A Study of Position Independent Algorithms for Phone-Based Gait Frequency Detection

Alexander Tarashansky, Harshvardhan Vathsangam, Gaurav S. Sukhatme

Abstract—**Estimating gait frequency is an important component in the detection and diagnosis of various medical conditions. Smartphone-based kinematic sensors offer a window of opportunity in free-living gait frequency estimation. The main issue with smartphone-based gait frequency estimation algorithms is how to adjust for variations in orientation and location of the phone on the human body. While numerous algorithms have been implemented to account for these differences, little work has been done in comparing these algorithms. In this study, we compare various position independent algorithms to determine which are more suited to robust gait frequency estimation. Using sensor data collected from volunteers walking with a smartphone, we examine the effect of using three different time series with the magnitude, weighted sum, and closest vertical component algorithms described in the paper. We also test two different methods of extracting step frequency: time domain peak counting and spectral analysis. The results show that the choice of time series does not significantly affect the accuracy of frequency measurements. Furthermore, both time domain and spectral approaches show comparable results. However, time domain approaches are sensitive to false-positives while spectral approaches require a minimum set of repetitive measurements. Our study suggests a hybrid approach where both time-domain and spectral approaches be used together to complement each other's shortcomings.**

Index Terms—**Mobile phone, Accelerometer, Fourier Transform, Peak Counting**

I. Introduction

Analyzing gait patterns in free living conditions is an important component in the detection and diagnosis of a variety of medical conditions such as injury detection [1], obesity [2], and Parkinson's disease [3]. Gait analysis has also been used as a tool to gauge the effectiveness of mobility-related physical therapy treatments outside the clinic to maximize the rate at which a patient's gait recovers to normal [1]. In additional to applications in medicine, gait measurement has also been used for human identification and classification [4].

An important component of any gait analysis is the estimation of gait frequency. In recent years, kinematic sensors such as triaxial accelerometers and gyroscopes have played a prominent role in gait frequency estimation. Approaches using these sensors place the devices on specific parts of the body such as an arm or ankle and extract specific gait features such as amount of arm swing, leg swing, the period of a walking cycle, etc [5, 4, 6, 7]. However, gait analysis using these sensors has traditionally taken place in controlled conditions within the confines of a laboratory with sensors worn in fixed locations [1]. It has been argued that laboratory-based gait studies do not even accurately represent the actual everyday activity pattern of a person [1]. A gait laboratory does not account for the variable external circumstances that can change a person's gait over a short or large amount of time. Consequently, a more portable gait-monitoring system that can be deployed in free living conditions is required.

Recent years have seen the emergence of smartphones to a nearly ubiquitous presence. Present day smartphones come shipped with the same kinematic sensors as those used in gait analysis. This growth provides the opportunity to enable gait monitoring in free living conditions using hardware already carried by millions of people. There are two issues associated with estimating gait frequency using smartphone-based sensors. The first issue is that one cannot make the assumption that smartphones will be worn in a fixed location or orientation on the human body [8]. Any model that estimates gait frequency must account for changes across phone locations and orientation of the phone. Previous research has addressed location independence by using magnitude or the sum of squares of triaxial accelerometer data [9] or by estimating a canonical vertical component in the world axis [10, 11]. The second issue in reliable gait monitoring is that one must be able to distinguish "true" gait from false positives or other irrelevant movement signatures. Approaches to tackle this issue either focus on peak counting [12, 11] or spectral analysis [6]. Little work has been done in comparing which of these algorithms are more suited to robust gait frequency estimation across different locations on the human body. This paper builds on previous work by comparing different methods to reliably estimate gait frequency from an accelerometer-based gait signal. A small-scale study was performed that collected data across multiple people and multiple locations per person in order to compare different processing algorithms to see which method shows the highest accuracy in gait frequency estimation.

II. Data Collection

This study examined gait data as measured with phone-based accelerometers across 10 participants with a phone worn in various locations on a person. The LG Nexus 4 Android phone was used to collect triaxial accelerometer, gyroscope, magnetometer, and rotation vector data at a sampling frequency of 50 Hz. Four locations were chosen for this experiment: side pockets, back pockets, in the hand as if using the touch screen, and on a phone call. The phone locations were chosen to capture the most common locations in which phones are worn while walking [13, 14]. For each phone location, the subject walked for 60 seconds at five different frequencies in sync with a metronome: 80 – 120 beats per minute (BPM) in increments of 10 BPM. This range (1.33 Hz - 2 Hz) encapsulates the complete set of frequencies at which people generally walk. For each 60 second sample, only the middle 40 seconds of data were considered to remove artifacts related to wearing and removing the phone. With five frequencies per four locations, the total amount of data per person amounts to 20 samples of sensor data. Across 10 people, this amounts to 200 samples or 133 minutes of sensor data. Testing environments included any kind of level terrain from indoor hallways to asphalt streets. Each data collection session took approximately forty minutes per participant. After the data collection, participants filled a survey collecting data about phone habits and usage. This study was approved by the Institutional Review Board of the University of Southern California.

III. Methods

Six different algorithms were compared for accuracy in detecting gait frequency. The algorithms were divided into two families: peak counting algorithms and periodogram-based (spectral) algorithms. Within each family, three time series were considered. Each time series was obtained by transforming triaxial accelerometer data into a uni-dimensional time series. The derived time series are described below.

A. Magnitude of accelerometer signals

Given the raw accelerometer data $\mathbf{a}_t = \begin{bmatrix} a_{x,t} & a_{y,t} & a_{z,t} \end{bmatrix}^T$, the magnitude time series is calculated using the relation $\mathbf{m}_t = \sqrt{a_{x,t}^2 + a_{y,t}^2 + a_{z,t}^2}$. This magnitude time series is then passed through a a second-order bandpass filter with cutoff frequencies $\begin{bmatrix} 0.9 & 2.1 \end{bmatrix}$Hz in order to filter out any noise outside the range of frequencies associated with walking.

B. Closest vertical component

The periodic nature of walking can be captured by the cyclical motion of the center of mass in the up-down direction[15]. Consequently, each time the foot is placed on the ground, that transitional phase between acceleration and deceleration of the center of mass corresponds to a peak in the time domain signal. Because the phone is usually attached to the human body, whether in the hand or in a pocket, the periodic movement of the body's center of mass translates to the periodic motion of the phone in the vertical direction. Therefore, the remaining two time series extract the component of motion from the accelerometer data that corresponds to the world-vertical direction in order to test if the vertical component of motion is required for location and orientation independent frequency estimation.

Raw accelerometer data $\mathbf{a}_t = \begin{bmatrix} a_{x,t} & a_{y,t} & a_{z,t} \end{bmatrix}^T$ are passed through three independent bandpass filters with cutoff frequencies $\begin{bmatrix} 0.9 & 2.1 \end{bmatrix}$Hz to obtained filtered three-dimensional time series $\mathbf{a}_{filt,t} = \begin{bmatrix} a_{x,filt,t} & a_{y,filt,t} & a_{z,filt,t} \end{bmatrix}^T$. In addition, the orientation of the phone given by the unit orientation quaternion $\mathbf{q}_t = \begin{bmatrix} q_{0,t} & q_{1,t} & q_{2,t} & q_{3,t} \end{bmatrix}^T$ at time t is also used. Given the orientation quaternion, it is possible to estimate the direction cosines of the z-components of the rotation matrix (corresponding to the world-vertical axis) using the relation:

$$\begin{aligned} \mathbf{n}_{z,t} &= \begin{bmatrix} x_{z,t} & y_{z,t} & z_{z,t} \end{bmatrix}^T \\ &= \begin{bmatrix} 2(q_{1,t}q_{3,t} - q_{0,t}q_{2,t}) \\ 2(q_{0,t}q_{1,t} + q_{2,t}q_{3,t}) \\ q_{0,t}^2 - (q_{1,t}^2 + q_{2,t}^2 + q_{3,t}^2) \end{bmatrix} \end{aligned}$$

where $x_{z,t}$,$y_{z,t}$, and $z_{z,t}$ are the z components of the normal vectors to the three planes of the phone. For the purposes of this study, we used the default orientation quaternion values provided by the phone's rotation vector sensor.

After calculating $\mathbf{n}_{z,t}$, the closest vertical component algorithm as determined by which of $x_{z,t}$,$y_{z,t}$, and $z_{z,t}$ has magnitude closest to 1. The intuition behind this approach is that if a certain axis is closest to the world-vertical direction, then that z component will have a value of 1 or -1 (since the normal of the plane in that direction has to be parallel to the world-vertical plane) and the remaining z components will be close to zero (since they are orthogonal). This signal corresponds to the axis of the phone that is closest to world-vertical.

C. Weighted-sum algorithm

The weighted-sum algorithm modifies the closest-vertical algorithm by calculating a weighted sum of filtered triaxial accelerometer data using the absolute value of the individual components in $\mathbf{n}_{z,t}$ as weights.

$$w_t = \frac{a_{x,t}\,|x_{z,t}| + a_{y,t}\,|y_{z,t}| + a_{z,t}\,|z_{z,t}|}{|x_{z,t}| + |y_{z,t}| + |z_{z,t}|}$$

Intuitively, this approach allows the algorithm to accurately calculate the vertical component of walking even when the phone is held in transitional states, orientations that do not fully align with any of the phone's three axes.

D. Peak-counting versus Frequency-based approaches

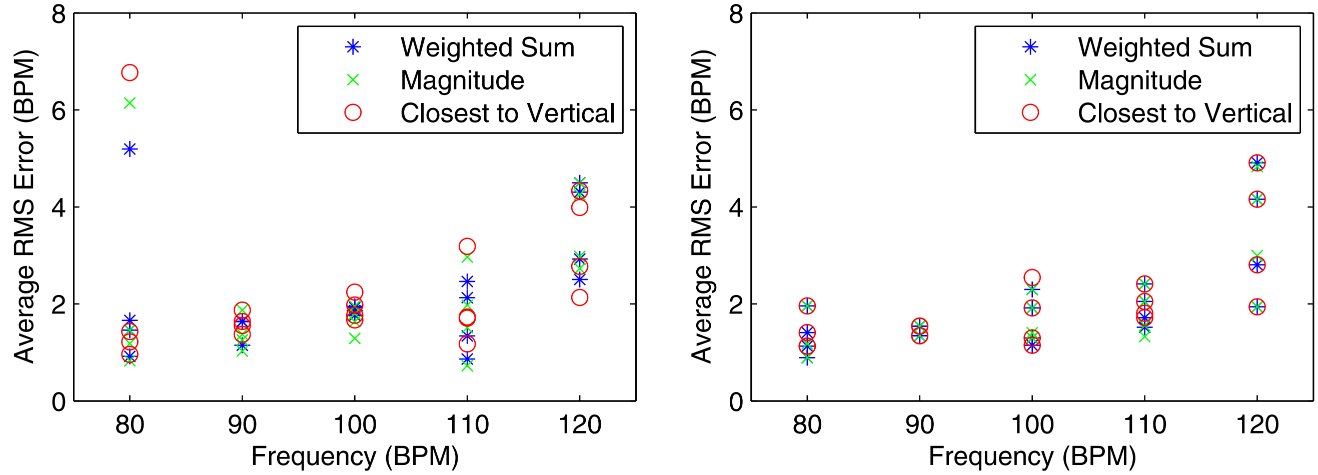
Given three time series, two types of gait frequency detection algorithms were used. The first algorithm, peak counting, estimates gait frequency by counting the number of peaks within a known sample length in seconds. After subtracting the mean of the source signal, the peak counting algorithm detects peaks in the source time series that are above a threshold value of zero (since the signal is centered around zero) and ignores peaks that are spaced closer than 0.4 seconds apart. This value was chosen because the maximum walking frequency assumed for this experiment is 2 Hz which corresponds to peaks spaced 0.5 seconds apart. Any peak closer than 0.4 seconds is considered as not due to peak counting and is thus ignored.

The second algorithm subtracts the mean of the signal and calculates the 2048 point periodogram of a time series. Under the assumption that our signal is strongly quasi-periodic (which holds for continuous walks), the average frequency can thus be estimated by determining the frequency value corresponding to the highest peak of the Fourier transform.

IV. Results

A. Effect of differing time series

Figures 1a and 1b compare the three types of input signals used in the peak counting and periodogram algorithms respectively. All three signals used output comparable



(a) Excluding the three outlying points at 80 BPM, peak counting exhibits low error in frequency estimation (under 5 BPM) for all phone locations and step frequencies in ideal conditions. There seems to be an increase in error with increasing step frequency.

(b) Similarly, using the periodogram algorithm, the above is a comparison of average RMS error for the three input signals over all phone locations and frequency values. A frequency-based analysis also exhibits low error in frequency estimation, except there are no outliers at 80 BPM.

Figure 1: Comparison of different algorithms in gait frequency error detection

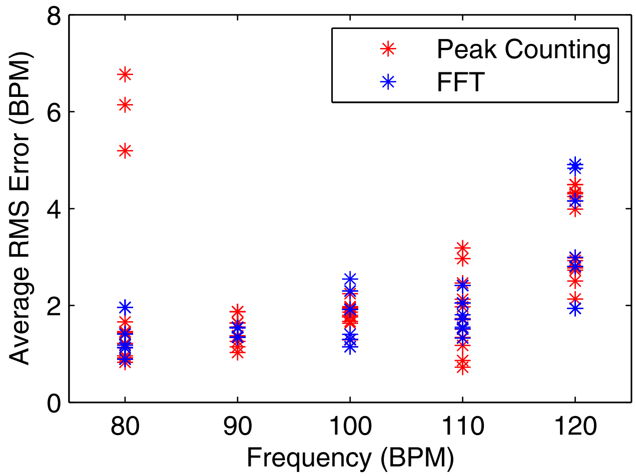


Figure 2: Scatter plot of average RMS error averaged across all subjects for all phone locations as a function of step frequency.

results in terms of deviation from the ground truth frequency values. This indicates that for both peak counting and periodogram algorithms extracting the vertical component of the accelerometer data is not mandatory for reliable cadence detection; simply taking the magnitude of the raw accelerometer data produces results with similar accuracy. For the case of steady state walking at different step frequencies, for different locations and different orientations of the phone on the body, taking the magnitude of the data detects cadence with relatively high accuracy for both peak counting and periodogram-based methods.

B. *Peak counting versus periodogram approaches*

Figure 2 indicates that in ideal metronome-regulated circumstances there is no substantial difference in error between the peak counting and periodogram-based methods for frequencies between 90 BPM and 120 BPM.

The main points of interest are the high outlier errors corresponding to 80 BPM as shown in Figure 1a. These outliers occur only for a few data points in the back pocket location. Further inspection of these signals revealed that even after filtering, the input signal for the algorithm was no longer a smooth, sinusoidal signal due to spurious sources of noise. The peak counting algorithm could not accurately determine the number and location of peaks for this signal as it generated false positives in the number of peaks. This resulted in higher peaks than actually present. The fact that this noise occurred only in one location hints at unique properties of the phone movement in that position. The noise issue did not occur for the periodogram algorithm. The frequency-based algorithm was able to smooth out sources of noise by considering the entire signal for its calculation. Thus even though peak counting failed only in a few cases for this study, these failures illustrate one of its limitations - it is difficult to generalize a suitable set of parameters that make the algorithm robust to noise in the input signal.

C. *Variation of error with ground truth frequency*

Both frequency and time-domain methods show an increase in root mean squared (RMS) error as the frequency increases. To ensure that this was not because of increased steps, the errors on a percentage basis were also calculated but showed the same trends. One reason for this could be that at higher metronome frequencies, subjects simply experience greater difficulty following the beat of the metronome. Also, the errors portrayed in figures 1a and 1b are calculated from frequency values that have been averaged over approximately 40 seconds worth of data. Therefore, small variations in the actual frequency with respect to time as the participant modulates his or her steps to match the metronome may account for a larger error. Because it is difficult to exactly monitor step frequency at every moment during the data collection, the assumption is made that the metronome value is the ground truth frequency. Nevertheless, except for the outliers, no data point reported an error greater than 5 BPM.

D. Minimum signal length for periodogram accuracy

While peak counting only requires one period of data (corresponding to one step) to detect a step, the periodogram algorithm needs a minimum number of periods in order to determine the cadence with sufficient accuracy. To determine the minimum number of periods required for periodogram-based step frequency, we calculated error in estimating step frequency as a function of window length. We found that the error stabilizes when a window of corresponding to approximately 6 periods (or steps) of data. This minimum number of periods applies as a general rule of thumb for all phone locations and step frequencies.

However, because peak counting does not distinguish between types of peaks, any random point that exceeds the chosen threshold would also count as a step. In order to account for this, the periodogram can be used to validate peak counting at the end of the delay period. If the periodogram detects a substantially different frequency from peak counting, then the algorithm will conclude that the peaks detected are not the result of periodic motion. In this way, the algorithm can prevent false positives in frequency estimation. This approach points to a more hybrid of short term and long term cadence detection algorithms.

V. Conclusion

This paper examined, implemented, and compared various algorithms for extracting step frequency in an experimental study that collected Android phone-based accelerometer and other sensor data from 10 volunteers. The accelerometer data was transformed into three different unidimensional time series and fed into two different processing pipelines that extracted the step frequency using their corresponding algorithms. Based on the error in step frequency measurements, the pros and cons of using one algorithm over another were discussed in depth.

Although the data indicates that the periodogram and peak counting algorithms are both equally generalizable and accurate under ideal circumstances with ideal input signals, in free-living conditions there is no guarantee that these conditions will remain true. As the data has shown, in non ideal circumstances (i.e. when the signal is noisy) peak counting overestimates the step frequency due to peaks that do not represent steps whereas frequency-based techniques do not. Consequently, in uncontrolled conditions, using the periodogram to detect step frequency could be more robust than using peak counting alone. However, because the periodogram requires a certain amount of data before reporting step frequency with high fidelity, peak counting can be used for short-term step frequency detection that can be confirmed by the periodogram once enough time periods are collected.

Within both periodogram and peak counting algorithms, three forms of input signals (magnitude, weighted sum, and closest vertical component) were tested in order to determine which input returns the most accurate step frequency across all the data points collected from various locations on the body and different orientations of the phone. The results in our study showed that, for both the peak counting and periodogram algorithms, the accuracy of estimated step frequency was largely independent of the input signal used. Previous research focused on normalizing the raw accelerometer data to its real gravitational (vertical) and horizontal components to account for orientation dependence. Our results suggested that calculating the canonical vertical orientation of the signal was an extraneous step since simply taking the magnitude of the raw accelerometer data was equally accurate.

A major extension of this work will be to perform a similar analysis in free-living, unsupervised conditions across a larger population. A larger dataset will also be collected to verify the obtained results. A deeper, biomechanical examination of why simply taking the magnitude of the data suffices for accurate step frequency estimation will then be the subject of future works. More investigation will be done in an attempt to explain why the signal is considerably noisier when the phone is located in the back pocket. Using the results of this paper, the next step is to implement a robust, real-time algorithm that detects step frequency on phones combining both peak counting and frequency-based algorithms.

References

[1] S. R. Simon, "Quantification of human motion: gait analysis - benefits and limitations to its application to clinical problems," *Journal of biomechanics*, vol. 37, no. 12, pp. 1869–1880, 2004.

[2] P. Spyropoulos, J. C. Pisciotta, K. N. Pavlou, M. Cairns, and S. R. Simon, "Biomechanical gait analysis in obese men." *Archives of physical medicine and rehabilitation*, vol. 72, no. 13, pp. 1065–1070, 1991.

[3] P. Bustamante, G. Solas, and K. Grandez, "Neurodegenerative disease monitoring using a portable wireless sensor device."

[4] A. Sharma, A. Purwar, Y.-D. Lee, Y.-S. Lee, and W.-Y. Chung, "Frequency based classification of activities using accelerometer data," in *Multisensor Fusion and Integration for Intelligent Systems, 2008. MFI 2008. IEEE International Conference on*. IEEE, 2008, pp. 150–153.

[5] L. Lee and W. E. L. Grimson, "Gait analysis for recognition and classification," in *Automatic Face and Gesture Recognition, 2002. Proceedings. Fifth IEEE International Conference on*. IEEE, 2002, pp. 148–155.

[6] M. Yang, H. Zheng, H. Wang, S. McClean, J. Hall, and N. Harris, "Assessing accelerometer based gait features to support gait analysis for people with complex regional pain syndrome," in *Proceedings of the 3rd International Conference on PErvasive Technologies Related to Assistive Environments*. ACM, 2010, p. 48.

[7] W. Tao, T. Liu, R. Zheng, and H. Feng, "Gait analysis using wearable sensors," *Sensors*, vol. 12, no. 2, pp. 2255–2283, 2012.

[8] S. A. Antos, M. V. Albert, and K. P. Kording, "Hand, belt, pocket or bag: Practical activity tracking with mobile phones," *Journal of neuroscience methods*, 2013.

[9] E. Miluzzo, N. D. Lane, K. Fodor, R. Peterson, H. Lu, M. Musolesi, S. B. Eisenman, X. Zheng, and A. T. Campbell, "Sensing meets mobile social networks: the design, implementation and evaluation of the cenceme application," in *Proceedings of the 6th ACM conference on Embedded network sensor systems*. ACM, 2008, pp. 337–350.

[10] H. Lu, J. Yang, Z. Liu, N. D. Lane, T. Choudhury, and A. T. Campbell, "The jigsaw continuous sensing engine for mobile phone applications," in *Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems*. ACM, 2010, pp. 71–84.

[11] Q. Cheng, J. Juen, Y. Li, V. Prieto-Centurion, J. A. Krishnan, and B. R. Schatz, "Gaittrack: Health monitoring of body motion from spatio-temporal parameters of simple smart phones," in *Proceedings of the International Conference on Bioinformatics, Computational Biology and Biomedical Informatics*. ACM, 2013, p. 897.

[12] F. Li, C. Zhao, G. Ding, J. Gong, C. Liu, and F. Zhao, "A reliable and accurate indoor localization method using phone inertial sensors," in *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*. ACM, 2012, pp. 421–430.

[13] L. Sun, D. Zhang, B. Li, B. Guo, and S. Li, "Activity recognition on an accelerometer embedded mobile phone with varying positions and orientations," in *Ubiquitous intelligence and computing*. Springer, 2010, pp. 548–562.

[14] F. Ichikawa, J. Chipchase, and R. Grignani, "Where's the phone? a study of mobile phone location in public spaces," 2005.

[15] H. Vathsangam, M. Zhang, A. Tarashansky, A. A. Sawchuk, and G. S. Sukhatme, "Towards practical energy expenditure estimation with mobile phones," 2013.