Fusion of Gait and ECG for Biometric User Authentication

Mohammad Derawi and Iurii Voitenko
Smart Wireless Systems
Gjøvik University College, Norway
[firstname].[lastname]@hig.no

Abstract: A new multi-modal biometric authentication approach using gait and electrocardiogram (ECG) signals as biometric traits is proposed. The individual comparison scores derived from the gait and ECG are normalized using several methods (min-max, z-score, median absolute deviation, tangent hyperbolic) and then four fusion approaches (simple sum, user-weighting, maximum score and minimum core) are applied. Gait samples are obtained by using a inbuilt accelerometer sensor from a mobile device attached to the hip. ECG signals are collected by a wireless ECG sensor, which is based on a 2 led ECG signals attached on the breast. The fusion results of these two biometrics show an improved performance and a large step closer for user authentication for biometric user authentication.

1 Introduction

The combination between gait and ECG recognition as a biometric is a relatively new area of study, within the realms of biometric user authentication. It has been receiving growing interest within the mobile phone community and a number of gait/ecg approaches have been developed, but to the best of our knowledge never fused for user authentication purposes. Initial studies into medical gait and ecg suggested that they had a ”unique” personal characteristic, especially gait with its cadence and was cyclic in nature in 1967 [Mur67]. Later, Johanssons' [Joh73] focus on gait attached moving lights onto human subjects on all the major body parts and showed these moving patterns to human observers. The observers could recognise the biological patterns of gait from the moving light displays (MLDs), even when some of the markers were detached, once again indicating gait as a potential candidate as a prominent biometric.

Research on accelerometer-based gait recognition started in 2005 by Ailisto et al. [ALM+05] and was further investigated by Gafurov [Gaf08]. In the initial stages, dedicated accelerometers were used and worn to different body parts like the feet, hip, arm or ankle. Only recently researchers started to use smart phones as ”sensors” [DNBB10].

This article focuses on the emerging biometric technology, namely the electrocardiography (ECG) recognition aswell. This modality has had about 15 years of development in research, but not in the field of biometrics. ECG are based on physiological signals, rather than more traditional biological traits. These have some advantages. Since every living and functional person has a recordable ECG signal, the ECG feature becomes universal.

Moreover heart damage is something that rarely occurs, so it seems to be quite invariant across time. The advantage of this bio signal is that it gives some sort of liveliness measurement to avoid spoof attack.

ECG and Gait recognition has something in common and can be seen as advantageous over other forms of biometric identification techniques. It is difficult to mimick ,and by trying to do so the mimicker must have a ECG/Gait scanner which is more unnatural and in the same time not possible [RDCR08].

In this paper we present a fusion of ECG recognition and accelerometer-based gait recognition as means of verifying the identity of the user of a mobile device. The main purpose of this paper is to study how it is possible to lower down the user effort while keeping the error rates in an acceptable and practical range.

2 Data Collection

2.1 ECG Signal Data

The low-consumption chip which is used for collecting ECG data is the BMD101 from NeuroSkyss 3rd generation bio-signal detection and processing SoC (3mm x 3mm in size) and gives real-time reporting of heart rate (+/- 1bpm) [Neu12]. It is designed with an analog front-end circuitry and a flexible, powerful digital signal processing structure. It targets bio-signal inputs ranging from uV to mV level and deployed passes the raw signal through with proprietary algorithms. The low-noise-amplifier and ADC are the main components of the BMD101 analog front end. Because of the BMD101âs low system noise and programmable gain, it can detect bio-signals and convert them into digital words using a 16-bit high resolution ADC. The AFE also contains a sensor-off detection circuit. The heart of the BMD101 digital circuit is a powerful system management unit. It is in charge of overall system configuration, operation management, internal/external communication, proprietary algorithm computation, and power management. BMD101 also comes with hardwired DSP blocks to accelerate calculations, such as various digital filtering, under the supervision of the system management unit and finally has 64-byte TX FIFO UART serial interface (57600). The BMD100 is main component for capturing ECG and is the black square in the middle illustrated in Figure 1(Left). The chip takes as input the signal from the electrodes and either sent it to bluetooth or any kind of Microcontroller or PC. The experiment was carried out on indoor. The 30 subjects who participated wore an wireless ECG device attached with 2-leads as seen in Figure 1. The two leds were placed above the right breast and the second sensor were placed below the left breast. The ECG placement had more or less had the same orientation for all subjects. The subjects made the experiment over the same day and were asked to sit and relax. The subject had to sit down for 5 minutes while the recording was active. After that, each minute was then stored as one session resulting in 5 sessions totally. The ECG sensor used was a BMD101 commercial sensor , with a high accurate sampling frequency rate. The data was sent real-time from the wireless device to an Android based phone as seen in Figure 1 (Right Image

Figure 1: *Left*: Chip Diagram. *Middle*: Two lead wireless ECG-monitor. *Right*: Android screenshot: The raw ECG signal from ecg device to the Android tablet

in realtime. The information retrieved retrieved was the time, raw signal of the ECG and heart-rate.

2.2 Gait Data

So as to obtain acceleration data we used the Samsung Nexus S smartphone as seen in Figure 2. It consists of a high quality accelerometer which can measure the body motion in three directions (x,y,z). The acceleration range of the accelerometer is between -2g and +2g. The sampling occurs at nonequidistant intervals with a frequency sampling about 150 samples per second in all three directions. The x direction indicates the vertical acceleration which does also contain the gravity. The y-acceleration corresponds to the forward-backward movement and the z-acceleration indicates the lateral acceleration.

In the experiment we requested volunteers to execute different activities, namely normal, fast and slow walking. In total, 30 subjects participated where most of them used shoes with flat sole. All volunteers were asked to perform the three mentioned types of activities 15 times for the same fixed distance of around 29 meters for one activity. That would give 29 * 15 = 435 meters of walking for one user per session. One session includes random chosen activities (normal, fast or slow) equally distributed. The volunteers in the experiment were students and employees from all places. In addition 5 random volunteers were asked to walk one extra time per activity per session. This will cause in (5 * 16) + (25 * 15) = 455 walks in total. The gender distribution was the same as with the ECG experiment.

2.3 Multi-biometric Data

The subjects in the ECG and gait experiments are different. However, assuming non-correlation of persons ECG patterns and gait (walking style) we randomly pick up a gait sample and assign it to ecg sample.

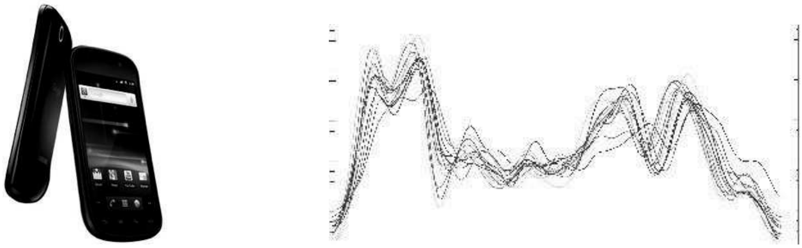

Figure 2: *Left*: Google Nexus S phone *Right*: Cycle samples of walks from the Nexus S.

3 Feature Extraction and Comparison

The raw data retrieved from the ECG and Nexus S sensor needs to be processed in order to create robust templates for each subject. The advantage with these two data output is that we can apply almost the same feature extraction method with small modifications and comparison. We apply the method from [DBH10] as this will serve well to our ecg and gait data. The cycle-detection is thus briefly explained below:

Preprocessing: At first we apply *linear time interpolation* on the raw signal data retrieved from the sensor to obtain a linear observation since the time intervals between two observation points are not always equal. Another weakness from the sensor is the fact that the ECG data will be outputted with some noise. This noise is removed by using a *weighted moving average*. This is applied both for ecg and gait cycles.

Cycle Detection: From the data it is known that one cycle-length varies between x samples depending on the gait/heartrate of the person. Therefore we need to get an estimation of how long one cycle is for each subject. This is done by extracting a small subset of the data and then compare the subset with other subsets of similar length (cross-correlation). Based on the distance scores between the subsets, the average cycle length is computed. Since both ECG and gait signals outputs time-values with peaks (minimas and maximas), the main difference here is that within ECG we make a maximum peak search from one cycle to another, whereas for gait we apply the minimum peak search.

Odd Cycle Removal: Before starting on the actual analysis, we ensure to skip cycles that are very different from the others. This is done by taking each cycle and calculate its distance to every other cycle by using dynamic time warping (DTW). This process is the same for both gait and ecg cycles.

4 Score Level Fusion

4.1 Score Normalization

The comparison scores at the output of the individual comparators may sometimes not be homogeneous. In that case we simple calculate the multiplicative inverse for the distance score.For our case the ECG and gait were of same kind, and thus no modifications were needed. However, the outputs of the individual comparators need not to be on the same numerical scale (range) and in the same time the comparison scores at the output of the comparators may also follow different statistical distributions [JNR05].

Score normalization is therefore used to map the scores of each simple-biometric into one common domain. Some of the methods are based on the Neyman-Pearson lemma, with simplifying assumptions. Mapping scores to likelihood ratios, for example, allows them to be combined by multiplying under an independence assumption. The other approaches may be based on modifying other statistical measures of the comparison score distribution. What is relevant to know is that score normalization is related very close to score-level fusion since it affects how scores are combined and interpreted in terms of biometric performance. The normalization functions, which are applied in this paper are the *Min-Max*, *Z-Score*, *Median Absolute Deviation* and *Hyperbolic Tangent*. Their formulas are described in details in [ISO].

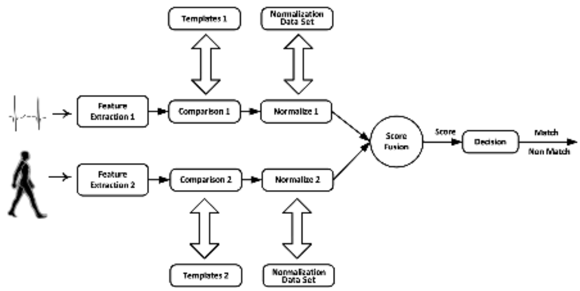

Figure 3: Overview of the proposed method in the score-level fusion. ECG is at the top and Gait at the bottom.

4.2 Score Fusion

When individual biometric comparators output a set of possible matches along with the quality of each match (comparison score), integration can be done at the comparison score level, see Figure 3. The comparison score output by a comparator contains the richest information about the input biometric sample in the absence of feature-level or sensor-level information. Furthermore, it is relatively easy to access and combine the scores generated by several different comparators. Consequently, integration of information at the comparison score level is the most common approach in multi-modal biometric systems. The fusion approaches applied are the *Simple Sum*, *Minimum Score*, *Minimum Score* and *User Weighting* which are further described in [ISO].

5 Results

The results shown below are algorithm performances for biometric verification purposes. Experiments were performed in order to compare the following configuration; *1* Performance of single modalities, i.e. ECG recognition and gait recognition separately and *2* Performance of multi-modalities, i.e. ECG recognition and gait recognition fused.

Table 1 takes all of ECG and gait, which are performing best, and is fused with gait data. Given an EER of 4.2 for ECG and an EER of 7.5 for Gait we gain an overall fused performance of EER = 1.26 %. However, Table 2 shows how large an improvement can be done

ECG	Gait	ECG + Gait	Normalization	Fusion
4.2	7.5	1.26	MinMax	Simple Sum
4.9	10.3	1.46	MAD	Simple Sum
5.1	15.5	1.58	MAD	Simple Sum
6.6	16.0	1.70	MAD	Simple Sum

Table 1: Smallest EERs after fusion.

by having high numbers of EERs. Given that ECG has an EER of 20 and gait has an EER of 40 we gain an improved EER of 7.3.

ECG	Gait	ECG + Gait	Normalization	Fusion
13	36	6.5	MinMax	Weigthed
15	38	7.0	MinMax	Simple Sum
19	40	7.1	MAD	Simple Sum
20	40	7.3	MAD	Simple Sum

Table 2: Most improved EERs after fusion.

6 Discussion

Since personal handhold devices at present time only offer means for explicit user authentication, this authentication usually takes place one time; only when the mobile device has been switched on. After that the device will function for a long time without shielding user privacy. If it is lost or stolen, a lot of private information such as address book, photos, financial data and user calendar may become accessible to a stranger. Even the networking capabilities on the handhold device can be used without restraint until the holder of the device discovers the loss of it and informs this to the network provider. In order to decrease the risks to the owner's security and privacy, mobile devices should verify its user regularly and discreetly who in fact is carrying and using them. Gait recognition is well-suited for this purpose but is difficult under unusual and challenging conditions. In view of the fact that the risk of a handhold device being stolen is high in public area (transport, shopping areas etc), the method for unobtrusive user authentication should work. Since people frequently move about on foot (at short distances) in places where the probability of losing a handhold device are high, a fusion of gait processing with biometrics such as ECG recognition is an opportunity to protect personal devices in noisy and normal environments. A possible application scenario of a multi-modal biometric user verification system in a mobile device could be as follows; When a device such as a mobile phone, is first taken into use it would enter a "practicing" learning mode for an appropriate time session, say 24 hours. For this period of time the system would not only form the gait and ECG templates, but also investigate the solidity of the behavioral biometrics with respect to the user in question. Password-based or PIN code user authentication would be used during the learning session. If the solidity of the gait and ecg biometrics was sufficient enough, the system would go into a biometric authentication "state", a state that will need confirmation from the owner. In this state the system would asynchronously verify the owner's identity every time the owner walked while carrying the phone different places or eventually talked into it. The system would be in a safe state for a certain period of time after verification. If new verification failed, the system would use other means to verify the user, e.g. asking for ECG.

Gait biometrics is a behavioral biometrics, and gait can be affected by different factors. Using wearable sensors in gait recognition is a quite new field and therefore a lot of further research would be needed. By looking at topics that are directly connected to this paper it is natural to include more testing conditions, like e.g. walking up- or downhill, injuries, tiredness, heavy load carrying , high-heeled shoes wearing etc. but it would also be interesting to look at several types of environments like the surface, e.g. walking on grass, bad grounds, gravel, sand, etc.

Although the use of gait biometrics alone might be insufficient for user authentication, experiments during this project has shown that its use as a complementary modality to ECG recognition improves the performance.

7 Conclusion

The multi-modal biometric method for frequent biometric user authentication of mobile devices proposed in this paper was investigated in a technology test. It contained ECG with placement of sensor on the chest and gait sensor with placement of the accelerometer module in the hip. ECG-based recognition resulted in different performances of using four different comparators. The best functioning comparator resulted in an EER of 4.2 %, while gait gained an EER of 7.5 %. Our experimental results show that in all cases that fused algorithm performance (ECG + gait) was significantly improved compared to performances of individual modalities. By using multi-modal authentication we achieved best EER interval of 1.26 % - 1.70 %. The shown results suggest the possibility of using the proposed method for protecting personal devices such as PDAs, smart suitcases, mobile phones etc. In a future of truly pervasive computing, when small and inexpensive hardware can be embedded in various objects, this method could also be used for protecting valuable personal items. Moreover, reliably authenticated mobile devices may also serve as an automated authentication in relation to other systems such as access control system or automated external system logon.

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