The Research of Stance-Phase Detection to Improve ZUPT-Aided Pedestrian Navigation System

MingKun Yang, Jianbo Liang, Zhuoling Xiao*, Bo Yan, Liang Zhou, Shuisheng Lin, Xinchun Liu
School of Information and Communication Engineering, University of Electronic Science and Technology of China
National Engineering Laboratory for Advanced Microprocessor Technology, Chengdu, P.R.China
Email:201822010430@std.uestc.edu.cn, {jianboliang,zhuolingxiao, yanboyu, zlzl, sslin}@uestc.edu.cn, liuxch@sugon.com

***Abstract*—Inertial navigation is a fundamental method for pervasive indoor tracking and navigation. Although PDR based on inertial navigation can achieve robust indoors and outdoors positioning, the positioning accuracy does not meet the accuracy we need, due to the error divergence of the system. We present ZUPT with Kalman filter, a precise, robust technique tracks well even when presented with very noisy sensor data. Key to our ZUPT is zero velocity detection, the step to determine if the person's foot is in stance phase during walking. We used three different methods to detect zero velocity moments and compare their accuracy. Finally, we found that ZUPT using asymptotic zero velocity detection greatly improved the accuracy of inertial navigation. We believe that such a convergent and high precision approach will improve the application of inertial navigation in indoor positioning.**

***Index Terms*—PDR, ZUPT, EKF**

I. Introduction

Indoor localization has drawn much attention in recent years because it can be of significant use in applications for both civilian and military. For indoor navigation, GPS-like satellite external positioning signals may be difficult to use due to poor penetration. To tackle this challenge, many approaches have been proposed to address the indoor localization problem such as Wi-Fi [1]-[3], Bluetooth, radio frequency identification (RFID) and inertial navigation system (INS) [4]-[5].

During indoor positioning technologies, Wi-Fi based on fingerprinting approach need collect the vector value of the strength of Wi-Fi signals, but Wi-Fi fingerprinting database is unstable, and needs to be updated manually to prevent the change of Wi-Fi signal sources [6]-[7]. Due to the short distance of Bluetooth communication, so many Bluetooth devices are required to cover the building, thus increasing the hardware cost of indoor positioning. Though RFID is more accurate and has strong penetration through walls and other barriers [8]. RFID tags are more expensive than other similar tags. In recent years, INS has become a popular solution for location applications, since they have obvious non-dependence and low-cost characteristics compared with above-mentioned wireless location technology.

Indoor localization based on INS relies on the system integrated inertial measurement unit (IMU), extrapolates the targets motion path and realizes the target accurate localization. However, it is difficult to meet high precision requirement using traditional algorithm by mathematical integrate acceleration and angular velocity, due to the error divergence of the system.

We propose an approach based on zero velocity update (ZUPT) with extended Kalman filter (EKF) to solve the divergence in this paper. To have a better performance, we also discuss three different methods for zero velocity detecting and greatly improve the precision of indoor localization.

The remainder of this paper is organized as follows: Sec. II describes the pedestrian dead reckoning (PDR) scheme. Sec. III introduces the trajectory reconstruction algorithm including EFK and three different zero velocity detection methods. Sec. IV presents our experimental results and improvement. Sec. V concludes the paper and discusses ideas for future work.

II. Overview of the Pedestrian Dead Reckoning Scheme

In this section, we give a brief description of PDR algorithm structure.

The form of the inertial navigation system used in this paper is to tie the IMU to the foot of a pedestrian.This method can significantly reduce the error rate caused by sensors using the footstep phases during pedestrian walking, and no additional auxiliary equipment is required. Since we use a recursive solution equation in strap-down inertial navigation system, the trajectory update rate can be tracked with IMU sampling rate. In this PDR algorithm, the method of reducing velocity divergence is based on the velocity measurement of pedestrian footstep on the ground. At this time, the velocity vector of pedestrian footstep is close to zero vector, which is an effective observation information. The method of error estimation based on this information is also called zero velocity update (ZUPT). The zero velocity in the zero velocity update is a pseudo observation, that is, judging whether the footstep is on the ground by the IMU data. However, the adaptive filter can make a good estimate based on sensors information and the INS calculation, and then improve the accuracy of pedestrian trajectory estimation.

Fig. 1 shows the scheme of pedestrian trajectory estimation based on IMU. We may assume that the process noise and the observation noise in the system are both Gaussian white noise with zero mean, and extended Kalman filter can be used as the system optimization method. In the above hypothesis, extended Kalman filter can best estimate the target state.The

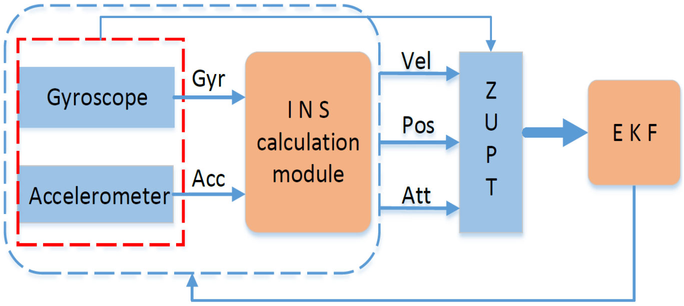


Fig. 1. The scheme of ZUPT+EKF algorithm.

method is to use the velocity observation during zero velocity as the Kalman filter observation, and to correct the velocity, trajectory and attitude angle of pedestrians according to the state transfer equation and the observation equation to obtain a more accurate system state value.

III. Pedestrian Trajectory Reconstruction Algorithm

In this section, a pedestrian trajectory estimation system is introduced [9]. In this system, the position is estimated according to Kalman filter, and ZUPT based on accurate zero velocity detection of gait. The calculation process of pedestrian trajectory estimation based on Kalman filter is shown as Fig. 2.

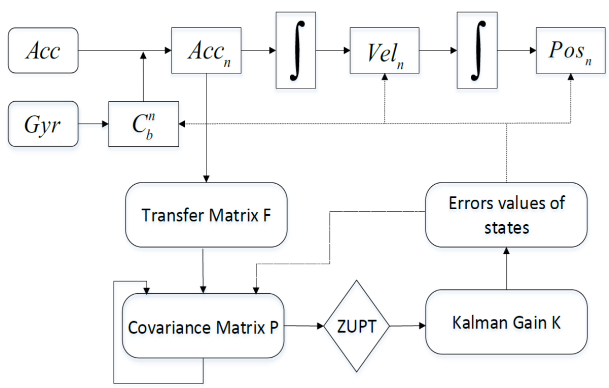


Fig. 2. The calculation process of pedestrian trajectory estimation based on Kalman filter.

A. Basic Calculation of Pedestrian Trajectory Reconstruction System

The recursive equation of attitude matrix of pedestrian trajectory estimation system based on IMU is

$$C_b^n(t_k) = C_b^n(t_{k-1})\frac{2I+[\varphi]}{2I-[\varphi]} \tag{1}$$

In this equation

$$\varphi = \begin{pmatrix} 0 & -\omega_z(t_k) & \omega_y(t_k) \\ \omega_z(t_k) & 0 & -\omega_x(t_k) \\ -\omega_y(t_k) & \omega_x(t_k) & 0 \end{pmatrix}\Delta t \tag{2}$$

ω_x, ω_y, ω_z are output data from triaxial gyroscope,$\Delta t = t_k - t_{k-1}$ is sampling time interval for gyroscope

After updating the attitude matrix at t_k time, the velocity and position of the sensors in the navigation coordinate can be calculated by compensating the local gravity. The net acceleration of the navigation coordinate system is obtained as follows

$$acc_n = C_b^n acc_b - G \tag{3}$$

where, $G = [0, 0, g]$, g is the acceleration of local gravity, acc_b is output data from triaxial accelerometer.

Finally, the position pos_n and vel_n are obtained by integrating the IMU inertial acceleration acc_n. Due to the high sampling frequency of IMU, the acceleration between two adjacent sampling times can be considered constant.So the equation of trajectory can be obtained in the following way

$$vel_n(t_k) = vel_n(t_{k-1}) + (acc_n(t_{k-1}) + acc_n(t_k))\Delta t/2 \tag{4}$$

$$pos_n(t_k) = pos_n(t_{k-1}) + (vel_n(t_{k-1}) + vel_n(t_k))\Delta t/2 \tag{5}$$

B. The EKF Algorithm

In this paper, there are nine states used in inertial navigation, namely, velocity, attitude and position, both are three dimensional vectors. We do not use these vectors directly as the state quantity of Kalman filter, but use the error state quantity associated with them. Therefore, the Kalman filter in this paper estimates the error state vector rather than the state itself.

Error state vector of filter is

$$\delta x_t = \begin{bmatrix} \delta\varphi_t & \delta p_t & \delta v_t \end{bmatrix} \tag{6}$$

in this matrix, $\delta\varphi_t$ is attitude error vector, $\delta\varphi_t = [\delta\theta_t \quad \delta\gamma_t \quad \delta\psi_t]$ contains roll, pitch and yaw. δp_t and δv_t are position and velocity error vector. After initializing the error vector and covariance matrix, Kalman filter is divided into two stages: predicting stage and updating stage.

1) Predicting stage: For each sample update, the covariance matrix of the error state is propagated as follows

$$P_{k|k-1} = F_k P_{k-1}(F_k)^T + Q_k \tag{7}$$

where Q_k and F_k are noise matrix and error state transition matrix. Commonly, Q_k is symmetric matrix. F_k is

$$F_k = \begin{pmatrix} I_{3\times3} & 0_{3\times3} & 0_{3\times3} \\ 0_{3\times3} & I_{3\times3} & \Delta t \cdot I_{3\times3} \\ -\Delta t \cdot S_k & 0_{3\times3} & _{3\times3} \end{pmatrix} \tag{8}$$

where S_k is an antisymmetric matrix consisting of the acceleration of a navigation coordinate system.

2) Update stage: In the system, the update stage of EKF is carried out when the zero velocity is detected, that is, the velocity vector of the observation is zero vector. With the observation information, the inertial navigation system can update the Kalman filter and correct the state quantity in the system.

Since the observation input in the system is only a velocity error vector, systematic observation matrix expression should be

$$H = \begin{bmatrix} 0_{3\times 3} & 0_{3\times 3} & I_{3\times 3} \end{bmatrix} \tag{9}$$

The attitude matrix, velocity and position vector of the initial calculation should be corrected after the optimal error state quantity is obtained in the system.

Therefore, in the pedestrian trajectory estimation system based on pure inertial navigation, the velocity, attitude angle and position vectors can be modified by EKF in the zero-velocity update stage. Finally, a more accurate pedestrian trajectory is obtained.

C. Zero Velocity Detection

Pedestrian walking consists of two phases: the stance phase and the swing phase [10]-[13]. The gait cycle is shown in Fig. 3.

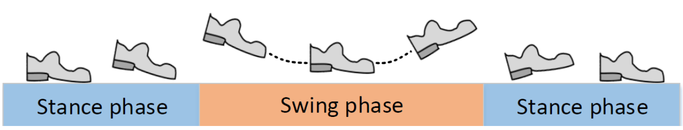


Fig. 3. The gait cycle.

To use the ZUPT properly, the stance phase should be correctly detected by inertial sensors. The detection algorithms in most papers are based on threshold [14]. Usually, using short-term statistics of accelerometers [15], angular velocity or a combination of two sensors, and compare it with predefined thresholds to detect zero velocity intervals.

But this algorithms have different thresholds for different people, depending on the walking pattern. As shown in Figs. 5(a)(d).

1) Variance zero velocity detection: The data of the gyroscopes appears to be stable when they step on the ground. Based on this consideration, we choose variance based on IMU mean squared value data to detect footsteps zero velocity. The specific method is to place the mean squared value data of the accelerometer or gyroscope into a sliding window of a fixed size. When the variance of the sliding window is less than the set threshold, it is determined to be zero velocity.

However, in Fig. 5(e) such an approach is not suitable for determining the zero velocity of the footsteps during running. Because the footstep is grounded in a running state and the variance is large, it is usually not enough to judge whether the footstep is grounded.

2) Differential zero velocity detection: With the data after the difference, the data curve will be sharper. The differential value of the gyroscope data when the pedestrian is stepping on the ground is closer to zero to the pedestrian movement and the accelerometer data and the gyro data modulus at this time are very high, this information can be used to detect zero velocity.

When the gyroscope data and acceleration data can satisfy the following conditions, it can be determined whether the step is the stance phase:

$$\begin{gathered} Gyr\_Difference < Dthreshold \\ Gyr\_norm < Gyr\_threshold \\ Acc\_norm < Acc\_threshold \end{gathered} \tag{10}$$

Where the $Dthreshold$ is the threshold value of the difference value. Gyr_norm and Acc_norm are the modulus values of the gyroscope and the acceleration three axes respectively. $Gyr\_threshold$ and $Acc\_threshold$ are the judgment threshold for the gyroscope and the acceleration. They are larger constants, which can not appear in the inertial sensor data under the stance phase, so as to avoid the zero speed misjudgment under the high dynamic condition as shown in Fig. 5(c)(f). $Gyr\_Difference$ is differential value for the three axes of gyroscope.

$$Gyr\_Difference = Gyr(t-\tau) - Gyr(t) \tag{11}$$

τ is empirical constant greater than zero.

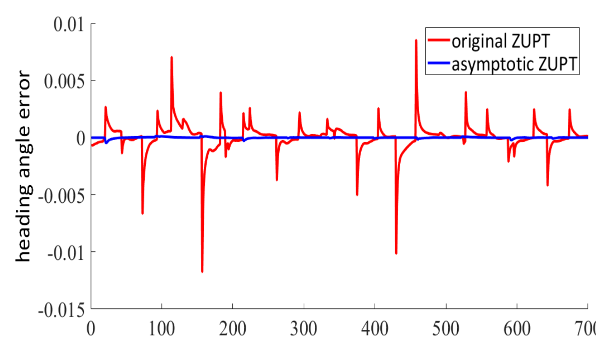
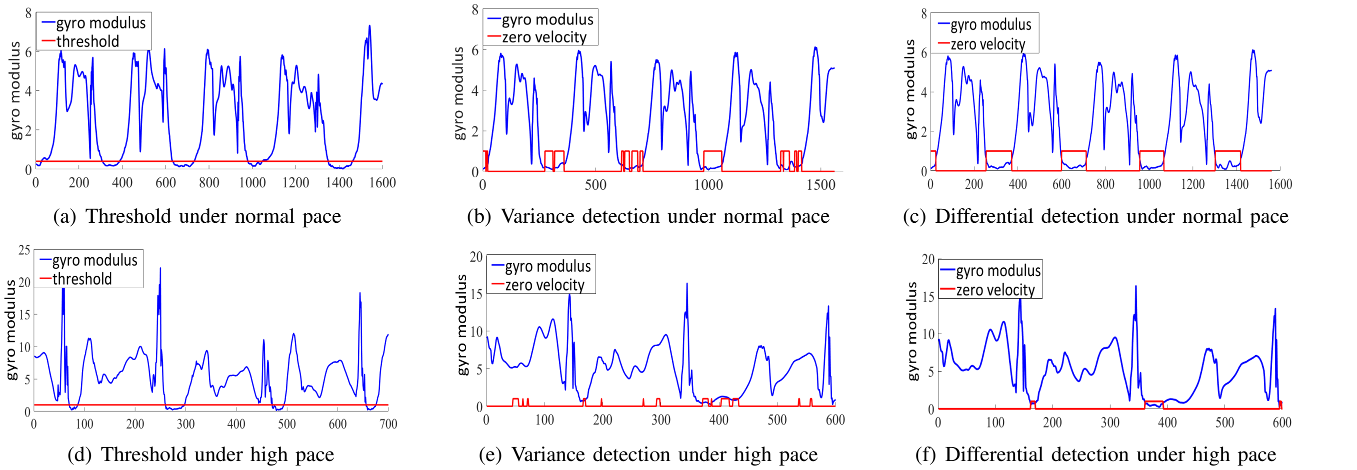


Fig. 4. The output of the yaw error from EKF using attenuation factor (blue) and without using attenuation factor (red).

3) Asymptotic zero velocity detection: The roll and pitch will converge to the correct value with the zero velocity updating, but the yaw will not, even will be prone to deviation.It can be seen in Fig. 4 that at the beginning of the zero-velocity updating of each step, the yaw error is estimated to be the peak. At some point, the yaw error estimation is almost 0.01, which is impossible for the true yaw error between pedestrian steps. The reason for this deviation is that the false observations of stance phase are too large in the initial moment. However, The excessive observation error is reflected by the increase of Kalman filter gain, which leads to the increase of the Kalman filter's yaw error estimation. Eventually the yaw of



(a) Threshold under normal pace (b) Variance detection under normal pace (c) Differential detection under normal pace

(d) Threshold under high pace (e) Variance detection under high pace (f) Differential detection under high pace

Fig. 5. Three different methods for zero velocity detection: based on fixed threshold, variance of gyro modulus and difference of gyro modulus. (a)(d) The change of the triaxial mean squared value of gyroscope under normal speed and running speed. (b)(e) Show the case where the zero-velocity detection is performed using the variance of the mean squared value of the IMU in two paces. (c)(f) We use the differential zero velocity detection on the mean squared sensors data in two paces.

the trajectory was wrongly corrected. Therefore, in this paper, the pedestrian trajectory reconstruction is improved by adding the asymptotic attenuation factor.

In the traditional zero velocity updating, the attenuation factor for the velocity observation is 1, that is, when the system enters the stance phase, the velocity is measured as

$$Z_{vel} = (v_{x,t}, v_{y,t}, v_{z,t}) \tag{12}$$

In this paper, the asymptotic correction of the velocity observation is performed, and the zero-velocity sliding window and the logarithmic function are used to attenuate the correction during initial zero-velocity updating time.

The calculation formula for observation input of EKF is as follows

$$Z_{vel} = \ln(\sum_{i=k-w}^{k} z_i/w \cdot (e-1) + 1) \cdot (v_{x,t}, v_{y,t}, v_{z,t}) \tag{13}$$

where w is the sliding window size, z_i is the zero speed judgment value, 1 is at stance phases, and 0 is at swing phases; e is a nature constant; k is the system time.

For the end of the zero-velocity updating, the attenuation factor is not required for the velocity observation because the compensation amount of the yaw of the reconstruction is small relative to the initial of the zero-velocity updating.

Obviously, in Fig. 4 the yaw output error based on the asymptotic zero velocity updating is more stable than the traditional zero velocity updating, reducing the additional yaw error caused by velocity which calculated by the navigation algorithm directly using as the observation of EKF.

IV. Experimental Results

In this section, We first compare the traditional zero velocity detection approaches and other zero velocity detection approaches in same states of the pedestrian trajectory.

Fig. 6 shows the results of trajectory running around the basketball court (half court) and return to the origin is reconstructed using different zero-velocity detection methods.

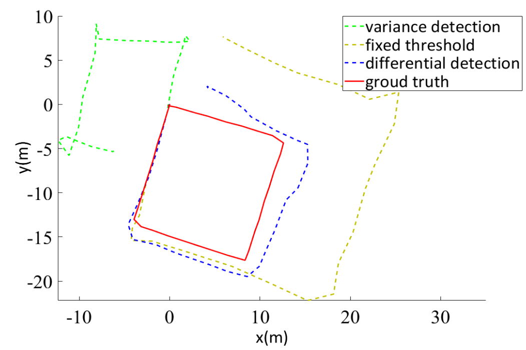


Fig. 6. The reconstruction of pedestrian trajectory using fixed threshold detection (dark yellow), variance zero velocity detection (green), difference zero velocity detection (blue), and pedestrian real path (red).

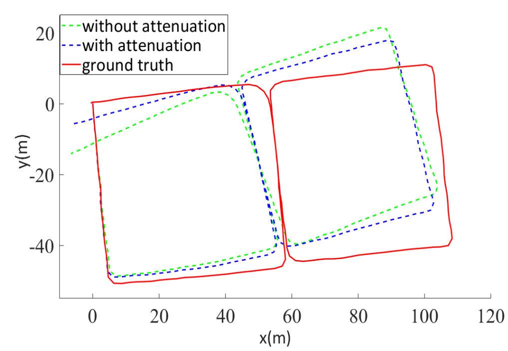


Fig. 7. The blue trajectory is the pedestrian trajectory based on the asymptotic zero-velocity detection; the green trajectory is the pedestrian trajectory based on the traditional zero-velocity detection, and the red trajectory is the reference trajectory of the pedestrian real path.

In Fig. 6, we can see that the zero velocity is detected by the fixed threshold of the mean square value of the gyroscope, which is scattered to a certain extent in both length and direction. Using the variance zero velocity detection has the fastest divergence. Among them, using the differential value of the gyroscope mean square value data to detect the zero velocity moment is the closest to the true trajectory of pedestrian. Because the pace of pedestrian in the experimental scene is relatively fast, the use of fixed threshold detection and variance zero velocity detection will cause missed detection, resulting in the pedestrian trajectory estimation effect does not converge in time, so that the pedestrian trajectory can be diverged. The use of differential zero velocity detection can accurately detect the stance phase of pedestrian.

In Fig. 7, it can be seen that the zero-velocity detection of the two methods are almost no difference in short distance, the pedestrian trajectory reconstruction based on the traditional zero-velocity detection method has a larger deviation from the asymptotic pedestrian trajectory with the time increasing. From the starting point after 400 meters walking and then back to the starting point, the error based on the asymptotic pedestrian trajectory is smaller than the traditional method of pedestrian trajectory error.

Differential zero velocity detection has a better performance compared to variance zero velocity detection and fixed threshold especially moving in high pace. But the trajectory is not smooth enough in relatively fast pace. We propose an asymptotic zero velocity detection with attenuation factor to tackle the problem that traditional methods meet. Asymptotic zero velocity detection is more smooth and less divergent compared to traditional methods in reconstructed trajectory from the experimental result.

V. Conclusion

This paper has described a pedestrian trajectory reconstruction algorithm using a sole foot-mounted IMU. The zero velocity interval is detected accurately by using attenuation factor at the initial of the stance phase on the velocity. As a result, the navigation error was corrected.

Acknowledgment

This work was supported by National Natural Science Foundation of China Grant No. 61703076, the Funds for the Central Universities under Grant ZYGX2016J008, and ZYGX2016KYQD125.

References

[1] A. Sciarrone, C. Fiandrino, I. Bisio, F. Lavagetto, D. Kliazovich and P. Bouvry, "Smart Probabilistic Fingerprinting for Indoor Localization over Fog Computing Platforms," 2016 5th IEEE International Conference on Cloud Networking (Cloudnet), Pisa, 2016, pp. 39-44.

[2] L. Pei, R. Chen, J. Liu, T. Tenhunen, H. Kuusniemi and Y. Chen, "An Inquiry-based Bluetooth indoor positioning approach for the Finnish pavilion at Shanghai World Expo 2010," IEEE/ION Position, Location and Navigation Symposium, Indian Wells, CA, 2010, pp. 1002-1009.

[3] F. Lemic, A. Behboodi, V. Handziski and A. Wolisz, "Experimental decomposition of the performance of fingerprinting-based localization algorithms," 2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Busan, 2014, pp. 355-364.

[4] F. Sun, W. Sun, W. Gao and Y. Y. Ben, "Research on the technology of rotational motion for FOG strapdown inertial navigation system," 2009 International Conference on Mechatronics and Automation, Changchun, 2009, pp. 4913-4918.

[5] H. G. WANG and T. C. WILLIA, "Strategic inertial navigation systems - high-accuracy inertially stabilized platforms for hostile environments," in IEEE Control Systems Magazine, vol. 28, no. 1, pp. 65-85, Feb. 2008.

[6] G. Han, G. J. Klinker, D. Ostler and A. Schneider, "Testing a proximity-based location tracking system with Bluetooth Low Energy tags for future use in the OR," 2015 17th International Conference on E-health Networking, Application & Services (HealthCom), Boston, MA, 2015, pp. 17-21.

[7] L. Pei, R. Chen, J. Liu, T. Tenhunen, H. Kuusniemi and Y. Chen, "An Inquiry-based Bluetooth indoor positioning approach for the Finnish pavilion at Shanghai World Expo 2010," IEEE/ION Position, Location and Navigation Symposium, Indian Wells, CA, 2010, pp. 1002-1009.

[8] A. F. G. Ferreira, D. M. A. Fernandes, A. P. Catarino and J. L. Monteiro, "Localization and Positioning Systems for Emergency Responders: A Survey," in IEEE Communications Surveys & Tutorials, vol. 19, no. 4, pp. 2836-2870, Fourthquarter 2017.

[9] H. Choi, K. W. Yang and E. Kim, "Simultaneous Global Localization and Mapping," in IEEE/ASME Transactions on Mechatronics, vol. 19, no. 4, pp. 1160-1170, Aug. 2014. doi: 10.1109/TMECH.2013.2274822

[10] Z. Wang, H. Zhao, S. Qiu and Q. Gao, "Stance-Phase Detection for ZUPT-Aided Foot-Mounted Pedestrian Navigation System," in IEEE/ASME Transactions on Mechatronics, vol. 20, no. 6, pp. 3170-3181, Dec. 2015.

[11] A. Norrdine, Z. Kasmi and J. Blankenbach, "Step Detection for ZUPT-Aided Inertial Pedestrian Navigation System Using Foot-Mounted Permanent Magnet," in IEEE Sensors Journal, vol. 16, no. 17, pp. 6766-6773, Sept.1, 2016.

[12] W. Zhang, X. Li, D. Wei, X. Ji and H. Yuan, "A foot-mounted PDR system based on IMU/EKF+HMM+ZUPT+ZARU+HDR+compass algorithm," 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Sapporo, 2017, pp. 1-5.

[13] C. Zhou, J. Downey, J. Choi, D. Stancil, J. Paramesh and T. Mukherjee, "A Shoe-Embedded RF Sensor for Motion Detection," in IEEE Microwave and Wireless Components Letters, vol. 21, no. 3, pp. 169-171, March 2011.

[14] R. Anacleto, L. Figueiredo, A. Almeida and P. Novais, "Localization system for pedestrians based on sensor and information fusion," 17th International Conference on Information Fusion (FUSION), Salamanca, 2014, pp. 1-8.

[15] C. Su, J. Chou, C. Yi, Y. Tseng and C. Tsai, "Sensor-Aided Personal Navigation Systems for Handheld Devices," 2010 39th International Conference on Parallel Processing Workshops, San Diego, CA, 2010, pp. 533-541.