An Analysis of Different Approaches to Gait Recognition Using Cell Phone Based Accelerometers

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ABSTRACT

Biometric gait authentication using Personal Mobile Device (PMD) based accelerometer sensors offers a user-friendly, unobtrusive, and periodic way of authenticating individuals on PMD. In this paper, we present a technique for gait cycle extraction by incorporating the Piecewise Linear Approximation (PLA) technique. We also present two new approaches to classify gait features extracted from the cycle-based segmentation by using Support Vector Machines (SVMs); *a*) pre-computed data matrix, *b*) pre-computed kernel matrix. In the first approach, we used Dynamic Time Warping (DTW) distance to compute data matrices, and in the later DTW is used for constructing an elastic similarity measure based kernel function called Gaussian Dynamic Time Warp (GDTW) kernel. Both approaches utilize the DTW similarity measure and can be used for classifying equal length gait cycles, as well as different length gait cycles. To evaluate our approaches we used normal walk biometric gait data of 51 participants. This gait data is collected by attaching a PMD to the belt around the waist, on the right-hand side of the hip. Results show that these new approaches need to be studied more, and potentially lead us to design more robust and reliable gait authentication systems using PMD based accelerometer sensor.

Categories and Subject Descriptors

D.4.6 [**Security and Protection**]: Authentication; H.1.2 [**User/Machine Systems**]: Human factors.

General Terms

Security

Keywords

Authentication, accelerometer, biometrics, gait recognition, machine learning

1. INTRODUCTION

Rapidly increasing computational and storage capabilities of Personal Mobile Devices (PMDs) are widening their usage on the private and business front as they are offering a multitude of services with greater mobility. The *Bring Your Own Device (BYOD)* trend demands enhanced security of PMDs. Consumers are not only using them for making calls and text messages, but also for accessing wireless local-area networks to corporate data network services, and from social, entertainment services to financial and mobile payment services.

Many of these services either offer low security in terms of standard requirements of confidentiality, integrity, availability, auditability and privacy for end users, or are too complicated to set up by typical end users. Despite their significance in our daily life, most of the latest PMDs are not sufficiently secured.

Personal Identification Number (PIN) or password based authentication systems with different complexity levels or graphical ways of entering the PIN are widely used to protect data stored in a PMD [22]. Studies have shown that a PIN based authentication system is less effective and indeed inconvenient [25] as the PIN or password needs to be remembered and has to be entered for authentication.

Therefore, a majority of PMD users do not use this authentication system as it implies extra work for the user. A survey [4] reported that only 13% of 584 PMD owners use PIN or password to protect their PMD in stand-by phases. Unfortunately, PMDs can easily be left unattended, lost or become a facile target of theft. With no or little authentication effort required, an attacker can analyze data, and use stored passwords to access emails and private information.

To offer enhanced end user security, it is important to ensure that PMDs are secured with more intuitive (e.g. unobtrusive, user-friendly, more reliable, and robust against fraudulent techniques, etc.) authentication systems. When unauthorized persons can physically access another user's PMD, they should not be able to access private and business-related information. Nowadays, accelerometers are integrated in most of the PMDs. Typically, these accelerometers are used to align the display according to the devices orientation. The presence of accelerometers, gyroscopes, and magnetometers establish an environment for developing a continuous and unobtrusive authentication mechanism for PDMs.

Gait is an individual's style of walking [1]. Thus, gait recognition is a process of using the distinctive walking style of individuals for their identification and verification [26].

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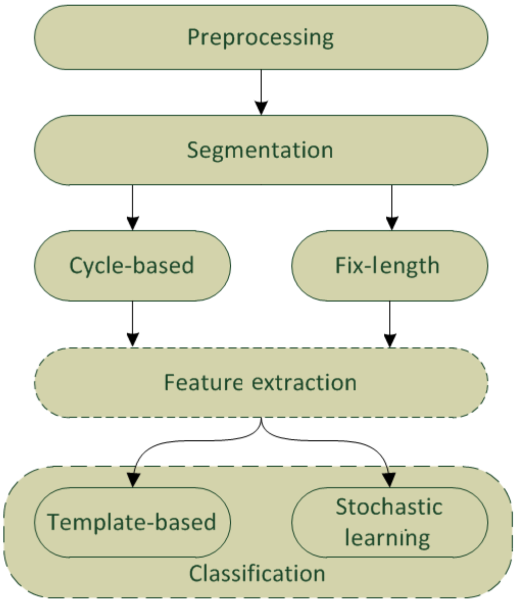

Figure 1: Different approaches to gait recognition, in wearable sensor based Technique.

Human walk is cyclic in nature and may be composed of one to many gait cycles, where each gait cycle consists of two steps [22]. There are three different types of biometric gait recognition systems [14]:

- ***Machine vision based*** technique is widely used for surveillance and forensic purposes. Gait data is captured by using various digital/analog cameras from certain distances. Later, different signal processing, image processing, and machine learning techniques are used for extracting gait-related information and identification of individuals [9, 11, 29].

- ***Floor sensor based*** technique utilizes various sensors, such as force, pressure sensors. These sensors are installed in the floor mats to collect gait data when an individual walks on them [5, 17, 24]. Subsequently, this information is processed to recognize individuals.

- ***Wearable sensor based*** technique is a relatively new approach to gait recognition as compared to machine vision and floor sensor based technique. This approach also utilizes various types of sensors such as, accelerometer, gyroscope, and force sensors. In 2005, Ailisto et al. [2] presented their work on identifying individuals using dedicated wearable sensors. Recently, researchers are using cell phone based sensors for identification and verification [12, 13, 22, 27].

In the wearable sensor based technique, there are two approaches for feature extraction (i.e. cycle-based or fix-length) and two (i.e. template-based or stochastic learning) for classifying these features [6, 22] as shown in figure 1.

In the cycle based approach, complete gait cycles are extracted from an individual's walk whereas in fix-length approach human walk is segmented into small fix-length segments. In literature, both (cycle-based and fix-length) approaches are studied well. However, template based classification is applied to features extracted using cycle-based segmentation of gait data. Stochastic or machine learning classification techniques are applied to features extracted using fix-length segmentation approach.

This study focuses on the wearable sensor based technique, where gait data is recorded by using PMD-based accelerometer sensors. For this study, we only used the cycle-based feature extraction approach and apply both classification techniques to find the influence of underlying classification approaches on cycle-based feature extraction approach. This study presents an extended method for biometric gait cycle extraction using Piecewise Linear Approximation (PLA). We also introduce two new approaches to classify gait cycles using Support Vector Machines (SVMs) with custom kernel i.e. Gaussian Dynamic Time Warping (GDTW) kernel.

The rest of the paper is structured as follows: a brief description of data set used in this study is given in section 2. Data preprocessing steps are explained in section 3. Section 4 describes the steps of the cycle extraction technique. An introduction to classifying gait cycles with SVMs is given in section 5. Subsequently, experiments and results details are presented in section 6. Section 7 is the discussion. Conclusion and outlook are given in section 8.

2. DESCRIPTION OF DATASET USED

For our experiments, we used the same data set as employed in [21]. This biometric gait data was collected using an Android phone *Google G1*. For data collection purpose, an Android application was developed that records three dimensional (X, Y, and Z) accelerometer data to a text file with time stamps. This data was recorded at 40-50 Hz sampling frequency. The recorded text files were stored on the SD-card.

In the data recording phase, the phone has been placed inside a pouch. This pouch was attached to the subject's trousers on the right-hand side of his hip with the help of a belt as shown in figure 2. From a practical point of view, the phone placement is a difficult choice as users have their own phone placement preferences when they walk. We have intentionally picked this position as it is more discriminant and would lead us to optimal results as compared to other

Figure 2: Phone attached to the subject and the three axes in which acceleration is measured [21].

Table 1: Age and gender distribution of volunteers.

age	*<20*	*20-24*	*25-30*	*>30*	*unknown*
male	1	2	25	9	2
female	0	5	5	0	2
total	1	7	30	9	4

common phone placements.

51 healthy subjects participated in the data recording process. Table 1 shows age and gender demographics of the participants. They were asked to walk at their normal pace on a straight carpeted corridor measuring length of 18.5 meters from the starting point to the end point on the other side of the corridor. In one session, every subject walked 37 meters from the starting point to the end point and from the end point to the starting line. When a participant walks from the starting point to the end point we name this one walk, and when he returns from the end point to the start line is called second walk as shown in figure 3. For every subject, one more session of data recording was conducted on a different day. In two sessions, four walks are recorded for every subject.

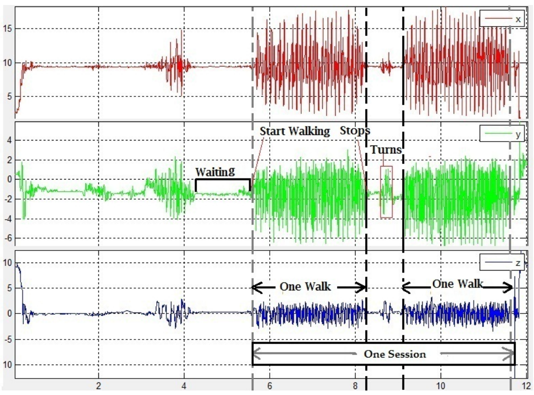

Figure 3: Acceleration recorded along X, Y, and Z axis [21].

3. DATA PREPROCESSING

During the data collection process, the phone was placed in such a way that vertical acceleration is measured along x-axis, forward-backward and sideways accelerations are measured by y-axis and z-axis, respectively. We used only x-axis data for our experiments because it is more discriminant as compared to y and z-axis [21]. One recorded file contains two walks as shown in figure 3. Therefore, before preprocessing the data, both walks are separated from each other. We refer these separated walks to raw walks. Raw gait data or raw walks, undergo preprocessing steps as shown in figure 4.

Linear interpolation: As a first step, linear interpolation is applied to the walks. Interpolation is necessary as the accelerometer sensor does not output acceleration data at equal intervals. The accelerometer sensor only outputs data when Android API's (onSensorChange) method is triggered. By applying interpolation, data can be reshaped in equal intervals and can also be up-sampled in order to avoid data loss of too many values.

Zero normalization: In the steady state, acceleration measured along the axis influenced by gravity must be equal to the earth's gravitational force. Acceleration along the remaining two axes, which are not influenced by the gravity must be zero. However, acceleration recorded by phone-based accelerometer sensors is not stable over the time. Therefore, acceleration along all three axes is zero normalized by subtracting their respective mean as shown in equation 1, where W is acceleration over time and μ is mean acceleration.

$$\bar{W}_i(t) = W_i(t) - \mu_i, i \in \{x, y, z\} \qquad (1)$$

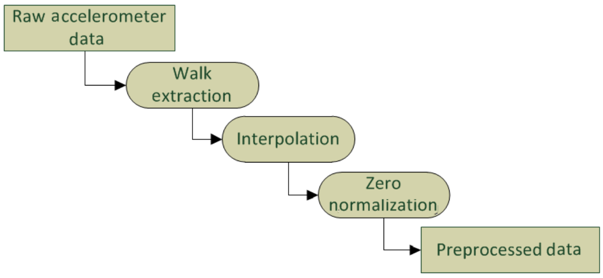

Figure 4: Data preprocessing steps.

4. SEGMENTATION

The process of extracting gait cycles from the preprocessed data is based on [21–23]. Gait cycle extraction steps are shown in figure 5.

Cycle length estimation: To automatically detect gait cycles in the walk, the first step is to estimate the cycle length. Cycle length estimation is done by computing the minimum salience vector [20]. A minimum salience vector contains one entry for each data point of the walk vector. This entry is a count of data values, which are between that data value and the following smaller value in the walk vector [20, 22]. Later, each value of minimum salience which is greater than ***minimal peak height***, and has at least distance of ***minimal peak distance*** is considered as a cycle start. Minimum peak height and minimum peak distance parameter are calculated experimentally. In our case ***minimum peak height*** $= 0.8 \times interpolation frequency$ and ***minimum peak distance*** $= 0.5 \times interpolation frequency$ gave best results.

Cycle detection: Minimum and maximum salient vectors are used for cycle detection. The minimum salient vec-

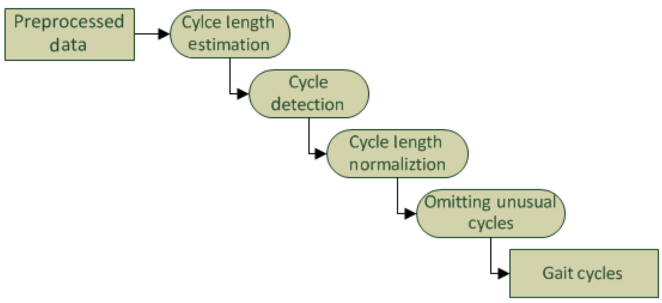

Figure 5: Gait cycle extraction steps.

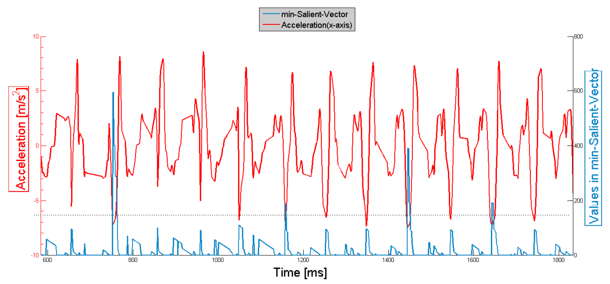

Figure 6: Gait cycle and its corresponding minimum salient vector.

tor is not adequate for determining gait cycles because sometimes minimum at a cycle start may not be greater than the minimum inside the cycles. In other words, minimums are not distinct enough. By using maximum salient vector maximums are computed. These maxima occur just after the cycle start, and these maxima are used to determine the exact minima. Later, peaks in the salient vector with ***minimum peak height*** of $0.7 \times$ *interpolation frequency* and have a distance half of the estimated cycle length are calculated. In minimum salient vector case these peaks are used as cycle starts as shown in figure 6. In case of maximum salient vector first minimum is determined, which occurs before the maximum and these minimum points are considered as instal cycle start. If there exist some cycles that are too long cycles, once again minimum and maximum salient vectors are computed for these long cycles. This process produces some more cycle starts, which are then used to produce the final cycle start vector.

Cycle length normalization: Detected cycles are normalized to equal length by using linear interpolation. This is done because some similarity measures such as Euclidian distance require that input vectors should be of same length.

Omitting unusual cycles: Normalized cycles are cleaned by deleting unusual cycles. This is done by computing the pairwise distance using Dynamic Time Warping (DTW). Cycles which have a distance to atleast half of the other cycles are removed [21].

5. CLASSIFYING GAIT CYCLES WITH SUPPORT VECTOR MACHINES

SVM is a relatively new classification method and is designed for binary classification. SVMs are one of the widely deployed learning schemes for biometric classification as they well suited for biometric recognition, where impostor and genuine data have to be classified. The basic idea behind SVM is that it finds a hyperplane that linearly separates $\mathcal{D}$ dimensional data into its two classes. Most of the time the example data is not linearly separable; to tackle this problem the idea of a *"kernel induced feature space"* is introduced in SVM [3]. A kernel function basically maps non linearly separable data to high dimensional space, where data is linearly separable. Therefore, it is very important to use an appropriate kernel for better classification accuracy. A kernel function is defined as [10]

$$K : X \times X \rightarrow \mathbb{R}, \forall\{\mathbf{x},\mathbf{z}\} \in X \tag{2}$$

$$K(\mathbf{x},\mathbf{z}) = <\phi(\mathbf{x}).\phi(\mathbf{z})> \tag{3}$$

The most commonly used kernel function is the Gaussian kernel, which is defined as

$$K(\mathbf{x},\mathbf{z}) = exp(-\gamma \parallel \mathbf{x} - \mathbf{z} \parallel^2) \tag{4}$$

Gaussian kernel function is commonly used with the Euclidian distance. Where $\gamma > 0$, a user defined shape parameter. Euclidian distance requires input feature vectors to be of same length. Therefore, if we use the Gaussian kernel in its pure form, we are bound to use fix-length gait cycles as input features. On the other hand, if we manage to use DTW distance instead of the Euclidian distance, we could solve the problem of fix-length input feature vectors. Furthermore, the DTW distance works better than the Euclidian distance in terms of finding the similarity. Therefore, we also want to take advantage of superiority of DTW distance over the conventional Euclidian distance [19, 28].

To classify gait cycles using SVM and DTW, we have adapted the following different approaches:

- ***Pre-computed data matrix:*** This approach is based on [16]. We represent gait cycles by DTW distance measure. DTW is capable of finding the distance between two input gait cycles of different length as well as of same length. To compute a DTW distance matrix, each sample (gait cycle) is presented by its DTW distances to all other samples (gait cycles). Since, $DTW(\mathbf{x}_m^{k_m}, \mathbf{x}_n^{k_n}) = DTW(\mathbf{x}_n^{k_n}, \mathbf{x}_m^{k_m})$, the resulting DTW distance matrix is symmetric. Later, this DTW matrix is used as an input data matrix for standard SVM. A Block diagram of this approach is given in figure 7. In order to prepare a training DTW distance matrix for SVM, we used all training data to compute the DTW matrix and it is named as *Train DTW matrix*. Later, we used this DTW matrix as input feature space for standard SVM. Therefore, for prediction, each test example must be mapped using the same representation as we have used for the training data set. In other words, we need to compute the distance between each test example and all training examples. We call this matrix as *Test DTW matrix*.

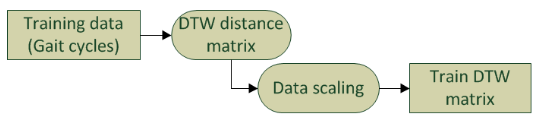

Figure 7: Preparing data for SVM.

- ***Pre-computed Kernel:*** This approach is based on the pre-computed kernel concept. Instead of using typical kernels we use the following kernel function and we refer it to GDTW kernel;

$$K(\mathbf{x},\mathbf{z}) = exp(-\gamma \parallel DTW(\mathbf{x}\ ,\ \mathbf{z}) \parallel^2) \tag{5}$$

  Although this kernel matrix is a symmetric matrix, the *Positive Definite and Symmetric* (PDS[1]) property can not be guaranteed at this stage. In our experiments, we have noticed that this kernel function for some of the subjects is indefinite. In this paper, we dealt with indefinite kernel matrix by flipping the sign of negative eigenvalues [8, 15].

[1]It is a matrix with all positive eigenvalues

6. EXPERIMENTS AND RESULTS

We have conducted two different experiments that utilize data preprocessing and segmentation approach for gait cycle extraction as explained in section 3 and section 4. However, experiment one is based on the template based classification and experiment two utilizes machine learning, i.e. SVMs as an underlying classification technique.

6.1 Template-based classification

As mentioned, we are using the same data preprocessing and segmentation approach for gait cycle extraction as presented in previous work [21]. We used an interpolation frequency of 100 Hz. However, we have introduced one more module called Piecewise Linear Approximation (PLA) just before the Cycle Length Estimation module of figure 5, as shown in figure 8.

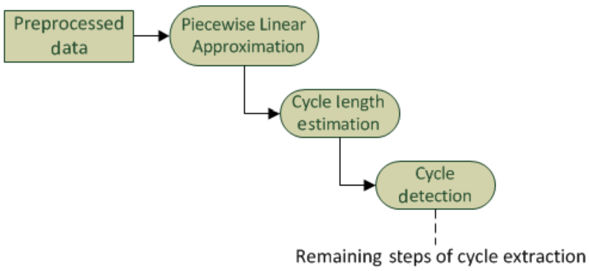

Figure 8: Gait cycle extraction steps with Piecewise Linear Approximation(PLA).

PLA representations are constructed using the Sliding Window And Bottom-up (SWAB) approach [18] as shown in figure 9. Later, this PLA representation of each walk undergoes the remaining steps of gait cycle extraction. Once we delete unusual cycles from detected cycles, all cycles are called remaining cycles and from these remaining cycles one best cycle, which is also called as the feature cycle, is picked. Best cycle is one, which has lowest DTW distance to all the remaining cycles. Remaining cycles are called probe cycles. An example of extracted gait cycles is shown in figure 10. To find best performing parameters such as buffer size and maximum error, for SWAB, we conducted the same experiment for 36 times with different parameters. We got best results with buffer size of 300 and maximum error of 15.

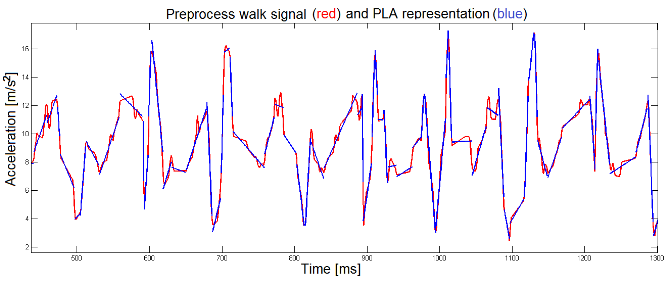

Figure 9: PLA of gait cycles using SWAB with buffer size of 300 and maximum error 15.

After computing reference and probe cycles for all walks, we compute intra class distance (genuine) and inter class distance (impostor) by comparing reference and probe cycles against each other using DTW distance. Distance for all gait cycles of each walk is computed, then majority voting with a preset threshold value is applied. If 50% cycles of one walk vote for an accept, then the result of the walk is an accept, otherwise reject.

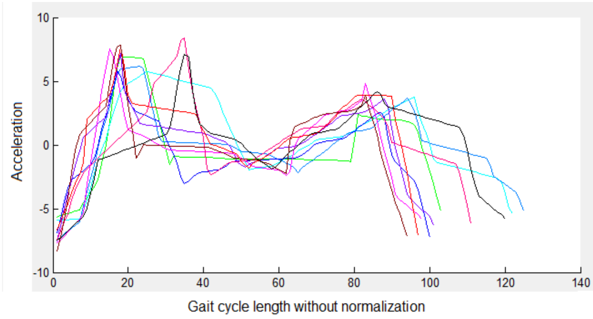

Figure 10: An example of extracted gait cycles.

As mentioned in section 2, gait data is collected in two different sessions. The results are presented in terms of Equal Error Rate (EER). This experiment yields EER of 22.49% for same-day, 29.4% for different-day and 33.3% for mix-days. Figure 11 shows Detection Error Tradeoff (DET) curves of the same day, different day and mixed day results.

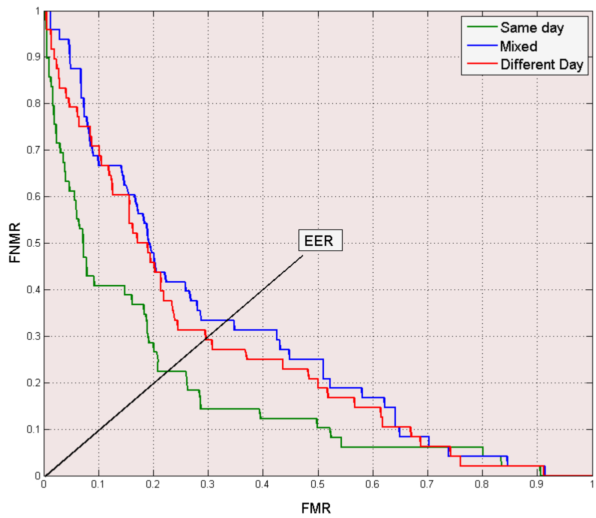

Figure 11: DET curves of same, different and cross day results.

6.2 Machine learning based classification

In this experiment, we have used LIBSVM toolbox [7]. For *pre-computed data matrix* classification approach, gait cycles are preprocessed and extracted as depicted in figure 4, and we have followed data preparation steps given in figure 7. Once all gait cycles are extracted, we separate them into training and testing data sets. First 80% gait cycles of every subject are placed in training data set and remaining 20% gait cycles are used for testing data set. The reason of choosing the last 20% gait cycles for testing is to check how our methods work for different day performance. Then we compute a DTW distance matrix from the training data set. In the next step, we scale the DTW distance matrix to bring all features to a common range and make them independent of each other. *Minimum - maximum* method as given in equation 6 is deployed to scale training data to a common range [0,1].

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{6}$$

Where, X' is normalized or scaled data value, X is the original data value. X_{min} and X_{max} are minimum and maximum values of the data set.

In the next step, we used this scaled DTW training data set to train multi-class SVM. We have used one-vs-one multi-class classification strategy. In this classification strategy N number of binary classifiers are constructed, where N is computed as given in equation 7 and K is the total number of classes. Later, the classification decision is made by aggregating the decisions of the binary classifiers.

$$N = \frac{K(K-1)}{2} \tag{7}$$

There are various approaches to aggregate classification decisions of binary classifiers. However, we have used simple majority voting, where each binary classifier votes for the predicted class. In the end, the class with the maximum number of votes is predicted as an aggregated result of classification.

In this approach, we have used Gaussian kernel as given in equation 4, there exist two hyper-parameters (regularization constant $\mathcal{C}$ and kernel parameter γ) that must be tuned to achieve better results on unseen data and for this purpose the grid search method is deployed with 5-fold, *Leave-One-Out Cross-Validation* (LOOCV) scheme for model selection with shuffling technique. Therefore, for every pair of ($\mathcal{C}$, γ), we train models with 5-fold LOOCV policy, and in every fold data is shuffled. In the end, we select parameters that achieve highest performance in terms of classification accuracy.

Each example from the test DTW matrix is tested against all trained models. For each testing example, every model predicts a label or votes for the predicted class. The predicted label with the maximum number of votes is assigned as a new class of an example. The classification accuracy achieved with this approach is 53%. Using SVMs, biometric performance measure such as, False Match Rate (FMR) and False Non Match Rate (FNMR) can be computed but not EER. For Better comparison of results Total Error Rate (TER) is computed, which is sum of FMR and FNMR. TER in this case is 47%.

Table 2: Results of different experiments conducted in this study, Where ml-based stands for machine learning based.

classification type	approach	different-day results%		
template-based	PLA and DTW	33.3 EER		
		FMR	FNMR	TER
ml-based (one-vs-one)	pre-computed matrix	2.6577	44.3424	47.01
ml-based (one-vs-all)	pre-computed kernel	1.4320	41.284	42.72
ml-based (one-vs-one)	pre-computed kernel	1.1159	35.7041	36.82

The second approach that we have used in this experiment is based on one-vs-one and one-vs-all stratergy, with pre-computed kernel idea. In this approach, we used a modified Gaussian kernel given in equation 5, and we call it Gaussian DTW (GDTW) kernel. Here, we don't compute the train DTW matrix and the test DTW matrix. We simply separate extracted gait cycles in 80% and 20% as we have done for the *pre-computed data matrix* approach, where 80 % of the data is used for training and the remaining 20% are used for testing. We once again used grid search method with 5-fold LOOCV policy and shuffling technique for the selection of hyper-parameters ($\mathcal{C}$ and γ) and model selection. The classification accuracy achieved using one-vs-one strategy is 63.18% and 57.28% using one-vs-all stratergy. TER for one-vs-one and one-vs-all for pre-computed kernel based approach are 36.82% and 42.72%, respectively. Table 2 shows the results of different experiments conducted in this study.

7. DISCUSSION

In this paper, we introduced new techniques for gait recognition using PMD-based accelerometer. We conducted two experiments. In the first experiment, we used the template-based classification, where we deployed PLA for gait cycle extraction. Piecewise linearly approximated cycles do speed-up the gait cycle extraction and their recognition process to approximately 2-3 minutes as compared to approach presented in [21]. However, results obtained without PLA are slightly higher than the ones achieved by introducing PLA for instance, different day performance. Table 3 gives a comparison of results with and without piecewise linearly approximated gait cycles.

Table 3: A comparison of results with and without PLA-based gait cycle extraction. Here EER is used as performance measure.

cycle extraction	*same-day%*	*mix-day%*	*different-day%*
with-PLA	22.49	29.4	33.3
without-PLA [21]	16.26	29.39	28.21

In our second experiment, instead of using single scalar value features extracted from fix-length segments we have used entire gait cycles as a single feature. This is inspired by time series classification. Here we have used state of the art, SVMs as a classification tool. In this experiment, we have proposed two approaches, which can handle different length gait cycles. In the first approach, pre-computed data matrices are used for training and testing the standard binary SVMs. This approach faces a challenge such as for classification, we need not only trained models but also the training data. Therefore, this approach is not suitable where the testing party has restricted access to the training data. In the second approach, which is called pre-computed kernel we have introduced GDTW kernel and achieved a TER of 36.82%. However, this approach suffers from the indefinite kernel matrix. This problem is dealt by flipping the negative eigenvalues.

It is quite difficult to make a true comparison of our approach with other approaches as results depend on various experimental setups such as, type of sensor used for data collection sensor frequency at which data is On the other hand different studies have reported different types of error rates such as, Crude Accuracy (CA), False Accept Rate (FAR), False Reject Rate (FRR), EER, FMR, FNMR, Receiver Operating Characteristics (ROC) and Area Under

Curve (AUC).Therefore, we have compared results of this study with our previous work [21] as given in table 3.

8. CONCLUSION AND OUTLOOK

We have introduced one new approach to gait cycle extraction using PLA, and two new approaches to use gait cycles as features and classifying them using SVMs. In our all approaches, we used DTW, a well known method for elastic similarity measure. DTW works efficiently for finding similarity between gait cycles of unequal length. We did not use variable length gait cycles in our study. However, approaches presented in this study are well suited for gait cycles of different length. To conduct experiments we used normal walk gait data. This gait data was collected using PMD-based accelerometer sensors. In this paper, we proposed a novel elastic kernel GDTW function which incorporates elastic distance metric in Gaussian kernel. The cycle-based feature extraction technique deployed in this paper does not suffer from the challenges faced by the fix-length segmentation based feature extraction approach, such as finding suitable window size and search of appropriate feature extraction methods from fix-length segments. In our future work, we are trying to improve the classification results by improving our gait cycle extraction techniques, incorporating various elastic similarity measures in kernel functions. Though, we have achieved best recognition rate when gait data recorded at 40-50 Hz is interpolated at 100 Hz but this might have included artifacts which degraded the overall performance of the system. We are already in the process of recording gait data at higher sampling rate and by considering more realistic phone placement scenarios, such as different pockets of the trousers. To improve post classification results in future, we will introduce a time based majority voting scheme.

9. ACKNOWLEDGMENTS

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