The Smartphone as a Gait Recognition Device
Impact of Selected Parameters on Gait Recognition

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Abstract: This paper aims to identify the impacts of a couple of parameters on gait recognition when a build-in smartphone accelerometer is used. The use of different types of shoes impacts significantly gait recognition while the matching rate on a different surface e.g. grass has only a minor impact. A correlation between accelerometer's data and the phone position was identified. For this, data originating from the Z-axis as well as from the X-Y-Z –axis was used together with Dynamic Time Warping (DTW) for template generation and matching tests.

1 INTRODUCTION

Security often refers to the process of assets protection. In this context, verification of identities, known as authentication, is used as a mean to ensure the right person is able to access information. Authentication mechanisms are used on almost any device. Especially on mobile devices, authentication is "not user friendly enough to be widely adopted" (Schloeglhofer et. al.,2012). As a consequence non-invasive, continuous methods of authentication like gait recognition are currently being explored.

Gait recognition is an emerging biometric technology that does not explicitly involve users' actions. It evaluates the manner of walking over a certain distance (Nambiar et al., 2012). and can be used to identify persons (Lu et al., 2014). First approaches used a visual evaluation of the recorded movements (Bouchrika, et al. 2008), while later approaches used sensors like accelerometers in mobile devices to record specific data (Gafurov et al., 2007). Factors originating from users (e.g. illnesses as Parkinson disease, etc.) as well as from the environment (e.g. ground the user is walking on, etc.) can impact the process of gait based authentication.

The aim of this research project is to find out how strong the impact of parameters like, e.g. types of shoes, types of floors and phone position, is on the process of gait recognition. The problem is worth giving attention since these environment-related parameters have an impact on the quality of the authentication process and as such on the level of Security provided.

The use of time domain analysis methods constitutes a limitation of this approach. However, the use of frequency based methods is planned for the future.

2 PREVIOUS WORKS

Significant research in gait recognition was done by several researchers, e.g. (Nickel, 2012). However, very few research projects took into consideration the impact of external parameters like type of floor/surface, different footwear and the position of the phone.

Details show that results with regard to the impact of surfaces on gait recognition are not as clear as they seem to be at the first sight. (Holien et al., 2007) identified that the modification of the surface does not have a significant effect on gait recognition but they showed that gait recognition is more efficient on gravel and grass than on indoor surfaces. Later, Muaaz and Nickel (2012) showed that walking on grass and on inclined surfaces impacts significantly gait recognition. Walking on gravels - although impacted - produced comparable results to normal gait.

In two studies, the impact of different footwear was examined using video analysis. The first report shows that all shoes excluding strapless open-toed sandals do not impact gait recognition (Bouchrika

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and Nixon, 2008). However, flip-flops have a significant impact. The second research highlights the significant impact of the type of shoes in the recognition process using the video analysis method (Matovski *et al.,* 2012).

None of the previous studies analysed the impact of shoes and the position of the smartphone on gait recognition using the accelerometer in a smartphone.

3 RESEARCH METHODOLOGY

In order to use the smartphone as a gait recognition device, an Android application was developed. Its main objective is to collect data from different sensors in the phone that was worn by the participant during the experiment, see Figure 3. Then, the data will be processed and interpreted using MatLab scripts. The impact of the different parameters used was analysed using data from two experiments.

3.1 Number of Participants

The identified impact of the parameters should be independent of the person who wears the phone. Therefore 19 volunteers within an age from 18 to 25 years participated in this experiment. Should the results be promising, a further evaluation with significant numbers (100 volunteers) will be implemented. The experiment is anonymous and each volunteer is represented by a number in the experiment. An additional letter identifies the type of experiment done.

3.2 Research Procedure

The research procedure is similar to the one used in (*Thang et al.,* 2012), where first a reference gait (called normal gait) is identified before additional measurements can be done, e.g. measuring the gait with different types of shoe.

In order to determine a reference gait for each participant the first step for each user consists in several measurements during walks on the pavement with the phone tied to the leg using a leg band (Figure 1).

The next measurements helped to identify the impact of the selected parameters like floors on gait recognition, e.g. by walking on grass with the smartphone tied to the leg with the leg band.

To measure the impact of shoes two extremes will be used: normal, closed shoes and flip-flops. Featured templates will be extracted from these recordings.

Figure 1: “Leg band” (Side view).

Finally, the impact of the smartphone positioning in the trousers’ front pocket will be tested. In this third part, participants with adequate trousers (tight to the body) will walk with the smartphone in their trousers’ front pocket. This will help to identify potential differences in measurements based on the position on the phone.

The second aim will be to understand how reliable the accelerometer’s data is, when the smartphone rotates around its Z-axis (Figure 2). This device will allow a rotation around the Z-axis of the phone (one degree of freedom) and be attached to the leg using a strap.

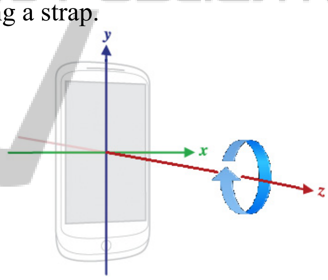

Figure 2: Smartphone axis (Android, 2014).

Figure 3: Data collection around the Z axis (Side view).

The last step of this methodology is the interpretation of data. Several choices will have to be made in order to select a suitable method. First of all, MatLab will be used for the interpretation of results. It was chosen because it simplifies handling of large amounts of data.

3.3 Selecting the Analysis Method

In this research area two analysis methods are traditionally used: the Dynamic Time Warping

(DTW) method in the time domain and the Fast Fourier Transform (FFT) method in the frequency domain.

Even though it was shown that the analysis in frequency domain (FFT) gives a better matching results than DTW (Thang et al., 2012), the latter was chosen for our experiment. It gives a better representation of the user's physical gait (acceleration as function of time) and is more suitable for the comparison of curves (Thang et al. 2012).

Additionally, DTW is a non-linear time alignment technique that allows matching of similar shapes out of phase in the same time axis (Danias, 2014) and thus avoids gait cycle length normalisation. This approach allows the measurement of similarities between two series of data that do not have the same length and as such fits our requirements.

4 RESULTS AND DISCUSSION

Before discussing results, it is necessary to explain how a confusion matrix works and to address decisions linked to measurements and evaluation that were made.

4.1 Confusion Matrix

A confusion matrix contains two inputs in which each letter (A – Z) is a label of a participant. The horizontal input represents each participant's featured template which is obtained after a training phase or by extracting the most representative vector of a record. This featured template is the curve which the vertical entry will be compared with. Indeed, the vertical input contains all curves representing each step for a specific record.

Each vertical input contains all the curves of the record for one person (one curve represents one step) and each curve is compared with all the featured templates of all participants. The comparison is done by calculating the distance between these curves using the DTW method, additionally the table's cell corresponding to the featured template is incremented by one.

The last column of this matrix contains the percentage of matches for each vertical entry. It shows the number of curves that match with the good featured template (corresponding to the same person) compared to the number of curves tested. Figure 4 illustrates in detail the operation on this type of matrix.

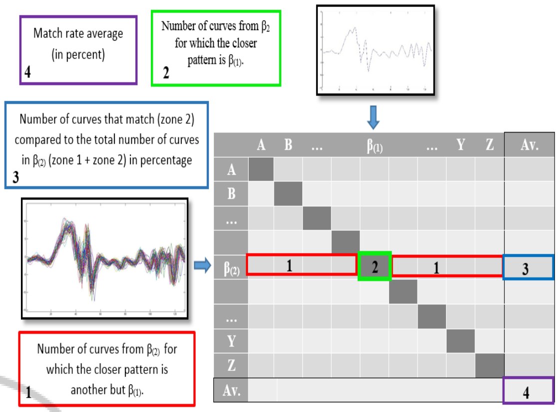

Figure 4: Explanation of the confusion matrix operation.

In this step three records belonging to normal gait records are used for comparison. The featured template is extracted from the first record and compared to the curves representing the second and the third record. The average matching rate is 73.41% against 73.85% when the featured template is extracted from the second records.

4.2 Choice of the Time Interpolation Frequency

The gait recognition algorithm developed collects data from the accelerometer sensor of the smartphone at the speed set by the phone.

A quick analysis of the first data extracted using the accelerometer showed that the smartphone does approximately a hundred measurements per second. In the first approach the closest time interpolation frequency (128 Hz) to one hundred (in power of 2) was selected.

This choice had to be confirmed by comparing matching results with other time interpolation frequencies. The algorithm was tested with the first two lower frequencies which are 64 Hz and 32 Hz. A higher frequency has not been tested for two reasons. Firstly, with this amount of points (256 points per second), the algorithm's execution time would have been too long and data interpretation would not have been possible with the laptop used. Secondly, such a frequency would have created too many missing points in the original recording and it might have influenced negatively the collected data. Comparisons of these three frequencies (128 Hz, 64 Hz and 32 Hz) are done using a confusion matrix. For the same recording, the average matching rate is 80.61% with a frequency of 128Hz against a rate of 44.22% with a frequency of 32Hz and with 62.03% at 64 Hz. This large difference shows clearly that the average matching rate considerably increases with the number of points per second.

In addition to this difference, the variation between two recordings is also impacted by the time interpolation frequency. Indeed, with a frequency of 128 Hz, the average matching rate difference between the two samples is 0.31% while for 64 Hz the difference is 6.92% and for 32 Hz, 6.04%.

The time interpolation frequency initially chosen is finally the best of the three tested because it produces the highest matching rate and will provide significant recognition results.

4.3 Detecting the Starting Point

In order to determine this starting point of gait, data collected following the Y axis of the accelerometer was analysed. This data is used to detect vertical acceleration. Moreover, in previous work (Gafurov *et al*., 2007) indicates that, from a standing position, starting to walk involves an acceleration of around 1.3g. It was suggested to identify the starting point when the measurement on the Y axis exceeds $12.74 m/s^2$ ($1.3g \times 9.8 m/s^2$).

4.4 Cycle Detection and Step Extraction

For cycle detection, data from mainly one axis (Y-axis) was used.

Data originating from several dimensions makes the detection of cycles hard. However, filtering one dimensional data will result in a sinusoidal curve that will allow the identification of cycles (Thang, et al. 2012). The measurement of each pattern length in this sinusoid will identify the cycle time of each step.

As such the first step of cycles detection is to filter the Y component of accelerometer using a moving-average filter with a 50 points window to clearly identify peaks. Each of these peaks represents the starting point of one step. The time interval between two peaks is the time of one step.

All these landmarks are then applied to the Z-axis. Steps and data between two consecutive landmarks are extracted. To avoid any error in this important extraction phase, the length of each step is compared to the cycle time of a normal person which is a value between 0.87 - 1.32 seconds (Levine *et al*., 2012). The multiplication of this time value with the time interpolation frequency indicates the range of acceptable values for a step.

4.5 Determination of the Featured Template

Once each step is extracted, the distance between them is calculated using the Dynamic Time Warping method (Lemire, 2009) which is a method to calculate the distance between two curves. Unlike Euclidean or Manhattan methods which align the x-th point of one curve with the x-th point of the other, the DTW method uses a non-linear time alignment. The distances between each curve are placed in a matrix and the average distance of each curve is calculated. The curve which has the lowest average distance is considered to be the featured template of the record.

4.6 Impact of the Smartphone's Position on Gait Recognition

The technical challenge when the phone is placed in a random position is to recognize this position and to adapt the algorithm to proceed with gait recognition. Each position has its own pair of X and Y central values, which makes the identification of the smartphone's position easily possible. Furthermore, the step detection is based on Y axis data when the phone is in its normal position (top of the phone oriented upwards) and each cycle time is delimited by two peaks of this axis. This axis has been chosen because its direction is parallel to the user and detects up and down variations. However, when the inclination of the phone is modified, this axis does not detect these variations anymore. As a result, a phase difference seems to exist between curves along the same axes in different position. This difference could be due to a different sampling of the original data. In order to avoid this problem, the selection of the axis which will determine the cycle time has to be linked to the phone position detection: Y-axis when the phone is oriented upwards, absolute value of the X axis when it is oriented forwards, absolute value of the Y axis when it is downwards and X-axis when the phone is oriented backwards.

4.7 Impact of the Curve Filter

The degree of filtering impacts the analyses of curves and as such the achieved results. Filtering is intended to reduce the existing error rate.

The application of filtering techniques gives several results depending on the filters applied. These results show a progressive increase of the average matching rate when the value of the filter is incremented. Furthermore, it proves that filtering has a positive impact on gait recognition.

This positive impact can also be identified by the increase of perfect matches. Indeed, when gait is analysed without filters, a perfect match occurs for one participant out of thirteen only, while with a filter of 90%, a perfect match occurs for ten volunteers. Furthermore, the use of an important filter removes intermediate values. Indeed, the average matching rates using an important filter are close to 100% or 0% which gives a binary answer to the gait recognition question.

Even if the highest filter seems to be the best solution, it is preferable to select an intermediate one in order to diversify the answer. Indeed, the binary answer provided by the highest filter avoids any interpretation of the result while it can be interesting, in a future application, to make a difference between a perfect match and an intermediate one.

4.8 Elimination of Abnormal Steps

Abnormal steps are steps for which representing curves have the highest average distance with the other curves using the DTW method. As they are not representative to the average gait, the curves with the highest variance from the average were removed. Indeed, these curves represent abnormal actions done by the user during the walking process (obstacle, loss of balance…).

During evaluation the presence of a few extreme values were noted. Whereas most of the values are included between 60% and 100%, some average matching rates are close to 0%.

The presence of these values is due to mis-measurement during the experiment and mainly with the use of the “leg band”. Indeed, this “leg band” slid down along few participant’s leg and they had to hold it to avoid this problem. The cause of this mis-measurement was confirmed by the experiment.

In order to avoid a misinterpretation of these errors, 10% of the extreme values are filtered when the sample of participant permits it.

4.9 Results

4.9.1 Impact of the Shoes

When gait using shoes is compared to the normal gait, the average matching sample obtained for each recording is relatively low (49.21% and 49.8%) as shown in table 1.

However, when gait data series are compared to each other, the result is significantly higher.

Table 1: Average values of shoe measurement series.

Average values	1	2
Normal gait vs. 2 samples of normal gait	70.56	69.54
Normal gait vs. 2 samples of gait on grass	49.21	49.8
Gait with flip-flops vs. 2 samples of gait on grass	84.13	80.24

The significant decrease of the average match using flip-flops means that the use of this type of shoes significantly impacts gait. Furthermore, the good match of two gaits using flip-flops confirms that the shape of the gait is linked to the type of shoes used and the strongest result identified with flip-flops shows that gait is more specific for each person using flip-flops making the recognition easier by not limiting movement as strongly as regular shoes do.
Flip-flops give a lot of freedom of movement, which leads to a stronger characteristic of movements. On the other hand, more sturdy, more closed shoes limit the movement. This can lead to higher false positives or negatives as the measured values might not differ strongly.

4.9.2 Impact of Different Floors

The comparison of the normal gait with gait on the grass gives an relatively high average match as shown in the Table 2.

Table 2: Average values of different floors measurement series.

Average values	1	2	Trim. mean 1	Trim. mean 2
Normal gait vs. 2 samples of normal gait	74.2	74.92	83.34	83.92
Normal gait vs. 2 samples of gait on grass	72.73	62.62	79.43	71.96
Gait with flip-flops vs. 2 samples of gait on grass	72.13	71.92	77.19	77.67

Whereas the variation of normal gait between two recordings is almost non-existent, a significant variation is identifiable when the gait on the grass is compared to the normal surface.

Contrary to the conclusion made in previous research (Holien *et al.,* 2007), when participants walk on the grass, the recognition probability is more variable and less predictable because of the irregularities in the floor. Furthermore, the comparison of the two records on the grass to each other (Table 2) shows that, for a same itinerary on this surface, the average matching rates are similar to normal gait recognition and the level of variation observed previously disappeared. For the same person, the gait is characteristic to the type of floor. The comparison of two gaits recorded on two different floors implies a decrease of the recognition probability.

4.9.3 Impact of Positioning the Phone in the Pocket

The comparison of the normal gait with the gait with the phone in the pocket (Table 3) gives a weak result with an average matching rate of 26.28% for the first recording and 22.96% for the second one. These weak matches are in contrast to the result of the comparison between the two recordings of the gaits with the phone in the trousers' pocket (Table 3): 82.29% and 76.77%.

Table 3: Normal Gait vs. 2 samples of Normal Gait.

Average values	1	2
Normal gait vs. 2 samples of normal gait	70.37	69.64
Normal gait vs. 2 samples of gait with the phone in the pocket	26.28	22.96
Gait with phone in the pocket vs. 2 samples of gait with the phone in the pocket	82.29	76.77

The comparison of normal gait with the gait with the phone in the pocket may seem disappointing at first sight since there are low average matching rates (Table 3). But these results have to be interpreted in context. Indeed, the modification of the position when the smartphone is placed in the pocket produces a modification of the phone's coordinate system and this difference changes the conditions of comparison (Figure 5). The matching rates are calculated with regard to variations along the Z axis which is oriented to the user's right side, whereas with the phone in the pocket the orientation of the Z axis is slightly different. Indeed, in the figure 5, Δ_1 and Δ_2 represent the same data variation but with a rotation of the reference system. The impact of this rotation implies a significant difference on the Δ variation.

However, when the two recordings of gait data with the phone in the pocket are compared to each other, the results are very successful. These matching rates are even higher than normal gaits. This improved result is probably due to a better stability in the pocket than with the leg band avoiding up and down movements of the phone. This hypothesis tends to be confirmed by the absence of extreme values when the phone is placed in the pocket. Indeed, the shape of the pocket ensures a better stability by holding the phone on each side.

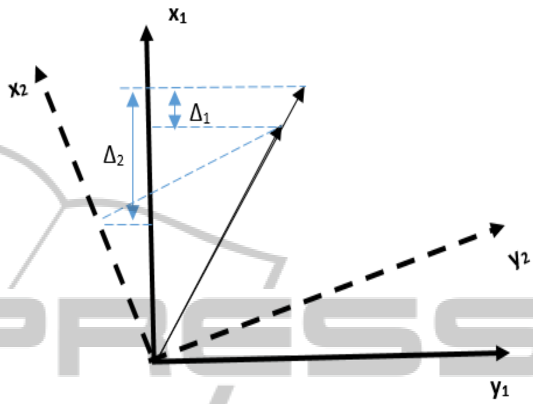

Figure 5: Impact of the modification of the phone position on the reference system.

4.10 Gait Recognition – Three-Dimensional Data Vs. the Initial Approach

The gait recognition algorithm developed to analyse data from the smartphone uses the Y axis to determine the starting point of the recording as well as the cycle time of each step. These cycle times are then applied to the data recording from the Z axis in which each step is extracted in order to be compared.

Another approach that was tested uses more than one axis to achieve the comparison. This is why, after the analysis of the Y axis in order to know the cycle time of each step, the three axes X, Y, Z are sampled step by step.

The results with the algorithm using three-dimensional data are more conclusive than the previous one. Indeed, for the normal gait, the comparison of data from three axes gives an average matching rate of 86.7% (against 73.41% with the previous method) and a trimming mean of 94.64% (against 80.30%). Regarding the gait on the grass, results are similare with 85.9% against 72.73% for the average matching rate and 92.89% against 82.57% for the timming mean. However, the most surprising result concerns gait using a different pair of shoes. While the first comparison method gave a match of 49.21%, the use of the three dimensional data gives a better result of 84.76%.

While the recognition following the Z axis is widely affected by the use of a different pair of shoes, the X and Y axes seem to be almost unchanged to ensure a similar recognition to normal gait. This seems logical since Z characterises a sidewise movement. Sturdy shoes reduce this movement significantly, while flip-flops offer freedom of movement on this axis.

Naturally, processing of three-dimentional data requires more computing power than data from fewer dimmensions. While the initial approach needed only a couple of seconds for the analysis, the approach using three-dimentional data needed more than one minute to process data. As such the initial approach constitutes a tradeoff time vs. security. With current hardware none of these approaches can be used in real-time.

5 CONCLUSIONS

This pilot project addresses a couple of factors, e.g. types of shoes, types of floors and phone position that might have an impact on gait recognition and as such on the security provided through authentication mechanisms using gait recognition.

While most of the factors do not have a significant impact on gait, a few factors like shoes can have a big impact. Gait is significantly modified if the user does not use close pairs of shoes. Open shoes produce impressive results.

A varying surface has only a limited impact on gait recognition. However, three-dimensional data can help to mitigate variations generated by the factors mentioned. In some cases they tend to disappear leading to a very good recognition rate.

Finally, when the phone is positioned in the trousers' pocket rather than tied to leg with a leg band, huge differences appear in the recognition process because of the modified position. Up and down movements along the leg introduce extreme values which impact the results.

Not all results identified were those expected. This means the problem is worth giving attention in the future, especially by observing new parameters together with new recognition algorithms.

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