Orientation Independent Cell Phone Based Gait Authentication

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ABSTRACT

Gait authentication using a cell phone based accelerometer sensor offers an unobtrusive, user-friendly, and periodic way of authenticating individuals on their cell phones. In this study, we present an approach to deal with inevitable errors induced by continuously changing sensor orientation and other noise under a realistic scenario (when the phone is placed inside the trouser pockets and the user is walking) by using the magnitude data of tri-axes accelerometer and wavelet based noise elimination modules. This study utilizes a gait data set of 35 participants collected at their respective normal walking pace in two different sessions with an average gap of 25 days between the sessions.

Categories and Subject Descriptors

D.4.6 [**Security and Protection**]: Authentication; H.1.2 [**User/Machine Systems**]: Human factors.

General Terms

Mobile devices, security

Keywords

Accelerometer, gait recognition, segmentation, variance, wavelets

1. INTRODUCTION

Nowadays, cell phones are used for accessing a multitude of services, such as e-commerce, m-banking, portable storage, business, social, and entertainment applications. As a result, cell phones hold a lot of sensitive information and user's whereabouts, etc. Due to their form factor and number of services they offer, we carry our cell phones throughout our daily routine. This leads to the risk that they can be lost, left unattended, or stolen. If not protected, anyone can access sensitive information stored inside. Typically, cell phones are protected by PIN/password based authentication mechanisms, which not only increases cognitive load on the users but also consumes time, if users are interacting with their cell phones on frequent basis.

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Physiological biometrics could overcome the issue of cognitive load, but they also face some other challenges such as their deployment on mobile devices increase the product cost alongside additional user time is consumed mainly due to their Failure To Acquire (FTA) errors. Therefore, we need to find a user friendly, robust, unobtrusive, and cost efficient authentication mechanism for mobile devices.

Gait authentication has been proposed as an alternative implicit authentication method for mobile devices and has achieved promising results [2,7,8,10]. Gait is an individual's style of walking and gait authentication is a process of identifying and verifying the individuals by the way they walk. Gait authentication using cell phone based accelerometers is an active research area since 2009. Studies have shown that cell phones with built-in accelerometers can learn to recognize their owners from their gait [10]. On the other hand studies have also reported various challenges that may influence cell phone embedded accelerometer based gait authentication [4], such as phone placement and orientation, sensor sampling rate, clothing, and shoes. Previous studies [6–8] have used the gait data-sets which were recorded under ideal scenarios. For instance a cell phone was tightly attached at a fixed position and orientation on every participants' body and they were asked to wear the same shoes or clothing when gait data was recorded in different sessions or on different days.

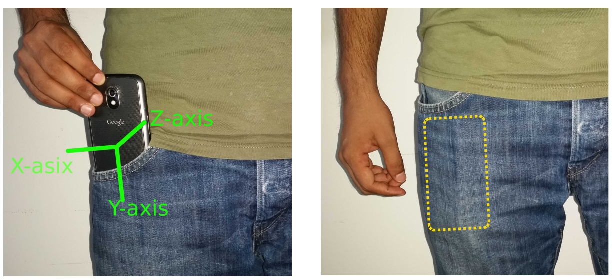
However, under realistic scenarios it is quite difficult to ensure that users will wear same cloths or will always place their cell phones in fixed orientation. Defining a realistic scenario for phone placement is quite subjective but we assume that cell phone users often place their phones inside their trouser pocket. Therefore, when a user walks with a cell phone inside the pocket, the cell phone changes its orientation during the walk.

This study focuses on solutions to deal with existing challenges such as changing orientation and other various noise induced during the walk. Orientation independent results can be achieved by using magnitude data of tri-axes accelerometer. So the main contributions of this paper are; *i*) we revisit the data processing steps of gait authentication [6,7] which mainly deal with issues like orientation and noise cancellation; *ii*) to evaluate our approach we used a data-set recorded under the realistic scenarios, *iii*) we also introduce our adapted version of a gait cycle length estimation algorithm [2].

2. DATA COLLECTION

We have recorded biometric gait data from 35 participants (6 females and 29 males) using a Google Nexus Android phone. For data collection purpose, we developed an Android application which records three dimensional (X, Y, and Z axis) accelerometer data at a sampling rate of 100 Hz and writes it to a text file with time stamps.

Participants were asked to wear a trouser with not-too-loose front pockets. For capturing a distinctive walking style, the phone or sensor must be placed close to the body otherwise it might pick up to much random noise. In the data recording phase the phone was placed inside the trousers right side pocket as shown in figure 1. Participants were asked to walk at their normal pace in a 68 meters long straight corridor (with no stairs). They were told to wait for 1 second at the end of walk then turn around and wait for another second before starting their new walk. In one session, every subject walked $4 \times 68 = 272$ meters or in other words completed two rounds of the corridor. For every subject, data recording was conducted in two different sessions. An average gap between the sessions is about 25 days. Eight walks were recorded for every subject in two different sessions.



(a) Phone being placed inside the pocket

(b) Phone postion inside the pocket

Figure 1: Phone placement and its orientation at the start of the session for all participants.

3. DATA DESCRIPTION AND PROCESSING

Figure 2 shows various activities performed in one data recording session. Approximately the first 10-20 seconds of data is when the phone was being placed inside the pocket, and next 100 seconds are when person is standing still and listening to the instructions. Then the participant starts walking and reaches the end point. This walking activity lasts around 50 seconds and varies from person to person as it highly depends upon the walking pace of the person. At the end of the the walk participant waits for a second, turns around and waits for another second before the new walk, and so on participant completes the session with four walks. Data processing begins by separating session-wise recorded walks and computing magnitude from tri-axes accelerometer data.

3.1 Walk separation

Walk separation is achieved by monitoring the variance of the y-axis data (any other axis, or the magnitude of accelerometer data can also be used) with a sliding window of one second. If the variance within this window rises above a certain threshold, this marks the start of an active walk segment and when the variance drops below that threshold it marks the stop of that active walk segment. In this study, we use a variance threshold of $0.8\frac{m}{s^2}$. Once all active walk regions are marked, we pick those segments which are longer than 10 seconds. Figure 2 shows the detected walk segments. In this step, we compute the resultant vector as given in equation 1 from individual axis data of each walk which undergoes further data processing steps described in the following subsections.

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

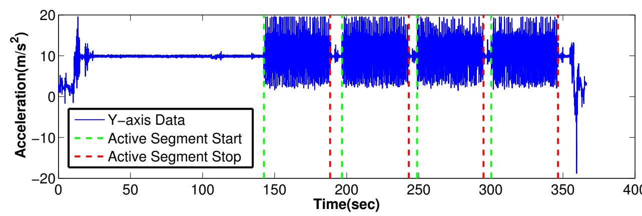


Figure 2: Acceleration recorded along the y-axis with detected four walk segments.

3.2 Interpolation

The accelerometer sensor on Android phones does not output equidistant data. It only outputs data when Android API's onSensorChanged[1] method is triggered. Therefore, the time interval between two consecutive sensor values is not equal. By applying interpolation, data can be reshaped in equal intervals of time and can also be up-sampled in order to avoid data loss of too many values, for this purpose, we have used linear interpolation as given in equation 2.

$$\acute{s} = s_0 + \frac{(s_1 - s_0)(\acute{t} - t_0)}{(t_1 - t_0)} \tag{2}$$

3.3 Zero Normalization

When the phone is in the steady state, acceleration measured along the axis influenced by gravity must be equal to the earth gravitational force. Acceleration along the remaining two axes, which is not influenced by gravity must be zero. However, acceleration recorded by a phone-based accelerometer sensor is not stable over the time. Therefore, acceleration along all three axes is zero normalized by subtracting their respective mean as shown in equation 3, where A is the acceleration over time and μ is the mean acceleration.

$$\bar{A}_i(t) = A_i(t) - \mu_i, i \in \{x, y, z\} \tag{3}$$

3.4 Noise Removal

The multi-level Daubechies orthogonal wavelet (DB6) is used to remove the noise picked up by the accelerometer such as bumps and taps on the screen during the data recording phase. In this study DB6 with level 3 and soft thresholding given in equation 4 is used to eliminate the noise from the walk signal. These equations for thresholding the time series are discussed in [9].

$$\tau = \sigma_{(mad)} \sqrt{ln(N)} \tag{4}$$

[1]http://developer.android.com/index.html

Where τ is the threshold and N is the length of the time series or walk signal.

$$\sigma_{(mad)} = \frac{median(|c_0|, |c_1|, ..., |c_2^{n-1} - 1|)}{0.6745} \quad (5)$$

Where c_0, c_1 are the wavelet coefficients ordered by the increasing frequency and $\sigma_{(mad)}$ is computed over the largest coefficient spectrum. As explained in [9], The denominator 0.6745 is a scaling factor to make $\sigma_{(mad)}$ a suitable estimator for Gaussian white noise.

4. SEGMENTATION

Various approaches to segment the gait walk have been proposed in previous studies. The two widely used methods are: *i*) cycle based segmentation, considering the fact that human walk is cyclic in nature and the walk is segmented into the cycles [1,2,7,8], and *ii*) the fix-length segmentation, where the walk is segmented into small frames of 3-5 seconds, irrespective of the cycles [8]. In this study we have used a cycle based approach to segment the walks. Before segmenting the walks, it is important to find the cycle length to automatically detect the cycles.

4.1 Cycle Length Estimation

Our cycle length estimation is based upon the approach presented in [2]. Steps of estimating the cycle length are given in algorithm 1.

It begins by extracting a small subset of samples around the center of the walk called reference window and compares it with the other subsegments of the same size extracted from that walk. The number of samples in the reference window must be less than the sampling frequency. In this study, we have used a reference window of 80 samples.

The comparison of the reference window with other subsegments results in a distance vector. From this vector we find the indices of the minimum distance values and store them to a minimum index vector. Later we compute a difference vector which contains the difference of every two adjacent elements of the minimum index vector. Finally, the cycle length is computed by taking the mode of the difference vector.

In case if mode does not exist (which means every step has different length which could happen if an individual is intentionally changing the walking pace) we compute cycle length by averaging the values of difference vector.

4.2 Cycle Detection

Cycle detection is based on algorithm 1. It begins by extracting a small segment ($2 \times$ estimatedCycleLength) around the center of the walk as it is the most stable section of the walk and we find minimum value in this section of the walk. Sometimes interpolation errors could effect this area of the walk and we might pick a wrong minimum, to reduce this risk we used segment size double of the cycle length. By this we assume to pick two minimas and we start cycle detection from the index of the most prominent minima and from this point cycle detection is done in forward and backward direction by adding and subtracting the cycle length. From our experiments we found that all minimas in the walk do not occur at equal intervals therefore, we select a small a offset ($0.2 \times$ estimatedCycleLength) area around the found end point and find minima in that region. Once all minimas in both direction are found they are called gait cycle starts.

Algorithm 1 Calculate $EstimatedCycleLength$

$L := WalkLength$ {samples in the walk}
$C := \lceil \frac{L}{2} \rceil$ {center point of the walk}
$N := 80$ {samples in the $referenceWindow$}
$Start := C - \frac{N}{2}$ {first index of the $referenceWindow$}
$End := C + \frac{N}{2} - 1$ {last index of the $referenceWindow$}
$ReferenceWindow \leftarrow walk(Start$ **to** $End)$
for $i = 1$ **to** $L - N$ **do**
  $subSegment \leftarrow walkSignal(i$ **to** $i + N - 1)$
  $D[i] := ED(BaseLine, subSegment)$ {find Euclidean distance between referenceWindow and subSegement}
end for
$minima := findMimum(D)$ {returns indices of local minimas of distance vector D}
$Difference := diff(minimas)$ {returns difference of every two adjacent elements of $minimas$ vector}
if $mode(Difference)! = NAN$ **then**
  return $cycleLength := mode(Difference)$
else
  return $cycleLength := average(Difference)$
end if

All detected gait cycles are normalized to equal length of 100 samples because distance measure such as Euclidean only works on equal length data series.

4.3 Omitting Unusual Cycles

Detected cycles are cleaned by deleting unusual cycles which are shown in figure 3. This is done by computing the pairwise distance using Dynamic Time Warping (DTW). Cycles which have a distance of at-least half of the other cycles are removed [7]. After removing the unusual cycles a cycle which has minimum distance to all other cycles is called reference cycle and the rest of the cycles are called probe cycles. If less than three cycles are remained threshold is raised and process of deleting unusual cycles starts again until three cycles are remained.

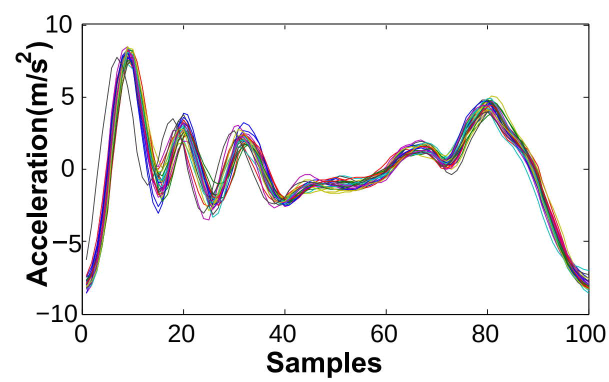


Figure 3: Gait cycles after removing outliers.

5. RESULTS

Once the Reference and probe cycles are generated they are compared against each other in order to compute the intra-class (genuine) and inter-class (impostor) distances by using the DTW distant metric. Computed distances are passed to a majority voting module to decide if a walk is

Algorithm 2 *GaitCycleStartDetection*

$L := WalkLength$ {samples in the walk}
$C := \lceil \frac{L}{2} \rceil$ {center point of the walk}
$subSegmentStart := walkSignal(C - cycleLength)$
$subSegmentStart := walkSignal(C + cycleLength - 1)$
$[minVal, index] = min(subSegment)$
$start := subSegmentStart + index$ {starting point for cycle Detection}
$offSet := 0.2 \times estimatedCycleLength$
$end := Start + estimatedCycleLength$
$j := 0$
$minimaIndexForward[j] := start$
Forward search
while $end < L - \frac{cycleLength}{2}$ **do**
  $segment := end - \lceil \frac{offSet}{2} \rceil$ **to** $end + \lceil \frac{offSet}{2} \rceil$
  $[minVal, index] := min(segment)$
  $minimaIndex[j] := end - \lceil \frac{offSet}{2} \rceil$
  $end := minimaIndexForward(j) + cycleLength$
  $j := j + 1$
end while
Same way we find minimum indices by moving backward till the start of the walk. then we sort minimaIndexBackward and join it with minimaIndexForward to have all gait cycle starts.

a genuine or an impostor attempt. If 50% cycles of a walk have distances lower than the threshold value then the walk is considered a genuine walk. Table 1 shows the results of this study and 2 shows results of other studies on this topic. We have recorded gait data in two different sessions with an average gap of 25 days. Therefore, we show the same-session (when reference and probe cycles are from the same session walks) and the cross-session (when reference and probe cycles are from different sessions) performance. Equal Error Rate (EER) is used as the performance measure in this study.

Table 1: Same-session and cross-session results.

Placement	*Subjects*	*Same-session* (EER%)	*Cross-session* (EER%)
trouser pocket	35	7,051	18.965

Table 2: Comparison of results with other studies, s stands for same, c for cross and m for mixed session.

Study	*Placement*	*Subjects*	*Settings*	*Best EER*
[3]	trouser pocket	25	s	100% CCR
[5]	trouser pocket	5	s	100% CCR
[2]	waist	48	m	20.1
[7]	waist	48	s	16.26
[7]	waist	48	c	29.39

6. CONCLUSION AND OUTLOOK

In this paper, we used a biometric gait data-set of 35 participants collected under a realistic scenario, by placing the cell phone inside the trousers right hand side front pocket. During the walk, the cell phone wobbles inside the pocket. This introduces orientation error. To compensate these errors we have revisited the data processing steps and used magnitude data, as well as wavelet based de-noising modules. We have also used the modified version of a cycle length estimation algorithm as it is one of the crucial requirements of automatic cycle detection used here. If we compare results given in table 1 with previous studies shown in table 2; we notice an improvement. However, results also indicate a big difference in same-day and cross-day performance, that supports the argument that gait varies over the period of time, therefore, in our future studies we are looking forward to introduce on-line learning methods to cope with gait aging factor.

7. ACKNOWLEDGMENTS

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8. REFERENCES

[1] H. Ailisto, M. Lindholm, J. Mäntyjärvi, E. Vildjiounaite, and S. Mäkelä. Identifying people from gait pattern with accelerometers. Number 7-14 in Biometric Technology for Human Identification II Bd. 5779, SPIE, 2005.

[2] M. O. Derawi. *Smartphones and Biometrics: Gait and Activity Recognition*. PhD thesis, Gjøvik University College, November 2012.

[3] J. Frank, S. Mannor, and D. Precup. Activity and gait recognition with time-delay embeddings. In *AAAI*, 2010.

[4] D. Gafurov. *Performance and Security Analysis of Gait-based User Authentication*. PhD thesis, Universitas Osloensis, 2004.

[5] J. R. Kwapisz, G. M. Weiss, and S. A. Moore. Cell phone-based biometric identification. In *Biometrics: Theory Applications and Systems (BTAS), 2010 Fourth IEEE International Conference on*, pages 1–7. IEEE, 2010.

[6] M. Muaaz and R. Mayrhofer. An analysis of different approaches to gait recognition using cell phone based accelerometers. In *Proceedings of International Conference on Advances in Mobile Computing and Multimedia*, pages 293–300. ACM, 2013.

[7] M. Muaaz and C. Nickel. Influence of different walking speeds and surfaces on accelerometer-based biometric gait recognition. In *Telecommunications and Signal Processing (TSP), 2012 35th International Conference on*, pages 508–512, 2012.

[8] C. Nickel. *Accelerometer-based Biometric Gait Recognition for Authentication on Smartphones*. PhD thesis, TU Darmstadt, June 2012.

[9] D. B. Percival and A. T. Walden. *Wavelet methods for time series analysis*, volume 4. Cambridge University Press, 2006.

[10] M. Tamviruzzaman, S. I. Ahamed, C. S. Hasan, and C. O'brien. epet: When cellular phone learns to recognize its owner. In *Proceedings of the 2Nd ACM Workshop on Assurable and Usable Security Configuration*, SafeConfig, pages 13–18. ACM, 2009.