

# Benchmarking the Performance of SVMs and HMMs for Accelerometer-Based Biometric Gait Recognition

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**Abstract**—Support Vector Machines (SVMs) and Hidden Markov Models (HMMs) have been in use for numerous classification tasks in pattern recognition. HMMs can be considered as a de-facto standard in speaker recognition. For accelerometer-based biometric gait recognition these methods have also shown good classification results, which are, however, not comparable as different data sets and features have been used. The contribution of this paper is a comprehensive benchmarking of the stated methods on a single database composed using a standard cell phone. In total, more than 19 hours of accelerometer data from 36 subjects were collected during two sessions. We analyze the influence of time on the recognition rates and state the results for normal and fast walk. In addition, we compare the results obtained when different amounts of training data are used. We show that SVMs are slightly superior to HMMs yielding an Equal Error Rate (EER) of around 10%.

**Keywords**—biometrics; gait recognition; accelerometers; support vector machines; hidden markov models

## I. INTRODUCTION

Although studies show that phone theft is widespread [8], most people do not sufficiently secure their devices [4], [20]. Often no authentication is required when using the phone after a stand-by phase. Therefore, each person who acquires physical access to the device can directly access all available data. By combining information from private and business emails, contacts and social networks an attacker can easily impersonate the victim. While the number of available features like high-quality cameras, GPS sensors and Internet access, is steadily increasing, most phones only offer one authentication method, namely PIN authentication. The problems with PINs are that they have to be memorized and entered for each authentication. Hence, this method is not very user-friendly.

The memorization problem can be solved by applying biometrics. There have been a few phones with fingerprint scanners, but these never really entered mass market. The primary reason lies probably in the rather high costs for the extra sensor that is not needed by the average end-user. Other modalities like face, voice or gait do not have this problem as the required sensors are already included in most modern smartphones. Compared to the mentioned modalities, gait recognition has one unique advantage: It does not require explicit user interaction during the verification process as the

phone does it literally on-the-go. When the owner is on the move, he is continuously authenticated by the device, thus an explicit user authentication is less often needed.

Research on accelerometer-based gait recognition started in 2005 by Ailisto et al. [1] and was further developed by Gafurov [13]. In the beginning dedicated accelerometers were used which were attached to different body parts like the arm, hip or ankle. Only recently researchers started to use mobile phones as sensors [10], [12], [15]. Research can be divided in two main groups. Either so-called gait cycles are extracted from the sensor data or the data are divided into segments from which features are extracted. Gait cycles correspond to two steps and can be compared using distances like Dynamic Time Warping (DTW) [19] or Cyclic Rotation Metric (CRM) [9]. For comparison of feature vectors the prominent 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 [15], HMMs [18] and SVMs [17]. The reported total error rates are 20.71% for HMMs and 30.0% for SVMs. Our results obtained in this evaluation are around 4% worse for HMMs but about 10% better for the SVMs. This gives an impression of the good level of our obtained results, although a fair comparison is not possible due to the different data bases.

Here, for the very first time a benchmarking of SVMs and HMMs for the purpose of classifying accelerometer-based continuous gait signals is presented. The methods are applied on one database, which was composed using a commercial off-the-shelf cell phone. In order to bring the technique quickly to an application level, a fair benchmark of different promising methods as presented in this paper is compulsory.

The remaining part of the paper is structured as follows. The next chapter describes the used database. In section III we explain the extracted features and afterwards give a short description of the used classifiers SVMs and HMMs in section IV. After describing the evaluation and initial results in section V, we explain the voting mechanism we applied to further reduce the error rates in section VI. Section VII gives conclusions and describes future work.

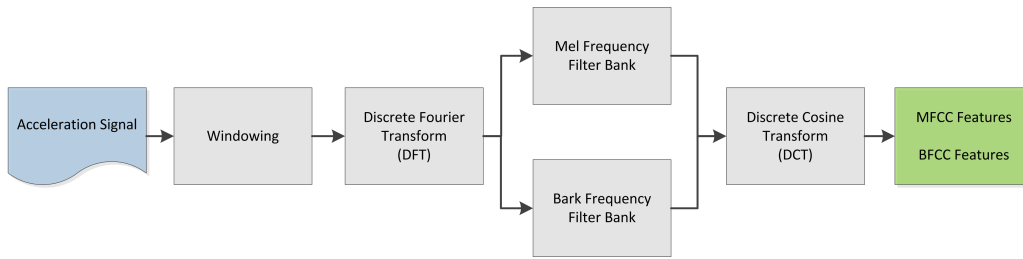


Fig. 1. MFCC and BFCC feature creation

## II. DATA COLLECTION

We collected data of 36 subjects on two different days. These two sessions were on average 24 days apart (min = 1, max = 125, median = 10.5). At each session the subjects had to walk up and down a straight hallway for about 37 meters on flat carpet. The data collected between starting to walk and stopping at the other end of the hall is called *walk*. We collected 12 normal walks, 16 fast walks, and again 12 normal walks of each subject in each session. This resulted in around 32 minutes of walking data for each subject.

The subjects carried a standard cell phone (Motorola Milestone using the Android operating system) in a pouch attached to the right hip. The phone contains a built-in accelerometer which measures accelerations in three directions (x-, y- and z-acceleration). An Android application was developed to access the accelerometer data and write it to text files.

## III. FEATURE EXTRACTION

Due to the Android API it is not possible to get accelerometer values at a fixed rate. Only when the event *on sensor changed* is triggered by the system we obtain new acceleration values (in x-, y- and z-direction) and the corresponding time stamp. It is not possible for our application to trigger this event itself. Running background services which need a high proportion of the CPU's capacity do increase the time between two of these events. Therefore, the first preprocessing step is to linearly interpolate the data in order to get a fixed sampling rate. The mean sampling rate of our database is 127.46 data values per second (min = 109.19, max = 128.88). We used interpolation rates of 50, 100 and 200 data values per second. The reason for upsampling the data was to not to lose too many data values. Peaks might get lost if their original time stamp is between two time values used for interpolation.

After interpolation, the data  $s$  were centered around zero by subtracting the mean  $\mu$ :  $\bar{s}_a(t) = s_a(t) - \mu_a$ ,  $a \in \{x, y, z\}$ . This is done because the phones are not well calibrated and the gravity has to be removed from the vertical acceleration ( $x$ ). Afterwards, the data were partitioned into segments of size 3000, 5000 and 7500ms with an overlap of 50%. In normal walking pace one gait cycle takes around one second, hence the segments include between three and seven gait cycles. As the correct detection of the cycle starts is a complex and error-prone process we decided to use the fixed-size segments without considering the course of the signal.

### A. Statistical Features

For each of the segments several statistical features were extracted for the accelerations in x-, y- and z-direction as well as for the magnitude vector  $s_m = \sqrt{\bar{s}_x^2 + \bar{s}_y^2 + \bar{s}_z^2}$ . These were the minimum (**Min**), maximum (**Max**), mean value (**Mean**), standard deviation (**Std**) and the following ones:

**Bin** Relative histogram distribution in linear spaced bins between the minimum and the maximum acceleration in the segment. Five and ten bins were used.

**RMS** Square root of the mean of the squares of the acceleration values of the segment:

$$rms = \sqrt{\frac{\bar{s}_a^2(1) + \bar{s}_a^2(2) + \dots + \bar{s}_a^2(n)}{n}}, \text{ where } n \text{ is the number of data points in the segment, } a \in \{x, y, z, m\}.$$

**Cross** Number of sign changes in the segment.

### B. Cepstral Coefficients

As they already had great success in speaker recognition, we also extracted Mel-frequency cepstral coefficients (MFCCs) and Bark-frequency cepstral coefficients (BFCCs) from the segments for each axis. The general work flow for each segment is shown in Fig. 1. More details about MFCCs can be found in [21]; we used the implementation by Dan Ellis [11]. The only difference between MFCCs and BFCCs is that for BFCCs the Bark-scale is applied instead of the Mel-scale (see [26]). In case of BFCCs we tested two different configurations. Window length and the distance between consecutive windows (hop time) are larger for BFCC2. In addition the data is mapped to a higher frequency range. The configurations have been determined to perform best in a previous study. This results in the following additional features:

**MFCC** Mel-frequency cepstral coefficients [window size = 1.44s, window hop time = 0.048s, max freq.= 10Hz]

**BFCC1** Bark-frequency cepstral coefficients [window size = 1.12s, window hop time = 0.032s, max freq.= 7.5Hz]

**BFCC2** Bark-frequency cepstral coefficients [window size = 1.92s, window hop time = 0.048s, max freq.= 8.75Hz]

## IV. CLASSIFIERS

For the purpose of pattern classification the SVM was introduced by Vapnik in 1982 [23] as a supervised learning method based on the theory of structural risk minimization. A SVM is a classifier which is inherently a solution for two class problems. The basic idea of the SVM is to construct a

hyperplane as the decision plane, which separates the patterns of the two classes with the largest margin.

For the experiments conducted we used the SVM implementation LIBSVM [6]. The Radial Basis Function (RBF) kernel was chosen and a parameter selection (grid search [14]) was done as part of the optimization process.

HMMs are commonly used for biometric authentication tasks, e.g. in speaker [16] or writer recognition [22]. They were introduced during the mid-60's by Baum et al. [2].

We use the *world model approach*, which was first introduced by Carey et al. in 1991 [5] and has become the predominate approach in speaker verification systems [3]. In this approach two HMMs are considered in each test iteration. One is the genuine model  $\lambda_{gm}$ , which has been trained with data of the genuine user, and the other is the world model  $\lambda_{wm}$ . This world model (also called general model or universal background model) is trained using data from a large amount of different subjects. Using the Viterbi algorithm [24], we obtain for each model the probability that the given probe data is represented by the model. Classification is based on the difference of these two probabilities. The differences are compared with a threshold to compute the error rates. The equal error rate (EER) can be determined by varying the threshold.

Different numbers of states as well as different numbers of mixtures per state were tested. Creating a 3-state HMM with one mixture per state yielded the best results. For our experiments we used the Hidden Markov Model Toolkit (HTK) [25].

## V. EVALUATION AND RESULTS

The evaluation consisted of several consecutive steps. First the discrimination properties of single features were analyzed, afterwards the best performing features were combined and the influence of the different axes evaluated. The feature sets of these tests identified to be the best ones, were used for further evaluation.

### A. Single Features

To analyze the discrimination capabilities of the single features, we tested them separately. We used the first 12

Axes	FMR	FNMR	TER
x	1.30%	48.80%	50.10%
y	2.70%	63.71%	66.41%
z	1.83%	63.52%	65.35%
m	1.34%	53.74%	55.08%
x, m	0.84%	43.73%	44.57%
x, y, z, m	0.13%	59.77%	59.90%

TABLE III  
SVM RESULTS WHEN COMBINING ALL FEATURES (M = MAGNITUDE VECTOR).

normal walks which were collected on the first day for training and the first 12 normal walks of the second day for testing. We tested different interpolation rates (50, 100, 200) for each segment length (3000, 5000 and 7500). For HMMs varying the interpolation rate and segment size did not significantly change the error rates. The SVMs showed best results when using a segment length of 5000 and a low interpolation rate of 50. Therefore we state the results for interpolation rate 50 and segment length 5000 for both classifiers in Table I. These settings are chosen for all remaining results stated in this paper.

Feature *cross* did not contain enough information to train the HMMs (indicated by '-' in the table). In case of SVMs we can only give the obtained false non-match rate (FNMR) and false match rate (FMR), not the EER. For a better comparison of the two approaches we also state the Total Error Rate (TER), which is the sum of FMR and FNMR.

### B. Combined Features

Because the results show that single statistical features alone do not contain enough information we combined the features. To evaluate the performance of the different axes and the magnitude vector, one feature set was created for each axis (for simplicity the magnitude vector, denoted with *m*, is referred to as axis as well). The x-axis and the magnitude vector yielded best results, therefore these were combined in one feature vector. In addition one feature vector containing all features for all axes was created. The results obtained using SVMs are given in Table III, applying HMMs yielded similar results.

Because using only the x-axis and combining x and m yielded the best results, we used only these axes for the

Feature Type	Feature Length	SVMs			HMMs	
		FMR	FNMR	TER	EER	TER
Max	4	5.43%	82.04%	87.47%	32.61%	65.22%
Min	4	3.00%	79.95%	82.95%	30.58%	61.16%
Mean	4	0.91%	90.90%	91.81%	31.48%	62.96%
Diff	4	0.19%	99.18%	99.37%	46.23%	92.46%
Std	4	4.30%	70.36%	74.66%	32.30%	64.60%
RMS	4	3.96%	73.77%	77.73%	32.30%	64.60%
Cross	4	1.44%	91.16%	92.60%	-	-
Bin5	20	3.25%	68.41%	71.66%	31.37%	62.74%
Bin10	40	2.45%	66.75%	69.20%	32.33%	64.66%
MFCC	52	0.36%	50.18%	50.54%	17.06%	34.12%
BFCC1	52	0.43%	49.45%	49.88%	19.80%	39.60%
BFCC2	52	0.64%	47.90%	48.54%	18.06%	36.12%

TABLE I  
CROSS-DAY RESULTS FOR SINGLE FEATURES WHEN USING INTERPOLATION RATE 50 AND SEGMENT SIZE 5000 (AS THESE PERFORMED BEST).

Algorithm	Feature Vector	Feature Length	FMR	FNMR	EER	TER
SVM	BFCC2_xm	26	1.15%	39.37%	–	40.52%
HMM	BFCC2MFCC_xyzm	104	–	–	17.30%	34.60%
HMM	MFCC_xyzm	52	–	–	17.06%	34.12%

TABLE II  
CROSS-DAY RESULTS FOR BEST PERFORMING FEATURES USING SVMs AND HMMs (NORMAL WALK).

cepstral coefficients. In addition we evaluated all different combinations of the features based on cepstral coefficients (using all axes). All these tests showed that for SVMs the feature set containing the BFCC2 from x-axis and magnitude vector (*BFCC2\_xm*) performs best. For HMMs the best combination is *BFCC2MFCC\_xyzm*, but using only MFCC still results in slightly better error rates (see Table II). Because a shorter feature vector requires less computational power, we select *MFCC\_xyzm* as the best feature vector for HMMs and use it in all following evaluations for this classifier.

So far all given results are cross-day results, meaning that training and testing data are collected on two different days. This is a realistic scenario, as one would not train the models each day. To see the influence of the variation of gait over time we also computed the same-day results. For SVMs we get as low as 16.60% TER for the *BFCC2\_xm* feature set and for HMMs we achieve an EER of 5.86% when using *MFCC\_xyzm*. These large differences show the importance of using a testing database containing data of different days.

As stated in section II, we also collected fast walks of the subjects on each day. We tested the same features sets based on the cepstral coefficients as for normal walk. As before, for SVMs the feature set *BFCC2\_xm* gave best results. This time, for HMMs the feature set *BFCC1\_xm* performed best. The results when using 12 walks for training and testing are given in Table IV. One can see that the results outperform the results of the normal walk, indicating that fast walk has better discriminative properties.

### C. Varying the Amount of Training Data

So far we only used the first 12 normal or fast walks for training. In this evaluation we analyze the influence of the amount of training data. We examine two different settings. In the first setting we use all available data of the respective speed from the first day for training. Hence, we increase the number of training walks to 24 in case of normal walk and to 16 in case of fast walk. For the second setting we use data of different speeds for training (12 normal and 12 fast walks) and either fast or normal walks from the second day for testing. The results for SVMs are given in Table V, the results for HMMs are given as Detection Error Trade-Off curves in Fig. 2. For an easier comparison we also give the initial results using only 12 normal or fast walks for training. All stated SVM results are for the best feature set *BFCC2\_xm*. For HMMs, the best feature set depends on the walking pace of the testing data. When only normal walks are used for testing, feature set *MFCC\_xyzm* performs best. When the testing data consists of fast walk, feature set *BFCC1\_xm* outperforms the others.

Alg.	Feature Vector	FMR	FNMR	TER
SVM	BFCC2_xm	1.87%	29.00%	30.87%
HMM	BFCC1_xm	–	–	29.04%

TABLE IV  
CROSS-DAY RESULTS FOR BEST PERFORMING FEATURES USING SVMs AND HMMs (FAST WALK).

Training	Testing	FMR	FNMR	TER
12N	12N	1.15%	39.37%	40.52%
24N	12N	2.64%	26.56%	29.20%
12N + 12F	12N	1.30%	35.96%	37.26%
12F	12F	1.87%	29.00%	30.87%
16F	12F	1.28%	32.47%	34.82%
12N + 12F	12F	1.17%	35.50%	36.67%

TABLE V  
SVM RESULTS AFTER INCREASING THE NUMBER OF TRAINING DATA, E.G. BY USING MIXED DATA OF DIFFERENT SPEEDS (N = NORMAL, F = FAST).

For both classifiers the influence of the amount of training data is visible for the normal walk. When using only 12 normal walks for training of the HMMs (corresponding to about 240 seconds of walking data), we get an EER of 17.06% (12N-12N). This can be decreased to 15.77% when using all 24 available walks (24N-12N). When 12 fast walks are added to the training data (12N12F-12N), the EER increases slightly to 18.38%. In case of SVMs one can see a higher decrease of FNMR for normal speed when increasing the amount of walks for training. When the fast walks are also added to the training set the results are worse than when using the same number of normal walks (24N-12N). Still, due to the higher amount of training data the results are better than when only

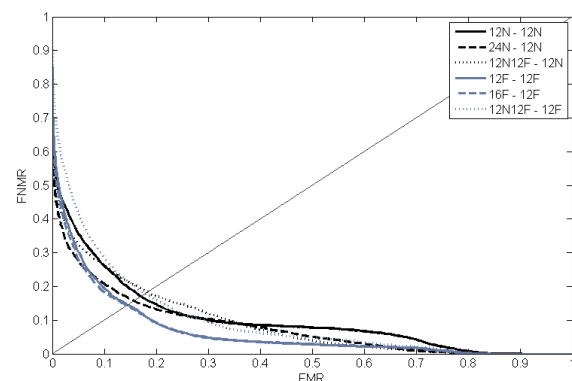


Fig. 2. HMM results after increasing the amount of training data, e.g. by using mixed data of different speeds (N = normal, F = fast).

using 12 normal walks for training.

An analysis of the fast walk, gives following results for HMMs: Increasing the number of training walks from 12 to 16 does not significantly influence the EER. Adding the 12 normal walks to the training data (12N12F-12F) increases the EER from 14.52% to 17.81%. For this setting a similar result is obtained for SVMs. Here, the TER is increased from 30.87% to 36.67%. This can be explained by the better discriminative properties of fast walks (see subsection V-B) which are decreased when fast and normal walks are mixed. When using 16 instead of 12 fast walks for training of the SVM, the error rates get worse. One reason for this might be that the subjects had been exhausted during the last fast walks and this influenced their walk in such a way that the SVM classification is degraded. We confirm this assumption by using the last twelve fast walks from the first day for training and using the first 12 fast walks of the second day for testing. We obtain an EER of 35.19%, which is worse than the corresponding 12F-12F scenario in Table V. This shows that the discriminative properties of the last fast walks is worse than that of the first fast walks.

From the normal walk results one can see that for both classifiers a higher amount of training data does improve the results, but only slightly for HMMs. Using four minutes of walking data for training seems to be sufficient in this case. On the other hand, for SVMs the TER for normal walk could be decreased by 25% when using the double amount of training data. Using mixed speed data for training for both classifiers decreases the biometric performance.

## VI. VOTING

The results stated so far for SVMs are highly unbalanced between FMR and FNMR. While the FMR is very low, the FNMR is still on an unacceptable level. To improve this situation we apply a voting mechanism that reduces the number of false non-matches by using multiple classifications for one recognition decision while incorporating a different confidence in the classification correctness.

More specifically the decision is based on  $\#V$  classifications, not only on one. An imaginable straightforward approach is to combine the  $\#V$  classification results using majority voting, but it is not likely to perform well for SVMs as the two error cases are so unevenly distributed. Therefore a *quorum* voting for a genuine is implemented, which is inspired by a petition quorum.

This quorum requires that out of the  $\#V$  classifications at least  $\#GV$  positive classification results are needed for an accept, otherwise the probe signal is rejected (see also [7]). Of course, while the FNMR is decreased by this approach, the number of false matches and thus the FMR increases. We conducted a series of experiments with the intention to find a balanced setting where both error rates are in the same range.

### A. Voting Results

For each classifier we get one classification result per segment. Only normal walk is used in this evaluation. The

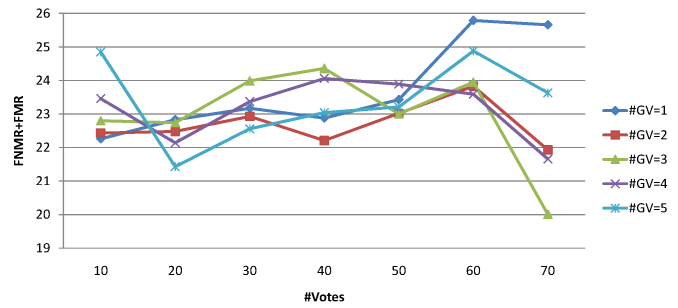


Fig. 3. Voting results for SVMs.

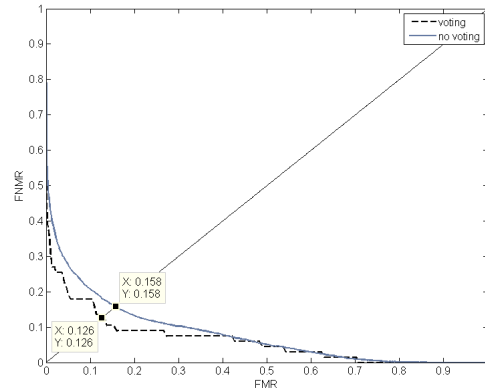


Fig. 4. Best voting results for HMMs, basing decision on one of 50 walks.

classifiers are trained using all 24 normal walks of the first session. 12 normal walks of the second day are used for testing. We varied the number of votes ( $\#V$ ) from 10 to the maximal possible number 70 and the number of required votes for genuine  $\#GV$  from 1 to 5. The results for SVMs are given in figure 3. The resulting TER are between 20.01% and 25.79%. The best result was obtained when using  $\#V = 70$  and  $\#GV = 3$ . At that point we got nearly balanced error rates. The FMR is 10.01% and the FNMR equals 10.00%. Because one segment is of length 5000 seconds and the segments overlap by 50%, the 70 votes correspond to 3 minutes of walking.

Using HMMs, the best results were obtained when using  $\#GV = 1$  and basing the decision on 50 votes, corresponding to around 2 minutes of walking. The corresponding DET-curve as well as the one without voting is given in Fig. 4. One can see that voting decreases the EER, but the effect is only minor (12.63% instead of 15.77%).

## VII. CONCLUSION AND FUTURE WORK

In the previous sections we comprehensively benchmarked the performance of HMMs and SVMs for accelerometer-based biometric gait recognition. Our database contains a large amount of data for each of the 36 subjects, which allows for a good training of the stated classifiers. The data were partitioned into fixed-length time segments. Best performing length was 5000ms. We used different feature sets through

our evaluation and determined the best for each classifier. For SVMs this is a combination of the BFCC2 of x-axis acceleration and the magnitude vector. For HMMs the best feature set is obtained by using MFCC of all axes when the test data consists of normal walk. When testing with fast walks, using BFCC1 of x-axis acceleration and the magnitude vector yields the best error rates. In general, one can say that the cepstral coefficients are outperforming the statistical features.

For most tests we used around four minutes of training data for each subject. Doubling this amount did further decrease the error rates by 25% for SVMs, but the improvement for HMMs was small. Having a user-friendly application in mind, we consider four minutes of training data as a good compromise of low enrolment time and low error rates.

Using mixed training data consisting of fast and normal walks increases the error rates when the subjects are walking fast or normal during authentication. Therefore, we suggest to train multiple models for multiple speeds. During authentication an activity recognition should be applied which identifies the speed of the probe data and selects the correct authentication model.

The best results obtained for the HMMs are an EER of 15.77% for normal walk and 14.39% for fast walk (cross-day scenario without voting using the maximal amount of available training data and 12 walks for testing). Without voting the SVMs best results are a TER of 29.20% for normal walk and 30.87% for fast walk. Hence, without voting both classifiers result in a similar biometric performance, with the SVMs being slightly better for normal walk. Applying the quorum voting further strengthens this difference: The TER of the SVMs is significantly decreased to 20.01% (10.00% FMR at 10.01% FNMR) for normal walk, while the EER of HMMs is only decreased to 12.63%.

When requiring a similar FNMR of around 10% for both classifiers, we get a lower FMR from the SVM than from HMMs (13.81%), resulting in higher security. This makes SVMs more suitable for accelerometer-based gait recognition.

In this evaluation we used fixed-length time segments as basis for our feature extraction. Future work will include the evaluation if a cycle based segmentation can further improve the results. In addition we will implement the classification using SVMs on the cell phone. To see how the methods perform in a more realistic scenario, we will apply SVMs and HMMs to an advanced data set containing not only walks on a straight flat floor.

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