HANDWRITTEN SIGNATURE VERIFICATION USING WEIGHTED FRACTIONAL DISTANCE CLASSIFICATION

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ABSTRACT

Signatures are one of the behavioural biometric traits, which are widely used as a means of personal verification. Therefore, they require efficient and accurate methods of authenticating users. The use of a single distance-based classification technique normally results in a lower accuracy compared to supervised learning techniques. This paper investigates the use of a combination of multiple distance-based classification techniques, namely individually optimized re-sampling, weighted Euclidean distance, fractional distance and weighted fractional distance. Results are compared to a similar system that uses support vector machines. It is shown that competitive levels of accuracy can be obtained using distance-based classification. The best accuracy obtained is 89.2%.

***Index Terms*—** Pattern Recognition; Biometrics, Handwritten Signatures, Optimized Re-sampling, Weighted Euclidean Distance, Fractional Distance

1. INTRODUCTION

Biometrics is the use of one or more intrinsic physical or behavioural human characteristics to verify or identify a person. Biometric traits should be unique, universal, long lasting, collectible, commonly accepted, difficult to falsely duplicate and identifiable efficiently and accurately by machine. Examples of physiological biometric traits include fingerprints, DNA, hand and palm geometry and iris recognition, whereas examples of behavioural biometric (behaviometric) traits include voice recognition, writing patterns and signatures [1].

The basic process of automated biometrics verification involves capturing the biometric traits onto a machine and then using biometric feature extraction algorithms to create a digital representation template of the trait. For authentication of an individual, the system creates a biometric template from newly captured data and compares the two templates [1].

A signature, which is one of the oldest used and most widely accepted biometric for identification and verification [2], is a handwritten depiction of a persons name, nickname or other personal symbol. It is classified as a behavioural biometric trait.

There are two ways to capture signatures: online and offline. Offline signatures are static images while online signatures are dynamic and capture the progress of signature writing as a function of time. Since online signatures hold a greater amount of information, they intrinsically allow greater accuracy than a static image. However, there are still many systems that require the improved accuracy of offline signatures. For instance, online signatures are not available for bank cheques or credit cards, and accurate offline signature verification is essential. The electronic writing pads for the capture of offline signatures are also much more cost effective than that for online signatures. Thus, the availability of competitively accurate offline signature verification could improve security measures for businesses in poorer emerging markets.

There are many different techniques for classifying signatures and other biometrics. They can be broadly categorized into supervised learning techniques (SLTs) and distance-based classification techniques. SLTs include neural networks [3], hidden Markov models [4], support vector machines [5] and fuzzy logic [6]. Distance-based techniques include Euclidean distance, Mahalanobis [7], Manhattan distance, weighted Euclidean distances [8] and fractional distances [9].

SLTs in general provide a greater accuracy than basic distance-based techniques. This paper aims to combine several distance-based techniques to gain accuracy comparable with SLTs. The weighted Euclidean distance and fractional distance classification techniques are investigated. The two are then combined to create a novel weighted fractional distance classification.

Individually optimized re-sampling space normalization of the feature vector is also investigated to further improve the overall accuracy of the system. The feature extraction techniques from Nguyen et. al. [5] are used, namely, the Direction, Modified Direction, Energy, Ratio and Maxima features. These features were re-sampled to a set static size so that all feature vectors were of equal length. Vivaracho-Pascual et. al. [9] tested several different re-sampled sizes for a different online feature extraction, but settled on a single re-sampled size for all signatures. However, they suggest optimization of the re-sampled size for each user as an interesting study. This paper aims to investigate the effect of individually optimized re-sampling on the modified direction feature from [5]. Results achieved are compared to those obtained with a supervised classification technique using the same feature extraction techniques .

Feature extraction and classification techniques are described in section 2. Results obtained are discussed in section 3 and the conclusion is given in section 4.

2. METHODS AND TECHNIQUES

Verification of signatures is a multi-step process.Firstly, preprocessing is performed to clean the original image and remove noise and other unwanted data and prepare the next step. The next step is feature extraction, which entails extracting essential information. The third step is training, where feature vectors from known authentic and forged signatures are compared for the calibration of the classification technique. The fourth step, classification, is where the system must accurately and independently determine whether signatures are authentic or forged.

In our context, preprocessing requires binarization, finding the bounding box and thinning of the signature image. The Zhang-Suen thinning algorithm [10] is used.

Features used in this paper are the one used in [5], namely, direction, modified direction, energy, ratio and maxima features.

In the training and classification phases, dynamic re-sampling to normalize the feature vector [11], Euclidean distance, weighted Euclidean distance [8], fractional distances [9], and weighted fractional distances are tested.

Feature extraction techniques used are described in section 2.1, and classification techniques are described in section 2.2.

2.1. Feature Extraction

2.1.1. Direction Feature

The direction feature extraction technique extracts the direction of each segment between intersections within a signature, i.e. whether the segment is horizontal, vertical, diagonal left or diagonal right. It yields 9 biometric features, namely, the total length of each line direction set (4 features), the number of lines in each direction set (4 features) and the total number of intersection points (1 feature). Detailed information on direction feature can be found in [11].

2.1.2. Modified Direction Feature

The modified direction feature extraction technique [11, 12] is the result of a combination of the direction feature [13] and the transition feature. It has been used as part of optical character recognition systems. A series of steps are required:

Firstly, the direction feature extraction is performed so as to label each line segment with a direction.

Then, the image is parsed in four directions, namely, right to left, left to right, top to bottom and bottom to top. In each direction, the location transition (LT) and direction transition (DT) features are recorded. LT is the location of the transition of pixels from background to foreground and DT is the direction of the line segment at the point of transition. For the sake of uniformity, limits are placed to the maximum number of transitions, $max\_transitions$, recorded in any given direction. This provided 8 arrays of features with sizes $max\_transitions \times (image\_height$ or $image\_width)$.

Finally, window re-sampling is performed. This means that the height and width values of each array are re-sampled for normalization, or averaging, so that feature vectors for all signatures of an individual are uniform in size. Different numbers of re-sampling strips (rs_strips) are tested.

To formalize the window re-sampling, let m be the number of $maximum_transitions$ and p be the number pf pixels in height or width where each pixel now stores the LT or DT value for the low or column, so that the transitioned image will be $I_T(p, m)$. Let s be the number of pixels in one strip, as calculated in Equation (1). Let r be the number of rs_strips and v be the value of an element in a calculated rs_strip.

$$s = p/r \tag{1}$$

Then the resulting set of rs_strip values is

$$
\begin{aligned}
v_1 &= (x_1^1, x_1^2, \ldots, x_1^r) \\
v_2 &= (x_2^1, x_2^2, \ldots, x_2^r) \\
&\vdots \\
v_m &= (x_m^1, x_m^2, \ldots, x_m^r)
\end{aligned} \tag{2}
$$

Let v_j^i be a single calculated component where $1 \leq i \leq r$ and $1 \leq j \leq m$. Then the value v_j^i is calculated as

$$
v_j^i = \frac{1}{s} \sum_{k=n \times s}^{k<(n \times (s+1))-1} I(k,j) \tag{3}
$$

This provides 8 feature vectors (4 $\times$ LT + 4 $\times$ DT) with sizes $max\_transitions$ x rs_strips (of height or width). Direction features are added to this feature vector. For example, if a maximum of 4 transitions are used, along with resampling of 5, the feature vector will have 169 components.

More detailed information on the modified direction feature can be read in [11].

2.1.3. *Other Feature Extractions*

The Energy, Ratio and Maxima feature extractions were used as described by Nguyen et. al. [5].

2.2. Classification

2.2.1. *Euclidean distance and thresholds*

One of the most common distance-based classification techniques for determining the accuracy of biometric systems is the calculation of the Euclidean distance between a reference vector (derived as a mean of several authentic signatures of an individual) and other feature vectors.

Authentic signatures are expected to have Euclidean distance values below a certain threshold while forged signatures would have values above that threshold. Authentic signatures with distances above the threshold are regarded as false negatives and contribute to the False Rejection Rate (FRR) while forged signatures with distances below the threshold are regarded as false positives and contribute to the False Acceptance Rate (FAR). This is further split into the FAR for skilled forgeries (FARS) and for random forgeries (FARR). The threshold is chosen where the distance for the FRR and FARS are equal. This rate is also called the Equal Error Rate (ERR).

The equation for determining the Euclidean distance between vectors x and y is computed as defined in Equation (4).

$$
||x - y||_p = (\Sigma|(x-y)|^p)^{1/p} \tag{4}
$$

where $p = 2$

2.2.2. *Weighted Euclidean distance*

The weighted Euclidean distance measure is a technique adapted from [8] to improve the classification accuracy by adding weight, or statistical importance, to the most reliable features from the feature vector. Firstly, the standard deviation for the reference signatures is obtained.

Let the n reference signatures be

$$
\begin{aligned}
x_1 &= (x_1^1, x_1^2, \ldots, x_1^m) \\
x_2 &= (x_2^1, x_2^2, \ldots, x_2^m) \\
&\vdots \\
x_n &= (x_n^1, x_n^2, \ldots, x_n^m)
\end{aligned} \tag{5}
$$

Let x_i^j be the j^{th} component of the i^{th} reference signature where $1 \leq i \leq n$ and $1 \leq j \leq m$.

Then the mean of the j^{th} component the reference signatures, μ^j, is computed as in Equation (6)

$$
\mu^j = \frac{1}{n} \sum_{i=0}^{i<n} x_i^j \tag{6}
$$

and their standard deviation σ^j is defined in Equation (7) as

$$
\sigma^j = \sqrt{\frac{1}{n} \sum_{i=0}^{i<n} (x_i^j - \mu^j)^2} \tag{7}
$$

The weighted Euclidean distance can then be calculated using the standard deviation as

$$
||x - y||_p = \left(\sum_{j=0}^{j<m} \frac{|(x^j - y^j)|^p}{\sigma^j} \right)^{1/p} \tag{8}
$$

where $p = 2$.

2.2.3. *Fractional distances*

A drawback of using Euclidean and other p-norm distances where $p \in \mathbb{N}_1$ is that as the vectors get larger, the distance values tend to cluster. This is called the concentration phenomenon. To overcome this limitation of distance-based classification, Vivaracho-Pascual et. al. [9] introduced the use of fractional p-norm distances.

The equation for determining fractional p-norm distance between vectors x and y is computed as defined in equation (9)

$$
min(||x - y||_p) = (\Sigma|(x-y)|^p)^{1/p} \tag{9}
$$

where $0.1 \leq p \leq 2.0$.

The optimal value of p is when the distance calculated using Equation (9) is at its minimum for all values of p within the given range.

2.2.4. *Weighted fractional distances*

The fractional distances and weighted Euclidean distance can then be combined to form the weighted fractional distance as defined in equation (10)

$$min(||x-y||_p) = \left(\sum_{j=0}^{j<m} \frac{|(x^j - y^j)|^p}{\sigma^j} \right)^{1/p} \qquad (10)$$

where $0.1 \leq p \leq 2.0$

Just like with Equation (9), the optimal value of p is when the distance calculated using Equation (10) is at its minimum for all values of p within the given range.

2.2.5. *Individually optimized re-sampling*

Re-sampling of the feature vector allows it to be re-sized. This is a form of spatial normalization. Different re-sampling sizes results in changing accuracies. By choosing the best re-sampling size per user, it is expected that the overall accuracy of the system may be optimized.

The re-sampling method is described in Section 2.1.2. Different rs_strips sizes were used to change the size of the feature vector. The smallest possible was an rs_strip size of 2. Tests with incrementally large sizes were used, until size 8. By this point, the re-sampling was having little positive impact on the accuracy and the last feature vector size was negatively affecting processing time. It was decided to keep the maximum rs_strip size of 8.

3. RESULTS AND DISCUSSION

3.1. Data Set

Experiments were performed using signatures from the Grupo de Procesado Digital de Senales (GPDS) signature database [14]. The database consists of black and white signatures of 300 different individuals, with 24 authentic copies and 30 skilled forgeries for each individual.

10 authentic signatures are used to create the reference signature, the other 14 authentic signatures and the 30 skilled forgeries are used for the classification and verification. For random forgeries per individual, a single authentic signature from each of the other 299 individuals is used.

3.2. Results

Quantification of result accuracy is measured in terms of the False Rejection Rate (FRR); False Acceptance Rate (FAR) which is further broken down into FAR for skilled forgeries (FARS) and FAR for random forgeries (FARR); and the Equal Error Rate (ERR), which is the point at which the FRR and FARS converge. Fig. 1 shows an example of the ROC curve for obtaining the EER.

Table 1. The effect of different re-sampling sizes using the Euclidean distance

rs_strips	**vector size**	**FRR /%**	**FARS /%**	**FARR /%**
2	49	20.11	20.11	0.7268
3	89	19.23	19.23	0.4436
4	145	19.41	19.41	0.3667
5	217	19.73	19.73	0.3633
6	305	20.17	20.17	0.3567
7	409	20.16	20.16	0.4391
8	527	20.35	20.35	0.4882
min(2:8)	mixed	15.32	15.32	0.5417

Table 2. The effect of different re-sampling sizes using the weighted Euclidean distance

rs_strips	**vector size**	**FRR /%**	**FARS /%**	**FARR /%**
2	49	15.19	15.19	0.2429
3	89	15.31	15.31	0.1973
4	145	16.14	16.14	0.3567
5	217	18.03	18.03	0.7101
6	305	20.15	20.15	1.8138
7	409	20.82	20.82	3.367
8	527	21.97	21.97	5.680
min(2:8)	mixed	11.72	11.72	0.7056

Table 3. The effect of different re-sampling sizes using fractional distances

rs_strips	**vector size**	**FRR /%**	**FARS /%**	**FARR /%**
2	49	15.99	15.99	0.5986
3	89	16.52	16.52	0.4525
4	145	17.07	17.07	0.4213
5	217	17.29	17.29	0.3767
6	305	17.39	17.39	0.4035
7	409	17.54	17.54	0.5217
8	527	17.61	17.61	0.6788
min(2:8)	mixed	12.85	12.85	0.5718

Table 1 shows the results of tests using different re-sampling sizes, without the weighting function in the Euclidean distance calculations. The resampling sizes are deter-

Table 4. The effect of different re-sampling sizes using weighted fractional distances

rs_strips	**vector size**	**FRR /%**	**FARS /%**	**FARR /%**
2	49	13.82	13.82	0.2541
3	89	14.31	14.31	0.2352
4	145	14.81	14.81	0.2942
5	217	15.71	15.71	0.5295
6	305	16.35	16.35	0.9821
7	409	16.52	16.52	1.512
8	527	17.09	17.09	2.457
min(2:8)	mixed	10.76	10.76	0.6655

mined by the rs_strip size in the MDF extraction technique. Sizes between 2 and 8 are tested. In the final row, results for individually optimized dynamic re-sampling are shown, i.e. for each individual, the best re-sampling between 2 and 8, is chosen. The worst EER was 20.35% for re-sampling size 8, while the best EER of 15.32% was for the dynamic re-sampling. Using dynamic re-sampling improves the EER over static re-sampling by up to over 5%.

This experiment is repeated using the weighted Euclidean distance, the fractional distance and weighted fractional distance functions. These results are shown in Tables 2, 3 and 4 respectively. In each case, the individually optimized re-sampling improved the accuracy of the classification.

An analysis of the static re-sampling results shows that the weighted Euclidean distance provides a great improvement over the traditional Euclidean distance when feature vectors are small in size, but it begins to have an adverse effect when the feature vectors become too large. By combining the weighted Euclidean distance with individually optimized resampling, the EER becomes 11.72%. This is better than the 15.32% from the combination of unweighted Euclidean distance with optimized re-sampling.

The unweighted fractional distances have slightly worse results compared to weighted Euclidean distance for smaller re-sampling sizes, but still better than the unweighted Euclidean distance. With larger re-sampling sizes, when the feature vectors become larger, the effect of fractional distances becomes more pronounced and provides better results than both weighted and unweighted Euclidean distances. By combining this with individually optimized re-sampling, the EER obtained is 12.85%. This is better in comparison to unweighted Euclidean distance, but worst in comparison to weighted Euclidean distance.

The final analysis was of the weighted fractional distances, which combines the weighted Euclidean distance and fractional distance measures. This provides the best accuracy for all static re-sampling sizes. By combining these weighted fractional distances with individually optimized re-sampling, an EER of 10.76% was obtained. This is better than all of the previous combinations.

In all cases, the dynamic re-sampling combination provides a much higher accuracy than any individual static re-sampling size. Thus, the greatest accuracy was achieved by a combination of weighted distances, fractional distances and dynamic re-sampling with an EER of 10.76%. This is more accurate by almost 10% in comparison to any non-optimized resampling with a standard Euclidean distance measure.

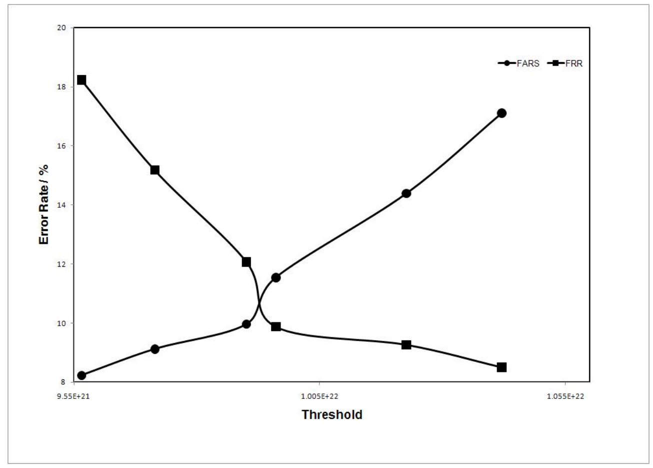

Fig. 1. Calculation of EER on applying the weighted fractional distances with individually optimized resampling

3.3. Literature Comparison

The work of Nguyen et. al. [5], [15] was chosen for the comparison in this paper. Their work is well documented and experimentally sound. They performed many different configurations to find the optimal supervised learning technique (SLT) classification technique for the chosen feature vectors. Tests were performed with multilayer perceptrons with both radial basis function (RBF) and back propagation kernels; support vector machines (SVM) with linear, polynomial and RBF kernels; and different configurations of authentic and forged signatures for the training and testing phase. Thier best results were found in [5], where an SVM with an RBF kernel were used to obtain an EER of 17.25% and FARR of 0.08%. In this work, we obtained a best EER of 10.76% with an FARR of 0.67% using locally optimized distance-based classification techniques instead. The obtained EER is better than the best results in the literature by 6.5%. While both systems obtained an FARR of below 1%, the better FARR by Nguyen et. al. can be attributed to their training of the SVM using random forgeries which was not done in our system.

While further tests need to be performed, especially with regards to the training set used, and different feature extractions from literature, the results are promising.

4. CONCLUSION

Using the Modified Direction, Energy, Ratio and Maxima feature extraction techniques; and a combination of weighted fractional distance and individually optimized re-sampling classification techniques, an improved Equal Error Rate (EER) of 10.76% is obtained against skilled forgeries. This is compared to literature results where supervised learning techniques were applied to the same feature extraction techniques, which obtained an EER of 17.8%.

The weighted fractional distances technique works better as a whole than either of its individual constituent parts, namely, the weighted Euclidean distance and fraction distances. Individually optimizing the re-sampling of feature vectors also allows for improvement of overall accuracy.

It can be concluded that in some instances of signature verification, a combination of distance-based classification techniques can to be more accurate than supervised learning techniques.

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