Pedestrian Navigation with Foot-Mounted Inertial Sensors in Wearable Body Area Networks

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Abstract—Recent advances in pedestrian navigation, a branch of wearable body area networks (WBAN), facilitate people’s lives to help them get access to location-based services (LBS) at anywhere easily. This paper proposes a pedestrian dead-reckoning (PDR) algorithm to track the trajectory of the person using foot-mounted inertial measurement unit (IMU) and the estimation of the foot orientation with extended kalman filter (EKF). The proposed PDR algorithm involves several algorithms: gait phases detection algorithm, orientation estimation algorithm and EKF algorithm with zero velocity update technique (ZUPT). Numerical experiments demonstrate that the proposed algorithm is capable of estimating the trajectory accurately with low computational complexity and estimation error.

I. INTRODUCTION

A high-precision navigation system is getting more essential, especially for urban lives, in wearable body area networks (WBAN). People with navigation system can enjoy considerable location-based services (LBS) in mobile media cloud effortlessly [1]. However, with the presence of the urban canyons environment, the signals from global position system (GPS) may be blocked and unavailable sometimes [2]. Fortunately, with the development of wireless sensor networks (WSN) [3], [4] and low-cost micro electro-mechanic system (MEMS), MEMS-based pedestrian inertial navigation system (PINS) has obtained substantial attention recently. MEMS-based PINS uses self-contained inertial sensors like accelerometers, gyroscopes and magnetometers to estimate the pedestrian trajectory. The PINS exhibits a number of advantages, such as small-sized, low-cost, good concealing performance and high independence. Accordingly, PINS can give full play to its advantages in the environment without available GPS signals. However, the system itself has several shortcomings, e.g., the MEMS-based inertial measurement unit (IMU) is low-precision and cannot carry out the navigation task for a long term [5].

A large amount of studies have been conducted to improve the precision of PINS. S.H. Shin et al. [6] presented an adaptive step length estimation algorithm with a simple pedometer recording the number of steps according to the walking or running status. This method is not accurate enough since the distance will be misestimated if the person walks back and forth. Foxlin [7] applied zero velocity update technique (ZUPT) into extended kalman filter (EKF). The attitude, gyro biases, position, velocity and acceleration errors were filtered in EKF to achieve a satisfactory result. Rajagopal [8] combined zero angular rate update (ZARU) with ZUPT, and used the same EKF as Foxlin’s. A.R. Jimenez et al. [9] implemented a Kalman-based framework, called INS-EKF-ZUPT (IEZ), following the Foxlin work and presented heuristic heading reduction (HDR) methods for heading drift reduction. X. Yun et al. [10] used the estimation of human foot motion method and ZUPT to track the trajectory of the pedestrian without EKF. However, they do not combine the orientation estimation with EKF to track the pedestrian’s trajectory jointly for better performance and do not analyze the computational complexity of their algorithms.

In this paper, we propose a Pedestrian Dead-Reckoning (PDR) algorithm with low computational complexity using foot-mounted IMU and orientation estimation of the foot. In particular, EKF is considered to correct the parameters of the walking and pursue accurate estimation results. The rest of papers is organized as follows. Section II describes the background theory of the PDR algorithm. The proposed PDR algorithm is explained detailedly in section III while the experimental results are analyzed in section IV. The last section draws the conclusion and gives the future work.

II. BACKGROUND THEORY

In pedestrian navigation, dead reckoning refers to the process of predicting one’s present position based on the previously estimated position, current speed as well as the heading orientation of the course [11]. The theoretical basis of the dead reckoning is the three laws of Newton. When the MEMS-based foot-mounted IMU works, we can yield the tri-axis accelerations, tri-axis angular rates and tri-axis magnetic measurements of the person in the body coordinate system. Then, we can obtain the tri-axis linear accelerations in the navigation coordinate system according to the transform matrix computed by the sensors outputs. Using the specified processing algorithm, the trajectory of the person could be estimated with quadratic integral of the linear accelerations:

$$p_e = p_0 + \int \left( (a^n + a^c) dt \right) dt,$$

where $p_e$ and $p_0$ represent the current position vector and the previous estimated position vector while $a^n$ and $a^c$ stand for...
According to the nature of quaternions, we obtain the relation
coordinate system:
transform of accelerations from the body to the navigation
the present linear 3-axis acceleration vector and acceleration
error vector in navigation frame. We have the following
transform of accelerations from the body to the navigation
coorinate system:
\[
\mathbf{a}^n = \mathbf{q} \otimes \mathbf{a}^b \otimes \mathbf{q}^* = \begin{bmatrix}
q_0^2 + q_2^2 - q_1^2 - q_3^2 & 2(q_1q_2 + q_0q_3) & 2(q_1q_3 - q_0q_2) \\
2(q_1q_2 - q_0q_3) & q_0^2 - q_1^2 + q_2^2 - q_3^2 & 2(q_2q_3 - q_0q_1) \\
2(q_1q_3 + q_0q_2) & 2(q_2q_3 + q_0q_1) & q_0^2 - q_1^2 - q_2^2 + q_3^2
\end{bmatrix}^{-1} \cdot \mathbf{a}^b
\]  

where \( \mathbf{a}^b \) is the acceleration vector in the body frame.

We assume the quaternion of the orientation of foot is \( \mathbf{q} \).
According to the nature of quaternions, we obtain the relation
between the accelerations in the navigation frame and in the
body frame as shown in (3) at the top of the page.

As the rotation matrix \( C_{b2n} \) is a unitary matrix, the matrix
can be also written as:
\[
C_{b2n} = \begin{bmatrix}
q_0^2 + q_2^2 - q_1^2 - q_3^2 & 2(q_1q_2 + q_0q_3) & 2(q_1q_3 - q_0q_2) \\
2(q_1q_2 - q_0q_3) & q_0^2 - q_1^2 + q_2^2 - q_3^2 & 2(q_2q_3 - q_0q_1) \\
2(q_1q_3 + q_0q_2) & 2(q_2q_3 + q_0q_1) & q_0^2 - q_1^2 - q_2^2 + q_3^2
\end{bmatrix}^T.
\]  

It is well known that the error \( \mathbf{a}_ε \) is inevitable on account of
the inherent property of MEMS-based inertial sensors. Thus, a
PDR algorithm using EKF is proposed in this paper to resolve
this problem.

III. PEDESTRIAN DEAD-RECKONING ALGORITHM

This section presents a multi-sensor data fusion algorithm
called PDR algorithm in PINS based on EKF. For this work,
an IMU comprised of the foot-mounted inertial sensors is
applied. The IMU is capable to provide tri-axis accelerations,
tri-axis angular rates and tri-axis magnetic measurements in
real-time. Fig. 1 shows the diagram of PDR algorithm. In
the following, gait phases detection algorithm, orientation
estimation algorithm and extended kalman filter algorithm
will be introduced explicitly.

A. Gait Phases Detection Algorithm

Periodicity and regularity of normal walking are utilized to
detect gait phases. Fig. 2 depicts a whole gait cycle to illustrate
the cycle period of normal walking vividly. Raul Feliz et al.
[2] divided the movement of the foot into two phases roughly.
One is the stance phase while the other is the swing phase.
However, after careful analysis of normal walking, the swing
phase is proved to be divided into three more precise phases,
i.e., toe-off phase, air-swing phase and heel-touch phase. The
cycle period begins from the stance phase, which means the
sole is on the ground, and then experiences the toe-off phase,
the air-swing phase and the heel-touch phase respectively.
With the consideration of the whole cycle of the normal walking,
we can discover that the angular rates \( \omega \) as well as pitch angle \( \theta \) of the foot can be used to distinguish different
gait phases. Fig. 3 depicts the relations between the pitch angle
gait phases. When a person is in the stance phase, the pitch
angle approximately equals zero. After that, the pitch angle
decreases sharply to the lowest level, which marks the toe-off
phase happening. Then, the digit begins to rise dramatically
to reach the peak in the air-swing phase. The cycle ends when
the pitch angle is close to zero again after a slight dip in the
heel-touch phase.

The gait phases detection algorithm uses a state machine
with four states. In general, when a person is in the stance
phase, the angular velocity of the foot is believed to be zero or
smaller than a relatively small threshold \( \omega_{TH} \). Nevertheless, a
detailed study of specific gyroscope’s measurements indicates
that the simple threshold algorithm is not able to detect gait
phases accurately since momentary fluctuations may affect the detection (angular rates $\omega > \omega_{TH}$ when the movement is essentially in the stance phase). Accordingly, a timer is utilized to eliminate the fluctuations. For instance, only when the angular velocity is essentially in the stance phase. Therefore, an angular velocity threshold $\omega_{TH}$ and a sampling count $\tau$ are defined to detect gait phases. The stance phase could be decided if the angular velocities at the $t_{i}^{th}$ sampling point and the following $\tau - 1$ sampling points satisfy the following condition:

$$\omega_{t} < \omega_{TH} \mid t_{1} \leq t \leq t_{1} + \tau - 1 \ ,$$  \hspace{1cm} (5)

where $\omega_{t}$ is the total angular velocity in three axes at the $t_{i}^{th}$ sampling point, i.e.,

$$\omega_{t} = \sqrt{\omega_{xt}^{2} + \omega_{yt}^{2} + \omega_{zt}^{2}}.$$  \hspace{1cm} (6)

Likewise, the similar method can be used to detect the toe-off phase when $\tau$ angular velocity measurements starting from the $t_{2}^{th}$ sampling point meet the following condition:

$$\omega_{t} > \omega_{TH} \mid t_{2} \leq t \leq t_{2} + \tau - 1 \ .$$  \hspace{1cm} (7)

As Fig. 3 shows, when the air-swing phase occurs, the pitch angle $\theta$ of the foot can be seen as a monotone increasing function about the sampling number $t$. So if the values of the pitch angle $\theta$ at the $t_{i}^{th}$ sampling point as well as the next $\tau - 1$ sampling points satisfy the following condition, it is believed that the person is in the air-swing phase:

$$\theta_{t} > \theta_{t-1} \mid t_{3} \leq t \leq t_{3} + \tau - 1 \ .$$  \hspace{1cm} (8)

Similarly, if the person is in the heel-touch phase, the pitch angle $\theta$ of the foot can be seen as a monotone decreasing function about $t$. Thus, the heel-touch phase will be detected if $\tau$ pitch angle measurements starting from the $t_{4}^{th}$ sampling point meet the condition:

$$\theta_{t} < \theta_{t-1} \mid t_{4} \leq t \leq t_{4} + \tau - 1 \ .$$  \hspace{1cm} (9)

Fig. 4 depicts the results of gait phases detection algorithm. It can be seen from the plot that the detection algorithm can distinguish four gait phases accurately.

B. Orientation Estimation Algorithm

When a person is walking, different estimation of the human foot motion algorithms are applied according to gait phases. If a person is in the stance phase, it is assumed that the foot is stationary. That is, the acceleration measured by the 3-axis accelerometer approximately is equal to the value of gravity. Then, the pitch angle $\theta^{n}$ and the roll angle $\varphi^{n}$ of the foot in the navigation coordinate system will be figured out by using the accelerations. Meanwhile, the yaw angle $\psi^{n}$ will be obtained after calibration of magnetometer measurements. On the other hand, if a person is in the swing phase, we assume that the 3-axis accelerometer measures not only the value of gravity but the linear moving acceleration in three axes. Therefore, the combination of an accelerometer and a magnetometer cannot estimate the orientation in the swing phase. The 3-axis gyroscope is in use instead. The use of current angular rates and the previously estimated orientation will track the foot motion in the swing phase. For the estimation of the foot orientation, we use the method in [12] to yield the quaternion of the foot orientation $q$.

C. Extended Kalman Filter

The Extended Kalman Filter (EKF) uses the accelerometer, gyroscope and magnetometer outputs in the body coordinate system ($a^{b}$, $\omega^{b}$ and $m^{b}$, respectively). The sampling period is $T_s$. The algorithm estimates 13 states: attitude errors $\delta_{\phi}$, position errors $\delta_{p}$, velocity errors $\delta_{v}$ and quaternion of foot orientation errors $\delta_{q}$. All the components are estimated in the navigation coordinate system. The first 3 components have three elements in three axes each and the last component has four elements. Thus, the 13-element state vector is expressed as:

$$x_{t} = [\delta_{\phi}, \delta_{p}, \delta_{v}, \delta_{q}].$$  \hspace{1cm} (10)

1) Process Model: The process model is used to describe the relations between the state variables at discrete sampling time $t$ and the last sampling time $t-1$. Generally speaking, the current state vector can be assumed as the function of the previous state vector and process noise $w_{t-1}$:

$$x_{t} = f(x_{t-1}, w_{t-1}) ,$$  \hspace{1cm} (11)

where the process noise $w_{t-1}$ is zero-mean Gaussian white noise. We have the state transition equation of the errors in position at time $t$:

$$\delta_{p_{t}} = \delta_{p_{t-1}} + \delta_{v_{t-1}} \cdot T_s .$$  \hspace{1cm} (12)

And the state transition equation of the velocity errors is:

$$\delta_{v_{t}} = \delta_{v_{t-1}} - S \cdot \delta_{\phi} \cdot T_s,$$  \hspace{1cm} (13)

where the matrix $S$ represents the skew-symmetric matrix of the accelerations $a^{n}$. The matrix is utilized to take the extra
accelerations generated from the rotation of the foot into the consideration of EKF to achieve more accurate results. The matrix $S$ is expressed as:

$$ S = \begin{bmatrix} 0 & -a_x^0 & a_y^0 \\ a_x^0 & 0 & -a_z^0 \\ -a_y^0 & a_z^0 & 0 \end{bmatrix}, $$  \hspace{1cm} (14)

where $a_x^0$, $a_y^0$ and $a_z^0$ stand for the accelerations in three axes in the navigation coordinate system.

According to the nature of quaternions, we have the following relation between the quaternion rates and the angular velocities in 3 axes in body frame:

$$ \begin{align*}
\dot{q}_0 &= \frac{1}{2} (-\omega_x^b \cdot q_1 - \omega_y^b \cdot q_2 - \omega_z^b \cdot q_3) \\
\dot{q}_1 &= \frac{1}{2} (\omega_x^b \cdot q_0 + \omega_y^b \cdot q_2 - \omega_z^b \cdot q_3) \\
\dot{q}_2 &= \frac{1}{2} (\omega_y^b \cdot q_0 - \omega_z^b \cdot q_1 + \omega_x^b \cdot q_3) \\
\dot{q}_3 &= \frac{1}{2} (\omega_z^b \cdot q_0 + \omega_x^b \cdot q_1 - \omega_y^b \cdot q_2)
\end{align*} $$  \hspace{1cm} (15)

Accordingly, the state transition equation of the quaternion errors is:

$$ \delta q_t = \delta q_{t-1} + \delta q \cdot T_s = A \cdot \delta q_{t-1}, $$  \hspace{1cm} (16)

where the matrix $A$ is given by:

$$ A = \begin{bmatrix}
1 & -\frac{\omega_y^b}{T_s} & -\frac{\omega_z^b}{T_s} \\
\frac{\omega_y^b}{T_s} & 1 & -\frac{\omega_z^b}{T_s} \\
\frac{\omega_z^b}{T_s} & \frac{\omega_y^b}{T_s} & 1
\end{bmatrix}. $$  \hspace{1cm} (17)

Hence, the state transition matrix $\Phi$ of the 13-element state vector is:

$$ \Phi = \begin{bmatrix}
I_{3 \times 3} & 0 & 0 \\
0 & I_{3 \times 3} & 0 \\
-\dot{S} & T_s & 0 \\
0 & 0 & 0 \\
0 & 0 & A
\end{bmatrix}, $$  \hspace{1cm} (18)

where $I_{3 \times 3}$ indicates a 3 by 3 unit matrix.

2) Measurement Model: In general, the measurement $z_t$ of the EKF is dependent on the current state variables and measurement noise $n_t$:

$$ z_t = h(x_t, n_t), $$  \hspace{1cm} (19)

where the measurement noise $n_t$ is zero-mean Gaussian white noise. After linearization of the measurement model, we assume:

$$ z_t = H_t x_t + n_t, $$  \hspace{1cm} (20)

where $H_t$ is the measurement matrix at time $t$.

As discussed above, when the person is in the stance phase, it is believed that the foot is still and the velocity of the foot is zero. However, due to the drift and accumulation errors, the calculated velocity of the foot cannot be zero. So, we apply this feature into EKF to overcome this problem. When the filter detects the stance phase, we regard the zero velocity as measurements from the filter. Meantime, the orientation estimated from the accelerometer and the magnetometer is assumed to be more accurate than the orientation estimated from the gyroscope since the former estimation method is independent on the previous orientation and, hence, it is free of the accumulation errors. Therefore, we consider the quaternion of the orientation computed by the accelerometer and the magnetometer as the measurements of the quaternion from EKF. Then, the measurement matrix, $H_t$, is a 7 by 13 matrix as follows:

$$ H_t = \begin{bmatrix} 0 & 0 & I_{3 \times 3} & 0 \\
0 & 0 & 0 & I_{4 \times 4} \end{bmatrix}. $$  \hspace{1cm} (21)

3) Filter Design: Since the orientation of the foot is estimated correctly, rotation matrix $C_{62n}$ that transforms from the body frame to navigation frame will be calculated using (4) and then the 3-axis accelerations will be obtained. The integral and quadratic integral for the accelerations in the navigation frame represent the velocity and the position, respectively. When every iteration is implemented, the orientation of the foot is updated and then the rotation matrix is computed again to yield the acceleration with reference to the navigation frame in next step.

Afterwards, we may now implement the EKF step-by-step. In the predict step of one iteration of the EKF, a priori estimate of the state vector $\hat{x}^-_t$ at time $t$ is calculated based on the posteriori estimate of the state vector $\hat{x}_{t-1}$ at time $t-1$ using (11), (12), (13) and (16) in process model. Then, the priori estimate of the covariance $P^-_t$ is predicted by using the posteriori estimate of the covariance $P_{t-1}$ at time $t-1$:

$$ P^-_t = \Phi_{t-1} P_{t-1} \Phi_{t-1}^T + Q_{t-1}, $$  \hspace{1cm} (22)

where the matrix $Q$ is the variance of the process noise.

In the update step of EKF, a posteriori estimate of the state vector $\hat{x}_t$ is updated with $\hat{x}_{t-1}$, the kalman gain $K_t$ and the residual $E_t$. As described in the measurement model, the residual $E_t$ can be given by:

$$ E_t = \begin{bmatrix} 0 & -v_{\phi}^0 & q_{\omega m} - q_t \end{bmatrix}^T, $$  \hspace{1cm} (23)

where the quaternion $q_{\omega m}$ denotes the orientation of foot estimated from the accelerometer and the magnetometer. Hence, the errors in the state vector $e_t$ is:

$$ e_t = [e_\phi \ e_p \ e_v \ e_q]^T = K_t \cdot E_t. $$  \hspace{1cm} (24)

Then, the four components of the state vector are updated as:

$$ \begin{align*}
\dot{\phi}_t &= \hat{\phi}_t^- + e_\phi \\
\dot{p}_t &= \hat{p}_t^- + e_p \\
\dot{\theta}_t &= \hat{\theta}_t^- + e_v \\
\dot{q}_t &= q_e \cdot \hat{q}_t^-
\end{align*} $$  \hspace{1cm} (25)

Moreover, the posterior covariance is given by:

$$ P_t = (1 - K_t H_t) P^-_t. $$  \hspace{1cm} (26)
The kalman gain is computed with:

\[ K_t = P_{t-1}^H \left[ H_t P_{t-1}^H H_t^T + R_t \right]^{-1}, \]

where the matrix \( R \) is the variance of measurement noise.

**IV. EXPERIMENTAL RESULTS**

We have implemented several experiments to validate our algorithm. The estimated trajectory is analyzed in comparison to the true trajectory.

**A. Overview of IMU**

We employed a commercial IMU from Shimmer Technology Company made in Ireland [13]. The size of this IMU is \( 53mm \times 32mm \times 15mm \) and the weight is approximately 22 grams. Thanks to its small-sized and low-power characteristics, these IMUs are widely applied in wearable applications, e.g., detection of human motion and daily activities. The IMU uses an 8MHz MSP430 processor with TinyOS and uses CC2420 as wireless communications module.

The IMU is comprised of a MMA7361 3-axis accelerometer [13] (with full scale of \( \pm 6g \)) from Freescale Semiconductor, Inc, a 500 series MEMS 3-axis gyroscope [14] (with full scale of \( \pm 500^o/s \) and sensitivity of 2mV/\(^o/s\)) from InvenSense, Inc and a HMC5843 3-axis magnetometer [14] (with full scale of \( \pm 4.5Ga \) and resolution of 7mGa) from Honeywell International, Inc.

**B. Practical Experiments**

In the following experiments, the IMU is mounted on the instep of the right shoe in Fig. 5. And the sample rate is set to 50Hz.

During practical experiments, we select a rectangular loop with length of 53m and a width of 50m in Fig. 6. The overall length of the loop is 206m. The person started walking towards south and walked around counterclockwise.

Since the person took a closed trajectory, the endpoint estimated by the algorithm should coincide with the starting point. Therefore, we take the following two indexes of qualitative assessment of PDR algorithm:

- The distance between the estimated endpoint and the starting point.
- The difference between the length of the estimated trajectory and real trajectory.

The dash line shown in Fig. 7 depicts the estimated trajectory without EKF. We can see that the trajectory was basically correct. The distance between the estimated endpoint and the starting point was 1.59m and the error was 0.772%. Moreover, the length of estimated trajectory was 171.4m and the error was 16.8%. The estimation error is significant.

The solid line in Fig. 7 presents the estimated trajectory obtained by the proposed PDR algorithm with EKF. We can see that the trajectory was basically correct. The distance between the estimated endpoint and the starting point was 1.59m and the error was 0.728%. Furthermore, the difference between the length of estimated trajectory and real trajectory was only 1.06m and thus the error was 0.515%. It can be apparently found that the results were much better than the previous experiment without EKF. It is evident that EKF eliminates the drift error as well as accumulated error to a large extent.

Afterwards, two more experiments were performed in the same trajectory. The comparison results were shown in the TABLE I. The experiments proved that the accuracy of the...
TABLE I. SUMMARY OF RESULTS FOR EXPERIMENTS

<table>
<thead>
<tr>
<th>Trial</th>
<th>Distance From Start(m)</th>
<th>Error(%)</th>
<th>Estimated Distance(m)</th>
<th>Error(%)</th>
<th>Distance From Start(m)</th>
<th>Error(%)</th>
<th>Estimated Distance(m)</th>
<th>Error(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.59</td>
<td>0.772</td>
<td>171.4</td>
<td>16.8</td>
<td>1.50</td>
<td>0.728</td>
<td>204.94</td>
<td>0.515</td>
</tr>
<tr>
<td>2</td>
<td>1.92</td>
<td>0.931</td>
<td>177.2</td>
<td>14.1</td>
<td>1.88</td>
<td>0.912</td>
<td>203.79</td>
<td>1.073</td>
</tr>
<tr>
<td>3</td>
<td>2.4</td>
<td>1.165</td>
<td>173.4</td>
<td>15.8</td>
<td>1.72</td>
<td>0.835</td>
<td>204.23</td>
<td>0.859</td>
</tr>
<tr>
<td>Average</td>
<td>1.97</td>
<td>0.956</td>
<td>174</td>
<td>15.5</td>
<td>1.7</td>
<td>0.825</td>
<td>204.32</td>
<td>0.816</td>
</tr>
</tbody>
</table>

Fig. 8. Comparison among the three algorithms in terms of consuming time

estimation of trajectory is greatly improved with the help of EKF and the error could be limited to the level of 1%. Thus, the proposed PDR algorithm is valid and accurate.

C. Complexity of the Proposed Algorithm

In [9], A.R. Jimenez et al. implemented a popular PDR algorithm, namely INS-EKF-ZUPT (IEZ) algorithm, following the famous Foxlin work [7] to track the position of a person while walking. They designed the EKF with 15-element state vector and the positioning errors were at the same level as our algorithm’s. Thus, we ran a group of experiments between the IEZ algorithm, the Foxlin’s algorithm and our proposed algorithm in the field of time consuming. For a fair comparison, the three methods started with the same precondition and proceeded the same data. Fig. 8 illustrates the comparison between the three algorithms in consuming time with the three above-mentioned trials. From the plot, we can see that the proposed algorithm is the fastest one among the three algorithms and processes faster than the IEZ algorithm by approximately 22%. Since we have less states to be predicted and updated in EKF, our proposed algorithm has lower computational complexity and consumes less processing resource as well as processing time.

V. CONCLUSION AND FUTURE WORK

This paper proposes a pedestrian dead-reckoning algorithm with foot-mounted inertial sensors. An orientation estimation algorithm is considered in this algorithm to obtain a precise transform matrix from the body frame to the navigation frame. And the EKF used in the algorithm helps improve the accuracy of the estimated trajectory greatly.

Future work will be focused on an extension to three-dimension scenario. Besides, additional technology aids will be employed, e.g., RFID, WLAN. Theoretically, the combination of RSSI fingerprinting algorithm and the proposed PDR algorithm will enhance the precision of the estimated trajectory further.

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REFERENCES


