Sigma J Eng & Nat Sci 8 (2), 2017, 175-182

Publications Prepared for the Innovations on Intelligents Systems and
Applications Symposium ASYU 2016
Akıllı Sistemler ve Uygulamalardaki Yenilikler Sempozyumu
ASYU 2016 için Hazırlanan Yayınlar

Research Article / Araştırma Makalesi

STEP COUNTING USING SMARTPHONE ACCELEROMETER AND FAST FOURIER TRANSFORM

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Received/Geliş: 12.12.2016 Accepted/Kabul: 13.12.2016

ABSTRACT

This paper suggests an easy to implement and battery friendly method to Step Counting problem, which is based on Android smartphone accelerometer, Fast Fourier Transform (FFT) and thresholding. The method, after applied preprocessing and FFT to the data gathered from smartphone's accelerometer (16hz), detects and counts steps by comparing the data to predefined thresholds. The predefined thresholds were specified by analyzing the accelerometer data obtained while users were sitting, standing, and walking. User experiments were conducted to test the method. Results showed 87.52% success for walking. Additionally, for sitting and standing the method had a success over 99%, as expected. And for running, only 41.7% of the steps were correctly counted.
Keywords: Step counting, walk detection, pedometer, smartphone, accelerometer.

1. INTRODUCTION

Smartphones, as well as plenty of appealing features, come with various embedded sensors, including gyroscope, accelerometer, magnetic field, etc. These sensors provide valuable information about users' context and activities [14, 10] and have been attracting attention of researchers from Ubiquitous Computing, Context-aware Computing, Biometric Identification and Medicine, in recent years.

Some of the important research areas taking advantage of smartphone sensors are Fall Detection [11], Indoor Location Tracking and Pedestrian Dead Reckoning [14], Activity Monitoring [10, 12], Health Monitoring [14], Gait Analysis [15], Walk Detection [14] and Human Motion Recognition [13]. Additionally, Step Counting (SC) using smartphones has emerged as an intriguing research topic in the last few years [16].

As a result of health advices, like "daily step goal of 10,000 steps", people would like to know the number of steps they take a day [1, 2]. Or, they want to have the statistics about their steps during or after sport activities such as walking or running. SC might also lead to a diverse set of applications by providing personalized support, including indoor navigation [16].

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In this study, we suggest a method for step counting using android smartphone accelerometer and Fast Fourier Analysis. The method is threshold based and therefore easy to implement and can be suggested as battery friendly.

The rest of the paper is organized as follows: Section 2 give some background information about smartphone sensors and summaries previous related studies about step counting. Section 3 introduces the suggested method and present the experimental methodology. And finally, while Section 4 encompasses results and discussion, Section 5 includes conclusions, outcomes and directions for future research.

2. BACKGROUND AND RELATED STUDIES

Step Counting (SC) means automatically detecting and counting steps taken by a human. It can be considered as a sub problem of human motion analysis or better walking detection and gait analysis. SC were realized once using steel ball movement. Later, more reliable and electronic devices called pedometers were used and are still in use especially in medical applications [16]. Pedometers are attached on waist, foot or arms.

In recent years, SC has become an intriguing research problem with the ubiquity and availability of smartphones equipped with various sensors, including gyroscope and accelerometer.

Gyroscope is used to measure the angular velocity and accelerometer is used to measure the acceleration [8]. Both sensors are suitable for motion analysis and step counting but accelerometer is more popular since its ability detect motion and the rate of change in motion speed.

Smartphone has certain advantages for SC and its applications. First, they are ubiquitous. Almost every people have one and carry at least one all the day. And, they have easy programming interface and large storage and processing capabilities, as well as Bluetooth, Wifi, and cameras.

Yet, smartphones have their own disadvantages: Battery life has been always a problem with smartphones, and studies addressing this problem already exist [16]. Moreover, people carry them all the day but they carry freely in their hands, pockets, or bags. They also continuously manipulate them and use for many different purposes from talking and internet surfing to game playing. In other word, it’s not easy to talk about a specific place on human body and stability for smartphones.

Various researchers have examined the SC problem so far. Lin et al. [8] suggested a decision tree based method using gyroscope and magnetic field sensors, as well as accelerometer. They classified tree different gait patterns, walking ground, up stair and down stairs and counted steps with a %89,4 success. The method was also able to discard irrelevant motions.

Seo et al. [16] presented a step counting algorithm for Android smartphones. The algorithm was based on zero crossing scheme and liner regression. They also stressed on subject dependency and preserving battery life in their study. The study reported 90.63% accuracy for subject dependent case and %91.09% accuracy for subject independent case.

Another study by Vyas et al. [9] reported %91,5 success using an arm mounted, commercial and advanced physiological signal measurement device and machine learning techniques.

Brajdic at al. [14] examined the SC problem with a wider perspective. With a large subject group, they evaluated various SC algorithms applied to smartphone sensor data. They also looked for optimal smartphone placements and algorithms. Brajdic at al. [14] reported that standard deviation thresholding and windowed peak detection had error rates less than 3% and, among six phone placement, only the pants back pack degraded the step counting performance significantly.

Das et al. [10] draw attention to a different topic in their work. They discussed security issues related to sensors embedded in smartphones and look for if those pose a security threat [10]. Sensors, with proper techniques, provide valuable and sensitive information about user activities, which could also be a privacy issue. The problem here is realted to Android system. The system normally requests permission from users for the usage of many sub systems and embedded devices, including contact list, galleries, cameras and Wifi. But it does not require permission for the use of any available sensors [10].

3. METHOD

3.1. Equipment

A General Mobile 4G smartphone with Android 6.0.1 operating system and Bosch accelerometer sensor (16hz) was used in the experiments. Android programming was realized using Android Studio IDE.

3.2. The Algorithm

The step counting method suggested in this study uses an algorithm based on thresholding the data gathered from smartphone accelerometer. But the thresholding is not directly applied to the data obtained from the sensor. Instead, the data is first preprocessed and then Cooley-Tukey Fat Fourier Transform is applied [4].

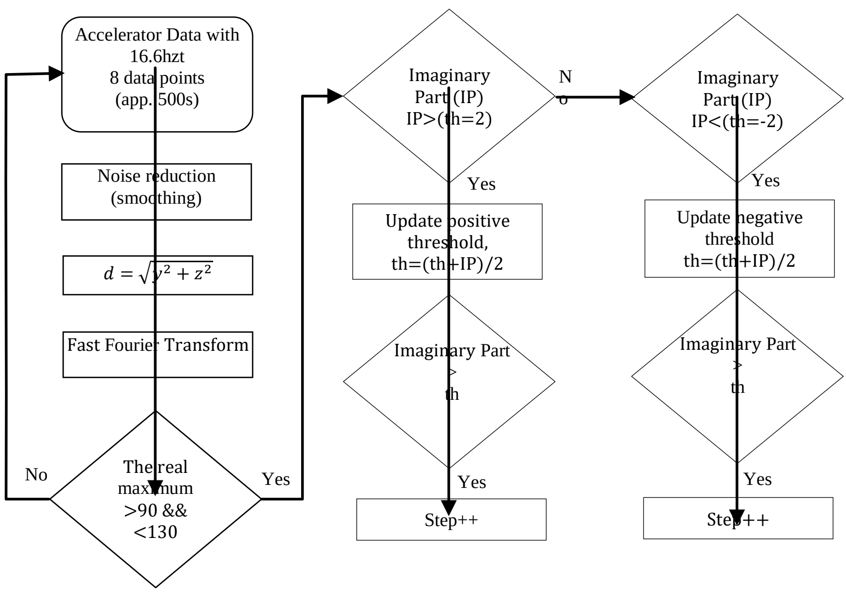

Figure 1. Step counting algorithm

Accordingly, the algorithm has four stages: Buffering, Preprocessing, FFT and Thresholding. At the buffering stage, the algorithm first gather data during approximately 500ms for further processing. Since the sensor produces data at approximately every 60ms, 8 consecutive measurements or data points are used for analysis or step detection each time.

At the preprocessing stage, the data is first smoothed for noise reduction. Then the smoothed data is merged as follows: The smartphone accelerometer produces 3D data in x (lateral), y (longitudinal), and z (vertical) axes. To simplify the computations and these are usually merged using equation (1) [8-10]. In our study, y and z data were found enough and merged using equation (2) (see Figure 2).

$$d = \sqrt{x^2 + y^2 + z^2} \tag{1}$$

$$d = \sqrt{y^2 + z^2} \tag{2}$$

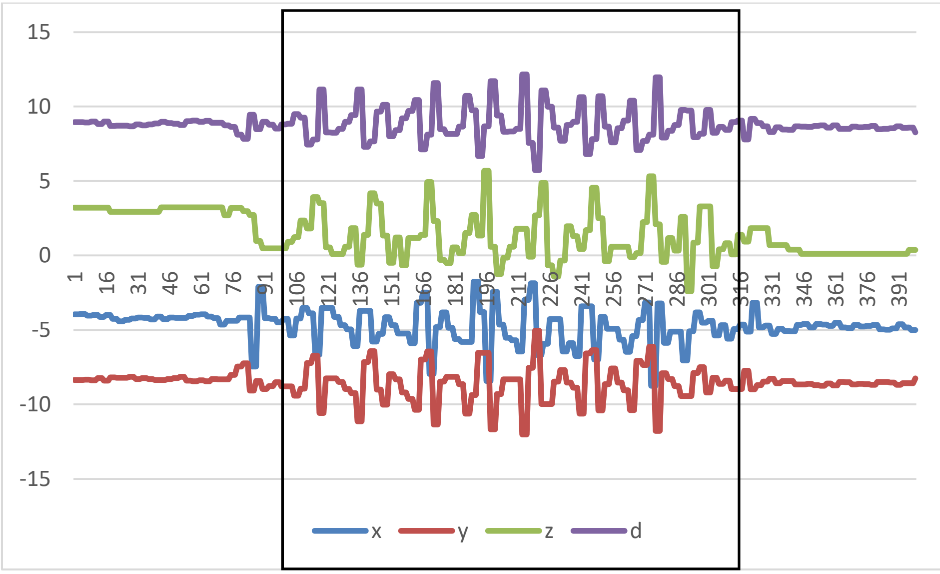

Figure 2. Accelerator data for standing, walking (black box) and sitting. Line,s denotes from top to bottom, d, z, x and y.

After that, the preprocessed data is applied Fast Fourrier Transfrom (FFT). FFT converts a signal from its original domain (often time or space) to a representation in the frequency domain and vice versa [4-7]. It detects periodic signals and split them into harmonic components. Practically, FFT produce 2^n converted complex numbers as a result of given 2^n complex numbers, (see Figure 3 and 4).

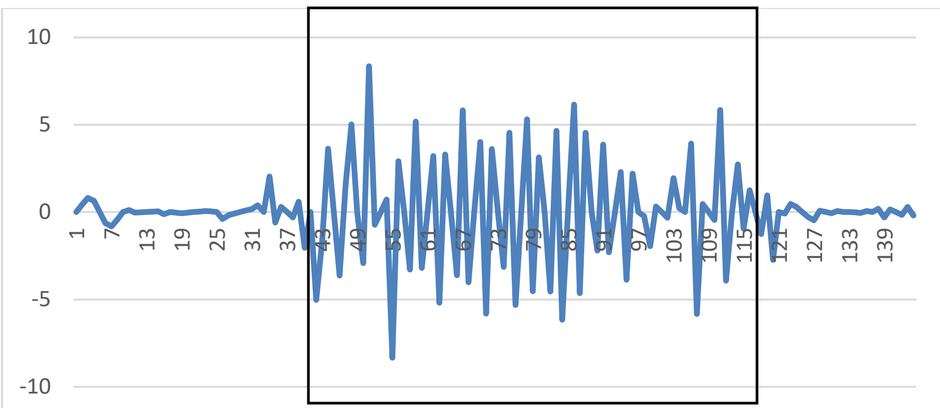

Figure 3. Imaginary part of the converted data with FF for standing, walking (black box) and sitting.

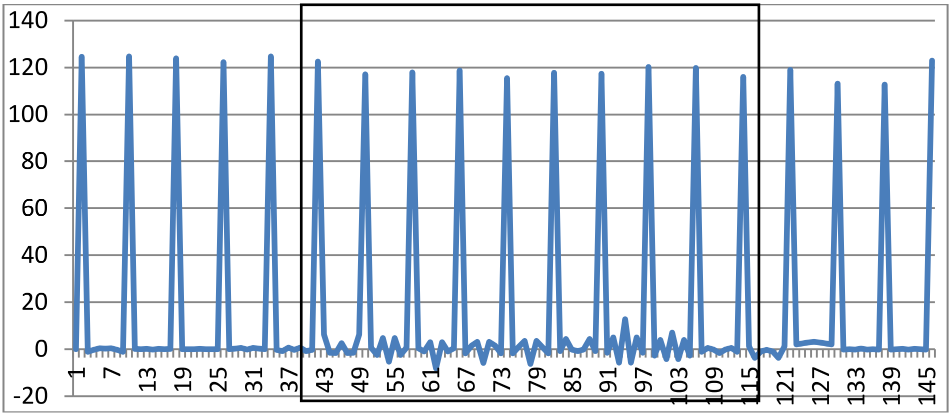

Figure 4. Real part of the converted data with FF for standing, walking (black box) and sitting.

At the final stage the algorithm applies thresholds to the converted data. Since the converted data at previous stage are complex, different thresholds are used for its real and imaginary parts. The thresholds are [90, 130] for real maximum. And 2.0 (leg is forward) and -2.0 (leg is backward) are for imaginary part. These thresholds were determined before the experiments as a result of user studies by analyzing the data while the phone is on a table; a person sits, stands and walks; and the phone is in the pant front pack in a vertical position.

Actually, in our study, what defines a step ia the thresholds. If the real maximum of data is in [90, 130] interval, the first condition of a step is fulfilled and the imaginary part of the data is looked at, otherwise it's neglected. Once the real maximum condition is fulfilled, finally, the algorithm checks the imaginary parts against the related thresholds and accordingly, increase step number or not.

While taking steps, the leg is normally in a forward or backward motion. We observed that when the leg is forward motion, the imaginary parts of all the data points should be greater than 2. And, when the leg is in backward motion, all the points must be smaller than -2.

But practically, we noticed that updating the thresholds of imaginary part gave better results. For that reason, after the first check of imaginary part with 2 or -2, we update the thresholds by taking the average of the current and previous thresholds. We think that this might be because of personal or physical differences of humans or the slope of the ground.

3.3. Participants

6 people (3 males, 3 females and average age is 26,5) participated in the experiments.

Figure 5. The experiment area and a participant (male, age:26)

3.4. Procedure

All the experiments were realized on a straight road, as shown in Figure 5. Participants completed respectively the four test stages: sitting, standing, walking and running. Each stages took approximately 30s.

In sitting stage, participants were asked to sit on a chair and to make movements such as crossing and stretching legs for the purpose of producing interference. During standing stage, participants are asked to stand and also to swing their legs, similarly.

Participants carried the smartphone in one of front pants pockets in a vertical position. They were left free about other details of the smartphone position in pocket, such as being upside down or not, and asked to behave habitually as much as possible.

4. RESULTS AND DISCUSSION

As shown in Table 1, the proposed method yielded %99.85 success for sitting, %99.7 success for standing, %87.52 success for walking and %41.7 success for running.

Table 1. Test Results

			Walking			**Running**		
Age	**Sex**	**Height**	**Computed Step Count**	**Real Step Count**	**Success (%)**	**Computed Step Count**	**Real Step Count**	**Success (%)**
23	M	169	202	173	83,2	29	77	37,7
26	M	176	214	180	81,1	47	103	45,6
52	M	168	213	177	79,7	65	110	59,1
20	F	165	199	193	96,9	32	94	34,0
21	F	166	191	175	90,9	35	100	35,0
17	F	160	176	165	93,3	38	98	38,8
				Average:	87,52		**Average:**	41,70

We observed that steps falsely counted for motions other than taking step are caused by motions of putting the smartphone in pocket or taking it out. For running, we think that the reason that the success rate of running is lower than walking is that the thresholds are specified for walking. Since the increase in step taking speed and the leg's getting higher during running compared to walking requires different thresholds for better step counting. Particularly, the imaginary part of the converted data part is altered with running. Moreover, the results show 90% success rate for females. We think that this is because that our method is sensitive to human height or physical differences.

5. CONCLUSIONS

In this study, a simple method with proper success was suggested for step counting problem using Android smartphone. The method is based on thresholding the data gathered from accelerometer sensor, after the data was preprocessed and applied Fast Fourier Transform.

User experiments showed that the method is promising for step counting and can be used at daily applications needing step counting. It's simple and easy to implement, and therefore, can be said that battery friendly. Although, its (87.52) success is lower compared to previous studies using advanced classification techniques, as a future study, we think the success will increase by developing the method with proper machine learning techniques.

Additionally, we think that the approach seems suitable for human motion analysis in general. It can be extended for the analysis of different human activities, including climbing, riding a bicycle, driving, waiting, interacting with smartphone, etc.

Step counting and walk detection problems depends on many things: human physiology, sensor quality, sensor placement, ground, and the motion in which people are. Although the topic is not in its infancy, we think that more struggle is needed for better step classification and counting.

Moreover, in the last decades, with the rise of internet and mobile devices, privacy issues have been a hot topic for users and researcher. It seems that valuable and sensitive sensor data provided by smartphones adds on the privacy issue another dimension. We think that Android OS developers should reconsider the security issues related to sensor data and usage permissions.

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