D-ZUPT based Pedestrian Dead-Reckoning System Using Low Cost IMU

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I. Introduction

Pedestrian indoor navigation systems constructed by foot-mounted inertial measurement units (IMUs) have shown promising prospects due to their potential applications in a wide range of services. Meanwhile, the improvements in accuracy of inertial sensors (e.g., gyroscopes, magnetometers, etc.) have made it possible to use them for navigation systems. Thus, numerous technologies of indoor positioning have been developed, and pedestrian dead-reckoning (PDR) system is known as one of the most perspective solutions.

The PDR system is tracking system using accruing vectors including both step length and step heading. As drift errors which come from the IMU sensing errors or data processing have serious impacts on the accuracy of the PDR system, researchers have carried out many methods to reduce the drift errors, such as Foxlin's zero velocity update (ZUPT), zero angular rate update (ZARU) [1], the kinetic models of human motion (e.g., a step-length model [2] or a velocity model [3]), analyzing the accelerometer and gyro outputs to determine an orientation [4], etc. According to these reports, the errors of the step length calculated from accelerations measured on the waist, torso, or head can reach accuracy between 3% to 10% [5], [6]. However, these errors will accumulate quickly if the user walks unsteadily or on slopes. So that these systems have not put into pratical application.

In this report, we propose a solution constructed by PDR and INS technologies, also with the application of human kinetics. We also suggest a new algorithm named as dual ZUPT (D-ZUPT) to derive step length and improve the whole accuracy of PDR system. Fig 1 shows the diagram of the system structure. The main function of the scheme is listed below, and the details of each module in the system are provided in the following section.

- Filter and correct the raw data form the several sensors;
- Utilize the acceleration and gyroscope data to detect the step and estimate the pedestrian's step length by D-ZUPT algorithm.
- The gyroscope and geomagnetic data is used to calculate the pedestrian's dynamic headings.
- Combined with the above two parts, we take full advantage of whole data to form the Step and Heading System (SHS).
- Finally, the SHS can return the pedestrian's real-time position after the calibration of Kalman filter.

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II. Methdology

This section presents the details of how a pedestrian is tracked with our PDR system. We use the D-ZUPT algorithm to estimate the dynamic step length. Several methods (i.g. ZARU and HDR) are adopted to reduce the heading drift in our system. Finally, a Kalman-based filter is applied to estimate the position and attitude of the pedestrian.

A. Dynamic Step Length Tracking

Fig.1 shows the flow of proposed whole algorithm [7]. As shown in Fig.1, the original sensing data contenting measuring errors (e.g. noise, temperature bias, gyroscope bias offset, etc.) are filtered and calibrated. Then, the calibrated tri-axial acceleration vector $a^m = [a^x \ a^y \ a^z]$ is transformed form IMU coordinate frame into navigation coordinate frame with formula (1) and (2). Where R is the rotation matrix, and $a^n = [a^N \ a^E \ a^D]$ is the acceleration vector based on navigation coordinate frame.

$$R = \begin{bmatrix} q_0^2+q_1^2-q_2^2-q_3^2 & 2(q_1q_2+q_0q_3) & 2(q_1q_3-q_0q_2) \\ 2(q_1q_2-q_0q_3) & q_0^2-q_1^2+q_2^2-q_3^2 & 2(q_2q_3+q_0q_1) \\ 2(q_1q_3+q_0q_2) & 2(q_2q_3-q_0q_1) & q_0^2-q_1^2-q_2^2+q_3^2 \end{bmatrix} \tag{1}$$

Where $q = [q_0 \ q_1 \ q_2 \ q_3]$ is rotation quaternion which can be derived by the gyroscope data sensed by IMU [8].

$$a^n = R \times a^m \tag{2}$$

After a^n is derived, the D-ZUPT points can be decided by analyzing the pedestrian movement. Fig.2 shows the decomposition of gait cycle and corresponding acceleration signals sensed by IMU.

Each step unit contains four special events: heel-lift, toe-off, heel-strike, flat-foot. Each step unit begins from

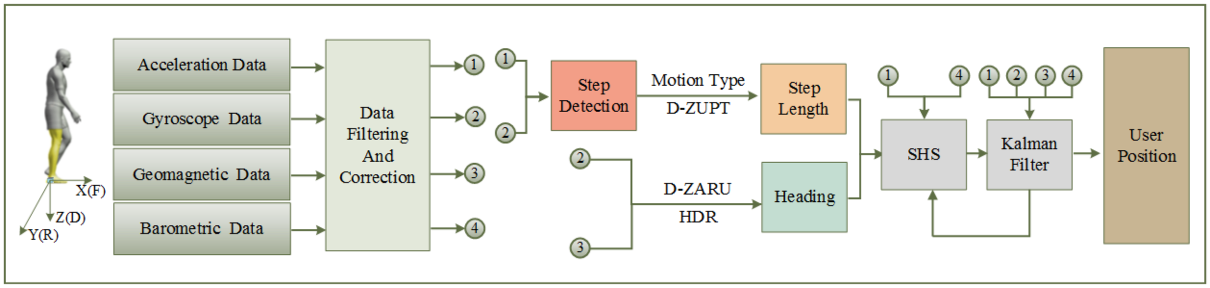

Figure 1. Scheme of proposed PDR system

heel-lift, and then experiences toe-off, heel-strike, flat-foot, finally end at heel-lift. In D-ZUPT algorithm, toe-off, which means the moment of toes leaving the ground, is defined as first zero velocity update (f-ZUPT), and heel-strike, which means the moment of heel touching the ground, is defined as second zero velocity update (s-ZUPT). The following methods are utilized to detect the moment of toe-off and obtain f-ZUPT.

$$\begin{cases} \mid \frac{\delta a_i^N}{\delta t} \mid + \mid \frac{\delta a_i^E}{\delta t} \mid + \mid \frac{\delta a_i^D}{\delta t} \mid \geq A_{th} \\ \mid a_i^N \mid + \mid a_i^E \mid + \mid a_i^D \mid \leq a_{th} \end{cases} \tag{3}$$

Where, t is the sampling interval, $[a_i^N \ a_i^E \ a_i^D]$is the tri-axial acceleration vector at the sampling point i, A_{th} and a_{th} stand for the slope threshold and the acceleration threshold respectively. The moments are set as f-ZUPT if the tri-axial acceleration vector meets formula (3) at the sampling point i. Based on abundant experimental data, we set A_{th} as $58m/s^3$, and a_{th} as $14m/s^2$ in our experiments.

When pedestrian's heel touches the ground, the acceleration vector have a turning-point. Thus the acceleration vector should meet formula (4):

$$\frac{\delta a_i^n}{\delta t} = 0 \tag{4}$$

In D-ZUPT algorithm, the sampling points which meet the formula (4) are define as heel points group (lpg), and s-ZUPT is derived by two steps:

1. Detecting the absolute value of the acceleration vector in lpg and obtain the maximum absolute value of the acceleration vector at the sampling point m.

2. The second sampling point after m at lpg is selected as s-ZUPT as shown in Fig 2.

After the f-ZUPT and s-ZUPT are obtained, the step length can be estimated by the double integration from f-ZUPT to s-ZUPT.

$$\begin{bmatrix} S_s^N \\ S_s^E \\ S_s^D \end{bmatrix} = \begin{bmatrix} S_0^N \\ S_0^E \\ S_0^D \end{bmatrix} + \begin{bmatrix} \sum\limits_{i=f-ZUPT}^{s-ZUPT} V_i^N \delta t \\ \sum\limits_{i=f-ZUPT}^{s-ZUPT} V_i^E \delta t \\ \sum\limits_{i=f-ZUPT}^{s-ZUPT} V_i^D \delta t \end{bmatrix} \tag{5}$$

Where $[S_s^N \ S_s^E \ S_s^D]$ is the tri-axial step length at s-ZUPT, $[S_0^N \ S_0^E \ S_0^D]$ is the tri-axial step length at f-ZUPT and set as zero, $[V_i^N \ V_i^E \ V_i^D]$ is the tri-axial velocity at sampling point i and calculated as following:

$$\begin{bmatrix} V_s^N \\ V_s^E \\ V_s^D \end{bmatrix} = \begin{bmatrix} V_0^N \\ V_0^E \\ V_0^D \end{bmatrix} + \begin{bmatrix} \sum\limits_{i=f-ZUPT}^{s-ZUPT} a_i^N \delta t \\ \sum\limits_{i=f-ZUPT}^{s-ZUPT} a_i^E \delta t \\ \sum\limits_{i=f-ZUPT}^{s-ZUPT} a_i^D \delta t \end{bmatrix} \tag{6}$$

Where $[V_s^N \ V_s^E \ V_s^D]$ is the tri-axial velocity at s-ZUPT, $[V_0^N \ V_0^E \ V_0^D]$ is the tri-axial velocity at f-ZUPT, $[a_i^N \ a_i^E \ a_i^D]$ is the tri-axial acceleration at sampling point i.

Therefore, based on the above-processing, the step length can be estimated by formula (7).

$$\begin{aligned} L &= \sum L_{unit} \\ &= \sum \sqrt{(S_s^N)^2 + (S_s^E)^2 + (S_s^D)^2} \end{aligned} \tag{7}$$

Where L is the total step length (moving distance of the pedestrian) and L_{unit} is the step length for one step unit.

B. Dynamic Orientation Tracking

The orientation of pedestrian is tracked by integrating the angular velocity vector $\omega(t) = [\omega_x(t) \ \omega_y(t) \ \omega_z(t)]$ obtained from gyroscope. In a short sampling period δt, let $\omega = [\omega_x \ \omega_y \ \omega_z]$ be the corresponding angular velocity

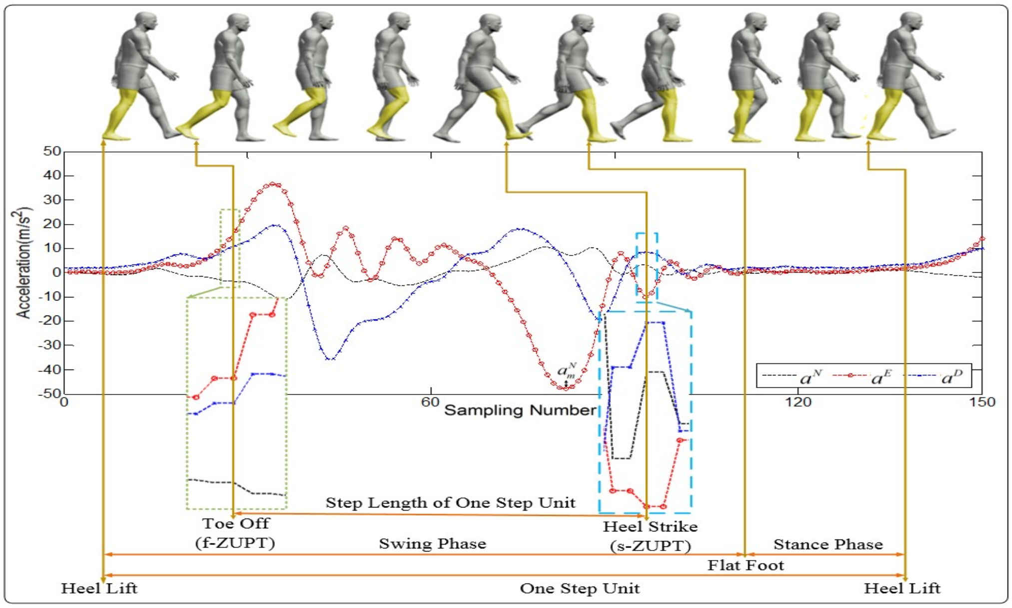

Figure 2. Decomposition of gait cycle and acceleration signals

sample, and $\delta\Psi = [\delta\psi\ \delta\theta\ \delta\phi]$ represent small rotated angle vector. The local coordinate system has its own x, y and z axes respectively. Hence, the rotation angles $\delta\Psi = \omega\delta t$. When δt is short, the angles $\delta\Psi$ become small. Using approximations and ignoring the products of angles in (1), the rotation matrix for this period is:

$$\begin{bmatrix} 1 & -\delta\psi & \delta\theta \\ \delta\psi & 1 & -\delta\phi \\ -\delta\theta & \delta\phi & 1 \end{bmatrix} = E_{3\times3} + \Omega\delta t \tag{8}$$

where $E_{3\times3}$ is a 3×3 identity matric, and

$$\Omega = \begin{bmatrix} 0 & -\omega z & \omega y \\ \omega z & 0 & -\omega x \\ -\omega y & \omega x & 0 \end{bmatrix} \tag{9}$$

Mathematically, the direct cosine matrix (DCM) is accomplished by transformation of three sequential rotations from the axes in the global coordinate system. If the DCMs are $R(t)$ and $R(t+\delta t)$ at time t and $t+\delta t$, respectively, $C(t)$ is the rotation matrix which relates the local coordinate at time t to the local coordinate at time $t+\delta t$. Then:

$$R\left(t+\delta t\right) = R\left(t\right)\ \times C\left(t\right) \tag{10}$$

Using (8) the change rate of DCM can be expressed by:

$$\frac{\delta R\left(t\right)}{\delta t} = R\left(t\right) \times \mathbf{\Omega} \tag{11}$$

For a period of $[t,\ t+\delta t]$, the solution to (11) is

$$R\left(t+\delta t\right) = R\left(t\right) \times exp\left(\int_{t}^{t+\delta t} \Omega\left(t\right) dt\right) \tag{12}$$

Let $\bar{\omega} = \left\| \begin{matrix} \omega_x & \omega_y & \omega_z \end{matrix} \right\|$, the DCM update equation is obtained as each new angular velocity sample as:

$$R\left(t+\delta t\right) = R\left(t\right) \times \left(E_{3\times3} + \frac{\sin\bar{\omega}}{\bar{\omega}}\Omega + \frac{1-\cos\bar{\omega}\delta t}{\bar{\omega}^2}\Omega^2\right) \tag{13}$$

C. Heading Drifts Errors Correction

1) Zero Angular Rate Update: Zero Angular rate update (ZARU) can help estimate the bias of gyroscope when the person is in a still phase. It reduces the heading drifts and provides a very good method (fully observable) to quickly find an approximation of gyroscope biases [9]. Besides, it can offer well performance in the situation where there is no initialization or where the stance is too short (unstable) or fast walking.

2) Heuristic Drift Reduction: Heuristic drift reduction works with the assumption that most of the time human walks in straight paths inside buildings along the corridors. With this assumption, it corrects the computed heading rate of turn. If the possibility of the pedestrian walks straight along a corridor is high, HDR will apply a correction method to the gyro output, which contains the bias error to reduce the heading error [10] To distinguish the near straight path from the curved path, we can use two different methods to analyze the orientation change among successive steps in yaw space as shown in equation (14).

$$\Delta\psi_k = \psi_k - \frac{1}{n}\sum_{m=1}^{n}\psi_{k-m} \tag{14}$$

If $|\Delta\psi_k| < th_{\Delta\psi}$, then we can supposed that the pedestrian is walking in a straight line. Where $th_{\Delta\psi}$ is the threshold value.

In our system, the $th_{\Delta\psi}$ is assumed between (0.5 2.5). However, varies based on the type of scenarios. The error corrector utilizes the error estimates to refine the raw INS states by

$$C_{bk}^{n} = \left[\frac{2E_{3\times3} + \Omega_k \Delta t}{2E_{3\times3} - \Omega_k \Delta t}\right] C_{bk-1}^{n} \tag{15}$$

$$V_k^n = V_k^n - \delta V_k^n \tag{16}$$

$$P_k^n = P_k^n - \delta P_k^n \tag{17}$$

Where C_{bk-1}^{n} is the corrected attitude matrix, Ω_k is the skew symmetric matrix used to refine the attitude matrix, V_k^n is the corrected velocity, and P_k^n is the corrected position.

Thus, in our system, we adopt both ZARU and HDR algorithms to reduce the heading drifts, and we have got encouraging results in the experiments.

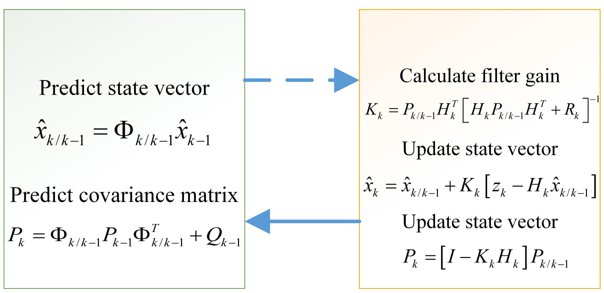

Figure 3. Working mechanism of Kalman Filter

3) Kalman-based Filter (KF): The Kalman-based filter is used to mash the data from different sensors and estimate the errors in the navigation solution of the inertial navigation system, and the error estimates are then fed back into the system to correct the navigation system. Theoretical analysis and experiential simulation show that, with the Kalman filter, our system can achieve good performance and high positioning accuracy.

Kalman Filter works based on a close-loop feedback mechanism: the filter estimates the process state and then obtains feedbacks from noisy measurements [11]. Therefore, the process for KF can be divided into two steps: prediction (or time update) and update (or measurement update). The diagram of the KF algorithm is shown in Fig.3. where $\hat{x}_{k/k-1}$ and $\hat{P}_{k/k-1}$ represent the a priori state estimation and covariance matrix at the epoch k; $\hat{x}_{k-1}$ and $\hat{x}_k$ are a posteriori state estimation at the epochs $k-1$ and k, P_{k-1} and P_k are a posteriori error covariance matrices; K_k is the filter gain; and I is the unit matrix.

Based on above techniques and algorithms, we constructed testing platform to verify the feasibility of

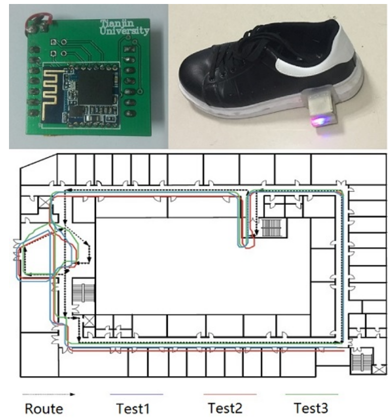

Figure 4. Foot-mounted module and a experimental sample

our system. As shown in the Fig.4 above, our module designed by ourselves is mounted on the heel and there is a sample of our experiments done in our research building. And our experimental simulation platform can reach an average error of about 5%. Besides, we are willing to integrate with this competition and check the stability and accuracy of our system.

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