A Smart Phone Based PDR Solution for Indoor Navigation

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Biography

Dr. Ruizhi Chen is a Professor and head of department of navigation and positioning in the Finish Geodetic Institute. His received a MSc degree in computer science and a PhD degree in geodesy. He has worked for Nokia as an engineering manager during 1998-2001. His current research interests include smart phone positioning, mobile location based service and indoor navigation.

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Dr. Ling Pei received his Ph.D degree in test measurement technology and instruments from the Southeast University, China, in 2007, joining the Finnish Geodetic Institute (FGI) at the same year. He is a Specialist Research Scientist in the Navigation and Positioning Department at FGI, where his research interests include indoor/outdoor seamless positioning, ubiquitous computing, wireless positioning, context awareness and location-based services.

Abstract

Most smart phones are embedded with low-cost navigation sensors such as GPS receiver, accelerometer, digital compass, and gyros. In addition to these low cost sensors, RF signals from WLAN (Wireless Local Area Network), Bluetooth, RFID (Radio Frequency Identification) and cellular networks are also available in smart phones. With the embedded navigation sensors, especially the GPS receiver, it is not a challenging task to locate the smart phone whenever an open sky is visible. However, it is still a challenging task to locate smart phones in GNSS signal challenging environments such as indoors. Therefore, indoor positioning problem has become attractive to the scientific community. This paper introduces a PDR (Pedestrian Dead Reckoning) positioning solution for indoors, especially for corridor environments. The solution is based on a low cost accelerometer and a digital compass embedded in a smart phone (Nokia 6710) plus the low energy Bluetooth RF chip that has a potential to become a standard component in smart phones in the very near future. It is an instant solution that requires any training phases for e.g. establishing the step-length model and the heading error model. The positioning process is initiated automatically when the mobile user passing a Bluetooth access point, for example the one installed at the front door of a building.

Introduction

There are four types of positioning solutions applicable to smart phone: GNSS(Global Navigation Satellite System)-based solution; RAN(Radio Access Network)-based solution, positioning solution based on Signals of Opportunity from short range RF (Radio Frequency) technologies, and hybrid positioning solutions. The GNSS-based solution is a well-known solution that can be found from many text books e.g. Kaplan & Hegarty (2006). The positioning accuracy of 5-10 meters can be obtained easily with a low cost receiver embedded in smart phones when an open view to sky is available. However, the GNSS signal is a very weak signal, it is attenuated significantly or blocked totally in indoors because of the nature of radio frequency signal. Positioning accuracy for indoors with a high sensitivity receiver is one order worse (Lachapelle 2007). The positioning accuracy of the RAN-based positioning solutions is in the order of 50-300 meters (Zhao 2002; Bull 2009; Lakmali & Dias, 2008) that is not sufficient for guidance in indoors. Positioning solution of using Signals of Opportunity of the short range RF technologies such as WLAN (Wireless Local Area Network) and Bluetooth attracts a lot of attention for indoor positioning. The most common positioning approach is fingerprinting that can provide a positioning accuracy of 2-5 meters (Bahl & Padmanabhan, 2000; Youssef et.al. 2003; Roos et.al, 2002; Pei et.al. 2011).

Fingerprinting works in two phases: a data training phase and a positioning phase as mentioned above. The data training phase includes the steps of generating the fingerprint database (sometimes called "radio map") for the targeted area, while the positioning phase includes the steps of finding a location by matching the snapshot of the real-time RSSI (Received Signal Strength Indication) measurements to a RSSI tuple stored in database. The signal matching can be implemented in different approaches. The most common approaches are the pattern recognition approach and the probabilistic approach. For the pattern recognition approach, the matching is achieved by finding such a reference point from which the RSSI tuple stored in the database has the shortest Euclidian distance to the observed RSSI vector (Bahl & Padmanabhan, 2000). For the probabilistic approach, the matching is achieved by finding a maximum conditional probability that, for a given RSSI vector (observed), the user is located on the particular reference point (Pei et.al 2011).

The generation of the fingerprint database (or sometimes called radio map) is a tedious work that requires taking a huge number of RSSI samples at the reference points. Furthermore, the fingerprints in the database become invalid subject to the change of the ambient environment. This makes it difficult to deploy this approach to a wide scope of applications.

This paper introduces an instant PDR (Pedestrian Dead Reckoning) solution that does not require any training phase. It is based on the low cost sensors embedded in smart phone and a low energy Bluetooth device. Although the low energy Bluetooth device is not an embedded component in smart phone yet, it has a high potential to become a standard component in the near future because of its advantages of low cost, low power consumptions, fast discovering and almost unlimited client connections. Therefore, the solution proposed will be applicable to the future smart phone.

Methodology

As we known, the position of the pedestrian can be propagated with the following equations:

$$N_{k+1}=N_k+SL_k \cdot \cos a_k$$
$$E_{k+1}=E_k+ SL_k \cdot \sin a_k \qquad (1)$$

where N_k and E_k are the North and East coordinates, SL_k is the step length and a_k is the heading (azimuth) at epoch k.

As long as we know the initial coordinates, the length and heading of each step, we can estimate the trajectory of the pedestrian.

In our approach the initial position is determined by the pedestrian's proximity to a Bluetooth access point. It is identified by detecting the peak of the time series of the RSSI measurements for the duration of passing the transmitter as shown in Figure 1. It is based on the fact that the RSSI reaches its maximum value when the pedestrian is closest to the transmitter.

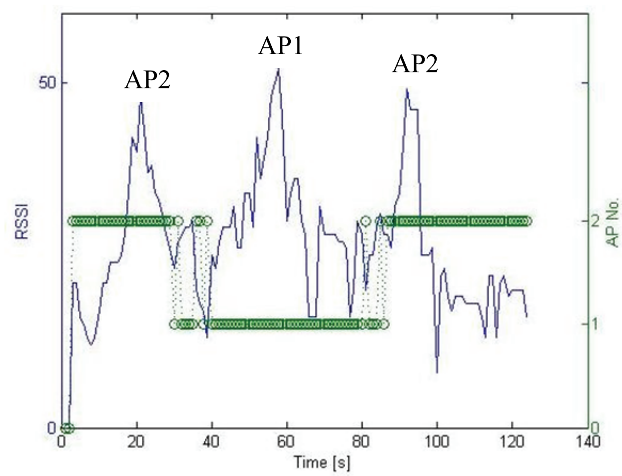

Figure 1. Peak detection of the RSSI measurements.

Step detection is needed in order to determine the step frequency, which is needed for estimating the step length, during the walking process. The cyclic pattern of the total acceleration is used to detect the steps. There are many approaches include zero-crossing (Beauregard & Haas, 2006; Käppi, Syrjärinne & Saarinen, 2001), peak detection (Fang et al, 2005; Ladetto, 2000), autocorrelation (Weimann & Abwerzger, 2007), stance-phase detection (Cho & Park, 2006), FFT (Levi & Judd, 1999), and a method of measuring the steps directly using sensors mounted on the shoes (Grejner-Brzezinska et al, 2007).

The peak detection approach is adopted in our PDR algorithm.

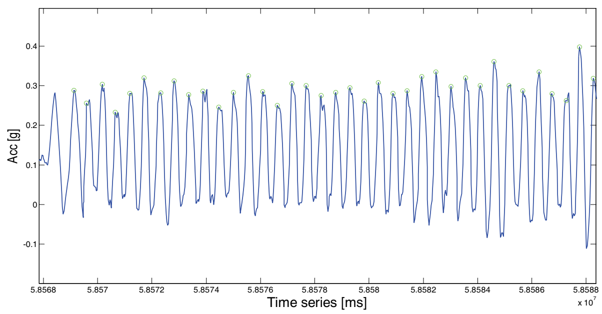

Figure 2. The cyclic pattern of the total accelerations during a walking process.

Step length is typically determined with a model. Different models have been proposed for this purpose. They can be grouped into four categories: constant/quasi-constant model, linear model, nonlinear model, and Artificial Intelligence (AI) model. Most of the models are established based on good correlation between the step length and some statistical features of acceleration, such as step frequency, maximum or minimum value per step, and variance per step. For example, the step length is proportion to the step frequency or walking speed.

In order to estimate the parameters in the model, a training phase is needed. For example, the model parameters can be estimated when GPS solutions is available. Step lengths estimated with the GPS solutions can be used as the samples for training the model.

Instead of training the model, we employ a empirical model for step-length estimation:

$$SL = \left(0.7 + a(H - 1.75) + b \cdot \frac{(SF - 1{,}79)H}{1.75}\right) \cdot c \tag{1}$$

where SL is the step length to be estimated, H is the height of the pedestrian, SF is the step frequency estimated in real-time with the measurements of the accelerometer. The coefficients $a=0.371$ and $b=0.227$ are two known parameters of the model; c is the personal factor that can be trained on-line. It is a parameter close to 1. In case no information available for training this parameter, the value 1 can be used for the approximation. The values of 0.7, 1,75 and 1,79 are constants representing the initial step length, height and step frequency. The model parameters a and b were estimated from 33 walking scenarios of 11 peoples on a surveyed baseline. The heights of the testers who contributed the step lengths for training the model range from 1.58 to 1.93 meters (5 women and 6 men). The minimum step length used for training the model is 0.56 meters, while the maximum step length is 0.86 meters.

The step length model can be used directly without any training samples in initial phase with a personal factor of 1. As mentioned above, the personal factor c can be calibrated on-line when travelled distances are available from other sources e.g. passing a path between two Bluetooth access points in our case. With the known distance between two access points and the step counts detected, the personal factor c can be estimated easily. The new personal factor will be employed immediately after the calibration.

As we know, the readings of the digital compass are affected significantly by the ambient indoor environments. The measurement error is typically in the order of a few tens of degrees. Therefore, positioning errors for the solutions of directly using the digital compass measurements are large. In our approach, the heading estimation utilizes the corridor layout information. The corridor segment is identified by a Bluetooth access point. Having identified the corridor segment, the two possible walking directions of A or $A\pm180$ degrees along the corridor can be classified by the readings of the digital compass (see also Ekahau 2007). For the cases with ambiguities while identifying the corridor segment, the heading will be obtained directly from the digital compass.

Having estimating the step length and the heading, the position can be propagated with Eq. (1).

Field Tests and Results

The performance of the proposed solution has been evaluated based on the field tests carried out in the office buildings of the Finnish Geodetic Institute. The test environment is a typical office environment with two long corridors. A round-trip walking distance is 156.2 meters as shown in Figure 3. Fifteen check points were surveyed along the corridors and used as the reference for assess the performance of the solution.

Two pedestrians with the heights of 1.71m, and 1.75m were involved in the test. Each tester carried out two walking rounds.

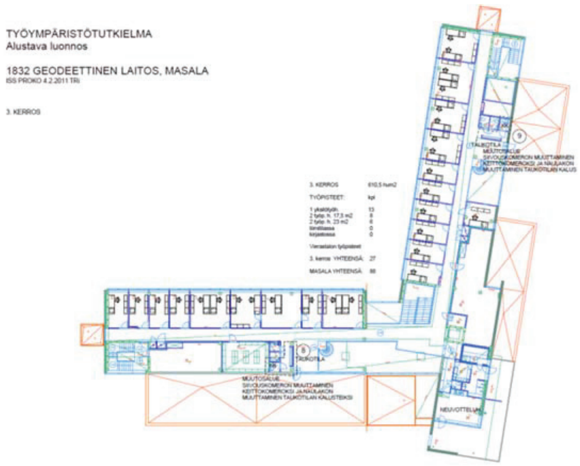

Figure 3. The test environments

In order to have more positioning solutions to evaluate the performance, the PDR solutions were initiated at one end of the corridor instead of being initiated by passing a Bluetooth access point. This assumption is valid and should have no impact to the performance assessment.

A personal factor $c = 1$ was used at the beginning for all test rounds. It is calibrated after passing two Bluetooth access points as the distance between two Bluetooth access points is known. The calibrated personal factor was then taken into use immediately. When the pedestrian walked passing the Bluetooth access point, the coordinates were calibrated as well with the known location of the corresponding access point. Therefore, the positioning errors are not propagated.

The empirical step-length model is accessed by the errors in travelled distances. It is 2.8% on average in terms of relative error in travelled distance as listed in Table 1.

Using the 15 ground checked points as the reference, the positioning accuracy of the PDR solutions can be estimated. The statistics of each test round are listed in Table 2. The maximum error distance is 4.79 meters while the minimum error distance is 0.22 meters. The average of the 2D position error distance for all four test rounds is 1.88 meters.

Table 1. Errors of the travelled distances estimated with the empirical step-length model.

Test Round	Estimated travelled distance	Error in meters	Error in %
1	164.6	8.4	5.4%
2	163.1	6.9	4.4%
3	156,0	-0,2	0,1%
4	158.4	2.2	1.4%
mean			2,8%

The true walking distance is: 156.2m

Table 2. The mean 2D position error distances of each test round.

Test round	Mean Error Dis.	STD	Max	Min
1	1,66	0,92	3,48	0,11
2	2,35	1,31	4,79	0,44
3	2,11	1,04	4,04	0,32
4	1,39	1,20	3,85	0,22
Average	1,88	1,12		

Conclusions

This paper introduced a PDR solution based on the embedded sensors in smart phones and the low energy Bluetooth devices. It is an instant positioning solution without any training phase by adopting an empirical model for step length estimation. The solution also applies the building layouts to constrain the heading estimation in corridor environments. The Bluetooth access points have been used to identify the corridor segments and to calibrate the PDR solutions. The solution has been evaluated by field tests of two pedestrians with two test rounds for each tester. The walking distance for each test round is 156.2 meters along corridors of a typical office environment. The performance of the empirical step length model is about 2.8% in terms of the relative error of travelled distance, while the accuracy of the PDR solution is 1.88 meters in terms of horizontal error distance.

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