Feature-based Analysis of Gait Signals for Biometric Recognition
Automatic Extraction and Selection of Features from Accelerometer Signals

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Abstract: Gait recognition has been traditionally tackled by computer vision techniques. As a matter of fact, this is a still very active research field. More recently, the spreading use of smart mobile devices with embedded sensors has also spurred the interest of the research community for alternative methods based on the gait dynamics captured by those sensors. In particular, signals from the accelerometer seem to be the most suited for recognizing the identity of the subject carrying the mobile device. Different approaches have been investigated to achieve a sufficient recognition ability. This paper proposes an automatic extraction of the most relevant features computed from the three raw accelerometer signals (one for each axis). It also presents the results of comparing this approach with a plain Dynamic Time Warping (DTW) matching. The latter is computationally more demanding, and this is to take into account when considering the resources of a mobile device. Moreover, though being a kind of basic approach, it is still used in literature due to the possibility to easily implement it even directly on mobile platforms, which are the new frontier of biometric recognition.

1 INTRODUCTION

Biometric traits are traditionally classified into physical and behavioral, and further denoted as strong and soft, mainly according to uniqueness and permanence. Strong traits mainly belong to the physical group, and the soft ones in this group generally identify classes of users instead of individuals (e.g., hair color, height, face shape, etc.). Almost all behavioral traits rather belong to the soft category, due to lack of sufficient permanence over the long period. This is because they can be affected by mood and speed of action execution, and in some cases by temporary impairment of the body part involved. Even if soft traits are not accurate and permanent as the strong ones, their analysis can be fused to enforce recognition accuracy. Behavioral traits have also the advantage to be more difficult to forge and replicate.

Gait recognition can be considered to belong to the behavioural biometrics, even if, especially in relation with computer vision-based approaches, it also presents some physical/visual characteristics. While this kind of approaches has been the first one adopted for recognition, the problem has recently gained new interest thanks to the new researches based on new wearable sensors or wider availability of existing ones. This paper focuses on Wearable Sensors-based techniques, exploiting sensors built in modern smartphones. In particular, the techniques proposed in this paper carry out recognition by the signals captured by the embedded 3-axes accelerometers.

Like other traits, gait recognition suffers from both intra-personal variations, either intrinsic or extrinsic to the walking person, and inter-personal similarities, possibly causing a subject to be confused with another. Variations of the walking pattern from the same individual mainly depend on speed, ground slope, kind of worn shoes (e.g., heels for women shoes, or heavy boats), and also on some temporary (if not permanent) illness, such as contusions or other problems affecting legs, articulations or feet. In addition to those factors, image-based techniques applied to video sequences, can be further affected by varying illumination, occlusion, pose, perspective with respect to the camera, and large clothes. Finally, a common problem, though producing different effects according to the adopted sensors, is the presence of carried objects, that modify the silhouette, generally exploited by computer vision approaches, as well as the walking dynamics, especially if heavy. A further disadvantage of computer vision-based approaches is the impossibility to carry out verification of the walker directly on a personal device, since videos are necessarily captured by an external device.

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Notwithstanding the above limitations, it is quite difficult to copy or forge the gait pattern produced by someone else. In addition, while gait recognition can operate at a distance (even 10 meters or more) with computer vision applications, there is not even this limitation with wearable sensors, since they are directly attached to the user body. Moreover, while video capture can mingle silhouettes of different subjects in the same frames, depending on the point of view and relative positions of these subjects, signals captured by wearable sensors are by definition isolated and independent from each other. Last but not least, in both cases the user is not asked to do any specific action but walk, and gait recognition can be effectively combined with other ”strong” biometrics to both enforce recognition accuracy and as an anti-spoofing support.

The aim of this paper is to report the results of investigations regarding the possibility to reduce the computational time for matching with respect to pure Dynamic Time Warping (DTW) that is still quite used in literature. In particular, a feature extraction, analysis and selection procedure is devised in order to achieve a faster yet still accurate recognition. The added value of this approach is the possibility to process the gait signal directly on a low-medium level smartphone without need of sending data to an external server. Of course, this holds for the verification of the owner identity (1:1 identity matching), which is implicitly assumed to be the person carrying the device. As for identification (1:N identity matching), privacy as well as security considerations would not allow anyway maintaining templates from other users (gallery) in one’s own device and processing them locally. Experimental setup exploits one of the largest available wearable sensor-based datasets, in order to provide a common benchmark for comparison with other works. Unfortunately, at present this is not always possible due to in-house and often private datasets used in several papers.

The paper continues as follows. Section 2 provides a summary of present research lines in this field. Section 3 describes the paper proposal, entailing the process of signal capture followed by feature extraction, analysis and selection. Section 4 presents the results from experiments carried out, and some comparison with raw signal matching. Finally, Section 5 draws some conclusions and sketches future work.

2 RELATED WORK

It is worth anticipating that most works in literature, addressing wearable sensor-based gait recognition, locate the acquisition device in different body locations, and use different (often in-house) datasets with a different number of subjects, so that a fair comparison is not always feasible. Moreover, most works only consider verification modality (1:1 identity matching with either implicit or explicit identity claim), a few ones also consider closed set identification modality (1:N identity matching with no identity claim but the assumption that all probes belong to enrolled users), and almost none considers open set identification modality (1:N identity matching with no identity claim and reject option). This is related to the main intended use of this kind of biometrics, devised to authenticate the owner of a mobile device against a stored template. However, it is worth considering that the possibility to automatically trigger signal capture by Bluetooth devices, and to transmit the captured signal to a remote server, allows hypothesizing a wider use of this biometrics for access control to restricted areas by user identification.

As for wearable sensor-based recognition, it is possible to identify two main categories of approaches.

The attempts in the first group generally try to match the template/templates of the users by signal matching techniques, such as Euclidean Distance (ED), Dynamic Time Warping (DTW), or Histogram Similarity (HS). These kinds of techniques, if applied to match the entire signals, generally provide quite good results. However, they drastically lose accuracy when the templates significantly differ in terms of number of samples. For this reason, some works in this group use the adopted matching strategies after dividing the signals into steps/cycles. This generally entails a segmentation procedure that tries to automatically identify the start and stop of a step/cycle in the walk signal, where step is intended as a single foot step, while cycle is intended as a pair of them (left-right or right-left). In these cases, it is worth noticing that the quality of the results of this operation have an high impact on the recognition accuracy, and developing a good segmentation algorithm is a crucial point.

In (Gafurov et al., 2010), the authors show the impact of different kinds of shoes in the recognition, using a in-house dataset of 30 persons. The proposed method uses a fixed threshold to identify cycles and then normalizes their sample length. Recognition entails measuring ED between all pairs of cycles, composed of one cycle extracted from a gallery sample and one cycle from the probe to match; the best achieved distance has to meet the fixed threshold for the acceptance. Results are in terms of Equal Error Rate (EER), the value where False Acceptance Rate is equal to False Rejection Rate, therefore the lower, the better. Values range from 1.6% with the lighter shoes to 5% with the heavier ones.

The work presented in (Gafurov et al., 2006) proposes two different approaches for gait recognition, tested on a in-house dataset of 21 users with only one single walk each, further divided into two parts. This causes a lack of most intraclass variation factors, and therefore the dataset hardly represents a realistic scenario. In real life settings, even the position of the sensors cannot be completely controlled and is not identical, and this fact in itself can produce variations in the captured signal. For both proposed methods, the 3-dimensional raw signals from the accelerometer are combined into a single 1-dimensional vector using the following *ad hoc* formula: $v_i = arcsin(\frac{z_i}{\sqrt{x_i^2+y_i^2+z_i^2}})$ where i represents the index of the sample within the signal. The first matching strategy exploits HS. To this aim, the obtained values are stored in a histogram representing the derived biometric template. Matching between the obtained histograms achieves a 5% of EER. The second attempt uses the 1D vector for cycle comparison and achieves a 9% of EER.

In (De Marsico and Mecca, 2016), the authors present a novel step segmentation procedure and show the performance of five different algorithms based on DTW, one dealing with the entire signal and the others using different strategies to match the detected steps. In this case no fixed threshold is used for segmentation. The algorithm exploiting the entire signal achieves 92.8% of Recognition Rate (RR) in closed set identification modality and 9.26% of EER in verification modality; the algorithms exploiting the step segmentation procedure achieve up to 82.7% of RR and up to 10.3% of EER. It is to underline that results in this latter work are obtained over a very large public dataset including 175 subjects with 12 walks each (Zhang et al., 2015).

The approaches in the second group, instead, try to exploit machine learning algorithms/classifiers in order to get the correct match between templates. These proposals generally work only in verification modality, training a classifier for each subject. A common pre-processing step is to fragment the signal in chunks with a fixed length (in terms of either time or number of samples, with or without overlap) in order to extract more data for the training phase. Of course, these approaches do not require any step/cycle segmentation procedure. After the training of the classifier, that can occur on a more powerful device, the trained system can be executed directly on a smartphone due to the low computational cost of the single recognition operation. In fact, several works in this category are generally designed to be executed directly on the mobile device in order to unlock it only for its owner, as an alternative to pins or passwords.

Two solutions in this category are presented in (Nickel et al., 2011b) and in (Nickel et al., 2011a). Both works exploit the same dataset, collected by a Google G1 phone. Such dataset contains walk signals from 48 subjects, 4 walks each. In the first work, signals are re-sampled to 200Hz. Afterwards, they are divided into fragments of 3 seconds with no overlap. Fragments are then grouped into two sets, one for the training and the other one for testing. The recognition is carried out by the HVITE tool and each subject is used one time as genuine and forty-seven times as impostor. This strategy reports an EER of about 10%.

In the second work, the walking signals are interpolated to 100Hz and then are fragmented into chunks of 7 seconds with an overlap of 50%. Each fragment is used as feature vector, adding some extra statistical parameters, and the Mel and the Bark frequency cepstral coefficients. Training and recognition are carried out exploiting the SVM classifier. This approach achieves a 5.9% of False Match Rate (FMR) with 6.3% of False Non Match Rate (FNMR).

In (Nickel et al., 2012), the authors try to exploit the k-NN algorithm for recognition. Walking data are collected during two sessions. Each of the 36 users is asked to walk 12 times at normal pace, 16 times at fast pace and again other 12 times at normal pace on a flat hallway. Each such group of walk signals is captured by a single recording operation. Single signals are divided using an automatic procedure according to some stop periods decided in advance, and the result is eventually manually corrected. All signals are then interpolated at 127Hz (this value is empirically chosen). After this preprocessing, the interpolated signals are fragmented. This work exploits three different fragment sizes, namely 3s, 5s, and 7.5s. In all three cases, the fragments have an overlap of 50%. The feature vectors are then created using some statistical parameters and by Mel and Berk coefficients. The recognition exploits the implementation of k-NN algorithm included in the WEKA library. The work reports a FMR of about 4% with a very high FNMR of about 22-23%, resulting in a Half-Total Error Rate (HTER - the average of the two) of about 13%. In order to improve performances, the authors try a voting approach using different fragments of the same subject; this significantly reduces the FNMR while increasing minimally the FMR, so achieving an HTER of about 8.5%.

The proposal in (Zhang et al., 2015) presents a large dataset of 175 subjects with 12 walks per person (the same used as benchmark by our proposal) and tests the extraction and the use of signature points

(SP). SPs are described as the fiducial positions within gait signals that should be both stable for the same person and distinctive for different persons. The authors propose to sparsely represent the SPs and then to create clusters, labelling them to make up a dictionary in a linear combination, in order to have a subject for each cluster. Recognition is described as a conditional probability problem solved by a sparse-code classifier. The result reaches an up to 95.8% of RR in closed set modality, and up to 2.2% of EER in verification modality. In this case, it is worth considering that the authors use 5 accelerometers of the same kind positioned in different body locations.

3 AUTOMATIC FEATURE EXTRACTION AND TEST SCENARIOS

3.1 Extracted Features

Notwithstanding the variety of solutions proposed in literature, DTW still plays a relevant role for wearable sensor-based gait recognition. Problems to address are related to the possible different length of walk signals, and to noisy acquisition. Moreover, computational complexity is not negligible when considering mobile processing. This work investigates the possible application of Machine Learning procedures in order to extract aggregate features from the signals, and to select the most relevant ones. The aim is twofold: from one side, to discard less robust or less informative features, i.e., those more subject to distortions, or that present quite flat values across signals; from the other side, achieving the goal of a lighter though accurate recognition procedure would be better suited to mobile settings.

In order to evaluate the possible influence of specific feature selection choices, 4 different scenarios have been configured, with different characteristics regarding both the use of training information and the way to exploit such information.

In all the test scenarios considered for the experiments presented below, the same Python libraries have been used for feature extraction and analysis. Tsfresh[1] library is used to automatically extract a large number of features from temporal series. It is usually exploited together with Pandas[2] for data analysis, and with Scikit-learn[3] library for Machine Learning. The extracted features can be later exploited to create regression or classification models, and to cluster or match time series.

Tsfresh includes library functions to extract a huge number of features (222) from a time series. Of course not all of them were taken into account for our experiments. Some examples follow, but it is not possible to provide the complete list of them.

- **abs_energy**: returns the absolute energy of the time series: $E = \sum_{i=1}^{n} x_i^2$ with n=number of points in the time series
- **absolute_sum_of_change**: returns the sum of absolute values of subsequent variations in the series: $E = \sum_{i=1}^{n} |x_{i+1} - x_i|$
- **approximate_entropy**: returns the approximate entropy of the signal
- **ar_coefficient**: returns the coefficient of the Auto Regressive (AR) process for a given configuration passed as parameter
- **augmented_dickey_fuller**: returns the result of Dickey-Fuller test
- **autocorrelation**: returns autocorrelation given a certain lag
- **count_above_mean**: returns the number of values in the time series higher than its mean
- **count_below_mean**: returns the number of values in the time series lower than its mean
- **cwt_coefficients**: computes the wavelet transform using this formula $\frac{2}{\sqrt{3a}\pi^{\frac{1}{4}}}(1 - \frac{x^2}{a^2})exp(-\frac{x^2}{2a^2}))$
- **fft_coefficient**: computes the Fourier coefficients applying Fourier Tranform
- **mean**: returns the mean of the signal
- **mean_abs_change**: returns the mean of absolute values of consecutive changes in the time series $\sum_{i=1}^{n-1} |x_{i+1} - x_i|$
- **standard_deviation**: returns standard deviation
- **variance**: returns the variance
- **median**: returns the median value
- **skewness**: returns the skewness (computed with the Fisher-Person standardized coefficient)
- **kurtosis**: returns the kurtosis (computed with the Fisher-Person standardized coefficient)

It is worth noticing that features are separately extracted from the signals produced by the three accelerometer axes, and the difference between test scenarios also regards the way to take their possible correlation into account.

[1] https://tsfresh.readthedocs.io/en/latest/index.html
[2] http://pandas.pydata.org/index.html
[3] http://scikit-learn.org/stable/

3.2 Test Scenarios and Feature Selection

This work analyzes 4 different test scenarios. Test Scenario 1 (T1) does not use any training phase, while the others do. Considering the different domains and scale values of extracted features, a standardization procedure is exploited to build homogeneous vectors, using the well-known Gaussian normalization formula. For each feature, the average μ and the standard deviation σ are computed over gallery templates and then, for each value x, the resulting standardized value z is obtained by the formula:

$$z = \frac{(x-\mu)}{\sigma} \tag{1}$$

The μ and σ values are then stored, in order to normalize the further incoming probes used for testing with the same gallery. The galleries that are used in turn for the experiments each contain a number of templates (more than 450) that allows considering these parameters stable enough to avoid recomputing them for each probe. All test scenarios entail recognition in multiple instance verification modality: each subject has more than one template, all of them are matched against the incoming probe, and the best match among the gallery and the probe is returned as verification result. A probe set vs. gallery set distance matrix is produced in order to evaluate the performances. For each scenario, distances are computed between pairs of vectors built according to the scenario setting. Experiments are carried out using both Manhattan and Euclidean Distance as alternative metrics.

3.2.1 Test Scenario 1 (T1)

In T1, all feature extracted by Tsfresh tool are exploited. For each axes, all 222 feature are taken into account, for a total of 666 features in the template vector. This scenario allowed to have a baseline performance. In order to get a fair comparison with the other scenarios, the templates from samples in the training set are not used during testing.

3.2.2 Test Scenario 2 (T2)

The strategy adopted in T2 aims at selecting and keeping only the most relevant features. For each axis, only the features that have a probability of at least 80% of changing across vectors are taken into account. In other words, only features presenting the highest variance are maintained. This analysis is carried out by Scikit-learn library. The next selection step entails a further pruning, that discards features that do not present this property for all axes, i.e., those that are informative enough but only for a subset of axes. This provides a total of 55 feature per axis, summing up to 165 features. This feature selection is carried out in the training phase, so that in testing only the identified features are taken into account for both gallery and probe sets.

3.2.3 Test Scenario 3 (T3)

In T3 the same first step of variance-based pruning is performed as in T2. As a second step of feature selection, the complement of the features identified in T2 is maintained. After discarding features that show a too high homogeneity of values across the training set, only the features that are relevant for a strict subset of axes (1 or 2) are maintained. In this case, this sums up to 24 features, 9 from the x axis, 10 from the y axis, and 5 from z axis. Even in this case, selection is carried out during training, and the features identified are then extracted from gallery and probe in the testing step.

3.2.4 Test Scenario 4 (T4)

T4 uses a totally different approach for feature selection. In this case the choice of features to be kept is based on the Principal Feature Analysis (PFA)(Lu et al., 2007). It uses the same principles of the well-known Principal Component Analysis (PCA), also exploited, e.g., in face recognition for feature space reduction. The same PCA criteria are applied to select a subset of dimension q of the most representative features from the complete original set. During training, the best results are obtained with q=60 and q=62.

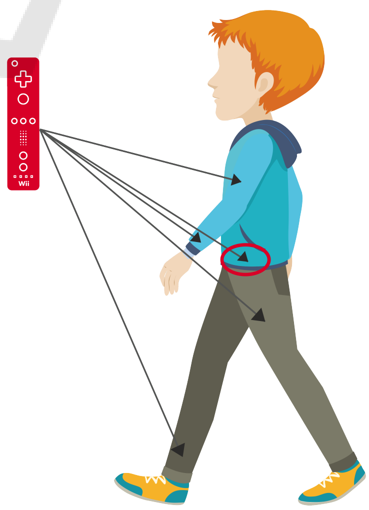

Figure 1: Body locations available from ZJU-gaitacc dataset. The red circle (pelvis zone), is the one exploited to get the experimental results.

Table 1: Results in term of EER for the 4 test scenarios.

TEST	EUCLIDEAN DISTANCE	MANHATTAN DISTANCE
T1	24.6%	22.4%
T2	22.5%	20.2%
T3	31.5%	30.6%
T4	19.6%	18.7%

4 EXPERIMENTAL RESULTS

4.1 Dataset

The dataset exploited for the experiments of this work is the one proposed in (Zhang et al., 2015), named ZJU-gaitacc. It collects walk signals from 175 subjects, out of which only the 153 selected for this work have 12 walks each, equally divided into two sessions, with data captured from 5 different body locations: upper arm, pelvis, wrist, thigh, ankle. In order to maintain consistency with real life use and possible positioning of smartphones, only the subset captured from pelvis has been used. Furthermore, this accelerometer positioning provides the best results. It is worth noticing that the proposal of this paper addresses the use of smartphones for gait authentication, and that embedded accelerometers presently achieve a higher signal resolution. However, this dataset is the best one viable for a fair comparison of methods. It presents the best characteristics in terms of both number and length of samples, and also provides data from two different sessions, so allowing to take into account time-related variability too.

The dataset has been divided into training and testing sets. The training set contains the first 3 walks of each session, while the testing set contains the remaining ones. As for probe and gallery partition of the testing set, in order to get more results, the walks from the first and from the second session has been used in turn as either probe or gallery. The obtained results have been averaged to produce the final performance measures. Figure 1 shows the body locations available from the dataset, and the red circle indicates the one used in this work.

4.2 Results and Discussion

The system has been tested in multiple instance verification modality (the best matching between the incoming probe and the gallery of the claimed identity is returned). Performances are reported in terms of Equal Error Rate (EER). T1 achieves EER=24.6% with Euclidean Distance (ED) and a slightly better EER= 22.6% with Manhattan Distance (MD). T2 shows an improvement, achieving EER=22.5% with ED and EER=20.2% with MD. This seems to demonstrate that selecting the features that provide the highest information for all axes improves recognition performance. On the contrary, T3 achieves worse performance than T1, namely EER=31.5% with ED and EER=30.6% with MD. This is probably due to the too low number of features (24) and possibly to the uneven distribution across axes. T4 achieves the best results, represented by EER=19.6% with ED and EER=18.7% with MD. Overall, the best results are always obtained by MD, independently from the test scenario. The performance of PFA demonstrates that reduction techniques exploiting data correlation are effective with this kind of temporal series, obtaining an improvement of about 7% over T2. This is not dramatically significant, but encourages continuing investigating along this line. Table 1 summarizes the obtained results. Figure 2 plots the EER trend of test scenarios. Figure 3 shows FAR and FRR curves for all scenarios with both exploited metrics.

It is interesting to make a comparison with results reported in (De Marsico and Mecca, 2016), obtained on the same dataset using pure DTW for the same multiple instance verification modality. On one hand, the algorithm matching the whole signal (EER=9.2%), as well as the best of those exploiting step segmentation (EER=10.25%), got better results than the approaches presented here. These two algorithms are the slowest and most computational demanding in (De Marsico and Mecca, 2016). Moreover, the first one requires signals to be not dramatically different in terms of length. On the other hand, the other three proposals in (De Marsico and Mecca, 2016) based on step segmentation compute distance with a matching strategy comparable in terms of computational costs and speed to those proposed here, and allow releasing the constraint of a similar number of steps. However, they show lower performances (EER of 0.328%, 0.4104%, and 0.3625% respectively) than the approaches presented here. Approaches based on feature extraction work on a kind of aggregated information that does not depend on the signal length, given that it is long enough. The above comparison seems to suggest a possible compromise between different application constraints, that deserves more investigation. As a further comparison, the results in (Zhang et al., 2015) are reported. We considered only the single accelerometer scenario (i.e., entailing the same setting of our experiments). That work achieves an EER that ranges from 8.6% to 13% (depending on the chosen body location), that is generally better than

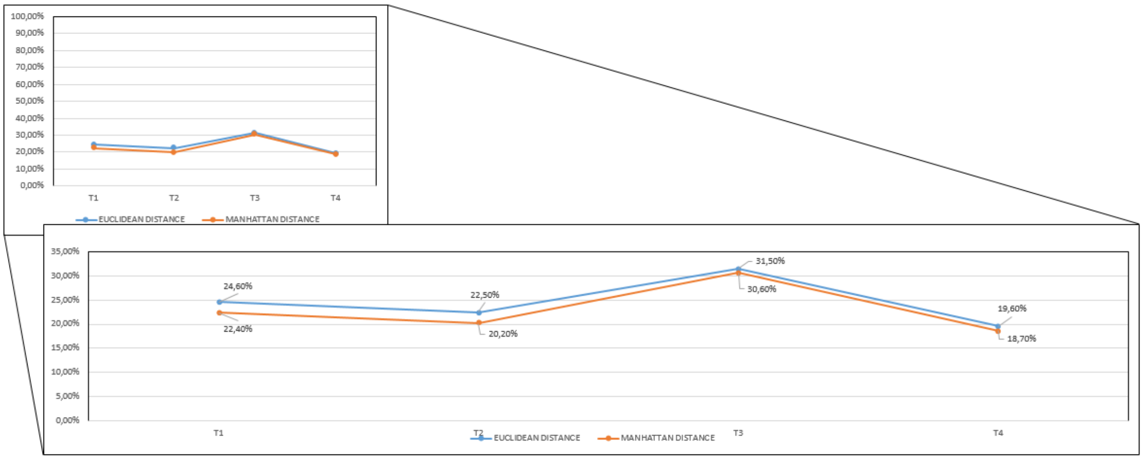

Figure 2: EER trend of the two metrics exploited.

our approach, but it is worth noticing that their procedure requires about 0.3 second to run on a powerful pc, while our approach is devised to work on smartphones that have lower computational power. It is further worth underlining that making more comparisons with other state of the art methods is not possible at present, due to the different (and generally much smaller) datasets used. The larger dataset introduced in (Ngo et al., 2014) contains very short signals that have been manually segmented from longer ones, acquired in a single session and with a single walk. Therefore we preferred to use data presenting more challenging variations.

5 CONCLUSIONS

The main aim of this work has been to try a feature based approach for gait recognition based on wearable sensors. The achieved results fall in between those provided on a similar dataset using pure DTW. It is worth noticing that, with respect to better ones in literature, they are produced by approaches especially devised to run on personal mobile devices. This entails aiming at lowest computational costs and execution times. In any case, performances are quite encouraging, and call for more investigation. As a future attempt, we plan to apply PFA to an already partially reduced feature set, possibly applying the best strategy presented here based on features which are equally informative for signals from all accelerometer axes. In addition, more and possibly wider feature sets can be investigated.

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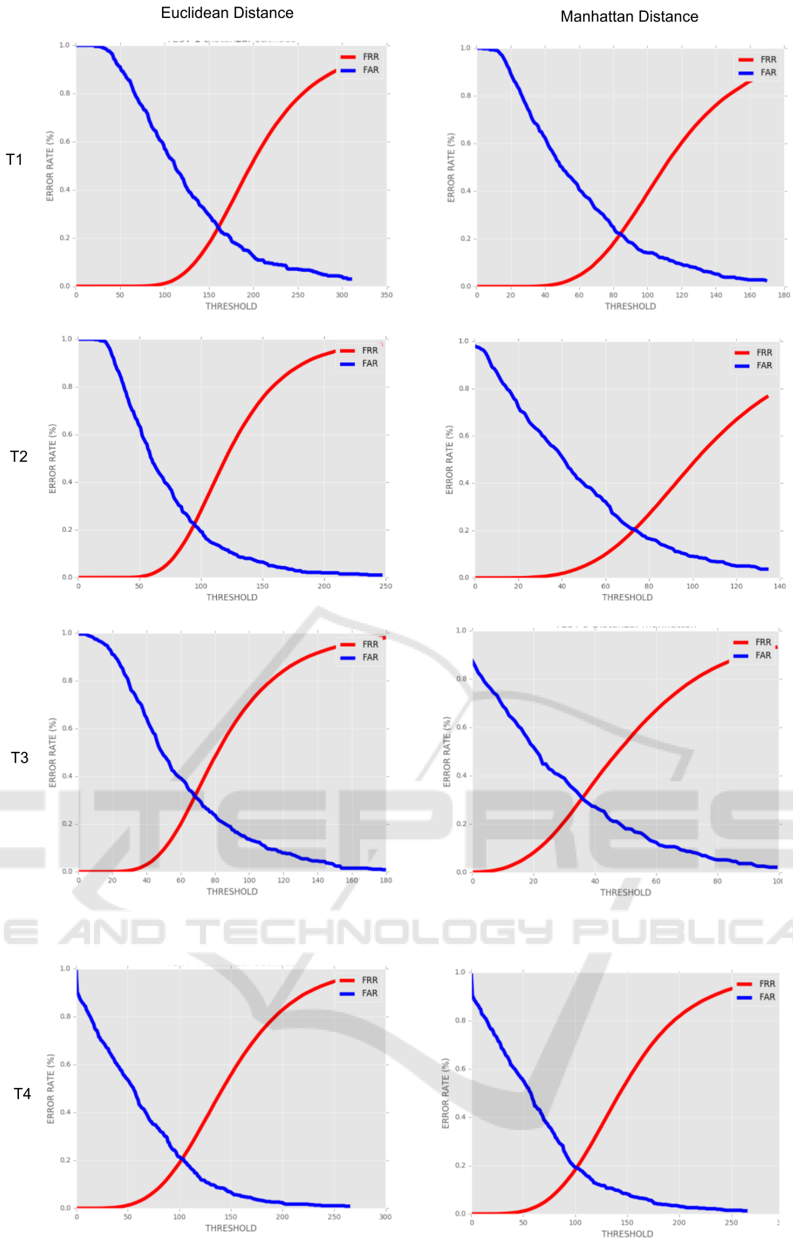

Figure 3: FAR and FRR for all test scenarios using both Euclidean Distance and Manhattan Distance.