# Gait-based User Classification Using Phone Sensors

Matthew Boyle (*mboy@bu.edu*)
Avraham Klausner (*aviclaws@bu.edu*)
David Starobinski (emphstaro@bu.edu)
Ari Trachtenberg (*trachten@bu.edu*)
Hongchang Wu (*wuhc@bu.edu*) *

**Abstract**

We investigate whether smartphones can be used to distinguish different users based on their gait, the rhythmical body movements of human beings as they walk. To this end, we propose, describe, and experimentally evaluate a system that classifies peoples' gait patterns using the tri-axial accelerometer of the Motorola Droid phone. The system employs the wavelet transform to extract features from raw acceleration data and the $k$ Nearest Neighbors ($k$NN) algorithm to perform the classification. Preliminary experimental results show that the system achieves high classification rates (i.e. above 90%) when users walk at approximately constant speeds regardless of variations in environment. Our results show promise toward using gait as a means of user recognition.

A version of this paper appeared in

M. Boyle, A. Klaustner, D. Starboinski, A. Trachtenberg, and H. Wu *Poster: gait-based smartphone user identification*, Proceedings of the 9th international conference on Mobile systems, applications, and services (MOBISYS '11), Bethesda, Maryland, USA, 2011, pp. 395-396.

*The authors are with Electrical and Computer Engineering department at Boston University, 8 St. Mary's St., Boston MA 02215.

# 1 Introduction

Cell phone technology has progressed rapidly in its roughly forty year history. Analog voice-only cell phones have given way to digital transmission phones, followed by non-voice data access and culminating with today's smartphones, which have full Internet access, processing power and storage space that are roughly one generation behind desktop computers, as well as a wide variety of on-board sensors. In today's world, about 83 % of U.S. citizens own a cell phone and 17 % of U.S. citizens (approximately 26.1 million people) own a smartphone [2].

Smartphone capabilities seem innumerable today, and we put this notion to the test by attempting to use the the on-board accelerometer of the Motorola Droid to advance the smartphone's user recognition. It is envisioned that this means of user identification could be utilized as a component of a larger recognition system, one that might fully amalgamate all relevant sensor/phone data to generate a "sense" of whether a legitimate user has possession of the phone at any given instant, and if so, which known user.

Biometric signatures, based on a user's natural features, are a natural approach to user recognition, as they are often high in entropy and hard to forge and forget. Human gait is a particularly appealing biometric feature for phones because it tends to be unique [22], is passively observable with the use of accelerometers, and is easily measured as a user carries his phone around. While measuring gait is not applicable to every scenario (i.e. when a user carries their phone in a purse or other attenuating medium, or when the user is driving, etc.), the goal of this paper is to show that a user's gait has a property of uniqueness that the on-board accelerometer can measure in some instances, a feature that indicates potential further use.

# 2 Background

## 2.1 Gait

When people walk, the movement of their limbs and body exhibits characteristic patterns. The word *gait* describes the manner or the style of walking–rather than the walking process itself [26]. It is a complex spatial-temporal behavior biometric [17] and a substantial amount of research suggests that it is sufficiently distinctive to allow for identity authentication [22, 5, 27]. One of the key advantages of gait compared to other biometrics is its unobtrusiveness [5], meaning that no special instructions are needed to get the user's walking gait. The implication here is that one can potentially use gait as a passive biometric, i.e. gait patterns can be captured without the user's constant involvement.

Gait analysis has long been a active research topic for a variety of applications. It has been used in medical and pathological research to detect motion patterns and abnormal walking [18, 3]. It has also been used to recognize friends without familiarity cues [8] and to classify gender [27].

A multitude of different techniques have been employed to generate gait analysis. Biomechanical models have been developed to specify gait characteristics such as joint moments and powers (kinetic analysis), joint angles, angular velocities and angular accelerations (kinematic analysis) [14]. Alternatively, a digital image processing system has been proposed to perform kinematic analysis of human gait [24]. Ultimately, most current approaches are vision-based, since they either extract features from the image or map the image to a specified set of models [7, 4, 10, 15]. However, the hardware associated with these systems is usually expensive and cumbersome, making them difficult to deploy practically with regards to smartphones.

Another interesting approach to gait analysis involves the use of accelerometers. Acceleration has been associated with gait analysis since at least 1964 [13], and the acceleration patterns of people walking on different surfaces have been explored in [21]. Accelerometers have also been used to detect leg injury [28].

Most previous works use multiple sensors on different parts of the body. Our goal here is to use just one tri-axial accelerometer on the phone to capture gait patterns. The work in [16] considers using a single accelerometer mounted on a cellphone to distinguish between *different types of gaits* (walking, running). Rather, the focus of our work is in distinguishing between *users*. Recent work [11] proposes an approach based on time-delay embedding to classify smartphone users. Our work is distinct from [11] in its processing method (our approach relies on wavelets). It should also be noted that our entire solution, *both* training and classification, is sufficiently light-weight to be executed on-line by the phone (i.e. without any additional laptop or desktop processing).

## 2.2 Sensors

Due to technological advancements in mobile phones, embedded sensors have become more common in a typical cell phone design. Models, such as the Motorola Droid, sport six different highly sensitive and accessible sensors. The Droid then can use these sensors for a variety of applications. For example, an ambient light sensor allows the Droid to adjust its backlighting for different ambient lighting conditions. Similarly, a magnetometer affords the Droid an accurate compass.

For our purposes, we chose to use the Droid's accelerometer alone to classify a user's gait. The highly sensitive accelerometer outputs acceleration data in the $x, y$, and $z$ axes of the phone. We chose to use the accelerometer over other on-board sensors in part because it is largely insensitive to the phone's orientation. In other words, the Euclidean norm of the acceleration vector remains unchanged regardless of the the phone's orientation within the user's pocket (one common mode of carrying a phone). As such, the accelerometer accurately captures the periodic motion of the user's leg during walking.

The Droid's magnetometer could also be used to help with measuring gait, but its accuracy can be significantly affected by proximate magnetic fields, which need to be considered within the consequent signal processing. The Droid phone also sports an orientation meter (outputting Azimuth, Pitch and Roll for the

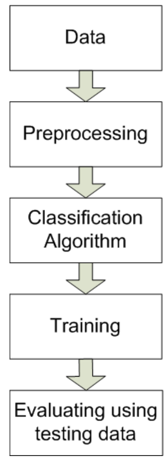


Figure 1: System Flowchart

device), but this is actually just an algorithmic combination of accelerometer and magnetometer data, so it provides no new information for gait analysis.

# 3 System description

The goal of our system is to demonstrate the classification and identification of several walking gaits based on extracted accelerometer data. Figure 1 shows the high-level flow chart of our system. The main components of our system are discussed in detail in the following subsections.

## 3.1 Preprocessing with wavelet transform

The system draws raw $x$, $y$, and $z$-axis accelerometer readings directly from the phone using the operating system's existing Application Programming Interface (API). Due to the asynchronous operating system structure [1], sensor data arrive at irregular intervals, controlled only by a suggested qualitative delay (fastest, game, normal and UI). As a result, interpolation (linear in our case) is needed to provide the regular sampling intervals needed for much of our discrete signal processing [25].

The goal of the preprocessing step is thus to transform the raw data into some desired form from which useful features can be extracted. The Fourier transform is an obvious candidate for such processing because it provides the frequency domain representation of the accelerometer signal. However, one of the major shortcomings of the Fourier transform is that it does not offer good localization in time, i.e. the transformed representation contains only information in the frequency domain.

The wavelet transform [20] is a tool that cuts up data, functions, or operators into different frequency components, and then studies each component with a resolution matched to its scale. The wavelet transform of a signal depends on two variables: scale (or frequency) and time, and provides a tool for time-frequency localization.

A mother wavelet $\psi(x)$ is a finite length and fast-decaying oscillating waveform. The mother wavelet “gives birth” to an entire family of wavelets by means of two operations: dyadic dilations (represented by $j$) and integer translation (represented by $k$) [23]:

$$\psi_{j,k}(x) = 2^{j/2}\psi(2^j x - k) \tag{1}$$

The set $\{\psi_{j,k}, j, k \in \mathbb{Z}\}$ constitutes a complete orthonormal system for $L^2(\mathbb{R})$.

A wavelet transform is the representation of the original signal by wavelets:

$$c_{j,k} = \langle f(x), \psi_{j,k}(x) \rangle \tag{2}$$

$$f(x) = \sum_{j}^{\infty}\sum_{k}^{\infty} c_{j,k}\psi_{j,k}(x) \tag{3}$$

where the $\langle\cdot\rangle$ is the inner product operator and $c_{j,k}$ are called wavelet coefficients.

One of the most interesting wavelet methods is multi-resolution analysis(MRA) [19], which decomposes a signal into approximate spaces and detail spaces. Multi-resolution analysis allows the wavelet decomposition to preserve the interesting features of the original function, but it will express the function in terms of a relatively small set of coefficients [23].

In addition, the wavelet transform is ideal for signals with discontinuities and sharp peaks, which are quite common in accelerometer readings. It can also accurately deconstruct and reconstruct finite, non-periodic and/or non-stationary signals.

For our analysis the Daubechies 4 tap wavelet family [9] and a multiresolution decomposition level of 4 are used. A typical decomposition is illustrated in Figure 2, where $s$ is the original signal, $\mathbf{d_1}, \mathbf{d_2}, \cdots$ are detail coefficients and $\mathbf{a_1}, \mathbf{a_2}, \cdots$ are approximate coefficients. The original signal is completely characterized by $[\mathbf{a_4}, \mathbf{d_4}, \mathbf{d_3}, \mathbf{d_2}, \mathbf{d_1}]$.

In order to include only the most relevant information, the dimension of the feature space should not be too high. Thus, the Euclidean norms of each level of coefficients are used as entries of the feature vectors, i.e.,

$$\big[\, ||\mathbf{a_4}||\, , ||\mathbf{d_4}||\, , ||\mathbf{d_3}||\, , ||\mathbf{d_2}||\, , ||\mathbf{d_1}||\, \big], \tag{4}$$

where $||\cdot||$ is the Euclidean norm operator. This approach greatly reduces the dimension of the feature space.

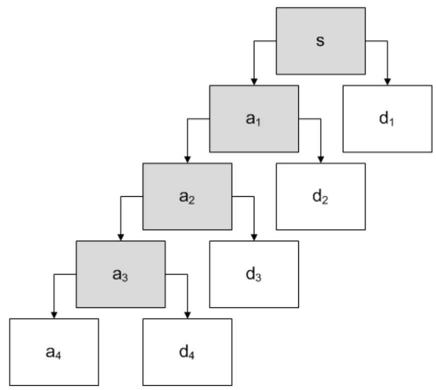


Figure 2: Multi-resolution wavelet decomposition of level 4

### 3.2 Classifier

After the multi-resolution wavelet decomposition, all input signals are represented as vectors in the feature space. Figure 3 shows a sample scatter plot of the first three dimensions of the feature space.

The operation of the system requires an initial training period, during which the classifier is provided with learning data with known ground truths. The system uses the $k$ Nearest Neighbors ($k$NN) algorithm as a classifier. $k$NN is a nonparametric pattern recognition technique that assumes no knowledge of the statistics of the underlying distribution. Let $\omega_i(i = 1, \cdots, L)$ be a class space of size $L$ (in our case, $\omega_i$ represents user $i$ and $L$ the total number of users). Given a test sample $X$, i.e., a transformed feature vector from the accelerometer reading, the number of neighbors from each class among the $k$ selected samples is counted. The test sample is then classified to the class represented by a majority of the $k$ nearest neighbors [12]:

$$k_i = \max\{k_1, \cdots, k_L\} \rightarrow X \in \omega_i \tag{5}$$

where $k_1 + \cdots + k_L = k$ and $k_i$ is the number of neighbors from $\omega_i(i = 1, \cdots, L)$ among the $k$ nearest neighbors. It has been shown that when the sample number is large, $k$NN yields the tightest error bounds possible above the Bayes optimal probability of error for all smooth distributions [6].

## 4 Experiments

### 4.1 Overview

The goal of our experiments, run on the Motorola Droid phones, is to determine the performance of the proposed system in classifying a user's gait, under simplistic conditions. To achieve this, we construct an Android application

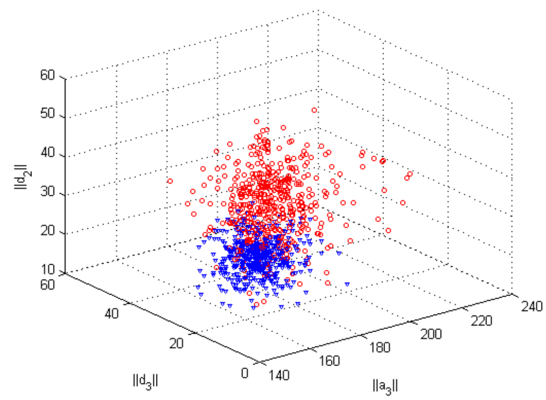


Figure 3: Scatter plot of feature vectors . Different colors represent different subjects

that constantly records accelerometer data (with corresponding timestamps) and stores the information into a file on the Droid's SD card. After initiating the application, a subject places the Droid into his or her pants' pocket. The application records accelerometer data as the subject walks. In each individual experiment, all subjects walk at a constant speed. After a set period of time, the subject stops walking, removes the Droid out of his or her pocket, and terminates the program. Data recorded during the action of taking the Droid in or out of a subject's pocket are trimmed from the data files. We collect two sets of data files. The first set provides training data, through which we compute the feature vectors corresponding to each user. The second set provides testing data that are classified using the techniques described in Section 3. Please note that although our experiments strive to include people of different heights and genders wearing different pants and shoes, they are by no means exhaustive and are not intended to be. Rather, the purpose of our experiments is to show the potential of using gait as a biometric on mobile phones.

### 4.2 Details and Results

We conduct five main experiments, in which set-up and results are explained in detail below. In each experiment, the accelerometer signal from each file is linearly interpolated with an interval of 10 ms and the Euclidean norm of the acceleration vector is calculated. The interpolated and vectorized signal is then divided into non-overlapping segments, each of which consists of 200 sample points. The wavelet transform is applied to each segment and the feature vector is generated using methods described in Section 3.

During the training period, the feature vector of each segment and its corresponding class are recorded. They form our training data. During the testing period, the feature vector of each segment is classified using the $k$NN algorithm, where the distance is measured as the Euclidean distance between vectors. The class of the integral signal is determined by doing a majority vote of the classification results of individual segments. The algorithm is run for different values of $k$, i.e., $k = 4, 8, 16, 32, 64$. Fig. 4 depicts the results of each of the experiments. The max and min bars respectively correspond to the highest and lowest classification rates obtained over all tested values of $k$.

**Experiment I** Our first experiment involves two subjects, $A$ and $B$. The two subjects follow the procedure detailed in Section 4.1, in which their walking motion consists of closely moving along a flat hallway over a distance of approximately 205.6 feet, within a 40 second time frame (i.e., the walking speed is 1.57 meters/second). Subjects $A$ and $B$ each provide 25 files of training data walking in this manner. Each subject then walks eight more times in a similar fashion, and submits the resulting files as testing data. In this experiment, our system correctly classifies all of the 16 testing data files, regardless of the value used for $k$.

**Experiment II** The second experiment involves the same two subjects, $A$ and $B$. The goal here is to determine whether our classification mechanism is equally effective at a slower walking speed. Please note that the subjects walk at close to the same speed as each other; if they do not, we run the risk of classifying subjects by the speed of their gait rather than the details unique to each person's gait. Both subjects obey the protocol described in Section 4.1, but this time they walk the hallway distance of 205.6 feet at a slower speed, that is, in 53 seconds corresponding to a walking speed of 1.18 meters/second. As in the first experiment, each subject provides 25 files of training data, and another eight files of testing data. In that case, the system reaches a maximum classification rate of 94% and a minimum of 88% over the different values of $k$.

**Experiment III** We conduct a third experiment to test the effect of a change in the environment on the classification abilities of the system. Previously, the subjects walked in a straight line down a flat hallway. Here, the subjects walk in a variety of different ways, such as around a circle with a 22-foot radius, along a hill (traveling both up and down), wearing different pants, using different Droid phones, or walking in a mostly-straight line only to suddenly and quickly change direction. Subjects $A$ and $B$ walk at the same speed as in the Experiment II. Since the goal here is to determine how significantly our classification rates are affected when the users walk in varied environments as opposed to a normal straight, flat walk, the subjects provide training data in which they walk straight down the hallway. Subjects $A$ and $B$ each provide 91 files of testing data, gathered during their walks in the various environments. The system classifies the testing data with a high level of accuracy: when the classification rates are averaged over all environments, the system achieves a maximum classification rate of 98% and a minimum classification rate of 85%.

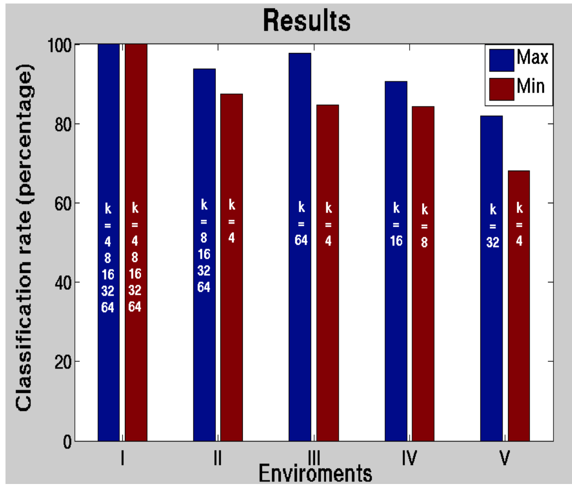


Figure 4: Results of the five experiments.

**Experiment IV** The first three experiments all involve binary classifications between subjects $A$ and $B$. In the fourth experiment, we introduce two more subjects ($C$ and $D$) for the purpose of testing the ability of the system to classify users correctly even in non-binary situations. All four subjects participate in this experiment, in which they walk 205.6 feet in 53 seconds (1.18 meters/second) down a straight hallway. Each subject provides a minimum of 20 training data files, and then an additional eight files for testing purposes. In this case, the system reaches a maximum classification rate of 91% and a minimum classification rate of 84%, across all tested variations of $k$.

**Experiment V** The intent of our last experiment is to determine how well the proposed system can classify subjects if they are not walking at a consistent speed, meaning each trail is walked at a different constant speed. Subjects $A$ and $B$ follow the protocol in Section 4.1, walking in a straight line down a hallway, but they do not walk at a constant speed across trials. In this experiment, 95 files of training data experiment are gathered for each subject, as they walk straight down a hallway (regardless of speed). Subjects $A$ and $B$ each provides 22 files in total for use as testing data. The results for classifying users across varies speeds prove decidedly inferior to the results of the other experiments. The classification rates for the twenty-two testing trials lie between a maximum of 82% and a minimum of 68%.

We conclude by noting that future work may include significantly exhaustive testing of this gait-based-recognition prototype, exploring different classification algorithms for performance comparisons, or incorporating other sensor/phone data for more advanced recognition abilities.

## References


[1] Android application fundmentals. `http://developer.android.com/guide/topics/fundamentals.html`.

[2] C. W. Association. October 13th marks 25th anniversary of the first commercial cellular phone call. Oct 2008.

[3] R. Baker. Gait analysis methods in rehabilitation. *J. NeuroEngineering Rehabil.*, 3:1–10, 2006.

[4] C. BenAbdelkader, R. Cutler, and L. Davis. Motion-based recognition of people in eigengait space. In *Proc. IEEE Int. Conf. Automatic Face and Gesture Recognition*, pages 254–259, Washington DC, USA, May 2002.

[5] N. V. Boulgouris, D. Hatzinakos, and K. N. Plataniotis. Gait recognition: A challenging signal processing technlogy for biometric identification. *IEEE Signal Process. Mag.*, pages 78–84, Nov 2005.

[6] T. M. Cover and P. E. Hart. Nearest neighbor pattern classification. *IEEE Trans. Inform. Theory*, IT-13(1):21–27, 1967.

[7] D. Cunado, M. S. Nixon, and J. N. Carter. Automatic extraction and description of human gait models for recognition purposes. *Computer Vision and Image Unerstanding*, 90(1):1–41, 2003.

[8] J. Cutting and L. Kozlowski. Recognizing friends by their walk: Gait perception without familiarity cues. *Bulletin of the Psychonomic Society*, 9(5):353–356, 1997.

[9] I. Daubechies. *Ten Lectures on Wavelets.* Society for Industrial and Applied Mathematics, 1992.

[10] J. P. Foster, M. S. Nixon, and A. Prugel-Bennett. Automatic gait recognition using area-based metrics. *Pattern Recognit. Lett.*, 24(14):2489–2497, 2003.

[11] J. Frank, S. Mannor, and D. Precup. Activity and gait recognition with time-delay embeddings. *Proceedings of the Twenty-Fourth Conference on Artificial Intelligence*, July 2010.

[12] K. Fukunaga. *Introduction to Statistical Pattern Recognition.* Academic Press, second edition, 1990.

[13] H. Gage. *Accelerographic Analysis of Human Gait.* ASME, Washington DC, USA, 1964.

[14] G. F. Harris and J. J. Wertsch. Procedures for gait analysis. *Arch Physical Medicine and Biology*, 75(2):216–225, 1994.

[15] D. Hogg. Model based vision: A program to see a walking person. *Image Vis. Comput.*, 1(1):5–20, 1983.

[16] T. Iso and K. Yamazaki. Gait analyzer based on a cell phone with a single three-axis accelerometer. *MobileHCI*, September 2006.

[17] A. Jain, R. Bolle, and S. Pankanti. *Biometrics: Personal Identification in Networked Society*. Kluwer, 1999.

[18] H. Lakany. Extracting a diagnostic gait signature. *Pattern Recognition*, 2008.

[19] S. G. Mallat. A theory for multiresolution signal decomposition: The wavelet representation. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 11(7):674–693, Jul 1989.

[20] S. G. Mallat. *A Wavelet Tour of Signal Processing*. Academic Press, second edition, 1999.

[21] H. B. Menz, S. R. Lord, and R. C. Fitzpatrick. Acceleration patterns of the head and pelvis when walking on level and irregular surfaces. *Gait and Posture*, 18(1):35–46, 2003.

[22] M. S. Nixon, T. Tan, and R. Chellappa. *Human Identification Based on Gait*. Springer, 2005.

[23] R. T. Ogden. *Essential Wavelets for Statistical Applications and Data Analysis*. Birkhäuser, 1997.

[24] P. O'Malley, D. Lynch, and A. M. de Paor. Kinematic analysis of human walking gait using digital image processing. *Mode. Biol. Comput.*, 31:392–398, Jul 1993.

[25] A. V. Oppenheim, R. W. Schafer, and J. R. Buck. *Discrete-Time Signal Processing*. Prentice Hall, second edition, 1999.

[26] M. Whittle. *Gait Analysis: An Introduction*. Butterworth-Heinemann, 2001.

[27] J. Yoo, D. Hwang, and M. S. Nixon. Gender classification in human gait using support vector machine. *Lecture Notes in Computer Science*, 3708:138–145, 2005.

[28] T. Yoshida, F. Mizuno, T. Hayasaka, T. Tsubota, and S. Wada. Gait analysis for detecting a leg accident with an accelerometer. In *1st Distributed Diagnosis and Home Healthcare (D2H2) Conference*, Virginia, USA, 2006.