able to meet the positioning requirements of pedestrians.

Keywords. adaptive step length model, heading estimate, least squares, personal dead-reckoning

Introduction

Traditional satellite navigation is currently in a dominant position in the field of pedestrian navigation, but it cannot accurately perform real-time navigation in dense woods or built-up urban areas because of weak or missing satellite signals. Gait analysis based navigation, as a new and important branch of pedestrian navigation, has become the hotspot in recent years. Compared to satellite navigation, it can provide accurate navigation information for emergency rescue, firefighting, and anti-terrorism operations in complex environments.

There are two primary kinds of gait navigation currently in use. The first is Foot-Mounted Personal Navigation. Jimenez [1-2] and Weixing Qian [3-4], et al. connected the inertial measurement unit to the foot or leg fixedly. They predicted the posture and positional information of the moving human body by processing the output acceleration and angular velocity values of the inertial measurement unit. With sliding variances of acceleration information, a fixed threshold was used for comparison. Then, zero speed moment was selected, and the error of strapdown inertial navigation system was
corrected. Positioning of this method is obtained by the double integral of the acceleration value, meaning the accuracy of positioning is poor. In addition, due to the unobvious zero speed characteristics of pedestrian waist acceleration during movement, it is difficult to obtain positioning [5-6], meaning these methods can only be used with the inertial measurement unit attached to the feet or legs, which is extremely inconvenient. Mitja Placer [7] used accelerometers and gyroscopes to count the number of steps and determine the direction of movement. A camera on the user’s shoes and identification marks were used for real-time measurement of step length. This method has higher location accuracy, but requires additional cameras to measure the length of steps. The second kind of pedestrian positioning system is pedestrian dead reckoning. This method can effectively avoid long drift errors due to its strap-down solution, which is not limited by the position of the inertial measurement unit and can be placed on the waist, legs, feet, or other parts of the user. It is convenient and wearable.

After analysis of a large amount of human motion data, an adaptive step length model for pedestrians was established, and based on this model, a method for autonomous positioning and orientation was proposed. A waist measurement scheme was used to perform zero-crossing detection so as to realize stride extraction after filtering of acceleration information, and the above model was used to estimate the step length. For issues including the severity of low cost gyro drift errors, magnetometers are vulnerable to a variety of magnetic interferences, and accurate heading issues are unobtainable. More accurate heading can be acquired by a combination of Kalman filter, gyroscope, accelerometer, and magnetometer. Based on the results of the moving distance and heading, the precise positioning of pedestrians in complex indoor environments was solved.

1. Dead Reckoning Based on the Adaptive Step Length Model

In personal dead reckoning, the step length and heading are two important positioning data. According to acceleration information, stride is extracted while steps are counted, and the stride start point is selected as the update point of the position. The step length is estimated based on the given model, and is used as the distance between points. Accurate heading information is obtained with the data from the EKF fusing sensor. Dead reckoning can be achieved according to the step length and motion heading. The whole architecture is shown in Fig. 1.

![Figure 1. Dead reckoning system architecture](image-url)
1.1. Stride Detection

The acceleration signals of the three axes of sensors fixed on the waist showed periodic characteristics during walking, wherein the data of -axis was particularly evident. Strides were detected from the periodic changes in the total acceleration. Fig. 2 illustrates how the hip and, by extension, the upper body, move vertically when walking. The total acceleration was calculated by each sample point, as shown in the following:

\[ a_i = \sqrt{a_{ix}^2 + a_{iy}^2 + a_{iz}^2} \]

(1)

where \(a_i\) is the total acceleration for \(i\) sample and \(a_{ix}, a_{iy}, \text{ and } a_{iz}\) are the accelerations of \(x\)-axis, \(y\)-axis, and \(z\)-axis for \(i\) sample, respectively.

Distortion of the accelerometer output signal caused by body vibration, sensor bias, and noise during walking can affect the detection of peak stride and stride estimation, and may even lead to pedometer errors. A smoothing filter was used to reduce the impact of external interference to improve the system performance.

\[ a_k = \frac{1}{2L+1} \sum_{i=k-L}^{k+L} a_i \]

(2)

\(2L+1\) was the length of smoothing filter. In order to avoid errors due to multiple peaks, the time interval between adjacent valid values was calculated at the same time. If the time interval was greater than the time threshold, it was identified as stride. The start point and end point of the stride were determined by the zero-crossing detection (only the acceleration of gravity). Zero point was the starting point during the ascending period and was the end point during the descending period. The total acceleration signals and the stride detection results before and after filtering are shown in Fig. 3, wherein the dot is the start point of the stride and the square point is the end point.

Figure 2. Vertical movement of hip while walking

Figure 3. The total acceleration signal

1.2. Step Length Estimation

When people are walking, the length of the step is not a fixed value. Instead, it changes with the person’s walking speed and the frequency of pace. Modeling of human gait through the Weiberg algorithm [8] assumes that the stride length is proportional to the vertical displacement of the hip at every step. After obtaining the signal vector magnitude of the hip, a low-pass filter was applied with a cut-off
frequency of 3 Hz, and the Weiberg expression allowed for an estimation of the stride length, as in the following:

\[ SL = K \times \sqrt[4]{A_{\text{max}} - A_{\text{min}}} \]  

(3)

where the pedestrian step length is \( SL \), \( A_{\text{max}} \) and \( A_{\text{min}} \) are the maximum and minimum values of the total acceleration output value in every step, and \( K \) is the stride factor. Different people have different stride factors, so it needs to be calibrated to ensure the accuracy of the step length. The fixed distance of uniform-velocity walking of pedestrians is \( S \), and the total number of steps is \( n \), so \( K \) can be determined by the following equation:

\[ K = \frac{S}{\sum_{i=1}^{n} \sqrt[4]{A_{\text{max}} - A_{\text{min}}}} \]  

(4)

In the actual application, it was found that \( K \) was slightly different due to the difference in the pace speed and way of walking, and a constant \( K \) value in Equation 3 will introduce step error, making the positioning accuracy decrease. In order to effectively solve this problem, an adaptive step length method of dead reckoning was proposed. Since the pace is associated with \( K \), while the acceleration output value is positively related with the pace, the following equation was established:

\[ K = a\overline{A}_{\text{max}} + b\overline{A}_{\text{max}} + c \]  

(5)

where \( \overline{A}_{\text{max}} \) is mean sequence, which is constituted with the maximum output values of the total accelerations in one-step space during uniform-velocity walking.

\[ \overline{A}_{\text{max}} = \frac{\sum_{i=1}^{n} A_{\text{max}}}{n} \]  

(6)

The distance was fixed according to the speed (fast, relatively fast, medium, and slow). \( K \) and \( \overline{A}_{\text{max}} \) were obtained, respectively, by Eq. 4 and Eq. 6. The unknown coefficients in Eq. 5 were calculated by the least squares method so that adaptive adjustment of stride factor \( K \) was achieved. Fig. 4 shows a corresponding model error comparison chart for randomly walking ten steps.
1.3. Heading Estimation

Through a triaxial gyroscope, the angular velocities of the $x$, $y$, and $z$ axes in the coordinates system of pedestrian can be obtained. And the current attitude angles can be obtained from the initial position through integrating the differential equations of rigid body kinematics based on quaternion. The attitude quaternion differential equation is as follows:

$$
\dot{Q} = \frac{1}{2} Q \otimes \omega(t) = Q_0
$$

(7)

In $Q = q_0 + q_i \hat{i} + q_j \hat{j} + q_k \hat{k}$, the $Q$ is called quaternion [9], $t_0$ is the initial moving time of the carrier, $Q_0$ is the attitude quaternion at the initial alignment time, $\omega = \omega_i \hat{i} + \omega_j \hat{j} + \omega_k \hat{k}$ is the quaternion of carrier angular velocity in the body coordinates system, and $\otimes$ denotes the quaternion multiplication. Eq. 7 can be expressed in matrix form, as follows:

$$
\dot{Q} = \begin{bmatrix}
q_0 \\
q_1 \\
q_2 \\
q_3
\end{bmatrix}
= \frac{1}{2} \begin{bmatrix}
0 & -\omega_3 & -\omega_2 & \omega_1 \\
\omega_3 & 0 & -\omega_1 & \omega_2 \\
\omega_2 & \omega_1 & 0 & -\omega_3 \\
-\omega_1 & -\omega_2 & \omega_3 & 0
\end{bmatrix}
\begin{bmatrix}
q_0 \\
q_1 \\
q_2 \\
q_3
\end{bmatrix}
= \frac{1}{2} \Omega(\omega)Q
$$

(8)

where $\omega_i (i = 1, 2, 3)$ is the corresponding attitude angular velocity that is the component in the body coordinates system along the $x$, $y$, and $z$ axes and $\Omega(\omega)$ is a $4 \times 4$ anti-symmetric matrix.

The angular velocities in the sampling time interval is usually assumed constant in order to facilitate the calculation, and then the differential Eq. 8 is solved to get a discrete-time attitude quaternion formula, which is as follows:

$$
Q_{k+1} = \exp\left(\frac{1}{2} \Omega(\omega)T\right)Q_k = \begin{bmatrix}
I & \Delta \theta \\
0 & 0
\end{bmatrix}
\begin{bmatrix}
\cos\frac{\Delta \theta}{2} + \Omega(\omega)T\sin\frac{\Delta \theta}{2} \\
0 & I
\end{bmatrix}Q_k
$$

(9)

where $\Delta \theta = T\sqrt{\omega_i^2 + \omega_j^2 + \omega_k^2}$, $k = 0, 1, \ldots$

Because of the random drift error of the gyroscope, the heading error of the gyroscope was divergent with the time; thus, the accuracy of the heading only based on the gyroscope was lower. In order to ensure the accuracy of the headings, information of the gyroscope and magnetometer/accelerometer was fused for heading angles. This paper adopted EKF to fuse the sensor data.

The discrete time model was updated by the gyro quaternion attitude method. The rotating quaternion was used as the state vector, and the state equation of the Kalman filter can be obtained by the following:
where $\mathbf{v}_k$ is the process noise vector.

The measurement value of the normalized triaxial accelerometer and the measurement value of the normalized triaxial magnetometer were used as the observables, and the observation equation is as follows:

$$z_{k+1} = f(x_{k+1}) + \mathbf{v}_k = \begin{bmatrix} T_a^T(Q_{k+1}) & 0 \\ 0 & T_a^T(Q_{k+1}) \end{bmatrix} \begin{bmatrix} g \\ h \end{bmatrix} + \begin{bmatrix} \mathbf{v}_k \end{bmatrix}$$  \hspace{1cm} (11)

where $T_a^T(Q_{k+1})$ is the attitude rotation matrix through quaternion updating, as shown in Eq. 12; $\mathbf{v}_k$ is the measurement noise vector of the covariance matrix $R$, as shown in Eq. 13; $g$ is the normalized vector of the local gravitational acceleration, as shown in Eq. 14; and $h$ is the normalized vector of local magnetic field intensity, as shown in Eq. 15.

$$T_a^T(Q_{k+1}) = \begin{bmatrix} 1 - 2(q_1^2 + q_3^2) & 2(q_1q_3 + q_2q_4) & 2(q_1q_4 - q_2q_3) \\ 2(q_1q_3 - q_2q_4) & 1 - 2(q_2^2 + q_3^2) & 2(q_2q_3 + q_1q_4) \\ 2(q_1q_4 + q_2q_3) & 2(q_2q_3 - q_1q_4) & 1 - (q_1^2 + q_2^2) \end{bmatrix}$$  \hspace{1cm} (12)

$$R = \begin{bmatrix} \sigma^2_g \mathbf{I} & 0 \\ 0 & \sigma^2_h \mathbf{I} \end{bmatrix}$$  \hspace{1cm} (13)

$$g = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}^T$$  \hspace{1cm} (14)

$$h = \begin{bmatrix} 0 \\ b_x \\ b_z \end{bmatrix}^T$$  \hspace{1cm} (15)

where $b_x$ and $b_z$ are the normalized components of the magnetic field strength in the horizontal and vertical directions, respectively.

The observation equation in the system was nonlinear, and the Jacobi matrix $F$ was obtained using Eq. 16, with which the linear processing can be performed:

$$F = \left. \frac{\partial}{\partial x_{k+1}} z_{k+1} \right|_{x_{k+1} = \tilde{x}_{k+1}}$$  \hspace{1cm} (16)
1.4. Dead-Reckoning

The basic principle of pedestrian dead reckoning is shown in Fig. 5 [10], where the eastern and northern directions are the x-axis and y-axis, respectively.

Taking \( P(t_0)(E(t_0), N(t_0)) \) as the initial position, and \( P(t_{k-1})(E(t_{k-1}), N(t_{k-1})) \) as the final position, position estimation of present step \( P(t_k)(E(t_k), N(t_k)) \) can be easily computed by Eq. 17, as follows:

\[
\begin{align*}
E(t_k) &= E(t_{k-1}) + SL(t_{k-1}) \cdot \sin \phi(t_{k-1}) \\
N(t_k) &= N(t_{k-1}) + SL(t_{k-1}) \cdot \cos \phi(t_{k-1})
\end{align*}
\]

where \( \phi(t_{k-1}) \) and \( SL(t_{k-1}) \) are the heading and step length at time \( t_{k-1} \) respectively.

![Figure 5. Dead reckoning diagram](image)

The user’s position can be renovated once a moving footstep is completed, and then the continuous motion trajectory can be acquired.

2. Experimental Results

To verify the effectiveness of the algorithm, walking experiments of closed curves were carried out. The IMU fixed on the waist was a SBG IG-500N in this experiment, which consisted of a 3-axis accelerometer, a 3-axis gyroscope, and a 3-axis compass. Sensor data were recorded and the trajectory of pedestrians was calculated with the method of dead-reckoning designed in this paper. The experiment was conducted on a male student in the authors’ lab. His stride factor \( K \) was calibrated, and the curve fitting results of the stride factor \( K \) and \( A_{\text{max}} \) are shown in Fig. 6. The closed curve trajectory is shown in Fig. 7.

In Figure 7, the curve called "Normal" is the trajectory at normal speed and the curve called "Mix" is the trajectory at variable speeds. From the figure, it can be seen that the two tracks are almost same. The results are shown in detail in Tables 1 and 2. The results show that the accuracy of the pedestrian autonomous positioning directional algorithm was overall higher. The relative errors of the step number and distance were less than 1.5% and 3.5%, respectively.
3. Conclusion

A MIMU was placed on the user’s waist based on the pedestrian navigation calculation method proposed in this paper. The stride was recognized with the accelerometer signal, and stride factor $K$ of different walking speeds was calculated. The correspondence between $K$ and the accelerometer output value was established. And the $K$ value was updated according to the measurement information of each step recorded by the accelerometer. Step length errors caused by different walking speeds and manners were reduced using this method. And in addition, information of the magnetometers, gyroscopes, and other sensor were fused to estimate heading; thus, the defect of heading computing divergence caused by accumulated errors of the gyroscope was overcome. Based on the above ideas, a waist-worn inertial navigation system was proposed, as shown in Fig. 8. Repeated experiments proved that the inertial navigation system has high reliability and positioning accuracy.

The adaptive step length method of the dead-reckoning method put forward effectively improves positioning accuracy in pedestrian paces while moving, and has some expansion. However, there are some shortcomings in this method, namely the adaptive step factor $k$ requires pre-calibration so that it can conduct more accurate positioning meaning it is not convenient to use. How to solve the problem of pre-calibration of the step factor $k$ will be the focus of further research.
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