IEIE Transactions on Smart Processing and Computing, vol. 4, no. 3, June 2015
http://dx.doi.org/10.5573/IEIESPC.2015.4.3.173

IEIE Transactions on Smart Processing and Computing

Exploring Smartphone-Based Indoor Navigation: A QR Code Assistance-Based Approach

Vinjohn V Chirakkal, Myungchul Park, and Dong Seog Han

School of Electronics Engineering, Kyungpook National University / Daegu, Korea
{vinjohnvc@gmail.com, wndcalm@gmail.com, dshan@knu.ac.kr}

* Corresponding Author: Dong Seog Han

Received May 5, 2015; Accepted June 11, 2015; Published June 30, 2015

** Regular Paper*

** Extended from a Conference: Preliminary results of this paper were presented at the IEEE ISCE 2014. This present paper has been accepted by the editorial board through the regular reviewing process that confirms the original contribution.*

***Abstract*:** A real-time, Indoor navigation systems utilize ultra-wide band (UWB), radio-frequency identification (RFID) and received signal strength (RSS) techniques that encompass WiFi, FM, mobile communications, and other similar technologies. These systems typically require surplus infrastructure for their implementation, which results in significantly increased costs and complexity. Therefore, as a solution to reduce the level of cost and complexity, an inertial measurement unit (IMU) and quick response (QR) codes are utilized in this paper to facilitate navigation with the assistance of a smartphone. The QR code helps to compensate for errors caused by the pedestrian dead reckoning (PDR) algorithm, thereby providing more accurate localization. The proposed algorithm having IMU in conjunction with QR code shows an accuracy of 0.64 m which is higher than existing indoor navigation techniques.

***Keywords*:** Indoor navigation, Inertial measurement unit, Location based services, Pedestrian dead reckoning, QR codes

1. Introduction

Increasing requirements for location-based services have caused indoor navigation to evolve into a major research area for human users as well as autonomous systems. Precise indoor localization opens up a new frontier of mobile services, and offers significant opportunities to enhance navigation in indoor environments. After a massive development effort to enable outdoor navigation using global positioning systems (GPS) [1], researchers are currently searching for an enhanced technology to facilitate accurate navigation in indoor environments. GPS, a technology commonly used for outdoor positioning and navigation, cannot be used in indoor environments. GPS signals suffer a significant amount of attenuation in indoor environments, thereby providing very low accuracy [3]. Besides GPS, technologies that have been utilized for indoor environment navigation include received signal strength (RSS)-based techniques that involve WiFi [4, 5], GSM [6, 7] and FM [2], as well as other techniques such as radio-frequency identification (RFID) [8, 9], ultra-wideband (UWB) [10], and other similar schemes. The technologies mentioned above require the installation of surplus infrastructure and sensors. This prevents these technologies from achieving large-scale deployments [11]. Moreover, a number of these wireless technologies consume large amounts of memory and battery power, and may threaten the user's privacy.

To overcome the above-mentioned hurdles, this paper utilizes inertial navigation systems (INS) for indoor navigation. This system records the navigation state, which contains orientation and acceleration in all three dimensions, with the aid of measurements from inertial sensors. These systems have been used as guidance systems [12] on ships, airplanes, submarines, satellites, guided missiles, and spacecraft. This system measures movements with an inertial measurement unit (IMU), a device that may include sensors such as an accelerometer, a gyroscope, and a magnetometer, depending on the degree of freedom to measure the orientation and the acceleration of the device. Owing to rapid advancements in the field of micro-electro mechanical systems (MEMS), IMUs can be produced in very small sizes, and have become a popular smartphone feature in recent years [13]. Using the information obtained from the IMU along with the user's initial position, the current motion of the user can be tracked; thus, the path traversed by the user can be recorded. Numerous methods can be used by IMUs to provide the relative location change of the user. The strap-down integration [14] and pedestrian dead reckoning (PDR) algorithms [15] are widely used positioning methods. However, the INS sensor may produce errors caused by bias, white noise, flicker noise, temperature effects, and calibration issues [16]. These errors increase drastically over time. Moreover, because of varying magnetic fields, huge deviations are caused by the compass, making INS unsuitable for use as a stand-alone indoor navigation system [17]. Hence, this system must be combined with another system that can compensate for the errors generated by the INS.

Recently, the features of quick response (QR) codes have been employed for the purpose of navigation, with the assistance of image processing and recognizing systems [18]. The QR code is a tag for a type of matrix barcode. Compared to a traditional one-dimensional (1-D) code, a QR code incorporates features such as rapid readability and large storage capacity. Considering minimal deployment costs for enabling indoor navigation, this approach is very cost effective when combined with other existing techniques. This paper proposes a QR code-aided, IMU-based indoor navigation model. This model effectively reduces the significant error propagations caused by the accelerometer and gyroscope and hence provide a better indoor navigation for human users and autonomous systems. This paper also provides a detailed discussion of various PDR methods proposed by Weinberg [19], Kim [20], and Scarlet [21], and also presents comparisons between them. In addition, error deviations of the conventional and proposed methods are discussed. This paper is an extended version of [22].

The paper is structured as follows. Section II provides a brief overview of the PDR approach and QR codes. The proposed model is discussed in section III. Experimental results for the proposed model and comparison results are exhibited in Section IV. Conclusions are presented in Section V.

2. Background

Existing methods for indoor navigation using IMU and a brief introduction to indoor navigation using QR codes are discussed in this section.

2.1 Pedestrian Dead Reckoning

The well-known methods utilized for indoor environment navigation with IMUs are the strap-down integration and PDR algorithms. In the strap-down integration algorithm, the attitude of the device to which an IMU is attached is computed using Euler angles, the direction cosine matrix, or quaternions. The quaternions method is advantageous because it is less complex, provides superior accuracy, and avoids singularity [23]. The strap-down integration method calculates the velocity and the position by double-integrating the acceleration obtained from the accelerometer. By integrating the rotation rate from the gyroscope, the angular orientation is determined. Because this process requires integrating the acceleration component, a minor error in acceleration would generate a significant error after integration. Hence, the accuracy of the strap-down integration is generally lower than other methods. In contrast, the PDR is a pedestrian positioning method, which is based on additive distance travelled from the initial position. The distance traversed can be tracked by step detection using an accelerometer, and the orientation can be calculated using a gyroscope.

Implementation of the PDR method typically involves operations such as orientation, projection, filtering, step detection and step length estimation [15, 24]. Step length estimation can be performed using either static or dynamic method. The static method assumes all valid steps will have equal lengths, whereas the dynamic method assumes that valid steps can have different step lengths. When compared to dynamic methods, static methods are less accurate [25]. Therefore, this study implements dynamic step length estimation, which will be discussed in detail in Section III.

The PDR with step detection has numerous advantages. It reduces errors accumulated by the navigation solution, because it utilizes the sequential nature of pedestrian motion [26]. The step detection approach confines the error to a certain range, because the step length is a random parameter, which is confined by the muscular force of a human body [27]. However, one of the major problems in using PDR for navigation is errors accumulated over a time span or a distance travelled, because the current location estimate is based on the prior estimate of the last step. In addition, PDR must be seeded with a precise initial position for effective estimation [28]. Hence, errors related to the stride length and orientation, which are unavoidable with currently available commercial grade sensors, make PDR unreliable when used for long time periods or long distances. Therefore, this technique is merged with other techniques to facilitate better positioning. Accordingly, this study uses PDR in conjunction with QR codes.

2.2 QR code

A QR code is a 2D image similar to a common barcode, featuring large information storage capacity and rapid readability [29]. The QR code is square shaped and is comprised of a coding region and a functional region [30]. The coding region is typically described by version, format, and data characters. The functional region is combined with localizing, correcting and seeking graphs. The QR code can be read and decoded by smart phones or tablets in a very straightforward manner. The QR codes in this paper are embedded with grid locations, to navigate the user

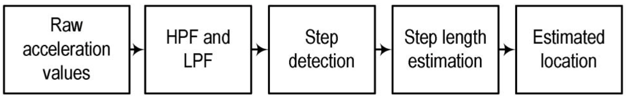

Fig. 1. The existing PDR model using scarlet approach.

from the source to the destination. Costa-Montenegro et al. [31] have demonstrated an indoor navigation system using the QR code. This method requires location and map servers to be deployed, thereby increasing the cost. Alghamdi et al. [32] have also proposed a method for indoor navigation using QR codes and RFID; however, large-scale deployments of this method have also been hampered because of high costs. Chiou et al. [33] proposed a similar algorithm using PDR and QR codes, but this algorithm provides lower accuracy than other methods.

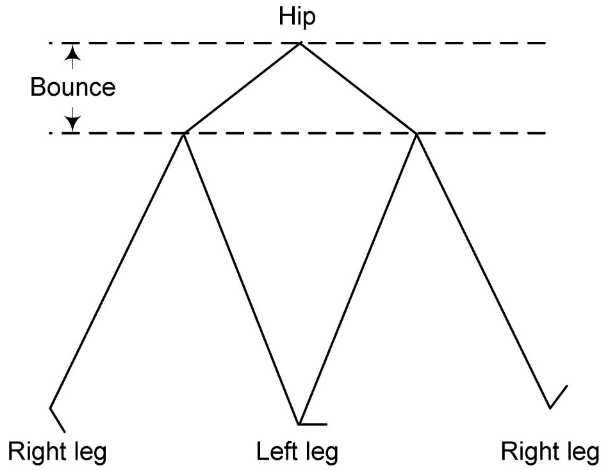

Fig. 2. Vertical movement of hip while walking [19].

3. Proposed QR Code-aided PDR system

In this section, one of the existing PDR models [25] is discussed, followed by a discussion of the proposed approach. The proposed approach is comprised of a modified PDR model and a QR code-assisted PDR approach.

The block diagram of the existing PDR method [25] using the scarlet approach [21] as step length estimation is displayed in Fig. 1. PDR Implementation using a smartphone includes various processes such as filtering, step detection, and step length estimation.

The raw values of three axis accelerometers and three axis gyroscopes are obtained from the IMU of the smartphone. As a first procedure, the absolute acceleration is obtained from the raw acceleration values. These absolute acceleration values are then filtered to obtain the desired output signal. The acceleration values are first filtered using a high pass filter and then using a low pass filter. The high pass filtering is performed to eliminate the influence of gravity and noise [24]. This can be implemented using the following equations:

$$y_h[i] = x[i](1-\alpha) + y_h[i-1]\alpha \quad (1)$$

$$z[i] = x[i] - y_h[i] \quad (2)$$

where $y_h[i]$ is the mean of the signal, $x[i]$ is the raw acceleration value, $z[\cdot]$ is the output of the high pass filtered signal, and α is a constant used to optimize the filter. Eqs. (1) and (2) represents the simplest way to perform high pass filtering. The mean of the obtained waveform, which represents the low frequency components as displayed in (1) is subtracted from the signal as displayed in (2); this ensures that only high frequency components appear in the output and the offset of the signal is zero. A low pass filter is applied to the resulting zero offset signal by implementing a moving average filter as

$$y_l[i] = \frac{1}{M} \sum_{j=-(M-1)/2}^{(M-1)/2} z[i+j] \quad (3)$$

where $y_l[i]$ is the average filtered output, $z[\cdot]$ is the signal from the high pass filter, and M is the moving window size.

The low pass filtering is implemented to decrease the noise in the signal. Averaging reduces the high frequency components in the signal, thereby smoothening the signal. The moving average signal is obtained based on a subset of the current and previously recorded data, thus attenuating the high frequency samples; however, signal flattening is performed in moderation to avoid losing the original features of the waveform.

After applying the filters to the values of the detected axis, the step detection algorithm should be applied, because the distance travelled is represented by the user's steps. There are two step-detection methods that can be used to analyze acceleration signals: peak detection [20, 24] and zero crossing detection [34, 35]. The zero crossing method tallies signals that cross the zero level to determine step occurrences. The time interval thresholding is employed to reject false step detection. This method is not suitable for detecting a user's step, because a certain time interval threshold is required to decide whether the zero crossing represents a valid step. The problem occurs when time intervals between footfalls vary for different subjects.

In the peak detection method, the main objective is to detect the peaks of acceleration. The peaks of vertical acceleration correspond to the step occurrences, because the vertical acceleration is generated by the vertical impact that occurs when the foot hits the ground.

In this paper, step detection is implemented using peak detection rather than the zero crossing method. Peak detection is performed using a variable threshold [15], thereby detecting the maxima and minima. The upper threshold is determined by adding the last valid minima with a threshold value, while the lower threshold is determined by subtracting the last valid maxima with a threshold value.

As mentioned in Section II, there are two methods for estimating the step length: the static and the dynamic method. The static method assumes that all the valid steps have the same step length, whereas the dynamic method assumes all valid steps have different step lengths, which can be estimated using certain approaches. This paper discusses three approaches, proposed by Weinberg [19], Kim [20], and Scarlet [21].

In the Weinberg approach, the vertical bounce, which is caused by impact while walking, is proportional to the step length as displayed in Fig. 2. The step length s_{w} is calculated using the peak to peak difference at each step as

$$s_{\mathrm{w}} = k_{w} \cdot \sqrt[4]{a_{\max} - a_{\min}} \tag{4}$$

The Weinberg distance D_{w} is calculated by multiplying the number of steps n as

$$D_{\mathrm{w}} = n \cdot s_{\mathrm{w}} \tag{5}$$

where $a_{\max}$ and $a_{\min}$ are the maximum and minimum acceleration, respectively, and k_{w} is a multiplier constant given as 0.41.

In the Scarlet approach, the accuracy problem caused by the spring variations in the steps of different people is solved. This approach demonstrates a relationship between maximum acceleration, minimum acceleration and average acceleration of the step length s_{s} as

$$s_{\mathrm{s}} = k_{s} \frac{a_{\mathrm{avg}} - a_{\min}}{a_{\max} - a_{\min}} \tag{6}$$

$$a_{\mathrm{avg}} = \sum_{m=1}^{N} |a_{m}| / N \tag{7}$$

where a_{avg} is the average acceleration, respectively, k_{s} is a constant multiplier given as 0.81, and moving average size N is given as 16. The measured acceleration values are denoted by a_{m}. The Scarlet distance D_{s} can be calculated by multiplying the number of steps n as

$$D_{\mathrm{s}} = n \cdot s_{\mathrm{s}} \tag{8}$$

In Kim's approach, a relation between step length s_{kim} and average acceleration a_{m} is given as

$$s_{\mathrm{kim}} = k_{k} \sqrt[3]{\sum_{m=1}^{N} |a_{m}| / N} \tag{9}$$

where k_{k} is a constant given as 0.98, and moving average size N is given as 16. The Kim distance D_{kim} can be calculated by multiplying number of steps n .

$$D_{\mathrm{kim}} = n \cdot s_{\mathrm{kim}} \tag{10}$$

However, the existing PDR model [25] using a conventional scarlet approach [21] for step length estimation, does not account for the orientation of the user and hence likely to get more erroneous location estimates. Hence, the proposed model as seen in Fig. 3 overcomes this drawback by implementing a gyroscope to track the

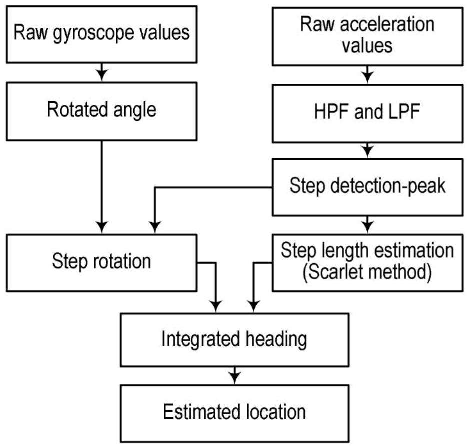

Fig. 3. Block diagram for the proposed PDR implementation.

orientation of the user with the scarlet approach. A better result is obtained in terms of accuracy when orientation is used with the scarlet method for location estimation. Furthermore, the proposed algorithm presents an efficient indoor navigation technique using QR codes as seen in Fig. 4 to compensate for errors in the modified PDR technique.

The block diagram of the proposed PDR model by incorporating orientation with scarlet method [21, 25] is shown in Fig. 3. Raw gyroscope values are obtained, in radians per second, from the IMU of the smartphone. These raw gyroscope values are converted to degrees per second to obtain the rotated angle. Using the rotated angle, the orientation is calculated. The rotated angle is merged with the step detection that utilizes peak detection, to acquire the orientation of the user.

Furthermore, the proposed system using QR codes as an error compensator is displayed in Fig. 4. This paper also proposes an indoor navigation technique using IMU in conjunction with QR codes. To enable the real time indoor navigation, the smartphone must be equipped with the blueprint of the building, as well as a database that stores the QR code location with respect to the blueprint. The user has the ability to key in the destination, in case the database must be consulted to determine the nearest QR code in the vicinity of the destination. The proposed algorithm uses QR codes to assist PDR, thereby reducing the drift errors generated by the accelerometer and gyroscope. Therefore, the QR code is used as an error compensator. Moreover, the important factor while implementing indoor navigation using IMU is the initial position, hence in order to have a more accurate initial position QR code is used in this study. The PDR algorithm runs continuously, tracing the path of the user. When a QR code is read, the position or location is corrected to the one represented by the QR code, thereby suppressing drift errors. A performance analysis comparing the proposed algorithm with a conventional algorithm using Weinberg and Kim's approach is presented in the subsequent section.

One of the primary considerations for the proposed QR code-based algorithm is determining the number of QR codes required for the implementation. Utilizing a greater number of QR codes considerably increases the size of the

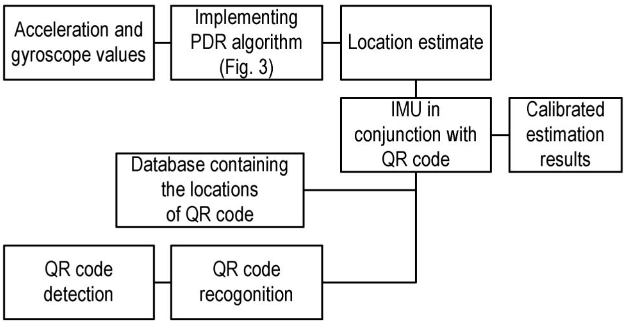

Fig. 4. Proposed PDR with QR code assistance for navigation.

database, thereby reducing the performance of the system. Based on the experimental data, an optimal performance is achieved by placing a QR codes 10 m apart. However, this represents a tradeoff because increasing the number of QR codes can increase the accuracy of the system. Considering this tradeoff between the number of QR codes and the accuracy of the system, the selected distance of 10 m demonstrates an optimal performance.

4. Experimental Results

In this section, the implementation of QR codes, the experimental setup and the performance analysis are presented. Unlike other techniques like foot or waist mounted IMU, this study implements the PDR technique on a smartphone.

4.1 QR Code Layouts

As an initial step, the blueprint of the entire building is placed on a grid to identify each location in terms of coordinates. The QR codes are placed 10 m apart on floorings of the corridor as displayed in Fig. 5. The 10 m separation is the result of the tradeoff considerations discussed in the previous section. Each QR code placed on the floor of the building will represent location coordinates, to help determine the location of the user. (X, Y) values are assigned to each QR code, based on the blueprint. Finally, the blueprint augmented with the QR codes is provided to the user through WiFi, Bluetooth, or other similar data sources. The QR codes can be generated using free software available online.

4.1 QR Code Layouts

To demonstrate navigation in an indoor environment, the proposed algorithm was tested using a smartphone. For experimental purposes, the path from room number 515 to 509 on the 5th floor of building IT-1 at Kyungpook National University is considered. The floor layout is shown in Fig. 5, where the entire layout has been augmented with a grid. The sampling rate of the smartphone's IMU is set to 100 Hz for the experiment. The smartphone was placed in the hand of the user with the camera facing the floor of the building, making it feasible

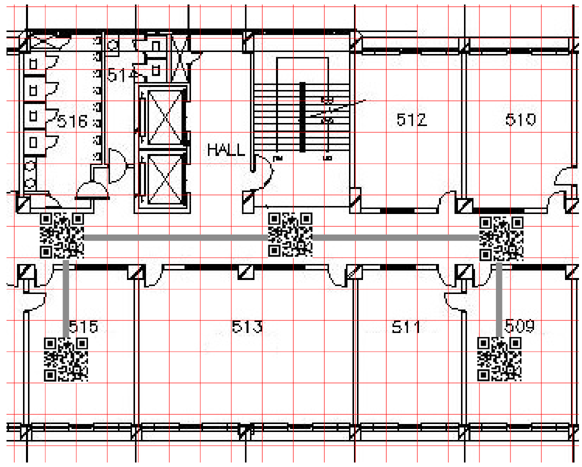

Fig. 5. QR code placement on the blueprint augmented with a grid, and the test path considered in the experiment.

for the QR code placed on the floor to be read by the smartphone. It is usually seen that during indoor navigation the user ideally places the smartphone as mentioned above rather than in other places.

In the real time navigating scenario, the blueprint augmented with QR codes is first downloaded to the smart phone or tablet using WiFi or Bluetooth, or directly from a PC. The user is then able to navigate by reading the QR codes, which are attached to the floor, with their smartphone. The QR codes read by the smartphone are utilized in conjunction with the PDR algorithm. The unique algorithm used in this study restricts the location estimates from deviating by using the QR codes. Once a QR code is read, the location determined by the values of the accelerometer and gyroscope is merged with the location of the QR code, thereby restricting the errors from the accelerometer and gyroscope.

4.2 Results

The simulation results of the PDR model presented in Section III are presented here. The absolute acceleration is obtained from the raw values of the three-axis accelerometer, as shown in Fig. 6.

Absolute acceleration output obtained from previous step is passed through a high pass filter using (1) and (2) is shown in Fig. 7. The weighting value α in (1) is considered to be 0.9 [24].

The low pass filter output applied to the high pass filter result is displayed in Fig. 8. The low pass filter in (3) is simulated with an M value of 15. On obtaining the filtered result the next step is to detect the steps of the user. Fig. 9 displays the zero crossing method for step detection. It can be seen that it is inefficient in detecting the user's steps due to a fixed time interval thresholding. Hence a peak detection method is employed instead of zero crossing method for step detection.

The peak detection employed in this study can be observed in Fig. 10. The threshold value is determined to be 0.8. To ensure a valid step, a time interval of 150 ms

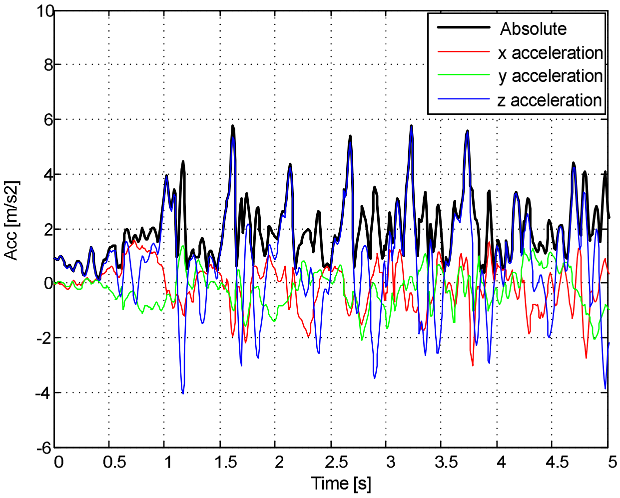

Fig. 6. Absolute acceleration from raw values obtained from the three- axis accelerometer.

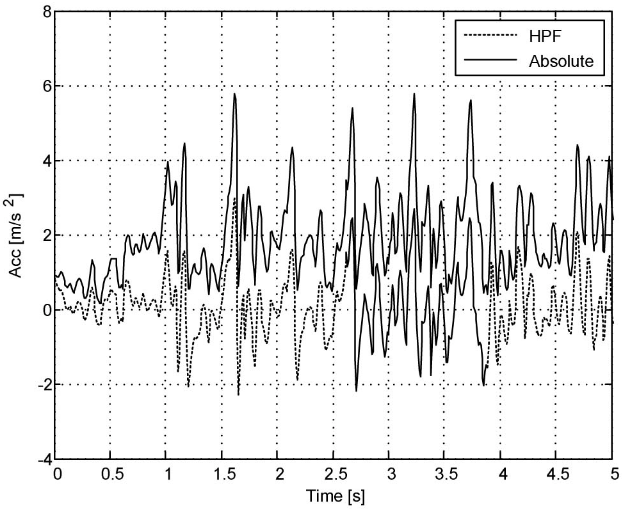

Fig. 7. Raw acceleration values filtered using a high pass filter (HPF).

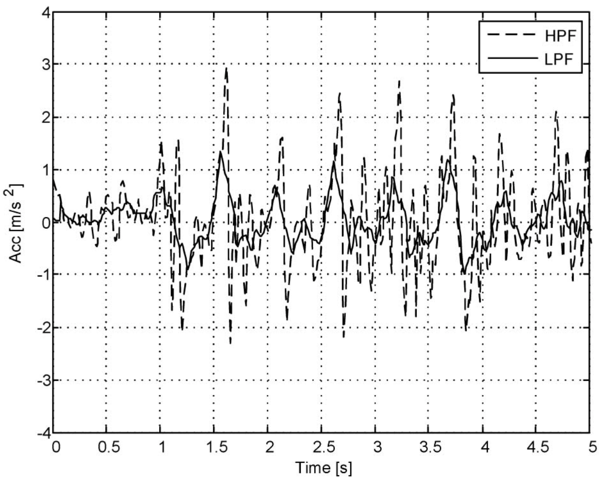

Fig. 8. The filtered signal after the HPF is filtered by a low pass filter (LPF).

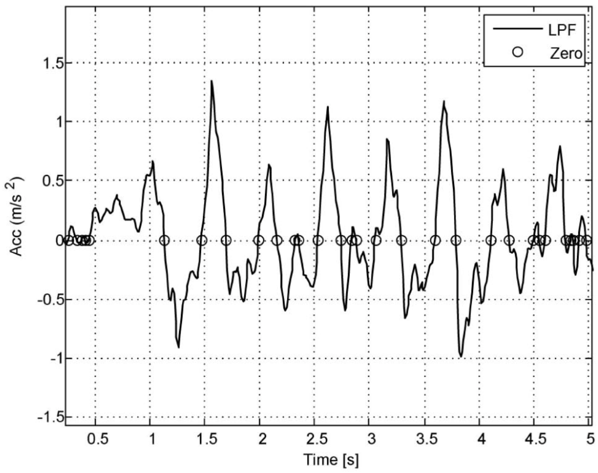

Fig. 9. Zero crossing method for step detection.

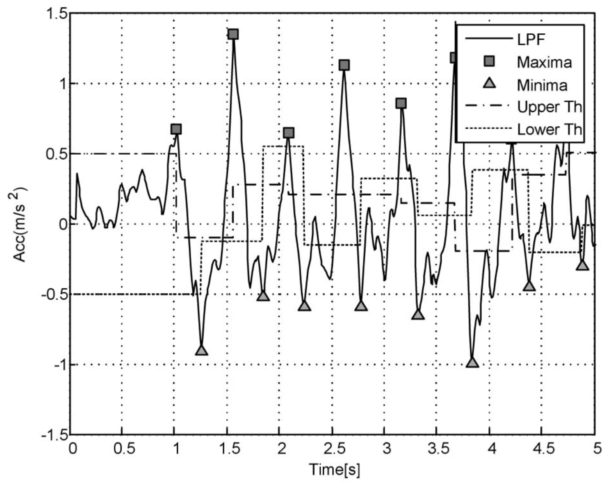

Fig. 10. Peak detection using a variable threshold.

between maxima and minima is also determined experimentally.

The obtained step detection is used to achieve step length estimation using the Scarlet approach as per (6) - (8). As per the proposed method, the orientation factor is used with the Scarlet approach for step length estimation for a better and accurate location estimation.

Hence, the gyroscope implementation as per Fig. 4 is displayed below. The raw values of roll, pitch, and yaw from a three axis gyroscope in radians per second are displayed in Fig. 11. These values are then converted from radians per second to degrees per second as displayed in Fig. 12, to obtain the orientation.

The obtained result in degree per second is augmented with step detection as per Fig. 4, to determine the step rotation. This is displayed in Fig. 13. Finally, the obtained step rotation is used along with the step length estimation in order to calculate the position of the user.

In order to analyze the system in terms of accuracy, a performance analysis is carried out on the proposed system.

The performance analysis of the system is divided into two parts. First, the analysis of different step length estima-

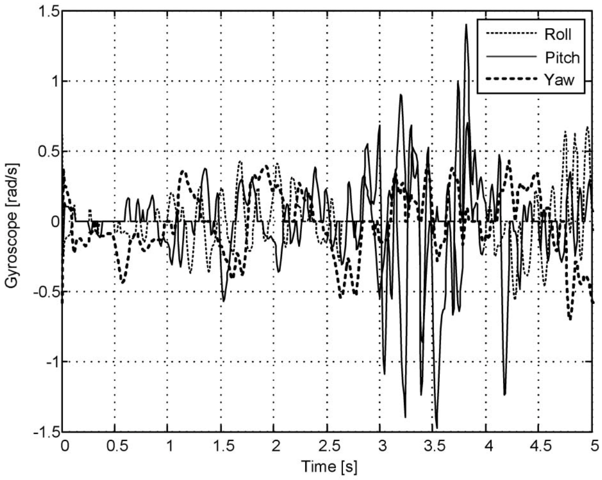

Fig. 11. Raw gyroscope values.

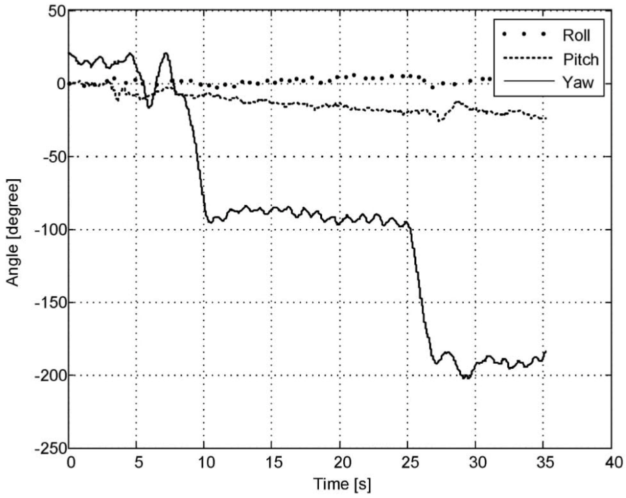

Fig. 12. Rotated angle in degrees per second.

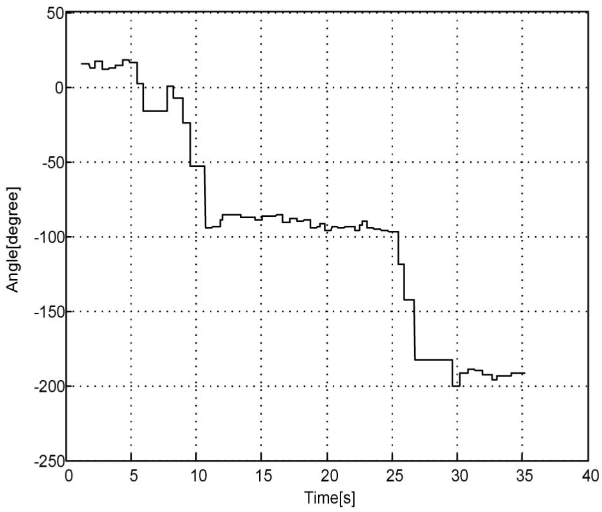

Fig. 13. Step rotation angle.

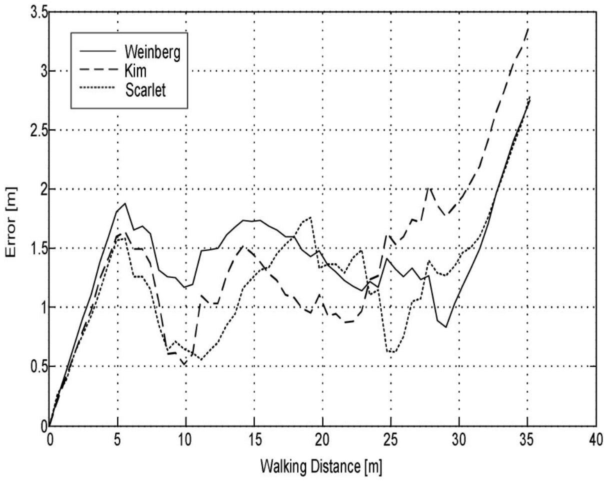

Fig. 14. Traversed distance using PDR and various step length methods.

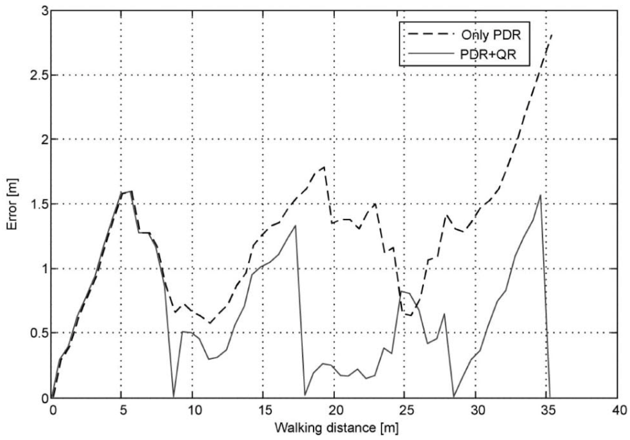

Fig. 15. Comparison between conventional PDR and the proposed method.

tion approaches is performed, followed by analysis of the proposed model. As mentioned in section III, this paper presents three step-length estimation approaches from Weinberg, Kim, and Scarlet. A comparison between these three approaches is presented in Fig. 14. Based on the comparison graph displayed in Fig. 14, it is evident that the average error rate of the Scarlet approach is much lower than the error rates of the other approaches. Therefore, the Scarlet approach is utilized to estimate the step length. The implementation of the Scarlet approach on the blueprint of the building is displayed in Fig. 16.

Employing the Scarlet approach, the proposed algorithm using QR codes is established. The QR code assists the PDR algorithm in determining the precise location of the user. This is displayed in Fig. 15. In this figure, the plot illustrates the comparison between the conventional PDR approach and the proposed algorithm using QR codes and PDR. As exhibited in Fig. 15, the proposed method demonstrates enhanced performance compared to conventional PDR approaches. The detailed comparison is listed in Table 1. The proposed algorithm provides an overall accuracy of 0.64 m, which is

Table 1. Distance estimation Error.

Method	Average Error (meters)
Proposed Kim approach	1.40
Proposed Weinberg approach	1.41
Proposed Scarlet approach	1.22
Proposed Scarlet + QR code approach	0.64

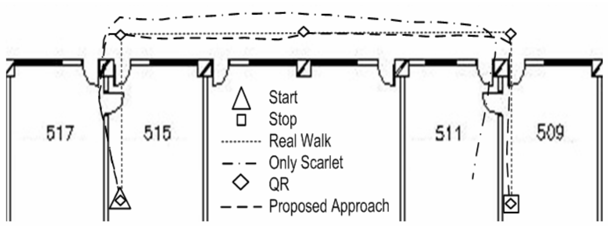

Fig. 16. PDR with QR Code navigation assistance in a real time scenario.

significantly better than the conventional PDR algorithm proposed in [24].

The implementation of the proposed algorithm using QR codes and PDR on a blueprint of a building is illustrated in Fig. 16.

5. Conclusion

This paper proposes two models for indoor navigation, an improvement in the existing PDR technique (that employs scarlet approach [21, 25]) by including the gyroscope values and using this improved PDR technique in conjunction with the QR code. Moreover, this paper also provides a comparison of various step estimation approaches and step detection methods; these results were utilized for selecting the most suitable step estimation and detection techniques for the proposed algorithm. Based on the results displayed above, the improved PDR technique used in conjunction with QR codes provides improved accuracy in comparison with other methods.

The following features make the proposed approach superior to other existing indoor navigation techniques. (i) This technique provides greater accuracy. (ii) This technique does not require the assistance of any wireless based networks, other than the initial downloading of the blueprint. (iii) Infrastructure costs are minimal, increasing the viability of a wide range of indoor navigation implementations. (iv) Real-time navigation is unaffected by network traffic, because this method is not dependent on wireless connections. (v) Memory requirements are reduced compared to the database concept of the RSSI based method. (vi) Finally, battery consumption is comparatively low. However, this technique has some disadvantages as well: if modifications are performed in the building, the whole system must be re-implemented. The resolution of the camera also plays a vital role, because adequate light is required for the QR code to be visible for detection. Considering the tradeoffs, the proposed technique is optimal for various location-based service systems. The system proposed is targeted for both autonomous system as well as human users

Acknowledgement

This research was supported by the MSIP (Ministry of Science, ICT & Future Planning), Korea, under the C-ITRC (Convergence Information Technology Research Center) (IITP-2015-H8601-15-1002) supervised by the IITP (Institute for Information & communication Technology Promotion).

References

[1] P. Groves, "Principles of GNSS, inertial, and multisensor integrated navigation systems," Artech House, 2008. Article (CrossRef Link)

[2] Y. Chen, D. Lymberopoulos, J. Liu and B. Priyantha, "Indoor localization using FM signals," IEEE Trans. on Mobile Computing, vol. 12, no. 8, pp. 1502-1517, Aug. 2013. Article (CrossRef Link)

[3] G. Dedes and A. Dempster, "Indoor GPS: Positioning challenges and opportunities," *In Proc. of the 62nd IEEE Vehicular Technology Conference*, pp. 412-415, Sep. 2005. Article (CrossRef Link)

[4] C. Feng, A. Au, S. Valaee, and Z. Tan, "Received signal strength based indoor positioning using compressive sensing," *IEEE Trans on Mobile Computing,* vol. 11, no.12, Dec. 2012. Article (CrossRef Link)

[5] V. Chirakkal, M. Park, D. S Han, "Navigating Through Dynamic Indoor Environments Using WIFI for Smartphones," *In Proc. Int. Conf. Consumer Electronics*, Berlin, Germany, pp. 376-378, Ssyep. 2014. Article (CrossRef Link)

[6] A. Varshavsky, D. Pankratov, J. Krumm, and E. de Lara, "Calibree: Calibration-free localization using relative distance estimations," *In Proc. Int. Conf. Pervasive Computing (Pervasive)*, Sydney, Australia, pp. 146-161, May 2008. Article (CrossRef Link)

[7] A. Varshavsky, E. de Lara, J. Hightower, A. LaMarca, and V. Otsason, "GSM Indoor Localization," *Pervasive and Mobile Computing Journal*, vol. 3, no. 6, pp. 698-720, Dec. 2007. Article (CrossRef Link)

[8] G.-y. Jin, X.-y. Lu, M.-S. Park, "An indoor localization mechanism using active RFID tag," *In Proc. IEEE Int. Conf. Sensor Networks, Ubiquitous, and Trustworthy Computing*, Taichung, Taiwan, Jun. 2006. Article (CrossRef Link)

[9] L. M. Ni, Y. Liu, Y. C. Lau, and A. P. Patil "LANDMARC: indoor location sensing using active RFID," *Wireless Networks*, vol. 10, no. 6, pp. 701-710, 2004. Article (CrossRef Link)

[10] A. Bensky, "Wireless positioning technologies and applications," Artech House, 2008.

[11] M. Jain, R. C. P. Rahul, and S. Tolety, "A study on indoor navigation techniques using smartphones," *in Proc. Int. Conf. Advances in Computing, Communications and Informatics*, Mysore, India, pp.

1113-1118, Aug. 2013. Article (CrossRef Link)

[12] A. D. King, “Inertial navigation-forty years of evolution,” *GEC review*, vol. 13, no. 3, pp. 140-149, 1998.

[13] A. K. Brown and Y. Lu, “Performance test results of an integrated GPS/MEMS inertial navigation package,” *in Proc. of ION GNSS*, Long Beach, USA, pp. 825-832, Sep. 2004. Article (CrossRef Link)

[14] G. Dissanayake, S. Sukkarieh, E. Nebot, and H. Durrant-Whyte, “The aiding of a low cost strapdown inertial measurement unit using vehicle model constraints for land vehicle applications,” *IEEE Trans. Robotics and Automation*, vol. 17, no. 5, pp. 731-747, Oct. 2001. Article (CrossRef Link)

[15] Y. Jin, H. Toh, W. Soh, and W. Wong, “A robust dead reckoning pedestrian tracking system with low cost sensors,” *in Proc. IEEE Intl. Conf. Pervasive computing and communications*, Seattle, USA, pp. 222-230, Mar. 2011. Article (CrossRef Link)

[16] O. Woodman, “Pedestrian localization for indoor environments,” Ph.D dissertation, Dept. Comp. Eng., St. Catharine’s college, Univ. of Cambridge, 2010.

[17] J. Collin, O. Mezentsev, and G. Lachapelle, “Indoor positioning system using accelerometry and high accuracy heading sensors,” *in Proc. of GPS/GNSS Conference*, Portland, USA, Sep. 2003. Article (CrossRef Link)

[18] Y. Gu, W. Zhang, “QR code recognition based on image processing,” *in Proc Int. Conf. on Information Science and Technology (ICIST)*, Nanjing, China, pp. 733-736, Mar. 2011. Article (CrossRef Link)

[19] H. Weinberg, “Using the ADXL202 in Pedometer and Personal Navigation Applications,” Analog Devices AN-602 Application Note, 2002. Article (CrossRef Link)

[20] J. W. Kim, H. J. Jang, D-H. Hwang, and C. Park, “A Step, Stride and Heading Determination for the Pedestrian Navigation System,” *Journal of Global Positioning Systems*, vol. 3, no. 1-2, pp. 273-279, 2004. Article (CrossRef Link)

[21] J. Scarlet, “Enhancing the Performance of Pedometers Using a Single Accelerometer,” Analog Devices AN-900 Application Note, 2005. Article (CrossRef Link)

[22] V. Chirakkal, M. Park, D. S Han, “An Efficient and Simple Approach for Indoor Navigation Using Smart Phone and QR Code,” *In Proc. Int. Symposium on Consumer Electronics*, Jeju Island, Korea, pp. 1-2, Jun. 2014. Article (CrossRef Link)

[23] H, Lee, Jang G., Yong R., and Chan Park, “Modelling quaternion errors in SDINS: computer frame approach,” *IEEE Trans. Aerospace and Electronic Systems*, vol. 34, no. 1, Jan. 1998. Article (CrossRef Link)

[24] I. Bylemans, M. Weyn, and M. Klepal, “Mobile Phone-Based Displacement Estimation for Opportunistic Localization Systems,” *in Proc. Int. Conf. on Mobile Ubiquitous Computing, Systems, Services and Technologies*, Sliema, Malta, pp. 113-118, Oct. 2009. Article (CrossRef Link)

[25] A. Pratama, Widyawan, and R. Hidayat, “Smartphone based pedestrian dead reckoning as an indoor positioning system,” *in Proc. Intl. Conf. System Engineering and Technology*, Bandung, Indonesia, Sep. 2012. Article (CrossRef Link)

[26] J. Kappi, J. Syrjarinne, and J. Saarinen, “MEMS-IMU based pedestrian navigator for handheld devices,” *in Proc. of the 14th International Technical Meeting of the Satellite Division of the Institute of Navigation (ION-GPS 2001)*, Salt Lake City, USA, pp. 1369-1373, Sep. 2001. Article (CrossRef Link)

[27] L. Helena, Takala, “Error analysis of step length estimation in pedestrian dead reckoning,” *in Proc. ION GPS*, Portland, USA, pp. 1136-1142, Sep. 2002. Article (CrossRef Link)

[28] N. Kothari, B. Kannan, and M. B. Dias. Robust indoor localization on a commercial smart-phone. Technical Report CMU-RITR- 11-27, Robotics Institute, Pittsburgh, PA, August 2011. Article (CrossRef Link)

[29] Y Liu, J Yang, M Liu, “Recognition of QR code with mobile phones,” *in Proc. Control and Decision Conf.*, Yantai, China, pp. 203-206, Jul. 2008. Article (CrossRef Link)

[30] A-L. Hou, Y. Feng, and Y. Geng, “QR code image detection using run-length coding,” *in Proc. International Conference on Computer Science and Network Technology*, Harbin, China, pp. 2130–2134, Dec. 2011. Article (CrossRef Link)

[31] E. Costa-Montenegro, F. J. Gonzalez-Castano, D. Conde-Lagoa, A. B. Barragans-Martinez, P. S. Rodriguez-Hernandez and F. Gil-Castineira, “QR-Maps: an efficient tool for indoor user location based on QR codes and google maps,” *in Proc. Intl. Conf. Consumer Communications and Networking*, Las Vegas, USA, pp. 928-932, Jan. 2011. Article (CrossRef Link)

[32] S. Alghamdi, R. Van Schyndel, and A. Alahmadi, “Indoor navigation aid using active RFID and QR code for sighted and blind people,” *in Proc. Intl. Conf. Intelligent Sensors, Sensors Networks and Information Processing*, Melbourne VIC, Australia, pp. 18-22, Apr. 2013. Article (CrossRef Link)

[33] Y.-S. Chiou, F. Tsai, S.-C. Yeh and W.-H. Hsu, “An IMU-Based Positioning System Using QR-Code Assisting for Indoor Navigation,” Computer Science and its Applications, Lecture Notes in Electrical Engineering, Springer, pp. 655-666, 2012. Article (CrossRef Link)

[34] S. Ayub, X. Zhou, S. Honary, A. Bahraminasab, and B. Honary, “Indoor Pedestrian Displacement Estimation Using Smart phone Inertial Sensors,” *Int. J. Innovative Computing and Applications*, vol. 4, no. 1, pp. 35-42, 2012. Article (CrossRef Link)

[35] S. H. Shin, C. G. Park, J. W. Kim, H. S. Hong, J. M. Lee, “Adaptive Step Length Estimation Algorithm Using Low-Cost MEMS Inertial Sensors,” *in Proc. IEEE Sensors Applications Symposium*, San Diego, USA, pp. 1-5, Feb. 2007. Article (CrossRef Link)

Vinjohn V. Chirakkal received his B. Tech in Electronics and Communication from Christ University, Bangalore, India in 2013. He is currently pursuing his M.S. degree in the School of Electronics Engineering, Kyungpook National University, Daegu, Korea. His main area of research is in indoor navigation, computer vision and image processing.

Myungchul Park received his B.S. degree in electronics engineering and computer sciences from Kyungpook National University (KNU), Daegu, Korea, in 2013. He is currently working toward his M.S. degree in the School of Electronics Engineering, KNU. His research interests include indoor navigation and MIMO-OFDM.

Dong Seog Han received his B.S. degree in electronic engineering from Kyungpook National University (KNU), Daegu, Korea, in 1987, and his M.S. and Ph.D. degrees in electrical engineering from the Korea Advanced Institute of Science and Technology (KAIST), Daejon, Korea, in 1989 and 1993, respectively. From October 1987 to August 1996, he was with Samsung Electronics, Co. Ltd., where he developed the transmission systems for QAM HDTV and Grand Alliance HDTV receivers. Since September 1996, he has been with the School of Electronics Engineering, KNU as a Professor. He worked as a courtesy Associate Professor in the Department of Electrical and Computer engineering, University of Florida in 2004. He was director at the center of Digital TV and Broadcasting in the Institute for Information Technology Advancement (IITA) from July 2006 to July 2008. His main research interests include digital broadcasting and communication systems.