How Different Surfaces Affect Gait Based Authentication

Kjetil Holien, Rune Hammersland and Terje Risa
{firstname.lastname}@hig.no
Norwegian Information Security Lab, Gjøvik University College

October 15, 2007

Abstract

The aim of this project was to figure out how much different surfaces affects our gait. The experiment was limited to consist of three different surfaces: concrete floor, grass and gravel. The concrete surface is a solid surface without any movement, the grass is a soft surface which will dampen your movement and the gravel is a rolling surface. We conducted the experiment with an accelerometer placed on the hip of 25 participants. The participants walked on all of the three different surfaces and we have analysed the data to see if we are able to draw a conclusion about how the surfaces affects the gait recognition.

1 Goal of the study

In an ideal world people would only walk on the same solid surface, this is however not the reality. People walk on different surfaces, for instance concrete floor or outside in the grass. Our goal of this study is to examine what kind of impact surface has on gait recognition. We have decided to use three different surfaces:

- Concrete Floor: the floor is a solid underlay with no movement.
- Grass: the grass is a soft surface which will dampen your movement.
- Gravel: on the gravel you will experience a more rolling surface.

If the surfaces does not significantly impact the recognizing process, there should be no problems using a training set from indoor walking for authentication on different surfaces. This implies that the place of authentication more easily could be moved to another place without having to train the system again to accommodate for the new surface.

2 State of art

Gait has become an area which has gained a lot of interest over the last decade. An important reason why gait has become attractive is that it is non-intrusive, can be measured without subject contact or knowledge and it can not easily be obscured [3]. Most research on gait recognition the last decade has been video-based, where the purpose has been for surveillance, for instance recognizing a criminal from a security camera video [1, 8, 9, 12]. There has also been some research on sensors installed in the floor [11]. However when using video-based recognition there is a lot of variables interfering which lower the performance, such as lighting and other objects. In 2005 a new identification method which utilize how people walk [10] was presented. This method use a device called an accelerometer which measure acceleration in three directions (up-down, forward-backward and sideways), and this method will be used in this project. Gait recognizing using accelerometer can be used to authenticate and protect mobile phones and other portable electronic devices, where the sensors are integrated into the hardware [6].

There has been some research on this matter, mainly a group from Finland and here at Gjøvik University College. The group from Finland used methods called correlation and frequency domain [2, 10]. These reports showed promising results, when you take into consideration that it has not been done before, they ended up with a error equal rate (EER) at 6.4% to 19 % depending on what method was used. In our study we will follow what the group here at Gjøvik did, they used methods called absolute distance,histogram similarity and two different cycle lenghts [5, 6, 7]. By using this methods they managed to get EER from 7.3% to 20%. They have also looked at what impact backpacks had.

3 Experiment

As mentioned in section 1, we have conducted an experiment where we look at how the surface impacts the ability to perform gait recognizing. In order to achieve this, the test-subjects was wearing an accelerometer attached to a belt. The accelerometer was on the right leg, placed by the hip. Another issue that must be taken into consideration is the fact that one loose ± 2 cycles at both the beginning and the end when one walks [6]. A sufficient number of cycles with decent quality would be 10 cycles, and since each cycle consist of a right step + left step and each step is about 1 meter, a subject walked 30 meters. By walking 30 meters we will have about 15 cycles in total and about 10 cycles of decent quality.

The walking session was conducted in this way:

- For each time the subject is supposed to walk, he had to wiggle the belt and wait 3seconds before he could start walking.
- The subject walked 30 meters, then stopped and turned, and then walked the same distance back. So the subject:
  1. Wiggled the belt
  2. Waited 3 seconds
  3. Walked 30 meters
  4. Stopped and waited for 3 seconds
  5. Wiggled belt and turned
  6. Waited 3 seconds
  7. Walked 30 meters
  8. Stopped and waited for 3 seconds
- The subjects started with the right leg each time.
- The procedure (walking back and forth) was done two times for the concrete surface, generating one template and three checks, and two times for the gravel and grass surface (generating four checks on each).
- The subjects tried to walk in his normal way all the time.
- After each gait-sequence the data was downloaded to the computer and verified.
- Each gait-sequence took approximately 2 minutes, therefore total time was around 15min for each participant.

The first walk (first 30m) of the first indoor walk was used to generate a template, and then rest of the indoor-walking (3x30m) was used to try to recognize the user by creating three gait-samples. After walking indoors, the user was asked to walk two times on both gravel and grass, which in turn generated eight separate gait-samples (four per surface). With this data we later tried to verify the user, in order to see if the results are considerably weaker or if the same template indeed can be used despite the different surfaces.

When conducting an experiment which involves participants it is always important to think about the ethics. The participant was asked to sign an informed consent, the data was made anonymous and stored according to regulations. This means that the data was not stored on a server or in a place where it can be easily accessed by others. A copy of the informed consent can be seen in Appendix A.

3.1 Volunteer crew

Our experiment participants consisteded of 25 students, 20 male and 5 female. In order to both make the experiment statistically significant and be finished in time we settled with 25 participants. In addition to the gait data, age and gender, other factors that might affect your walking, such as shoe wear and injuries was also collected. No special skills were needed to participate in our experiment, so we didn't exclude anyone.

3.2 Environment

There was three different locations for the gait-sequences:

- Concrete Floor: We used the basement in the A-building. This floor has a solid underlay with no movement.
- Grass: We used the grass outside the entrance to the basement. The grass has a softer surface.
- Gravel: We used the gravel outside the entrance to the basement. On the gravel one will experience a more rolling surface.

A possible error that might occur is that the accelerometer is placed on different places among the subjects, in order to avoid this we were precise and checked that the sensor was placed correctly. Another possible error in our study can be that the participants use different shoes. Since all measurements were taken at almost the same time, they used the same footwear. The shoe wear will perhaps affect the gait data in a special way if you e.g. walk with high heels on the gravel. Another influence which might give the same kind of error is if the participant has an injury and therefore walks in a particular way. The weather might also have an impact on both the surface outside and how people walk. All the surfaces were more or less flat, to rule out the effect a sloping surface might have.

3.3 Enrollments and verifications

As explained above, the enrollment is the first gait-sequence, which is indoors. All gait-sequences was guided and supervised. In the event of a problem, the participant was asked to redo the sequence. After the enrollment had taken place, we needed to process and cut the data gathered as explained in section 4. A possible problem that can occur here, is wrong preprocessing of the data, meaning that we for instance cut the raw data to much or do some sort of other mistake when processing the data.

4 Recognition algorithm and the data analysis

Due to the short time span on this project we have chosen to look at only one detection algorithm. This algorithm is called averaged cycle method and is used in [4] among others.

4.1 Averaged cycle method

Preprocessing: The data is represented in g, and each sample contains a time stamp, and acceleration values on the x-, y- and z-axis. The euclidean distance of the x-, y- and z-values (Equation 1) is used to create a resultant value, and in addition plotted as a graph, see Figure 1.

$$r_i = \sqrt{x_i^2 + y_i^2 + z_i^2}, i = 1, ..., k \tag{1}$$

where r_i, x_i, y_i, and z_i are the magnitudes of resulting, vertical, horizontal, and lateral acceleration at the observation point i, respectively, and k is the number of recorded observations in the signal. The collected data is first normalized. Since the timing in the sensor is not very accurate, it does not record data every n millisecond, so the first step is to interpolate the data to make sure the distance

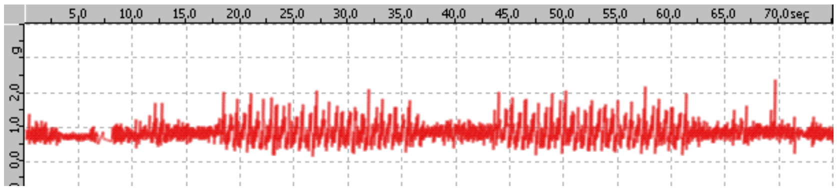

Figure 1: A graph of the resultant value of the gait data.

between the samples are the same. In our case we chose a time interval of 0.1ms between each sample. Then we remove noise using a weighted moving average with a window size of 5, see Equation 2.

$$\sigma_i = \frac{\sigma_{i-2} + (\sigma_{i-1} * 2) + (\sigma_i * 3) + (\sigma_{i+1} * 2) + \sigma_{i+2}}{5} \tag{2}$$

Cycle detection: We discard the start and the end of the data collected, as no "normal" walking is done here - the subject is either speeding up, slowing down or simply standing still. It is known that the natural cadence of human walking is in the range [90,130] steps/min [4], and since the sampling frequency of the sensor was about 100 observations/s we knew that each cycle consist of approximately 100 observations. With this in mind we could start the detection: let $R = (r_1,...,r_K)$ be a resulting acceleration signal, and $[r_{m1},...,r_{mL}]$ be the local minimum in this signal which needs to be found. The first challenge in this method is to locate the minimum of the first cycle, this was done semi-automatic, meaning that we manually removed the unnecessary data in the beginning and used a program to locate the local minimum of the first 35 samples, $r_{m1} = min(r_1,r_2,...r_{30})$, see Figure 2. The recognition algorithm is based on choosing a recurring pattern in the cycle obtained from the subject. Our cycle detection method jumps 90 samples ahead and looks for the local minimum in the next 25 samples and hopefully finds the end of the cycle, $r_{m2} = min(r_{m1+M},...r_{m1+M+D})$, where M = 90 and D = 25. In our experience, this was not always sufficient, some subject had between 115 and 155 samples on each cycle, so we had to add more to the algorithm than Gafurov et al. did in [4]. Three things could happen:

- We checked whether the minimum point found was in between [M..M+5] (meaning between sample 0 and 5 in the lookahead), if that was the case the algorithm might have jumped to far and we therefore searched 10 more samples backward. If a lower point was found in the range [M-10..M-1] then we continued to search 10 additional samples backwards. This was repeated until we found the lowest point, see Figure 3.

- If the minimum point found was in between [M+6..M+14] (meaning between sample 6 and 14 in the lookahead), we kept it, see Figure 4.

- Similar to the first point, we checked if the minimum point was in between [M+15..M+25] (meaning between sample 15 and 25 in the lookahead), if that was the case the algorithm might have jumped to short and we therefore searched 10 more samples forward. If a lower point was found in the range [M+26..M+35], then we searched 10 additional samples forward. This was repeated until the lowest point was found, see Figure 5.

The end of one cycle is considered the start of the next cycle. Therefore this procedure was repeated until the last cycle was located. Due to the fact that the first and last cycles still will consist of abnormal walking we threw away the first and the last three cycles from the data set and ended up with between 10-15 cycles on each trial, see Figure 6.

Time normalization: The fact that each observations in a cycle may vary mean that we need to do some time normalization on the cycles. This is achieved by interpolating each cycle so that it consist of exactly 100 observations, see Equation 3. By doing this we will be able to calculate an average cycle of the person.

$$y'_i = \frac{max(y_{0..i} < y_i) + min(y_{i..n} < y_i)}{2} \tag{3}$$

Average cycle When the data is normalized and cycles are found we can calculate an average cycle, A. $A = (a_1, \ldots a_n)$, and where a_i is calculated from Equation 4.

$$a_i = median(w_{ij}) \tag{4}$$

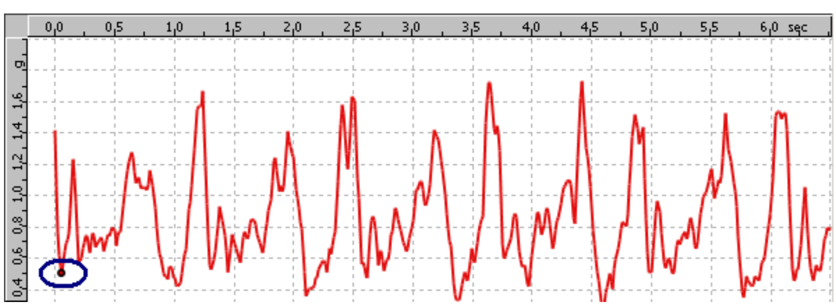

Figure 2: A graph of the pre-processed data where the unnecessary data in the beginning has been removed. The first local minimum is pointed out.

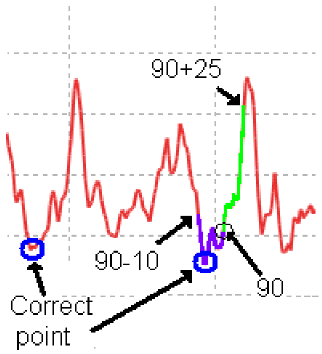

Figure 3: Searching backwards. The green area indicates $[r_{m1+M}, \ldots r_{m1+M+D}]$ ([90..90+25]) the search area, since the lowest point is in the beginning of the green area, 10 additional samples backwards are searched, indicated by the purple area, and the correct minimum is found.

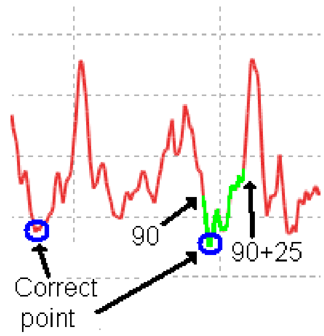

Figure 4: The correct minimum is found in the green area $[r_{m1+M}, \ldots r_{m1+M+D}]$ ([90..90+25]).

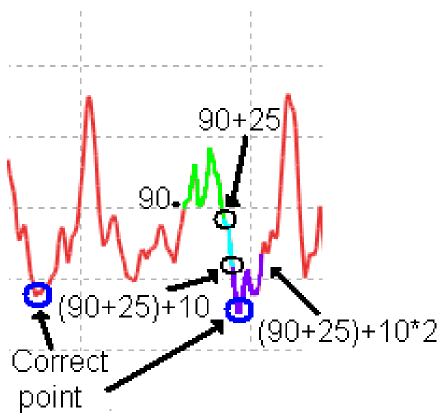

Figure 5: Searching forward. The lowest point in the green area is at the end, meaning that we search additional 10 samples forward. In the indigo area a lower point was found, meaning that we search additional 10 samples forward, into the purple area. Here we find the correct minimum point and the next 10 samples will not contain a lower point.

where $i = 1, \ldots n$, $n = 100$ and (w_{ij}) is the observation value at observation number i in the normalized cycle j, $i = 1, \ldots m$, m is the number of detected cycles in the

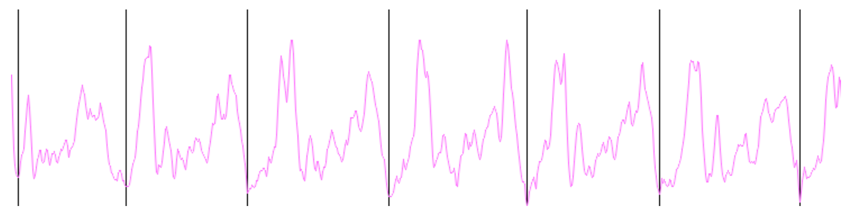

Figure 6: An illustration showing cycles detected in a part of a sequence

signal being processed. This means that the each observation in the averaged cycle is the median of the corresponding observation in the normalized cycle. By choosing the median in stead of e.g. the average value an unusual step will not have that big impact on the averaged cycle.

Similarity score: After we have found the median step for each cycle on each surface for all subjects, we compare them. We first choose a step from walking indoors on the hard surface as a template $\theta = (\omega_1, \ldots \omega_n)$. Then we find the distance from the other steps by using the euclidean distance, see Equation 5.

$$dist(\theta, C) = \sqrt{\sum_{i=0}^{n} (\theta_i - c_i)^2} \tag{5}$$

where θ_i and c_i are the resulting acceleration values at observation point i and $n = 100$. This distance will give us the similarity score between the two gait signals, θ and C. The score should be smaller for genuine trials than for impostor trials. The whole recognition process is illustrated in Figure 7.

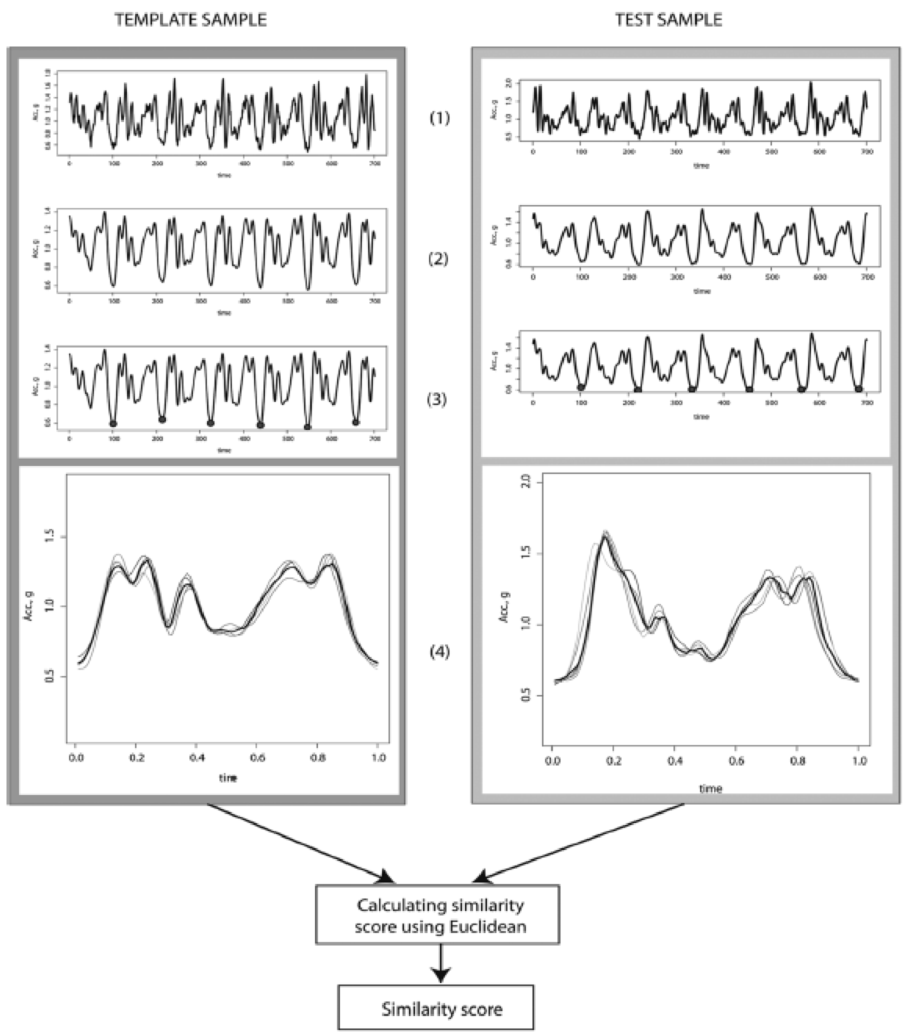

Figure 7: The recognition process, (1) Computing the resulting vector. (2) Interpolation and noise reduction. (3) Cycle detection. (4) Calculating the average cycle. (from [4])

Table 1: Sequences on grass checked against grass template

	P_1 C_1	P_1 C_2	P_1 C_3	P_2 C_1	P_2 C_2	P_2 C_3
Template P_1	**0.944**	**1.095**	**2.792**	3.240	3.419	3.301
Template P_2	3.509	3.489	1.700	**0.722**	**0.840**	**1.258**
Template P_3	4.187	4.012	2.597	2.602	2.855	2.950
Template P_4	2.200	2.552	1.857	2.502	2.638	2.565
Template P_5	3.428	2.396	1.627	1.633	1.377	1.265

5 Results overview

After computing the different matching scores for the different surfaces we were able to get some results in order to draw some conclusions, see Table 1 (where P_i is participant number i, and C_i is check number i, the bold numbers are the genuine attempts). In this experiment we had 25 participants walking four times on three different surfaces, this gives us 275 (25*1*11) genuine attempts and 6600 (25*24*11) fraudulent attempts. First we wanted to see if each surface was stable, so we used the first sequence on each surface to generate a template and then used the remaining three walks as checks against this. By doing this we got the DET curves shown in Figure 8 to 10. The results show that walking on gravel and grass does barely differ, both have 12% EER and with a threshold of 1.56 and 1.59 respectively. A rather surprising result was that the EER for the indoor walking is 18%, 50% higher than for both gravel and grass, with a threshold of 1.63.

The performance for the total system, using the first indoor walk as a template and all the other walks (on all surfaces) as checks gave us the DET curve shown in Figure 11. The EER in this case was 27% with the threshold at 1.83. Since indoor gave the highest EER we also tried to use grass as the main template (first walk on grass as template and all the other walks as check). This yielded an EER of 18% and a threshold of 1.74, DET curve shown in Figure 12.

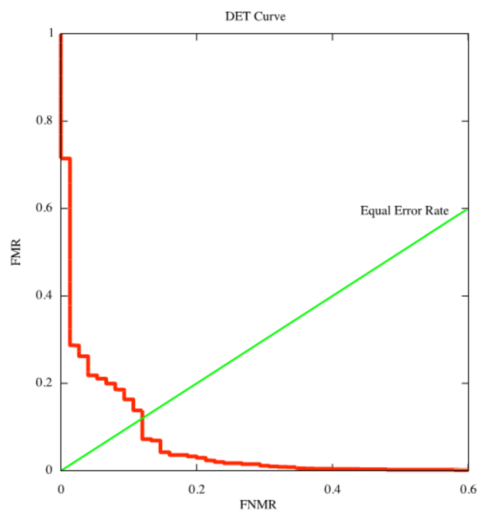

Figure 8: The DET curve using only grass data, EER = 12%.

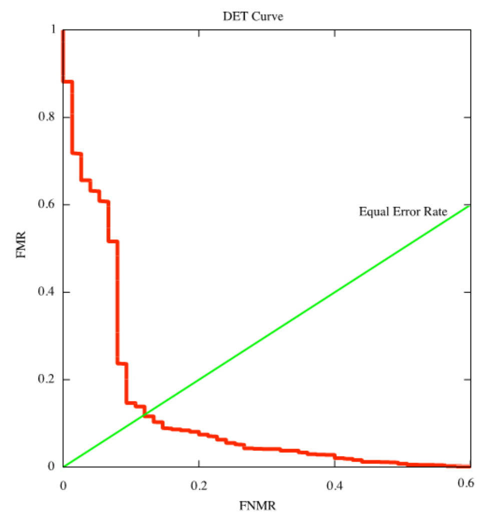

Figure 9: The DET curve using only gravel data, EER = 12%.

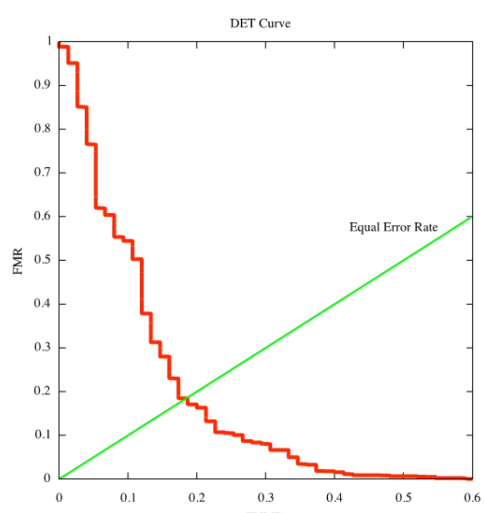

Figure 10: The DET curve using only indoor data, EER = 18%.

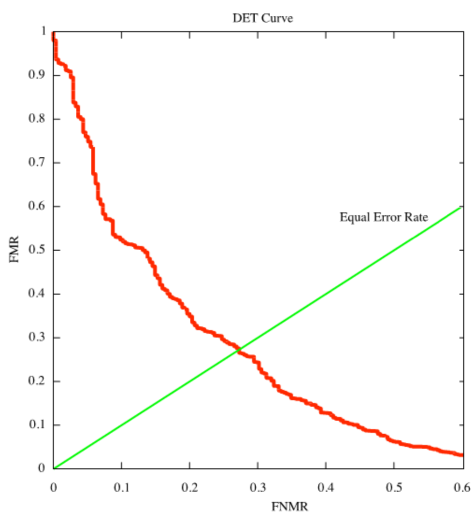

Figure 11: The DET curve of the total system, using the first walk indoor as template, EER = 27%.

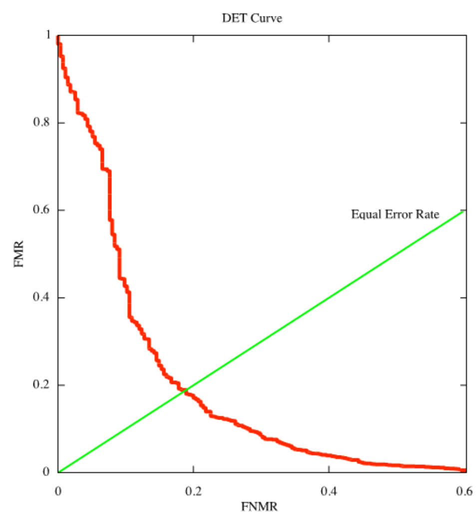

Figure 12: The DET curve of the total system, using the first walk grass as template, EER = 18%.

6 Discussion

Some problems we encountered were stability issues with the software and sensor, especially if the sensor was low on battery (or some other malfunction made it crash). Then the data gathering usually failed, and we needed to make the participants redo the experiment to get the correct data. This made us loose some participants, because it took to long to perform the experiment and the participants had to get back to class. The placement of the sensor could also have an effect on the participants, as it could hamper or be somewhat in the way of the participants and their walking. Another effect we noticed were the fact that it could be somehow difficult to walk in a normal way when you knew you were being measured.

One fault we encountered with our recognizing algorithm were the fact that on some participants a smaller minimum occurred straight after the "correct" start of the cycle. This resulted in the algorithm choosing the wrong minimum as a starting point for a step cycle, and then it produced successive errors. This can be shown in the figure 13, where you also can see that the next cycle will be wrong because the algorithm jumps to far ahead and looks for the minimum point in the wrong location. This error will propagate throughout the gait-sequence if not a correct starting minimum is chosen later in the sequence. Due to this error, the performance of the system is somewhat reduced.

The rather surprising results we encounter with the EER being quite much higher in the indoor sequence opposed to the grass and gravel sequence, can have several explanations. In addition to faulty step detections, the indoor sequence were the first sequence for the participants. This could result in the participants not walking as "normal" as they normally do, because they know they are partici-

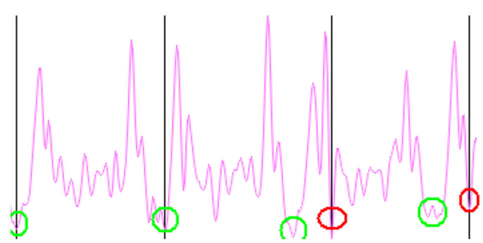

Figure 13: An example of a problem that can occur when using minimum values as a reference point, and the following successive error that occurs when a faulty cycle is detected. Green circles indicate correct minimum, red circle indicate the erroneous identified minimums

pating in a experiment and that their gait are being recorded. By simply looking at the result one can not rule out the possibility that by using an accelerometer placed on the hip, grass and gravel yields better results than indoor does. By knowing this it is reason to believe that continuous authentication in mobile devices could be implemented even if a user walks on different surfaces.

7 Conclusion

Our experiment has shown that changing surface does not have a significant impact on the ability to recognize a person. In fact grass and gravel performed better than indoor surface.

8 Further work

This experiment have just checked three different surfaces (indoor, grass and gravel) against each other, and a natural expansion of the project is to do checks on more surfaces (for instance mud or snow). Another limitation of this project is the fact that there is only 25 participants, so to be able to get more statistically significant results there should be even more participants.

Some other work that remains to be done is to check the data against different algorithms. The step detection algorithm could also be fine tuned to get it to match more of the participants' gait sequences. By improving the step detection algorithm the performance of the system will increase. It would be interesting to see what kind of results you would get by manually detecting the steps to exclude the successive faults that our algorithm generated.

References

[1] Chiraz Ben Abdelkader. Motion-based recognition of people in eigengait space. In *FGR '02: Proceedings of the Fifth IEEE International Conference on Automatic Face and Gesture Recognition*, page 267, Washington, DC, USA, 2002. IEEE Computer Society.

[2] Ailisto, Lindholm, Mantyjarvi, Vildjiounaite, and Makela. Identifying people from gait pattern with accelerometers. In Ratha Jain, editor, *Biometric Technology for Human Identification II. Edited by Jain, Anil K.; Ratha,*

Nalini K. Proceedings of the SPIE, volume 5779 of *Presented at the Society of Photo-Optical Instrumentation Engineers (SPIE) Conference*, pages 7–14, mar 2005.

[3] D. Cunado, J.M. Nash, M.S. Nixon, and J.N. Carter. Gait extraction and description by evidence-gathering. In *AVBPA99*, 1999.

[4] D. Gafurov, E. Snekkenes, and P. Bours. Spoof attacks on gait authentication system. *Information Forensics and Security, IEEE Transactions on*, 2(3):491–502, 2007.

[5] Davrondzhon Gafurov, Kirsi Helkala, and Torkjel Søndrol. Gait recognition using acceleration from MEMS. In *Proceedings of The First International Conference on Availability, Reliability and Security (ARES 2006)*, pages 432–439, 2006.

[6] Davrondzhon Gafurov, Einar Snekkenes, and Patrick Bours. Gait authentication and identification using wearable accelerometer sensor. In *Proceedings of the IEEE Workshop on Automatic Identification Advanced Technologies (AutoID 2007)*, 2007.

[7] Davrondzhon Gafurov, Einar Snekkenes, and Tor Erik Buvarp. Robustness of biometric gait authentication against impersonation attack. In *OTM Workshops (1)*, pages 479–488, 2006.

[8] Zongyi Liu and Patrick Grother. The humanid gait challenge problem: Data sets, performance, and analysis. *IEEE Trans. Pattern Anal. Mach. Intell.*, 27(2):162–177, 2005. Member-Sudeep Sarkar and Member-P. Jonathon Phillips and Member-Isidro Robledo Vega and Fellow-Kevin W. Bowyer.

[9] Zongyi Liu and Sudeep Sarkar. Simplest representation yet for gait recognition: Averaged silhouette. In *ICPR '04: Proceedings of the Pattern Recognition, 17th International Conference on (ICPR'04) Volume 4*, pages 211–214, Washington, DC, USA, 2004. IEEE Computer Society.

[10] Jani Mäntyjärvi, Mikko Lindholm, Elena Vildjiounaite, Satu-Marja Mäkelä, and Heikki Ailisto. Identifying users of portable devices from gait pattern with accelerometers. In *VTT Electronics*, 2005.

[11] J. Suutala and J. Röning. Towards the adaptive identification of walkers: Automated feature selection of footsteps using distinction-sensitive LVQ. In

Proceedings of International Workshop on Processing Sensory Information for Proactive Systems (PSIPS 2004), pages 61–67, Oulu, Finland, June 14-15 2004.

[12] Rong Zhang, Christian Vogler, and Dimitris Metaxas. Human gait recognition. In *CVPRW '04: Proceedings of the 2004 Conference on Computer Vision and Pattern Recognition Workshop (CVPRW'04) Volume 1*, page 18, Washington, DC, USA, 2004. IEEE Computer Society.

A Appendix

Participation agreement to gait experiment, Fall 2007

1. I am informed about the goals of this experiment.
2. I allow gait data to be collected from me.
3. The data will only be used for analysis in this experiment; in case of future experiments, a new permission should be given.
4. The data will not be used in possible future publications on this experiment, unless I give my permission.
5. I know that I can withdraw my participation anytime I want without giving any explanation and all data collected from me will be deleted permanently.

Place, date	Signature