

Multi-Mode Dynamically Switching Pedestrian Navigation Using Smart Phone Inertial Sensors

Yu Liu¹, Yanping Chen^{1*}, Mu Zhou², Yibing Wang¹, Shuang Gong¹, and Xin Zhang¹

¹Chongqing Municipal Level Key Laboratory of Photoelectronic Information Sensing & Transmitting Technology, Chongqing University of Posts and Telecommunications, Chongqing 400065, China

²Chongqing Key Lab of Mobile Communications Technology, Chongqing University of Posts and Telecommunications, Chongqing 400065, China

E-mail: {liuyu, zhoutu} @cqupt.edu.cn; chongyouchenyp@sina.com; {mr_yibingwang, xouxousun, Clara_zx}@163.com

Abstract—The demand for navigating a user with a hand-held device, especially in Global Position System (GPS) denied environments, has tremendously increased over the last few years. Accelerometers, gyroscopes, and magnetometers are the most commonly found sensors in the smartphones that provide Three Dimensional (3D) acceleration and attitude of the phone. Algorithm of pedestrian navigation with smart phones modes switching is studied. When the sensor is rigidly mounted on the user's body, the trajectory of the user can easily be reconstructed. The placement of the phone can vary overtime as a user performs different tasks. When the sensor's location is dynamically changing, the situation becomes much more complex. Smartphone modes among three most commonly used are considered in this research, texting mode, ear-talking mode and waist mode. Using the machine learning method of decision trees is developed to recognize smartphones' modes. The average accuracy of the selected classifier is > 92.8%. According to the detected smartphone mode, adaptive heading angle compensation algorithms are applied, the location error in the horizontal direction from the starting point to the ending point is approximately less than 30 meters when people with smartphone mode switched walk a distance of 1000 meters, and the feasibility of the algorithm is verified. The dynamic measurement precision of pedestrian navigation using a smart phone is improved, and it is more accurate to use a smart phone to realize pedestrian navigation in different smartphone modes.

Index Terms—Phone inertial sensors, pedestrian navigation, smartphone mode, decision trees

I. INTRODUCTION

Pedestrian navigation is a new and exciting field that has a wide range of applications and a large number of potential end users [1]. For most of smart phones have Micro Electro Mechanical Systems (MEMS) accelerometer, MEMS magnetometer and gyroscope inside, which make it possible to realize the pedestrian navigation. It can improve the quality of life by providing the means for navigation to aid visually impaired people in unknown

environments (Wieser *et al.* 2007). In general, pedestrians spend most of their time indoors, the rest of the time they are moving around outside, in parking lots or going to work in urban environments. Pedestrian motion is extremely random and at a relatively low velocity. Furthermore, a person may turn suddenly at high angular velocities (Syed 2009).

A lot of research of pedestrian navigation based on the sensor is fixed at a certain position, such as on the helmet [2], stability handheld [3], fixed to the shoulder and backpack [4], mounted on the waist [5], [6], and mounted on the foot [7]. But, few research is focused on mode changing among different modes. Pedestrian and sensors can be seen as a rigid body when the sensor is rigidly mounted on the user's body, during which the sensor and the pedestrian keep relative motionless [8]. Then the orientation calculated according to the data collected by sensors can be used to express the orientation of the pedestrian, and the trajectory of the pedestrian recurrence is corrected with no error. However, it is inconvenient when we use mobile devices to realize pedestrian navigation while the mobile devices are fixed in only one place. Especially for smartphones, the requirement for rigid attachment and specified placement are incompatible with the way in which people use smartphones. It can be interrupted during the process of mobile phone positioning, for there are many breaking things, for instance, getting a call. Then the phone should change its mode adaptively, or the trajectory of the pedestrian will be wrong, thus positioning is incorrect. During the transition from one mode to another, the heading angle estimation process becomes a challenging task [9]. Another method is to restart the locating software, but it goes against the hope measuring the relative position of reference point. Furthermore, the heading angle error can be occurred without heading angle compensation between different modes, which will affect the final accuracy of positioning.

This paper is organized as follows. Section II introduces the principle of dead reckoning and the attitude calculation. Section III discusses the two key algorithms of the Multi-Mode Dynamically Switching Pedestrian Navigation (MMDCPN) one by one according

Manuscript received May 26, 2015; revised December 7, 2015.

This work was supported by The National Natural Science Foundation of China under Grant No. 51175535, and the International Joint Research Center technology platform and base construction under Grant No. cstc2014ghz0038.

Corresponding author email: chongyouchenyp@sina.com.
doi:10.12720/jcm.10.12.955-962

to the dataflow. Section IV shows the experimental results of the MMDCPN. Finally, conclusions are given in Section V.

II. MULTIPLE SENSOR FUSION POSITIONING

A. Principle of Dead Reckoning

Pedestrian Dead Reckoning (PDR) [10] technology is a kind of technology based on sensor information to calculate relative position of pedestrian. Algorithm of PDR is widely used in pedestrian navigation frame. Firstly, both the steps of pedestrians and the step length are detected and estimated through acceleration sensors data, then heading information of pedestrians is calculated through the data collected by the magnetic sensor and gyroscope, finally positioning is realized by getting the relative position of human body movement.

Its principle is assuming pedestrians walk at a constant speed in a Two Dimensional (2D) plane in a short time. Under the premise of the starting point is learned. The next moment pedestrians position coordinates are obtained according to the current pedestrian movement direction and step length. Recurrence equation is as follows:

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \end{bmatrix} = \begin{bmatrix} x_k \\ y_k \end{bmatrix} + \begin{bmatrix} \cos \theta_{k+1} \\ \sin \theta_{k+1} \end{bmatrix} d_{k+1} \quad (1)$$

where d_{k+1} and θ_{k+1} stands for the step length and the heading angle of pedestrian during k-k+1 period of time, respectively.

In order to apply the dead reckoning technique efficiently, we need: 1) an accurate detection of the user's displacement and 2) a precise estimation of the heading angle. In this paper we focus on the second problem using commodity mobile phones.

B. Attitude Calculation

Assume the body coordinate frame as b, the navigation coordinate frame as n (Namely northeast days coordinate frame). The matrix of transformation coordinates from body coordinate to navigation coordinate frame is as follows:

$$C_b^n = \begin{bmatrix} \cos r \cos \theta - \sin r \sin p \sin \theta & -\cos p \sin \theta & \sin r \cos \theta + \cos r \sin p \sin \theta \\ \cos r \sin \theta + \sin r \sin p \cos \theta & \cos p \cos \theta & \sin r \sin \theta - \cos r \sin p \cos \theta \\ -\sin r \cos p & \sin p & \cos r \cos p \end{bmatrix} \quad (2)$$

where θ , p and r stands for heading angle, pitch and roll, respectively.

The angle of the solid rotation in space can be expressed through quaternion, a quaternion shows as follows:

$$\mathbf{Q} = q_0 + q_1 \mathbf{i} + q_2 \mathbf{j} + q_3 \mathbf{k} \quad (3)$$

Another expressive method of attitude rotation matrix can be achieved through utilizing the relationship between quaternion and the attitude rotation matrix, it is expressed as below:

$$C_b^n = \begin{bmatrix} q_0^2 + q_1^2 - q_2^2 - q_3^2 & 2(q_1 q_2 - q_0 q_3) & 2(q_1 q_3 + q_0 q_2) \\ 2(q_1 q_2 + q_0 q_3) & q_0^2 - q_1^2 + q_2^2 - q_3^2 & 2(q_2 q_3 - q_0 q_1) \\ 2(q_1 q_3 - q_0 q_2) & 2(q_2 q_3 + q_0 q_1) & q_0^2 - q_1^2 - q_2^2 + q_3^2 \end{bmatrix} \quad (4)$$

where θ , p and r can be calculated by combing (2) and (4), and its equation is as follows:

$$\begin{cases} r = \arctan\left(-\frac{2(q_1 q_3 - q_0 q_2)}{q_0^2 - q_1^2 - q_2^2 + q_3^2}\right) \\ p = \arcsin(2(q_2 q_3 + q_0 q_1)) \\ \theta = \arctan\left(-\frac{2(q_1 q_2 - q_0 q_3)}{q_0^2 - q_1^2 + q_2^2 - q_3^2}\right) \end{cases} \quad (5)$$

To update the attitude angle, gyro data is used, which update the quaternion matrix in real-time.

$$\dot{\mathbf{q}} = \frac{1}{2} \begin{bmatrix} 0 & \omega_x & -\omega_y & \omega_z \\ -\omega_x & 0 & \omega_z & \omega_y \\ \omega_y & -\omega_z & 0 & \omega_x \\ -\omega_z & -\omega_y & -\omega_x & 0 \end{bmatrix} \begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix} \quad (6)$$

where $\omega = (\omega_x \ \omega_y \ \omega_z)^T$ is the angular velocity of the moving device. Combine (6) and (4), then the real-time attitude angle can be updated. We have based our multi-sensor data fusion algorithm on the method described in [3] and [11]. Update quaternion in real time and from (5) can we get stable attitude information.

III. KEY ALGORITHMS OF SMARTPHONE MODE SWITCHING AND PROCESSING

A. Smartphone Mode Analysis

Here, we define three most commonly used smartphone modes [12]:

Ear-talking mode: The smartphone is held close to the ear as if it was talking over the phone while walking, we keep EM for short.

Texting mode: The smartphone is held in front of the user while walking, we keep TM for short.

Waist mode: The smartphone is put in a waist pocket while walking, we keep WM for short.

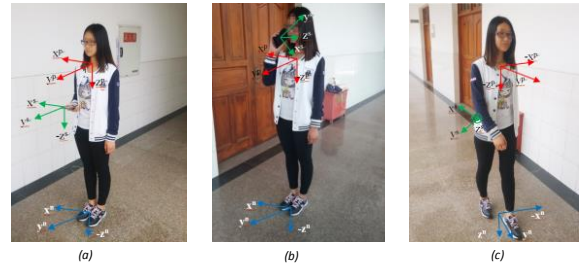


Fig. 1. Definition of the sensor-frame with respect to the other frames in different modes

When the phone is in the mode TM, each angle of the attitude position reference to the navigation coordinate frame is shown as Fig. 1, the direction of the pedestrian is parallel to the smartphones' in mode TM, we can use the heading angle of the smart-phone instead of the heading angle of the pedestrian to conduct accurate location.

The relative location between sensor coordinate frame and the user varies when the user switched the phone's mode (TM changed to EM or on the contrary, TM changed to WM or on the contrary) during the moving. During the mode changing process, the position of sensor coordinate frame is dynamically changing refer to the pedestrian coordinate frame. It comes to a relative static state after the mode changing process finished.

In order to realize keeping the sensor coordinate frame stay in initial relative static state to the pedestrian coordinate frame, the sensor coordinate should be

transformed. Thus the sensors' heading angle can be used instead of the pedestrians' heading angle, and the pedestrian location can keep on without errors.

The raw data of an example of walking along a straight line with mode switching where the smartphone orientation changes from texting to ear taking and waist without coordinate transform is shown in Fig.2. From the figure, we can see that the initial data of the phone is jumping, which will lead to angle errors between pedestrian and smartphone, thus leading to the error in trajectory.

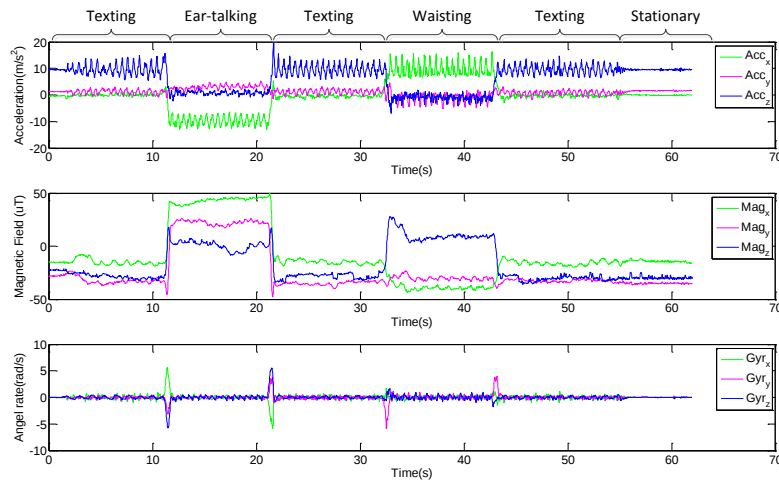


Fig. 2. Raw data of the sensor

The sensor coordinate frame should be transformed correctly so as to realize right pedestrian navigation with mode switch freely. In order to make sure the trajectory is correct, the steps following should be finished. Firstly, right distinguish between different modes is necessary.

Secondly, chose right switching coordinate. Thirdly, compensate for misalignment angle. Right smartphone mode recognition and compensate for misalignment angle correctly are becoming more and more important.

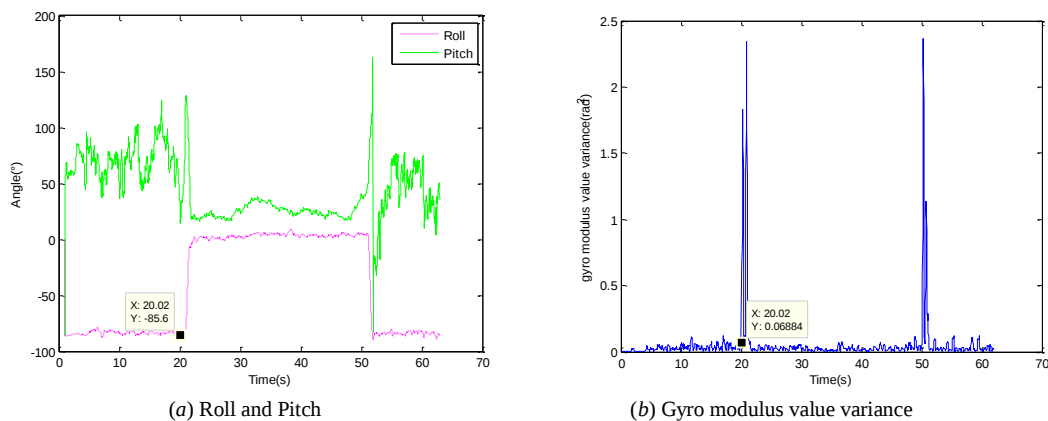


Fig. 3. T-E variation of gyro modulus value variance and Roll and Pitch during mode switching

B. Smartphone Mode Classifier Design

Mobile phone classifier design: classifier is used to distinguish the specific smartphone mode. Machine learning method is widely used to distinguish behaviors and modes. Classifiers based on machine learning widely used are Naïve Bayes, decision trees, artificial neural

network and Support Vector Machine (SVM) [13]. Using the machine learning method of decision trees is developed to recognize smartphone modes. It is enough for the three modes mentioned in this research. And the accuracy rate of classify satisfies the accuracy requirement of pedestrian navigation.

Gyro modulus value variance [14] and the angle of pitch and roll of phone are selected as the discriminant conditions in this paper. Define $\sigma_g^2 \omega$ as gyro modulus value variance, it is the average of the squared differences from the mean. The computational equation is as follows:

$$\sigma_g^2 \omega = \frac{1}{N} \sum_{l=0}^N \left(S_{rms}^w[n] - \frac{1}{N} \sum_{l=0}^N S_{rms}^w[n] \right)^2 \quad (7)$$

where S_{rms}^w is the modulus value of the gyroscope's data and $S_{rms}^w[n] = \sqrt{\omega_x^2[n] + \omega_y^2[n] + \omega_z^2[n]}$. N is the number of the gyro modulus value variance, which is obtained by experiments and is set as 25 in this paper.

The waveform of the angle of roll and pitch when pedestrian walk straight switching mobile phones mode is shown in Fig. 3 (a). From Fig. 3 (a), we can see that the angle calculated by sensor data varieties greatly while the real heading angle of the pedestrian varieties little during phone's mode switching time. The waveform of gyro modulus value variance is shown in Fig. 3 (b). We can see that the gyro modulus value variance varies greatly during the mobile phones' mode switching. Therefore, it can be set as one of the features to identify whether the phone's mode is switched or not. The gyro modulus value variance threshold is got from experiments data analyses and test results, and threshold is set as $\Delta_1 = 0.5$.

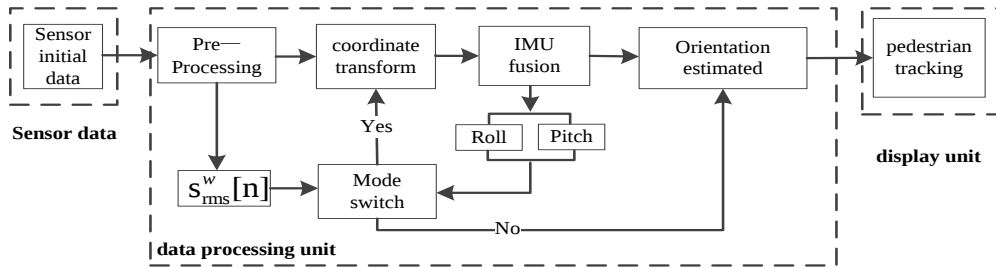


Fig. 4. General block diagram of the inertial pedestrian navigation system.

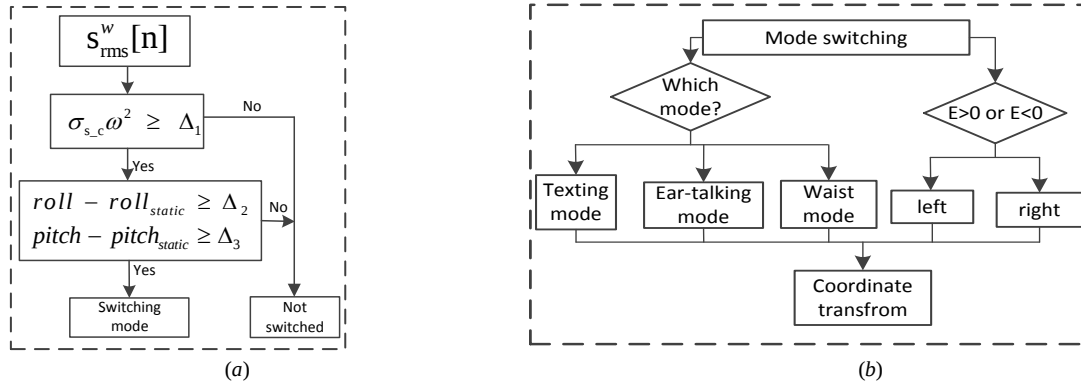


Fig. 5. (a) Process of determination smartphone mode (b) Decision tree for smartphone mode classification.

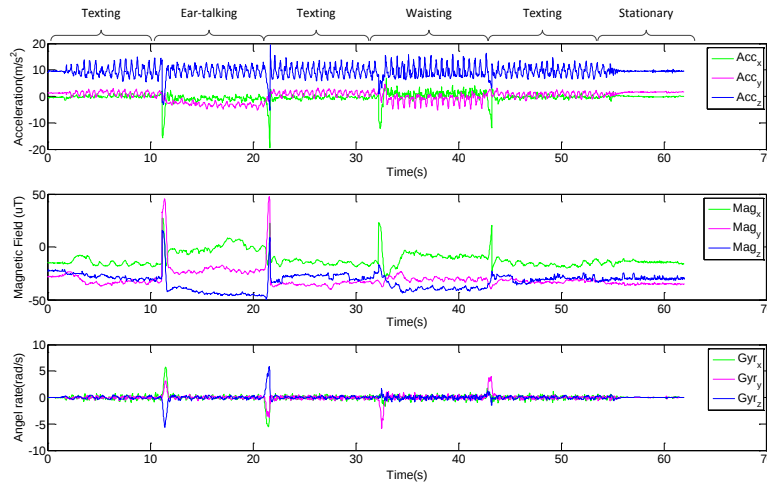


Fig. 6. Raw data of the sensor coordinate transformed

The gyro modulus value variance also varies greatly when the pedestrian's walking direction changed suddenly. The gyro modulus value variance and the real-time angle of roll and pitch calculated by sensor data are combined to avoid the situation mentioned above. Fig. 4 is the flow diagram of determining, the identification process and decision tree for smartphone mode classification designed is shown in Fig. 5. The threshold Δ_2 , Δ_3 of roll and pitch are got from experiments data analyses and test results, and they are set as 50 degrees in this paper, which can be proved to be effective in Fig. 3(a). Chose the right matrix for coordinate transform after the smartphone mode classifying is finished. Following is the matrix for coordinate transform:

$$\begin{bmatrix} \text{new_}x_{s_ear_r} \\ \text{new_}y_{s_ear_r} \\ \text{new_}z_{s_ear_r} \end{bmatrix} = C_t^e \begin{bmatrix} x_s \\ y_s \\ z_s \end{bmatrix} \quad (8)$$

$$\begin{bmatrix} \text{new_}x_{s_pocket_r} \\ \text{new_}y_{s_pocket_r} \\ \text{new_}z_{s_pocket_r} \end{bmatrix} = C_t^w \begin{bmatrix} x_s \\ y_s \\ z_s \end{bmatrix} \quad (9)$$

where $C_t^e = \begin{bmatrix} 0 & 0 & -1 \\ 0 & -1 & 0 \\ -1 & 0 & 0 \end{bmatrix}$, $C_t^w = \begin{bmatrix} 0 & 0 & -1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix}$, C_t^e stands for

smartphone mode is switched from texting mode to ear-talking mode, and C_t^w stands for smartphone mode is switched from texting mode to waist mode. After the coordinate changed, the initial data satisfies the real moving. The data of Fig. 2 after coordinate transformed is shown in Fig. 6.

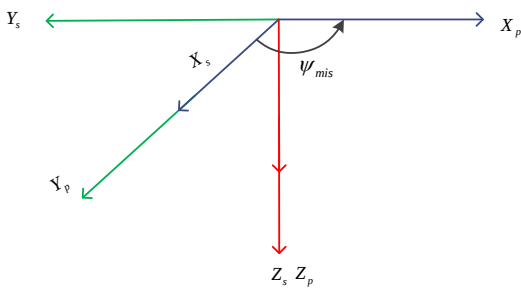


Fig. 7. Misalignment angle

C. Compensation for Phone Attitude

The majority of research on orientation tracking in the context of indoor positioning is to determine the heading angle of the pedestrian rather than the heading angle of the device. Most researches assume the position where the mobile device attached is known, thereby making the assumption that the heading angle of the pedestrian is always consistent with the heading angle of the mobile device [15]. This is not always true. The relative position has changed between sensor coordinate frame and the pedestrian coordinate frame when the smartphone's mode

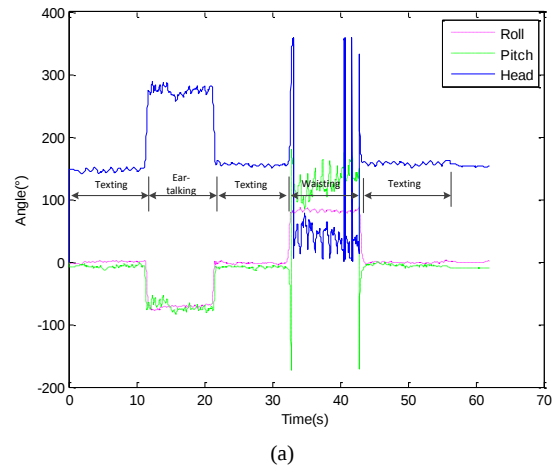
changes, which will lead to misalignment between the sensor and the pedestrian, thus the heading angle of the sensor is discrepancy with the pedestrian's. ψ_{mis} is the misalignment angle between the smartphone forward and user direction, in the event they are not aligned in the same direction, as shown in Fig. 7.

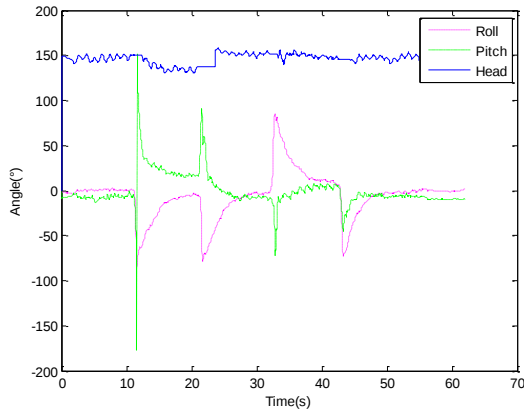
Therefore, the misalignment angle should be compensated when the phone's mode switching finished. During the process of smartphone mode switching, the attitude information calculated by sensor can't be used for the pedestrian, for the sensor coordinate frame is a relative movement changing process to the pedestrian coordinate frame dynamically. Usually, the time of smartphone mode switching process is short, switching time $\leq 2s$, during the mode switching time, the direction of pedestrian moving changes little. Therefore, we can use the heading angle of pedestrian walking in line before as the heading angle of the pedestrian during smartphone mode switching process.

The specific steps are: when the smartphone mode switching is detected, linear fitting three steps' heading angle to judge whether the pedestrian is walking in line or not, keep a record of the heading angle as θ_{before} if it is true, and use it during the mode switching process. Record the heading angle of the last step before mode switching instead if it is not true. When the phones' mode switching finished, record the heading angle as θ_{after} , which is calculated through EKF, then the value of the misalignment angle between θ_{after} and θ_{before} can be calculated through the following equation:

$$\psi_{mis} = \theta_{after} - \theta_{before} \quad (10)$$

When the phone in a stable situation, the heading angle calculated in real time should be compensated for the misalignment angle, which is brought during the phone's mode switching. Fig. 8 is the changing curve of the heading angle compensated before and after when pedestrian walking straight switching mobile phones mode, for we only use the heading angle of smartphone during the positioning, the roll and pitch angle are not compensated.





(b)

Fig. 8. Result of compensation for angle. (a) Angle of heading, roll and pitch before compensation (b) Heading, roll and pitch after compensation

From Fig. 8, we can see that after compensating for the misalignment angle, the heading angle calculated through sensor data can be used to express the heading angle of the pedestrian, it fits well with the actual situation.

IV. EXPERIMENTS AND RESULTS

A. Experimental Setup

For all tests, the tri-axial accelerometer, LIS303DLHC, a tri-axial gyroscope, L3G4200D, a tri-axial magnetometer, AK8963, equipped in a HUAWEI smartphone was selected. The tests were conducted in two parts, one for classifier, and the other one for trajectories. The trajectories test is conducted to include trajectories and turns, specifically keeping in mind the normal human walking behavior with normal smartphone mode switch frequency.

B. Classifier Performance Experiment

20 testers including 15 male and 5 female were selected to conduct the experiment to verify the algorithm of smartphone mode proposed above, each tester do 20 times as the stipulated smartphone mode switching. In Table I the performance of the smartphone mode detector algorithms are reported for male and female testers. The male testers are indicated with the letter M and the female with the F. Furthermore, the performance of the smartphone mode classifier for this data collection has been reported in Table II.

TABLE I: SMARTPHONE MODE DETECTION ALGORITHM PERFORMANCE FOR THE “CONTROLLED” DATA COLLECTION

Input \ Output	Texting	Ear-talking	Waist
M-Texting	300	0	0
M-Ear-talking	53	243	4
M-Waist	8	0	292
F-Texting	100	0	0
F-Ear-talking	18	81	1
F-Waist	2	0	98

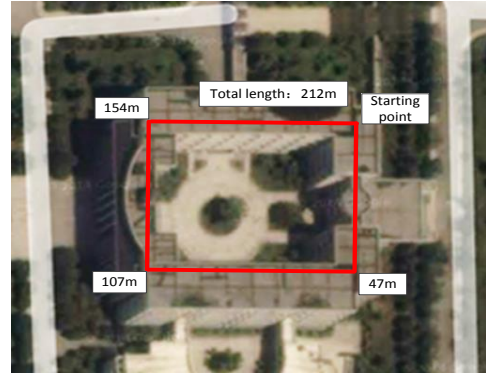
From Table II, we can see that the comprehensive accuracy of phone’s mode classification is 92.8%, the algorithms achieve high performance regardless of the phone position for all 20 testers, which confirms the algorithm of phone’s mode determination proposed above.

TABLE II: CONFUSION MATRIX FOR THE “CONTROLLED” DATA COLLECTION

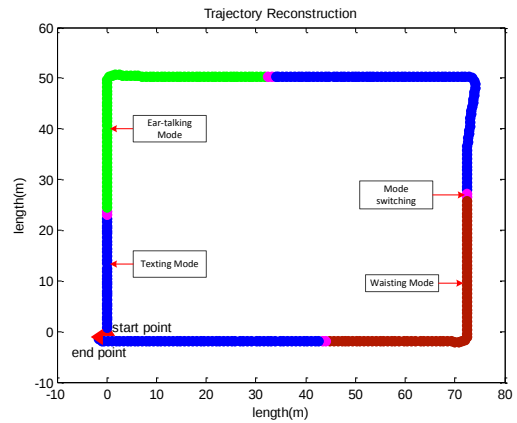
Output \ Input	Texting	Ear-talking	Waist	Accuracy
Texting	100%	0	0	100%
Ear-talking	18%	81%	1%	81%
Waist	2.5%	0	97.5%	97.5%

C. Pedestrian Location Experiments

The Third Teaching Building of Chongqing University of Posts and Telecommunications was selected for the tests to confirm the validity the algorithm of compensation for heading angle mode switch proposed in this paper.



(a)



(b)



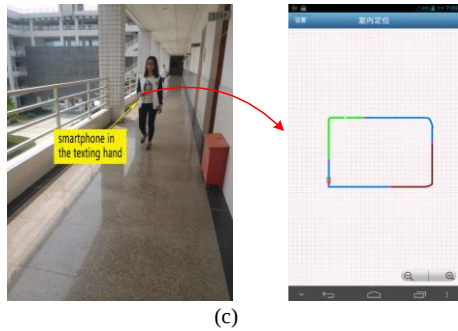


Fig. 9. (a) Reference trajectory with tracking along a closed building corridor (b)Simulation result of estimated position of 2D pedestrian tracking(c)A tester in testing and smartphone in three modes and the screenshots of the result of smartphone application is shown in the last one.

During the test, tester walked along the corridor of the building selected and finished TM changing to EM, EM changing to TM, TM changing to WM and WM changing to TM. The blue line is smartphone in the TM, the green line is smartphone in EM, the brown line is smartphone in WM and the pink line is the mode switching time.

The tracking results by our proposed smartphone mode changed pedestrian navigation algorithm are shown in Table III. Ten groups of data collected by ten different testers are used to evaluate the positioning accuracy. The 5 male and 5 female testers are notated as M1, ..., M5 and F1, ..., F5 respectively.

TABLE III: TRACKING RESULTS

Volunteer s	Reference distance (m)	Tracking error (m)	Relative error rate (%)
F1	212	2.0276	0.96
F2	212	1.9615	0.93
F3	212	3.7761	1.78
F4	212	1.8253	0.86
F5	212	3.4505	1.63
M1	212	4.2219	1.99
M2	212	3.3475	1.58
M3	212	2.9985	1.41
M4	212	5.3642	2.53
M5	212	4.6529	2.19
Mean	212	3.3626	1.59

The location error in the horizontal direction from the starting point to the ending point is approximately less than 3 meters when people with smartphone mode switched walk a distance of 100 meters, which is close to the length of an office, and the feasibility of the algorithm is verified.

V. CONCLUSIONS

The phone's mode switching during the process of pedestrian navigation is solved in this paper, including TM switched to EM, EM switched to TM, TM switched to WM and WM switched to TM. The algorithm of phone's mode determination proposed in the paper can work well during the test, the average accuracy of phone's mode classify is 92.8%, and the compensation for mode switched heading angle is verified to be

effective during the pedestrian navigation process and the position error in the horizontal direction from the starting point to the ending point is approximately less than 3 meters when people with smartphone mode switched walk a distance of 100 meters. Thus the accuracy of using smart phones to pedestrian navigation positioning is improved and smartphones' using adaptability in the pedestrian navigation is improved, too. Its application will be more widely.

ACKNOWLEDGMENT

This research was supported by the "The National Natural Science Foundation of China" (51175535). And, this subject is partially supported by "The International Joint Research Center technology platform and base construction"(cstc2014gjh0038).

REFERENCES

- [1] A. Ali and N. El-Sheimy, "Low-cost MEMS-based pedestrian navigation technique for GPS-denied areas," *Journal of Sensors*, vol. 2013 pp. 572-575, July 2013.
- [2] S. Beauregard, "A helmet-mounted pedestrian dead reckoning system," presented at the 2006 3rd International Forum, Applied Wearable Computing (IFAWC), Bremen, Germany, March, 1-11, 2006.
- [3] Z. S. Tian, Y. Zhang, M. Zhou, and Y. Liu, "Pedestrian dead reckoning for MARG navigation using a smartphone," *EURASIP Journal on Advances in Signal Processing*, vol. 65, pp. 87-92, May 2014.
- [4] C. Randell, C. Djalllis, and H. Muller, "Personal position measurement using dead reckoning," presented at the IEEE 2012 16th International Symposium on Wearable Computers, White Plains, NY, October 166-173, 2003.
- [5] K. C. Lan and W. Y. Shih, "Using simple harmonic motion to estimate walking distance for waist-mounted PDR," presented at the IEEE Wireless Communications and Networking Conf. (WCNC), Shanghai, April 2445-2450, 2012.
- [6] J. C. Alvarez, D. Alvarez, A. López, and R. C. González, "Pedestrian navigation based on a waist-worn inertial sensor," *Sensors*, vol. 12, no. 8, pp. 10536-10549, Aug. 2012.
- [7] I. Skog, P. Handel, J. O. Nilsson, and J. Rantakokko, "Zero-velocity detection—an algorithm evaluation," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 11, pp. 2657-2666, Nov. 2010.
- [8] C. Ascher, C. Kessler, M. Wankler, and G. F. Trommer, "Dual IMU indoor navigation with particle filter based map-matching on a smartphone," in *Proc. IEEE Int. Conf., Indoor Positioning Indoor Navigat*, 2010, pp. 1-5.
- [9] F. Li, C. Zhao, G. Ding, J. Gong, C. Liu, and F. Zhao, "A reliable and accurate indoor localization method using phone inertial sensors," in *Proc. ACM Conf., Ubiquitous Comput. (UbiComp '12)*, Pittsburgh, 2012, pp. 421-430.
- [10] L. Ojeda and J. Borenstein, "Personal dead-reckoning system for GPS-denied environments," in *SSRR 2007. IEEE International Workshop on Safety, Security and Rescue Robotics*, Rome, 2007, pp. 1-6.
- [11] A. Khayatyan and P. Setoodeh, "Attitude estimation by separate-bias Kalman filter-based data fusion," *Journal of Navigation*, vol. 57, pp. 261-274, Feb. 2004.
- [12] M. Aiden, V. Renaudin, J. B. Bancroft, and L. Gérard, "Design and testing of a multi-sensor pedestrian location and navigation platform," *Sensors*, vol. 12, pp. 3720-3738, Mar. 2012.

- [13] H. M. Zhang, W. Z. Yuan, Q Shen, T Li, and H. L. Chang, "A handheld inertial pedestrian navigation system with accurate step modes and device poses recognition," *IEEE Sensors Journal*, vol. 15, pp. 1421–1429, Mar. 2015.
- [14] M. Susi, V. Renaudin, and G. Lachapelle, "Motion mode recognition and step detection algorithms for mobile phone users," *Sensors*, vol. 13, pp. 1539-1562, Feb. 2013.
- [15] A. Ali, *et al.*, "An improved personal Dead-Reckoning algorithm for dynamically changing smartphone user modes," presented at the 25th International Technical Meeting of the Satellite Division of the Institute of Navigation (ION GNSS 2012), At Nashville, TN, January 2012, pp. 2432-2439.



Yu Liu was born in Chongqing Province, China, in 1972. He received the Ph.D. degree from the Chongqing University of China in 2006. His research interests include vibration inertial sensors, optical fiber sensor, inertial navigation, sensors and signal processing.



Yanping Chen was born in Chongqing Province, China, in 1990. She is now studying in Chongqing University of Posts and Telecommunications of China. Her research interests include inertial navigation, sensors, artificial intelligence, and signal processing.



Mu Zhou was born in Chongqing Province, China, in 1984. He received the Ph.D. degree from the University of Hong Kong University of Science and Technology. His research interests include wireless localization and navigation, natural language processing and artificial intelligence and satellite communications.



Yibing Wang was born in Hubei Province, China, in 1990. He is now studying in Chongqing University of Posts and Telecommunications of China. His research interests include inertial navigation, sensors, artificial intelligence, and signal processing.



Shuang Gong was born in Gansu Province, China, in 1991. He is now studying in Chongqing University of Posts and Telecommunications of China. His research interests include inertial navigation, sensors, artificial intelligence, and signal processing.



Xin Zhang was born in Jilin Province, China, in 1992. She is now studying in Chongqing University of Posts and Telecommunications of China. His research interests include inertial navigation, sensors, artificial intelligence, and signal processing.