EE327: Wireless Communication and Mobile Network Course Project Final Report

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Abstract—Location based service (LBS) is considered as a promising area in modern commercial mode. There are two existing problems for improving performance of LBS, the one is how to increase accuracy of indoor localization system and another is how to provide personalized service according to clients positions. In order to improve the accuracy of indoor localization, we proposed an improved algorithm, LSBPM, whose idea is mainly came up by **Wu Xudong** and **Shen Ruofei**. In our work, we combine iBeacon with inertial sensors and magnetic signals. Through experiments, we prove the effectiveness of our work, which has better performance than previous work.

Index Terms—Indoor Localization, LSBPM, Magnetic Signal, iBeacon

1 Introduction

With the rapid development of smartphones, people rely more and more on smartphones to simplify their daily life. Meanwhile, those powerful features provided by smartphones make it possible for people to get various services, especially some location based services (LBS), which is estimated more than $4 billion by 2019. Thus, indoor localization with high accuracy is of vital important and has become the key technology for market of LBS. Examples of LBS include navigation in airports and railway stations and pushing advertisements in shopping malls and museums. Users need know their own exact locations in unfamiliar scenes and service providers need know location context of every user in order to provide personalized services.

Up to now, GPS-enabled localization technologies achieve meter-level positioning accuracy in outdoor environments and bring tremendous benefits for location-based services market. But signals of GPS are weak or even not available in indoor environments, so indoor localization technologies are still an open research area and have attracted much attention in the past several decades. Although much effort from research community has devoted to studying indoor localization technologies, accurate localization is still very challenging in large open indoor environments, so performance of state-of-the-art LBS remains unsatisfactory.

Major existing work is mainly based on two different technologies, including fingerprint of radio frequency signals, the most representative one is WiFi, and mobility estimation using inertial sensors. Although WiFi fingerprint based indoor localization has been studied for years, its performance is still unsatisfactory especially under large open indoor environments. This is due to random signal strength fluctuation arise from inevitable multi-path effects, dynamical state of signal transmission channel, and transmission power control techniques of WiFi routers. The expensive energy consumption is another factor hides its usage because battery capacity in smartphones is small. The mobility estimation technologies using smartphones inertial sensors (accelerometer, gyroscope, magnetometer) neither work well in large open environments. That is because the freedom for user mobility is difficult

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to be characterized for the unstable human locomotion during walking. The accumulated errors in inertial sensing further undermine the fidelity of localization using inertial sensors.

Recently, Shu et al. present design and evaluation of a magnetic field based indoor localization and tracking system for smartphone users named MAGICOL[1]. Since the magnetic sensing consumes much less energy scanning than WiFI scanning, it is a useful idea to take advantage of magnetic signals for localization. In their paper, although their work get pretty performance in small environment, they meet problems in large open environment. As highly accurate indoor localization is essential to enable many location based services, a natural question to ask is: can we further improve the performance of the localization using magnetism in large open indoor environments?

In this paper, we show that using iBeacon (a kind of Bluetooth Low Energy) can improve performance of magnetic field based localization in large open indoor environments. iBeacon, which utilizes Bluetooth Low Energy (BLE), is proposed by Apple Inc to localize users accurately in the vicinity of pre-deployed iBeacon devices using both triangulation and trilateration. But the valid distance measurement range of iBeacon is only several meters. The functions of iBeacon is not only localization, but also as modules for many LBS such as mobile advertisements, ticket validation ,etc. So accurate localization using iBeacon only is impractical and wasteful and combining iBeacon with other existing localization technologies is necessary.However, how to use this combination for accurate localization in large open area remains unsolved. This problem is the first time solved in this paper.

We propose LSBPM ł an indoor localization system using iBeacon, inertial sensors and magnetism in large open environments. In LSBPM, a user's real time location is estimated according to the output of inertial sensors and the measurements of magnetic field sensing through an improved particle filter. When a user entering the vicinity of at least three iBeacon devices, location is calculated through triangulation and trilateration based on the received signal strength of iBeacon devices. We improve the algorithm of augmented particle filter to adapt to the great variation of magnetism in this scene. And we use iBeacon to ensure the errors of localization always in the acceptable range and reduce computational overhead of particle filter. We give the fundamental insight on iBeacon based localization system and analyze its advantages and limitations. Then we show how to make use of iBeacon devices solving heading offset problem(user's heading direction may be different from phone heading), which hides any inertial sensor based localization system.

We have implemented real-world experiments in the library of Shanghai JIao Tong University, which contains a large services hall with crowded people in its first floor. Comparing with commonly used dead reckoning and fingerprint based localization systems, we demonstrate that LSBPM achieves higher accuracy than existing works.

The remainder of the paper is organized as follows. Section 2 presents related work. Section 3 illustrates design of LSBPM. Section 4 presents our contributions of improving systems robustness using iBeacon devices. Section 5 presents experimental setup and results. The conclusion remarks and future work are provided in Section 6 and Section 7. Finally, I will introduce another two work I have participated in within the indoor localization group during this semester in Appendix.

2 Related Work

THIS paper combines iBeacon devices, magnetic field sensing and inertial sensors for indoor localization. Indoor localization and location-based services are extensively studied topics. There have been many works on using sensor fusion and magnetism for localization . We only discuss closely related work in this section.

2.1 Sensor Fusing Approaches for Indoor Localization

The design rational for sensor fusion is that mobility estimated by inertial sensors is by nature related to location in the physical world[2], and a position is characterized by its detected fingerprint of signal patterns (received signal strength(RSS) from different WiFi APs)[3]. Integrating mobility and fingerprint can restrain the localization errors from sensor measurement noise and fingerprint variation, some existing works uses the integration through particle filter to improve accuracy[6], [7], [8]. GIFT[4] is a system using the spatial correlation of WiFi signal as location feature. A gradient-based fingerprint map (Gmap) is constructed by comparing absolute RSS values at nearby positions.Users' motion and WiFi RSS observations are combined using an extended particle filter. Particles are driven by detected motion and their weights are determined by comparison results between RSS observations and Gmap. Using gradient of WiFi signal can handle the changing transmission power of APs and devices diversity problem (different devices may have different measurements for same WiFI signal). SLAC[5] is a system that fuses step counter and WiFi fingerprints to optimize location estimations, wireless signals and user motion jointly using a specialized particle filter. It learns parameters in user step mode (the relationship between step length and stride frequency), calibrates RSS measurements due to heterogeneous devices and, simultaneously estimates the location of walking target by solving a convex optimization problem. However, existing works cannot achieve satisfactory accuracy in large open area due as wireless signal is vulnerable to changing environments and crowded people. The high probability for RSS deviation may change the RSS gradient and the parameters learning may be error-prone. The computational overhead for solving a convex problem is large, so SLAC is unable to serve many users.

2.2 Magnetism-based indoor Localization

The magnetic filed is omnipresent and, due to the fluctuations arise from steel, concrete structures and electric systems, nonuniform in indoor environments. The location specific magnetic field readings are stable over time and magnetic sensing consumes little energy, so leveraging magnetic filed as locations signatures for indoor localization is workable[1], [9], [11]. J Chunget al. designed a geo-magnetism based localization system in[10], which estimates users' locations by comparing magnetic field measurements with a pre-established magnetic fingerprint database. The system uses magnetic fingerprint only, so that the sensing noise dominates the localization errors. And this system command magnetic sensor keep same orientation all the time, which is impractical for pedestrian tracking. FollowMe[12] is an novel indoor navigation system based on magnetism. In trace collection module, it records the leader's walking trace (inertial sensors' readings) from a origin to a destination and magnetic fingerprint along the trace. In navigation module, it estimates follower's location by matching magnetic measurements and then generates navigation notification according to user's position on restored walking trace. However, in large open area, the trips to a same destination are too diversity to be collected completely and users are easily get lost for large magnetic sensing noise. Above reasons hinder FollowMe's usage in airports, museums and large shopping malls etc.

In LSBPM, we use the magnitude of the magnetic signal only which is independent from phone orientation. We consider the magnetic field sensing noise and then enhance traditional particle filter against the problem. We further use iBeacon devices to approach errors accumulation problem and restrain computational overhead in localization process.

3 Our Method – LSBPM

In this section, we first describe the details of previous work, MAGICOL, and the existing defects of it. Then we will introduce our improved work, LSBPM, and give a certain condition where we can guarantee a better performance.

3.1 MAGICOL – Existing Defects

Recognizing that indoor geomagnetic field anomalies are omnipresent, location specific, and temporally stable, the work proposed by Shu et al.[1] leverages the locally disturbed magnetic signals as location-specific signatures and a location database is built offline with mappings between magnetic signals collected by magnetometer on smartphones and their locations. The localization process is realized through an augmented particle filter in which the similarity between the magnetic signal collected online and that in database is used to weigh particles. In particle motion model, map information and inertial sensors are used to drive particles. The whole process is shown in Algorithm.1.

Algorithm 1: *Particle Filter of MAGICOL*

Input:
  Online Mapping $\overline{X}$,
  Offline Mapping $\overline{Y}$,
  Particle Set M,
  Iteration Number T
Output:
  Real Position P,
  Estimated Position P_0
Initial Position P = $P_0 \longleftarrow Origin$;
Initial Weight Set $W \longleftarrow$ [1, 1, ..., 1];
Initial Estimation Set $E \longleftarrow [Origin, Origin, ..., Origin]$;
Initial iteration $itr \longleftarrow 0$;
while $itr < T$ **do**
  $P \longleftarrow P + RandStepLen$;
  $S \longleftarrow \overline{X}[P]$;
  for $i < Size(M)$ **do**
    $E[i] \longleftarrow E[i] + M[i]$;
    $S_0 \longleftarrow \overline{Y}[E[i]]$;
    $W[i] \longleftarrow exp(-||S - S_0||_2^2/10) \times W[i]$;
  end
  $W \longleftarrow \sum_{i=1}^{n} W[i]$;
  for $i < Size(W)$ **do**
    $W[i] \longleftarrow W[i]/W$;
  end
end
$P_0 \longleftarrow P_0 + \sum_{i=1}^{n} E[i] \times W[i]$;

As they mentioned, MAGICOL can achieve localization accuracy of 0.9m for tracking in the office environment, but only 8m in supermarkets. This is because in large indoor open environments with high human beings density, characterizing user movements is difficult, magnetic measuring noise is large under the influence of smartphones and other electronic devices, and errors accumulation of particle filter is unavoidable.

3.2 LSBPM – Improved Algorithm

In MAGICOL, they only use the similarities between online and offline fingerprints to weigh particles for their particle filter, which can be regarded as a kind of posterior probabilities. However, they didn't consider the empirical features of human step lengths and angles measured by inertial sensors, which have impact on the calculation to some degree.

Therefore, we modify the previous work and propose an improved particle filter. This idea is mainly came up by **Wu Xudong** and **Shen Ruofei**. Here the mainly contribution of our algorithm is to consider the prior distribution of human step lengths as well as the turning angles measured by gyroscope. Specifically, we assume that both of them follow the Gaussian distributions:

$$StepLength \sim Gaussian(0.6, 0.18)$$
$$MeasuredAngle \sim Gaussian(\pi/4, \sqrt{\pi/18})$$

The whole process is shown in Algorithm.2.

3.3 Condition

Although the introduction of prior do great help to the improvement of localization accuracy, it is not always effective. Because of trace error accumulation, the reliability of prior will also decrease with the increasing distance humans make up. Thus, the better performance of our work will be guaranteed under a certain condition. Here we will give a simple proof.

The weights calculation in MAGCOL can be simply represented as $P_{posterior}$, while the weights calculation in our work can be represented as $P_{posterior} \times P_{prior}$, and what we want to find is the condition making errors meeting:

$$E[P_{prior} P_{posterior}] < E[P_{posterior}] \quad (1)$$

By inquality:

$$E[P_{prior} P_{posterior}] <= \sqrt{E[P_{prior}^2]} \sqrt{[P_{posterior}^2]} \quad (2)$$

Algorithm 2: *Particle Filter of LSBPM*

Input:
  Online Mapping $\overline{X}$,
  Offline Mapping $\overline{Y}$,
  Particle Set M,
  Iteration Number T
Output:
  Real Position P,
  Estimated Position P_0

Initial Position $P = P_0 \longleftarrow Origin$;
Initial Weight Set $W \longleftarrow$ [1, 1, ..., 1];
Initial Estimation Set $E \longleftarrow [Origin, Origin, ..., Origin]$;
Initial iteration $itr \longleftarrow 0$;
while $itr < T$ **do**
  $P \longleftarrow P + RandStepLen$;
  $S \longleftarrow \overline{X}[P]$;
  for $i < Size(M)$ **do**
    $E[i] \longleftarrow E[i] + M[i]$;
    $S_0 \longleftarrow \overline{Y}[E[i]]$;
    $W[i] \longleftarrow exp(-||S - S_0||_2^2/10) \times W[i]$;
  end
  $W \longleftarrow \sum_{i=1}^{n} W[i]$;
  for $i < Size(W)$ **do**
    $W[i] \longleftarrow W[i]/W$;
  end
end
$W_1 \longleftarrow Gaussian(M.step, o.6, 0.18)$;
$W_2 \longleftarrow Gaussian(M.angle, \pi/4, \sqrt{\pi/18})$;
$W \longleftarrow \sum_{i=1}^{n} W[i] \times W_1[i] \times W_2[i]$;
for $i < Size(W)$ **do**
  $W[i] \longleftarrow W[i]/W$;
end
$P_0 \longleftarrow P_0 + \sum_{i=1}^{n} E[i] \times W[i]$;

Thus, we have the following relation:

$$\begin{aligned} \sqrt{E[P_{prior}^2]}\sqrt{[P_{posterior}^2]} &< E[P_{posterior}] \\ \sqrt{E[P_{prior}^2]}\sqrt{pa^2]} &< pa \\ \sqrt{E[P_{prior}^2]} &< \sqrt{p} \\ E[P_{prior}^2] &< p \end{aligned} \tag{3}$$

where p represents the probability of fingerprint fluctuation.

Thus the condition is: **The mean squared error (MSE) is less than the probability of fingerprint fluctuation.**

In order to meet the condition, we use iBeacon to assist localization, which will be discussed specifically in next section.

4 Assistant Localization – iBeacon

In this section, we give the fundamental insight on localization using ibeacon. We first introduce LBS systems based on iBeacon devices, and then explain how to use iBeacon-based localization in our work to improve localization accuracy.

4.1 Introduction of iBeacon

iBeacon is announced by Apple Inc in 2013 as a new technology for accurate indoor localization. A great advantage of iBeacon is its low power consumption for utilizing BLE (the forth major revision of the Bluetooth specification), so it is applicable to mobile usages. Most smartphones which run on Apple iOS 7+ and Android 4.3+ operation systems all support iBeacon protocol[13]. iBeacon devices are designed to work as an important module in location-context-aware systems. Taking museum as an example, a visitor comes into a museum, his smartphone receives broadcast packets transmitted by iBeacon devices deployed at entrance. The packets contains the URL for ticket purchase, then visitors can buy ticket through the URL instead of queueing for manual ticket. When visitors want to learn more knowledge about an exhibit, they can obtain the transmitted packets from the iBeacon devices around through a manner similar to WeChat shake. They can also finish choose and payment in souvenir retail stores conveniently with the help of iBeacon devices. These applications are also in demand in large shopping malls to, airports and cinemas etc. Therefore, iBeacon based LBS systems can improve effectiveness of business management and lower commercial cost especially labor cost.

4.2 Localization Using iBeacon

In order to reduce the influence of error accumulation, we need the help with iBeacon technology. Since iBeacon can get pretty good performance in short-distance localization, which

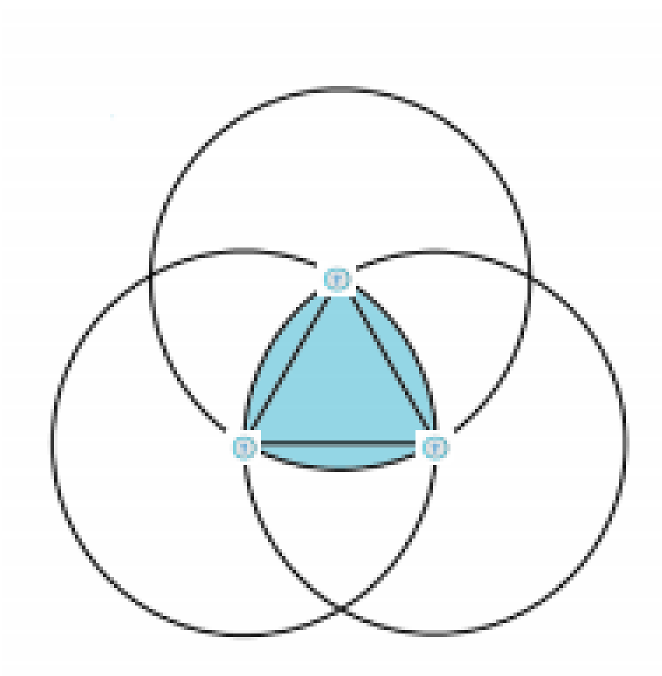


Fig. 1. Traingulation & Trilateration in iBeacon

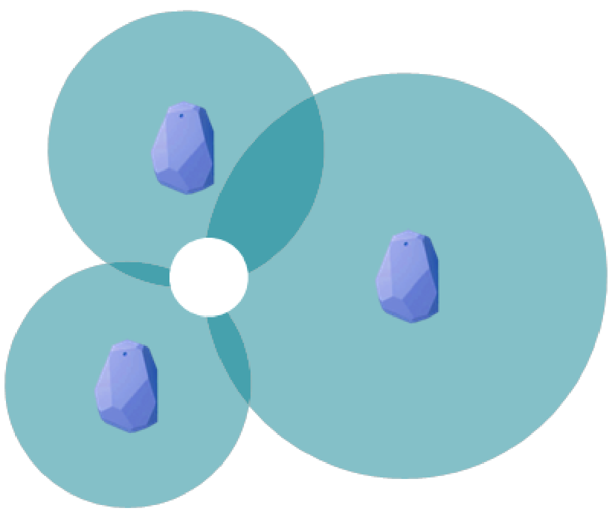


Fig. 2. Example of iBeacon Localization

is almost the state-of-the-art, it can eliminate accumulated errors when users approach iBeacon nodes.

With the help of pre-deployed iBeacon devices, we can measure the distances to three nodes. And then we use triangulation and trilateration as Fig.1. Through gradient descent algorithm, we can get users' accurate locations as Fig.2. By this assistant localization, we can fix accumulated errors and restore the reliability of prior probabilities.

5 Experiment

In this section, we will give a brief explain about data acquisition and process of simulation. Finally we will analyze the results drawn by experiment.

5.1 Data Acquisition

For experimental data acquisition, we measure magnetic signals in the first-floor services hall and Room-B200 of the school library of *Shanghai Jiao Tong University*, just as Fig.3 shows.

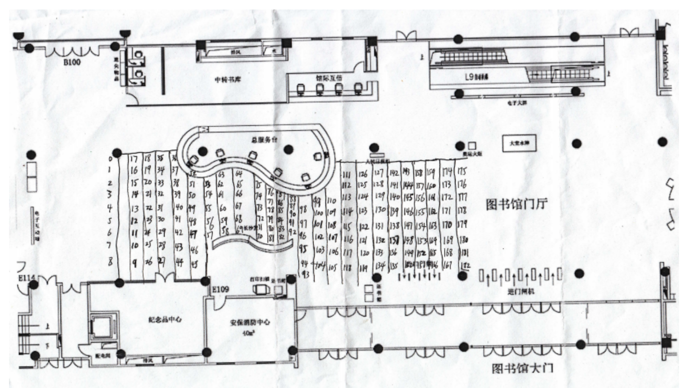
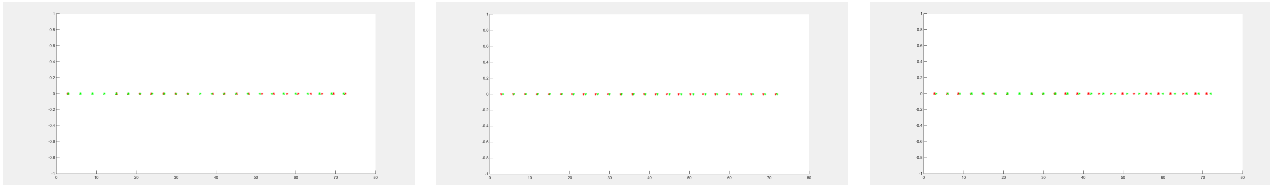


Fig. 3. Plan of First-Floor Service Hall of School Library

Meanwhile, we also measure step length of 50 different students in order to analyze the average step of human and the distribution that step-lengths follow.

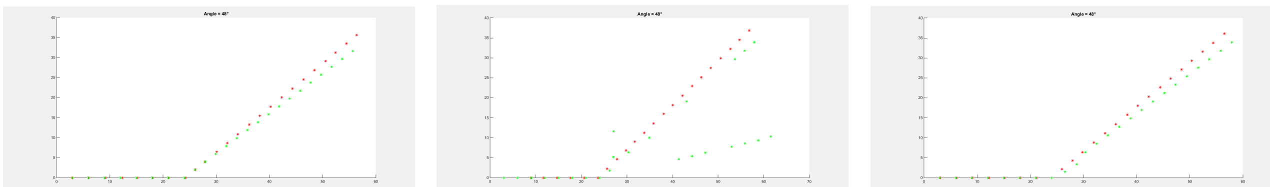
5.2 Simulation

In order to test the performance of our work, we use **MATLAB** to write programs to simulate the whole process. In the simulation, we generate real positions by step lengths chosen randomly between 0.5m and 0.7m, and angles chosen randomly between $\pi/6$ and $\pi/3$. We give an example of our simulation results as Fig.4 and Fig.5.



(a) Naive (b) MAGICOL (c) LSBPM

Fig. 4. The Simulation of 1-Dimensional Case: a)Naive Algorithm; b)MAGICOL Algorithm; c)LSBPM Algorithm



(a) Naive (b) MAGICOL (c) LSBPM

Fig. 5. The Simulation of 2-Dimensional Case: a)Naive Algorithm; b)MAGICOL Algorithm; c)LSBPM Algorithm

5.3 Result Analysis

By simulation, we can get real positions and related estimated positions. In order to show effectiveness of our work more persuasively, we do experiments repeatedly and calculate average errors by different algorithms. The results are shown as Table.1:

	Naive	MAGICOL	LSBPM
1-Dimension	0.8856	0.8444	0.8155
2-Dimension	16.9643	7.1647	3.1653

TABLE 1
Average Errors of Different Algorithms

By analysis, we find that all three algorithm get similar performance in 1-dimensional case, all less than 1m. However, when we focus on 2-dimensional case, more close to reality, our work performs the best, with radial distance within 4m. That' s enough to prove that our work is really effective.

6 Conclusion

In this work, we propose a new improved algorithm mainly based on magnetic signals as well as iBeacon and inertial sensors for large open environment. Here we estimate user's real-time location by output of inertial sensors and we design an improved particle filter for magnetic field sensing. Besides, we solve the problem of error accumulation by iBeacon assistant nodes. By experiment, we have proved the effectiveness of our work and its better performance for large open area, compared with previous works.

7 Future Work

Although the results of **MATLAB** simulation show a better performance of our work, it doesn't mean that the effectiveness of our work has been proved. After all, there is still a gap between theory and reality, not to mention applying to practical. In the next stage, we consider to porting our algorithm to the Android platform to test its effectiveness. Thus, we need to consider the limitation of battery energy and computational cost. Besides, we can apply it to our indoor localization project for the school library of SJTU or the Foxconn factory to get better performance.

Appendix A
Code Refactor

THE first work I want to introduce is about code refactor for our indoor localization project for school library of *Shanghai Jiao Tong University*. What I am mainly responsible for is the part related to BLE information and map information. Although it seems a little simple, it is a good chance for me to learn about the whole process of our project, especially the working principle of BLE and some implemental tricks.

For example, when we use BLE to help navigation, we must rely on the value of received signal strength (RSS). We assume that the effective range of BLE node covers a circular surface and the signal strength increases with the distance to BLE node decreasing. Thus, the signal will lead users to approach the predeployed device. But when the user walk into the range holding the smartphone, he/she may be stuck into the circle because of the local maximum RSS. In order to avoid this case, we will set the RSS of current BLE node be zero for the next scanning of smartphone until the user leave the range of current node. In other words, we will disable the current node temporarily to avoid local optimal case.

APPENDIX B
PEDOMETER OPTIMIZATION

ANOTHER work I did in the indoor localization group is about pedometer optimization, in collaboration with Han Yutong and Zhang Jialu. What I am mainly responsible for is to analyse the data collected by mobile phone accelerometer. With the help of **MATLAB**, we deal with the collected data in time domain and get the corresponding acceleration-time figure, just as Fig.6 and Fig.7. And the related code can be found at my github website: *https://github.com/EricXingSJTU/Pedometer-Analysis*.

B.1 Existing Defects

For general Android pedometer in the market, the common index for counting steps is the peaks of acceleration and the algorithm based on peak detection becomes a industry standard. However, popularity doesn't represent its

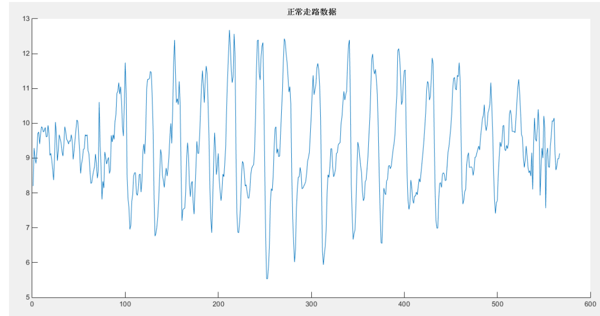


Fig. 6. The Acceleration-Time Figure of Normal Walking

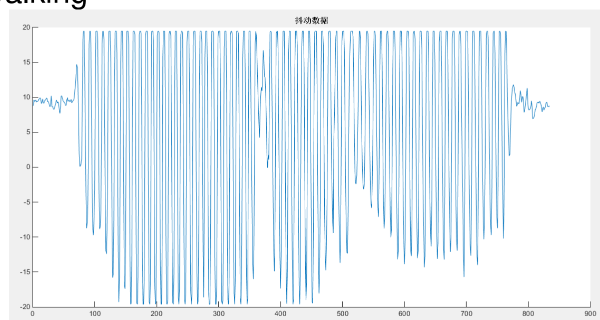


Fig. 7. The Acceleration-Time Figure of Shaking

effectiveness and accuracy. According to the figure we drawn, we find that there exists some inevitable slight jitters even during normal walking, which will impact on the counting more or less. Thus, the primary task is to find methods to reduce the influence of the jitters.

B.2 Feasible Solutions

Here we mainly propose some strategies which seem simple but are useful to some degree.

Firstly, it is obvious that the jitters can be eliminated by making the waveform more smooth and we can set a sliding window to smooth the data by moving average. We have tried different window size and compared them as Fig.8.

By comparison, we find that it can get pretty performance when size is equal to 4.

Secondly, we can set a sample threshold in time domain to filter the useless data. But the value of threshold is strongly relevant to walking frequency. Although we measured data with different walking frequency, we cannot find the most reasonable threshold suitable for all cases.

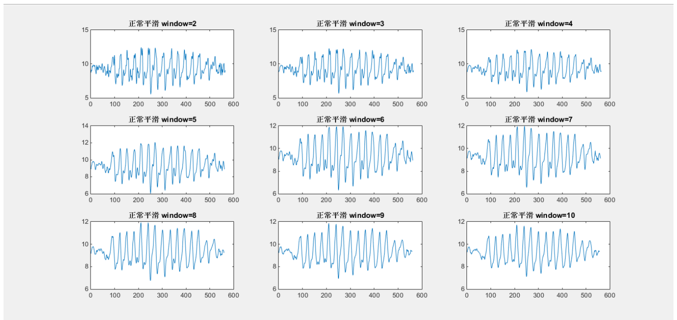


Fig. 8. Figure of Smoothing Results with Different Window Size(size = 2, 3, 4, ..., 10)

Finally, also the most interestingly, we find that there exist similarities between data waveform and stock market quotation. According to [14], combining the analysis of K-line in stock where points above average may be the peak while points below average may be a trough, we can set sample points every fixed interval as 'trading day': If two consecutive 'trading days' are above average, there may be a peak because of the rising trend; If two consecutive 'trading days' are below average, there may be a trough because of the downward trend. We have not applied it to our pedometer and proved its effectiveness, but I think it provide a new idea at least.

The research about this issue is far from over. Up to now, we just have used single-axis acceleration to count steps, but we believe that it can get better performance combining three-axis accelerations[15], [16], and we will focus on it in the future.

Acknowledgments

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