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Gait and activity recognition using commercial phones

Mohammad Derawi, Patrick Bours*

Norwegian Information Security Laboratory, Gjøvik University College, Teknologivegen 22, 2815 Gjøvik, Norway

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ABSTRACT

This paper presents the results of applying gait and activity recognition on a commercially available mobile smartphone, where both data collection and real-time analysis was done on the phone. The collected data was also transferred to a computer for further analysis and comparison of various distance metrics and machine learning techniques. In our experiment 5 users created each 3 templates on the phone, where the templates were related to different walking speeds. The system was tested for correct identification of the user or the walking activity with 20 new users and with the 5 enrolled users. The activities are recognised correctly with an accuracy of over 99%. For gait recognition the phone learned the individual features of the 5 enrolled participants at the various walk speeds, enabling the phone to afterwards identify the current user. The new Cross Dynamic Time Warping (DTW) Metric gives the best performance for gait recognition where users are identified correctly in 89.3% of the cases and the false positive probability is as low as 1.4%.

1. Introduction

The combination of gait and activity recognition as a biometric is a relatively new area of study, within the realms of mobile smartphones (for a definition of a smartphone see Theoharidou et al. (2012)). It has been receiving growing interest within the research community and a number of gait approaches have been developed. Initial studies from 1967 into gait suggested that gait is a ”unique” personal characteristic and is cyclic in nature (see Murray (1967)). Later Johansson (1973) attached moving lights onto human subjects on all the major body parts and showed these light patterns to human observers. The observers could recognise the biological patterns of gait from the moving light displays (MLD’s), even when some of the markers were detached, once again indicating gait as a candidate for biometric recognition.

Research on accelerometer-based gait recognition started around 2005 independently by Ailisto et al. (2005) and by Gafurov et al. (2006). In the initial stages, dedicated accelerometers were used and worn on different body parts like the hip, arm, chest, or ankle. The optimal position to attach the sensor is still an open problem. Only recently researchers started to use smartphones as “sensors”, e.g. Derawi et al. (2010b), Frank et al. (2010), Kwapisz et al. (2010a). Smartphones are equipped with many different sensors and can be used for more than biometric research only, e.g. in Marquardt et al. (2011) is a smartphone used to reconstruct typed text of a nearby keyboard by measuring the vibrations produced when typing on this keyboard. In Bujari et al. (2012) the authors perform activity recognition on walking and stopping for traffic lights of pedestrians in traffic situations. In Lane et al. (2010) the authors present an overview of all kinds of sensors present in a smartphone and ways to use these sensors.

Research in accelerometer based gait recognition can be divided in two main groups, where (1) so-called gait cycles are extracted from the sensor data, or (2) the data is divided into segments from which features are extracted. Gait cycles correspond to two steps of a human and can be compared

* Corresponding author. Tel.: +47 611 35 250.
E-mail addresses: mohammad.derawi@hig.no (M. Derawi), patrick.bours@hig.no (P. Bours).
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using distances like the well-known Manhattan and Euclidean distance (see Holien (2008)), or the lesser known Dynamic Time Warping (DTW) (see Holien (2008) or Nickel et al. (2011c)), Principle Component Analysis (PCA) (see Bours and Shrestha (2010)), or the Cyclic Rotation Metric (CRM) (see Derawi et al. (2010a)). For comparison of feature vectors for activity recognition the dominant approach is to use machine learning algorithms that are well established in other pattern recognition domains such as speaker recognition. These promising approaches include neural networks (see Kwapisz et al. (2010a)), Hidden Markov Models (see Nickel et al. (2011b)), and Support Vector Machines (see Nickel et al. (2011a)).

Gait recognition can be seen as advantageous over other forms of biometric identification techniques for the following two reasons: (1) *user-friendliness*, because the gait of a person can be captured unobtrusively and continuously, unlike for example fingerprinting or retina scans, and (2) *security*, due to the fact that the gait of an individual is difficult to mimic (see Mjaaland et al. (2011)). Other biometrics modalities such as fingerprints are relatively easy to copy and security depends much more on the resistance of the sensor against fake inputs (see Matsumoto et al. (2002)).

On the other hand, there are challenges related to person identification via gait recognition (see Gafurov (2008)). Gait will be affected by (1) *stimulants*, like drugs and alcohol; (2) *physical changes*, for example pregnancy, an accident or disease affecting a leg or foot, or severe weight gain/loss; (3) *psychological changes*, where the mood of a person influences his/her gait; and (4) *clothing* and in particular shoe wear.

Activity recognition has become a very important area of research due to its application in many different areas such as health care, fitness, industrial application, security, entertainment, etc. (see Bao and Intille (2004); Choudhury et al. (2008); He and Jin (2009); Kwapisz et al. (2010b); Long et al. (2009)). The goal of activity recognition is to recognise and track human activities, which is also an important goal of ubiquitous computing (see He and Jin (2009)). The idea of ubiquitous computing is to integrate smartphones into our environment, everyday objects, and activities, to assist in our everyday live and work (see Huynh (2008)).

The combination of gait and activity recognition will be used as a continuous authentication control mechanism to secure smartphones from unauthorised access. Nowadays, smartphone users only perform authentication at login time with either a PIN-code or touch-pattern, both of which have weaknesses (see Angulo and Wastlund (2011)). Gait recognition will give a stronger guarantee that the user who tries to get access is not an impostor but the genuine user. Besides that, PIN-code and touch-pattern check only the credentials of the user at the start of a session, while gait and activity recognition continuously check the genuineness of the user. Potential applications for gait and activity recognition on mobile devices can be for example in health care where information becomes available on general mobile devices based on the identity of the person using it. Other possible applications can be gaining direct access, for example to a room or computer, through wireless communication between the door or PC and the mobile device that has identified the person carrying it.

The research described in this paper extends on the work in Derawi et al. (2010b) and Kwapisz et al. (2010b). The main difference is that a complete system is implemented on the mobile phone, including real-time analysis of the collected acceleration data. Compared to the work of Derawi et al. (2010b), this paper also considers variations in walking speed and comparing the performance of various analysis methods. In the work of Kwapisz et al. (2010b), the authors analysed segments of 10 s of walking data. Any change of activity or speed within such a 10 s segment might likely lead to not recognising the activity within that segment correctly. The reason for this is that features extracted from such a segment will be a mixture of the features related to the two different activities. This means that the particular segment then represents both activities poorly leading to not recognising it correctly. In this paper the focus is on single cycles in the walking data, so if a user changes his walking speed, then only a few walking cycles will be affected and recognition before and after these few cycles will not be disturbed.

This paper is divided into five further sections. Section 2 gives a brief explanation on the application software that has been used on the Samsung Nexus S smartphone for gait and activity recognition. Section 3 describes the experiment setup and the technology used for data collection. Section 4 presents the feature extraction and analysis. Experimental results are presented in Section 5. Finally, Section 6 presents conclusions and suggestions for future work.

2. Application software

An application for activity and gait recognition has been implemented for the Samsung Nexus S smartphone, running on Android 2.3.3 (Gingerbread). This application will also run on other smartphones that support the Android OS, but has only been tested on the Samsung Nexus S. The application can be used on Android 2.3.3 or newer versions of the Android OS.

The application can create templates for various users and different walking circumstances and perform identification of unknown users based on these templates. The data used for these tasks is the accelerometer data collected on the mobile phone. The application is able to perform real-time recognition and classification on the phone, due to optimisation of the algorithms for activity and gait recognition. During the experiments no drainage problems of the battery were experienced, but this was not the focus of the experiment. The application needs to be optimised and tested for battery usage in the future.

The application provides a graphical user interface that supports enrollment and authentication. The authentication methods that are implemented in the application at this moment are gait, fingerprint and password, but the application leaves room for future implementations of other biometric modalities, like face, voice, or gesture recognition. In this paper the only focus will be on the gait recognition method implemented on the mobile phone. During enrollment users can register themselves with various types of walking and are then required to walk for a certain time in that particular walking type. Walking once will already be sufficient for enrollment, but the application supports also enrollment based on multiple walks. Enrollment based on multiple walks will result in more stable reference templates.

In the authentication mode, one can choose the length of time in which data is collected for authentication. Typically 10 s of unobtrusive data collection is already enough for gait recognition. The length of the data collection was determined based on experience from previous experiments (for example Holien (2008)) and some testing with the current phone and software done before the actual data collection started. Furthermore, the smartphone does not need to be attached in a specific way to the body of the individual, and can be placed wherever the subject wants. For recognition purposes is it only required that the user attaches the phone always at the same position. Orientation of the phone is not important for recognition purposes.

3. Experiment

To obtain gait acceleration data the Samsung Nexus S smartphone was used. A high quality accelerometer is embedded in this phone, which can measure acceleration in three perpendicular directions (x, y, z). The measurement range of the accelerometer is between $-2g$ and $+2g$. The sampling occurs at non equidistant intervals with a sampling frequency of 150 samples per second in each of the three directions. The three measured acceleration value represent the direction of the acceleration, relative to the phone. These three values are then combined into a single value, which represents the magnitude of the acceleration. Obtaining the magnitude r from the measured accelerations (x, y, z) is simply done by taking the Euclidean norm (also known as L^2-norm), i.e.:

$$r = \sqrt{x^2 + y^2 + z^2}. \quad (1)$$

The magnitude of the acceleration does not depend on the orientation of the mobile phone, but it does depend on the location where the mobile phone is attached to the body.

The goal of the experiment was to research if accelerometer based gait data of different persons, when walking at different walking speeds, could be used for identification of these persons in real-time on the mobile phone. The application on the mobile phone should be able to identify either (1) which of the legitimate users was walking with the phone, or (2) that an unknown, illegitimate person was walking with the phone. In the experiment volunteers were requested to perform different activities, namely normal, fast, and slow walking. It was left to each of the volunteers to determine what normal, fast, or slow walking meant for them personally. The volunteers were not restricted to a specific walking speed as that would have influenced their natural walking behaviour.

In total, 25 subjects participated and most of them wore shoes with flat sole. The participants for this experiment were students and staff from our institute that volunteered to participate. The volunteers carried the Samsung Nexus S phone in a pocket of their trousers. The group of participants was split into 2 parts: (1) a group of 5 volunteers for which templates were stored on the phone for each of the 3 walking speeds; and (2) a group of 20 volunteers to test against the stored templates. In fact, the first 5 volunteers also tested the phone against their own stored templates.

During the template creation each of the 5 volunteers was asked to walk approximately 30 m for each walking speed and the collected acceleration data was used to create a template. This means that, in the end, the phone contained 3 templates per volunteer, so 15 templates in total. The templates were named in such a way that both the volunteer and the walking speed could be identified from the name of the template.

In the second stage of the experiment all 25 volunteers walked again the approximately 30 m with the phone which contained the 15 stored templates. Each of the volunteers walked this distance 15 times, namely 5 times at normal speed, 5 times at slow speed, and 5 times at fast speed. The order of the activities was randomised. In total this gives 25*15 = 375 data samples, of which 20*15 = 300 are impostor samples and the remaining 75 are genuine samples. The comparison between the stored templates and the test samples was performed on the phone and the results of the analysis were displayed on the screen. These results were available almost immediately after each walk. The time it took to remove the phone from the pocket and unlock it was enough to perform the analysis and display the results.

The accelerometer data that was collected on the phone was analysed in real-time, but was also stored on the device for later download and analysis on a PC. This allowed for more thorough analysis with methods that might take too long computation time on the mobile device. The comparison method that was implemented on the phone used the Manhattan distance metric which can be computed very fast.

4. Feature extraction and analysis

In order to be able to perform activity or gait recognition analysis, the collected, raw acceleration data needs to be preprocessed and cycles need to be extracted. This process is described in Section 4.1. In Section 4.2 a description is given on how the analysis for gait recognition is done and in Section 4.3 the focus will be on activity recognition.

4.1. *Extraction of cycles*

For each of the collected data samples, independent of volunteer or walking speed, the raw data was processed to extract separate cycles. The extracted cycles can then be used for gait or activity recognition. A brief description of the steps conducted for cycle extraction is given below. For more details see the work by Holien (2008) or Gafurov (2008).

4.1.1. *Calculating the acceleration magnitude*

The phone records the acceleration in 3 perpendicular directions (x_i, y_i, z_i), which represent the direction of the acceleration relative to the orientation of the phone. These three acceleration values are combined to a single value r_i representing the magnitude of the acceleration according to equation (1). The magnitude of the acceleration is independent of the orientation of the phone, but depends on the location of the phone on the body. So the user should carry the phone in the same position, but he/she does not need to worry about the orientation of the phone.

4.1.2. *Linear time interpolation*

The Samsung Nexus S outputs acceleration data values at approximately 150 samples per second. There is however some jitter on the sampling clock which causes the time intervals between two consecutive sample points to not always be equal to exactly 1/150 s. Linear interpolation was applied on the sampling points to ensure that they were equidistant in time. The resulting data consists of 150 equidistant triples of acceleration values per second.

4.1.3. *Filtering*

Removal of noise is done by applying a weighted moving average (WMA) filter. For details see (Holien, 2008). This ensures a smooth signal where high peaks are somewhat reduced. The WMA filter takes a weighted average of a number of samples. In the performed analysis a WMA filter of length 5 was used, in particular the following formula was used for filtering:

$$R_i = (r_{i-2} + 2 \cdot r_{i-1} + 3 \cdot r_i + 2 \cdot r_{i+1} + r_{i+2})/9,$$

where r_i represents the unfiltered signal, R_i represents the filtered version of the signal, and the divisor 9 equals the sum of the weights.

4.1.4. *Cycle length estimation*

To compute the average length of a cycle, a subset from the center of the data is extracted and compared to other subsets of similar length. Based on the displacement and the correlation between these subsets, the average cycle length is computed.

4.1.5. *Cycle detection*

The cycle detection starts from a minimum point $P_{start} = P_{min}$ near the center of the data sample. From this starting point are cycles detected in both directions. By adding the average length to P_{start}, the estimated ending point $P_{estimated} = P_{start} + averageLength$ is retrieved (in opposite direction: $P_{estimated} = P_{start} - averageLength$). Not all cycles are equally long and from experience (see (Holien, 2008)) it is known that the length of the majority of cycles deviates up to 10% from the average cycle length. The cycle end P_{end} is therefore defined to be the minimum in the interval of +/− 10% of the average cycle length from the estimated end point, see Fig. 1. This process will be repeated with the newly found end point as the starting point until all cycles are detected.

Finally after going through the previous phases and finding the starting points of all the cycles, the actual extraction of the cycles can be performed. Cycles are normalised in length (again using linear interpolation) to assure that each cycle contains 150 data points. Fig. 2 shows an overlay of the cycles extracted from one particular data file.

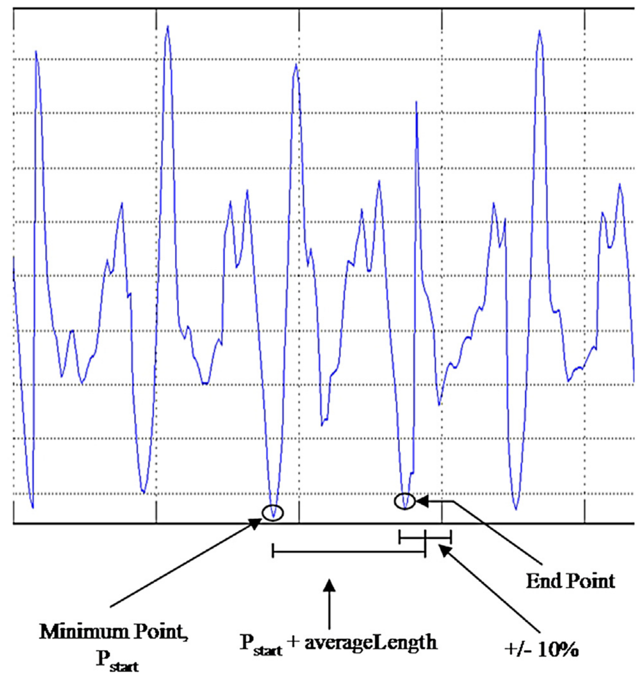

Fig. 1 – Cycle detection (from Derawi et al. (2010b)).

4.2. *Gait recognition analysis*

Gait recognition is performed as follows. Assume that from the test sample N cycles are extracted, which will be denoted by $C_1^{test}, C_2^{test}, \ldots, C_N^{test}$. Also assume that this test sample will be compared to a template from which M cycles are extracted. The M cycles of the template will be denoted by $C_1^{template}, C_2^{template}, \ldots, C_M^{template}$. Furthermore, let the average cycles for the test sample and for the template be denoted by $C_{average}^{test}$ and $C_{average}^{template}$.

4.2.1. *Real-time comparison on the phone*

The Manhattan distance was implemented in the application for the real-time comparison on the phone of a test sample with the 15 stored templates. The distance between test sample and template is defined as the Manhattan distance between the average cycle from the test sample, $C_{average}^{test}$, and the average cycle from the template, $C_{average}^{template}$. The Manhattan distance was chosen because this is easy and fast to compute on a mobile device.

4.2.2. *Comparison on the PC*

When doing the analysis on the computer, also the Euclidean distance and the Dynamic Time Warping (DTW) distance (see Nickel et al. (2011c)) were used. In both cases the distance between the average test cycle and the average cycle from the template was calculated in the same manner as it was done on the phone with the Manhattan distance.

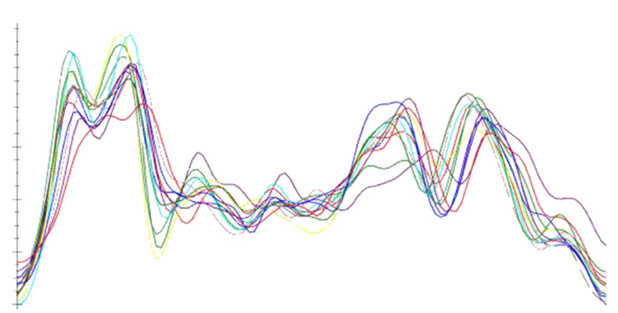

Fig. 2 – The cycles extracted from normal walk.

A modified distance metric, named the Cross DTW metric (CDM) was also applied to the dataset. This metric cross-compares two sets of cycles to find the best matching pair. The algorithm will compare each cycle C_i^{test} from the test sample to each cycle $C_j^{Template}$ from the template using the DTW distance metric. The result will be an $N \times M$ matrix which contains all the distances between any cycle from the test sample and any cycle of the template. This matrix is then reduced to a single value, representing the CDM distance between the test sample and the template, by taking the minimal value of the entries in the matrix, i.e.:

$$d_{CDM} = \min_{i,j}\left\{DTW\left(C_i^{test}, C_j^{template}\right)\right\},$$

where $i = 1...N$ and $j = 1...M$. The pair of cycles with the minimal DTW distance is considered the best matching pair. Note that for CDM it is not needed to calculate the average cycle from the extracted cycles of a gait data sample. For that reason, and the fact that DTW also works on inputs of unequal length, it is not necessary to normalise the length of the extracted cycles to a fixed length.

4.2.3. Performance analysis

The distance metrics described in the previous sections were used to analyse the performance of the system. The result of a comparison between a test sample and the set of 15 templates would be one of two values. The result could be the name of the template which had the closest distance to the test sample, or would be "unknown" if the minimal distance between the test sample and any of the 15 templates would be above a specific threshold T. More precisely, assume the 15 templates are denoted by $Templ_1, Templ_2, ..., Templ_{15}$ and let S denote the test sample. Furthermore, let d_i denote the distance between the test sample and the ith template, i.e. $d_i = distance(S, Templ_i)$ for $i = 1...15$. Finally let m be such that $d_m = \min\{d_i | i = 1...15\}$, then for this test sample S the result of the comparison would be "Template m" if $d_m \le T$ and "unknown" otherwise.

Ideally all test samples of the 20 not-enrolled volunteers would be identified as "unknown" and all the test samples of the 5 enrolled volunteers would be identified with one of the templates of the correct volunteer. The errors that can occur are (1) a not-enrolled volunteer is identified as an enrolled one; (2) an enrolled volunteer is identified as another enrolled volunteer; and (3) an enrolled volunteer is identified as "unknown", i.e. he/she is not recognised by the system. The probabilities that these errors occur will be denoted by e_1, e_2, and e_3. In Section 5 first some other probabilities will be derived directly from the collected acceleration data and then the probabilities e_1, e_2, and e_3 are calculated from these other probabilities.

4.3. Activity recognition analysis

For activity recognition a similar analysis is performed as in Section 4.2 for gait recognition. In this case however the focus will be on the type of activity instead of the identity of the person performing the activity. Two different approaches will be applied: (1) statistical analysis, using the same distance metrics as described in the previous section; and (2) a machine learning approach. The results will be reported in terms of correct identification of a particular activity.

For the machine learning approach a number of features were extracted from the collected accelerometer data. These features were then analysed using the open source software program WEKA (online freely available from http://www.cs.waikato.ac.nz/ml/weka/). In WEKA a number of machine learning algorithms are implemented and it contains tools for data preprocessing, classification, regression, clustering, association rules, etc.

The general activity recognition process is displayed in Fig. 3. It can be seen that feature extraction is one of the steps in activity recognition. These features need to be carefully chosen since they can have a significant influence on the result of the classification. For each of the data samples of the 25 users, eight features were extracted from each of the cycles: (1) the standard deviation; (2) the minimum value; (3) the maximum value; and (4) the length of the cycle; (5) the root mean square; (6) the mean value; (7) the entropy; and finally (8) the energy of the signal. However, the performance when using all 8 features was not significantly higher compared to only using the first 4 features. Therefore it was decided to only use the 4 first mentioned features in the analysis.

The extracted features were used in the next phase for classification (see Fig. 3). Note that in this case, because the features represent a single cycle in a full walk, the cycles are classified and not the walks. Different classification techniques available in WEKA were applied to the extracted features, for example Support Vector Machine (SVM), Bayes network, and Random Tree. Table 7 lists all the classification techniques that have been applied for classification.

5. Results

This section is split into a part that describes the results of the analysis for gait recognition and a part that describes the results of the analysis for activity recognition.

5.1. Gait recognition

In Section 4.2.3 it was mentioned that three types of error can occur. In this section the results related to these three types of errors will be presented. To do so, first a number of probabilities are derived directly from the data, from which later on the error probabilities will be calculated. In our analysis the distances calculated from the collected data were compared to the used threshold. From this, the probability p_1 that a not-enrolled user is indeed classified as "unknown" was calculated. Note that p_1 actually represents the True Negative (TN) probability. Next the True Positive (TP) probability (i.e. that an

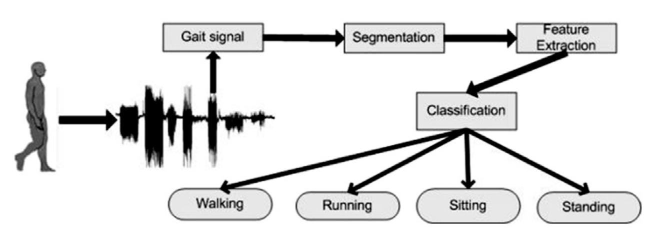

Fig. 3 – Classification of the activities.

enrolled user is classified as him/her-self), denoted by p_2, was calculated. Finally p_3 will denote the probability that an enrolled user is not recognised by the system, i.e. that he is classified as "unknown". Clearly p_3 represents the False Negative probability.

The error probabilities e_1, e_2, and e_3 can be calculated from the values p_1, p_2, and p_3. In fact e_3 equals p_3. The probability e_1, that a not-enrolled person is recognised as an enrolled person, is simply $e_1 = 1 - p_1$. Finally the error probability e_2, that an enrolled person is recognised as another enrolled person, equals $e_2 = 1 - p_2 - p_3$. In Table 1 the results are displayed. Do note that in this analysis only the identities of the users are considered and not the particular walking activities. This means that it does not matter at this moment, that an enrolled user U, when for example walking slowly, is identified as "user U walking normally". In that case still the correct user is identified!

In Table 2 the False Negative (FN) and False Positive (FP) results are presented for the various distance metrics described in Section 4.2. The probability of a False Negative can be calculated as $e_2 + e_3 = 1 - p_2$, i.e. the probability that an enrolled user is not identified as him/herself. The probability of a False Positive depends on e_1 and e_2, and on the number of enrolled and not-enrolled users, and can be seen to be equal to:

$$\frac{20 * e_1 + 4 * e_2}{24} = 1 - \frac{20}{24}p_1 - \frac{4}{24}p_2 - \frac{4}{24}p_3.$$

It is obvious that the values of p_1, p_2, and p_3 (and hence also the values of e_1, e_2, and e_3) depend on the threshold and therefore also the values of FN and FP depend on that threshold. The results displayed in Tables 1 and 2 are based on the threshold for which the sum of FN and FP is minimal.

The performance for the CDM method is best, but this is the computationally most intensive method. The results should be interpreted as follows. If the phone is used by one of the genuine owners, then approximately 9 out of 10 times (TP probability is $p_2 = 89.3\%$ for the CDM distance metric) the user is recognised correctly and when needed he/she can start using the phone directly. Only in 1 out of 10 occasions the user is not recognised and he/she needs to use the backup solution to get access to the phone. This backup solution will generally be entering the PIN code. So in other words, in almost 90% of all cases has the user a user friendly method of getting access to the phone while not reducing the security significantly (FP probability of 1.4%). The user only needs to use the backup solution in 2 out of 9 cases, in case the faster DTW metric is used. We know from the findings in Mylonas et al. (2013) that users have a tendency to not use access control mechanisms. One reason for this could be that users find it cumbersome to always have to use a PIN code, password or swipe pattern to unlock their smartphone. Using gait recognition could in such a case reduce the number of times a user has to use his/her access control mechanism and as a consequence hopefully increase the percentage of people actually using access control mechanisms on their smartphone.

Table 2 – Probabilities for false negatives and false positives.

Distance metric	*Prob (FN)*	*Prob (FP)*
Euclidean	30.7%	15.7%
Manhattan	28.0%	19.5%
DTW	22.7%	1.1%
CDM	10.7%	1.4%

5.2. *Activity recognition*

Two different ways of activity recognition were performed (see Section 4.3). The first is similar to the analysis above on gait recognition, while the other uses machine learning. The results are given in Section 5.2.1 for the statistical analysis and in Section 5.2.2 for the Machine Learning approach.

5.2.1. *Statistical approach*

In this analysis, any test sample will be compared with each of the 15 stored templates. Based on the distances calculated in this way will a test sample be classified as either "slow walking", "normal walking", or "fast walking". Note that in this case only the walking activity is considered and not the identity of the walker. In Tables 3–6 an overview is given for the correctly recognised activities. The rows represent the test data samples, while the columns represent the recognised activities. Each of the tables represents the results for a particular distance metric that is used in the analysis.

The probability for correct recognition of a walking speed can be calculated from the tables by taking the average of the 3 values on the diagonal. This probability equals 78.7% for the Manhattan distance, 78.9% for the Euclidean distance, 81.3% for the DTW distance and 86.4% for the CDM distance. So, with statistical analysis, the best performance is again obtained with the CDM distance metric.

5.2.2. *Machine learning approach*

The test samples of all 25 participants were used for the machine leaning analysis. Table 7 shows the list of algorithms used for the supervised learning approaches. The data was split into a training and a test set using both personal and global *k*-fold cross validation. The features of the cycles, as

Table 1 – Performance for gait recognition.

Distance metric	p_1	p_2	$p_3 = e_3$	e_1	e_2
Euclidean	82.0%	69.3%	26.7%	18.0%	4.0%
Manhattan	77.7%	72.0%	22.7%	22.3%	5.3%
DTW	99.0%	77.3%	21.3%	1.0%	1.4%
CDM	98.3%	89.3%	10.7%	1.7%	0%

Table 3 – Correctly recognised activity for Manhattan distance.

	Slow	Normal	Fast
Slow	72.0%	24.0%	4.0%
Normal	9.6%	74.4%	16.0%
Fast	0.0%	10.4%	89.6%

Table 4 – Correctly recognised activity for Euclidean distance.

	Slow	Normal	Fast
Slow	68.8%	27.2%	4.0%
Normal	4.8%	79.2%	16.0%
Fast	0.0%	11.2%	88.8%

Table 5 – Correctly recognised activity for DTW distance.

	Slow	Normal	Fast
Slow	92.0%	8.0%	0.0%
Normal	18.4%	68.8%	12.8%
Fast	0.0%	16.8%	83.2%

described in Section 4.3, were used for both the training and the test set. The results in Table 7 represent the correct classification probabilities of separate cycles that are extracted from a walking sample.

5.2.2.1. *Personal cross validation*. First the performance of cross validation for individual-based activity recognition was evaluated. This means that the activity performance was considered for each user separately. The learning algorithm was trained and tested with the cycles extracted from a single person. The first column in Table 7 shows the results of this classification for the different classifiers that were used. Each value in this first column is the average of the correct classifications for all 25 participants. From the table it can be seen that the best result was obtained with LibSVM (Library for Support Vector Machine), with an accuracy of 99.6%. The next best performance is an accuracy of 98.9%, achieved by using the Radial Basis Function Network (RBFNetwork).

5.2.2.2. *Global cross validation*. When performing global cross validation the data from all 25 subjects was merged, hence the system was trained independent of the identities of the users. The results are shown in the second column of Table 7. These results indicate how different normal, fast and slow walking are within a group of users. The LibSVM and Logistic Model Trees (LMT) slightly outperformed the other methods with recognition rates of 87.6% and 86.7%.

The correct classification probability of a walk can be estimated from the correct classification probability of the cycles, by simply using majority voting over the cycles in a walk. Assume that at least 9 cycles are detected in a walk, and assume that the correct classification probability of a single cycle is as low as $p = 80\%$. Even under these assumptions will a walk be classified correctly in over 98% of the cases. The data samples in the experiment represented a walk of approximately 30 m. For all these data samples was the assumption that at least 9 cycles were detected always true.

Table 6 – Correctly recognised activity for CDM distance.

	Slow	Normal	Fast
Slow	93.6%	6.4%	0.0%
Normal	18.4%	71.2%	10.4%
Fast	0.0%	5.6%	94.4%

Table 7 – Cross validation.

Classifier	Personal	Global
BayesNet	97.9%	81.9%
LibSVM	99.6%	87.6%
LMT	98.1%	86.7%
MultilayerPercepton	96.8%	83.3%
NaiveBayes	97.3%	80.5%
RBFNetwork	98.9%	81.1%
RandomTree	97.9%	80.9%

6. Conclusions and future work

This paper describes how a Samsung Nexus S smartphone, when carried in the trouser pocket of a user, can be used to perform activity and gait recognition. Beside real-time analysis performed on the mobile phone also additional analysis of the collected data was performed on the computer.

The results for both gait and activity recognition are at an acceptable level. The Manhattan distance metric is implemented in the current gait recognition method on the mobile phone. This distance metric gives the least results of the 4 tested distance metrics in this research. A future task will be to create an efficient gait recognition implementation on a mobile phone using the DTW or the CDM distance metric that can run in real time. If the current application, used for the experiment, is updated in that manner, then it can be used for protection of the mobile phone. In such a case the phone will need to be trained with the various activities of the owner of the phone.

Future research will consider the combination of gait and activity recognition to see if the combined results improve over the separate results. In this case the activity will be recognised first and the information will then be used in gait recognition to identify the correct user.

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Patrick Bours studied mathematics at the Eindhoven University of Technology in the Netherlands. He got his MSc and PhD with a specialization in coding theory. After his studies he worked at the Netherlands National Communication Security Agency (NLNCSA) in the area of cryptology. In July 2005 he moved to Norway where he joined the Norwegian Information Security Laboratory (NISlab) which is a part of Gjøvik University College. Since September 2009 he holds a full Professor position. He is specialized in behavioural biometrics. His current research focus is on gait recognition and on static and continuous keystroke dynamics.

Mohammad Derawi studied Computer Science at the Technical University of Denmark – Department of Informatics and received his BSc and MSc degree in 2007 and 2009 respectively. His final project for his MSc degree involved fusion of biometric fingerprint and gait information to enhance security of mobile devices. He started his PhD research in April 2009 at the Norwegian Information Security Laboratory (NISlab). He is the author of 14 publications in the area of biometric authentication and activity recognition. Since January 2013 he holds an Associate Professor position at the Faculty of Engineering at Gjøvik University College.