Local Directional Pattern Based Signature Verification using Weighted Fractional Distance Classification

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ABSTRACT

Although handwritten signature verification has been extensively researched, it has not achieved optimum accuracy rate yet. Therefore, efficient and accurate signature verification techniques are required since signatures are still widely used as a means of personal verification. This paper presents an alternative efficient classification technique to supervised learning classification techniques. The signature features are extracted using the Local Directional Pattern algorithm, and classified using a combination of multiple distance-based techniques: *weighted Euclidean distance*, *fractional distance* and *weighted fractional distance*. This combination of multiple distance-based classification techniques achieved accuracy rate of 87.8%, which is comparable to a similar system that used Support Vector Machines, a supervised learning technique. Therefore, competitive levels of accuracy can be obtained using distance-based classification.

Categories and Subject Descriptors

I.5.3 [**Pattern Recognition**]: Clustering—*Similarity measures*; I.4.7 [**Image Processing**]: Feature Measurement—*Feature representation*

General Terms

Pattern Recognition; Biometrics

Keywords

Handwritten Signatures; 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 [6].

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 [6].

Signatures, which are one of the oldest used and most widely accepted biometric for identification and verification [13], are handwritten depictions of a person's name, nickname or other personal symbol. They are 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 factor 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.

Many techniques exist for the classification of signatures and other biometrics. They can be broadly categorized into supervised learning techniques (SLTs) and distance-based classification techniques. SLTs include neural networks [4], hidden Markov models [1], support vector machines [11] and fuzzy logic [8]. Linear techniques include Euclidean distance, Mahalanobis [9], Manhattan distance, weighted Euclidean distances [10] and fractional distances [12].

SLTs, in general, provide a greater accuracy than basic distance-based classification 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. This paper aims to investigate this novel classification technique. The results are compared to those of a SLT that classified signatures using the same feature extraction techniques.

The feature extraction and classification techniques are described in section 2. The results obtained are discussed in section 3 and the conclusion is given in section 4.

2. TECHNIQUES AND METHODOLOGY

The first step in image processing based signature verification is to capture the signature image. The likelihood of this image containing noise is high. The next important step is then to preprocess this image, in order to remove noise and unwanted data, while preserving essential information for the final decision. Features are thereafter extracted and represented in a certain way; in this article, they are represented as vectors. A training is the carried out, where feature vectors from known authentic and forged signatures are compared for the calibration of the classification technique. The last step, classification, is where the system must accurately and independently determine whether signatures are authentic or forged.

Preprocessing includes smoothing, binarization, dilation and finding the bounding box of the signature image.

For feature extraction, Local Directional Pattern (LDP) is used. LDP is a gray-scale texture based feature method that characterizes the spatial structure; it was first introduced by Jabid *et al*[5], and used to classify gender; Kabir *et al*[7] later used one of its variant for facial expression recognition. More recently Ferrer et. al [3] performed signature verification with LDP.

In this paper we evaluate Local Directional Pattern performance in signature verification when combining multiple similarity measures, namely Euclidean distance, weighted Euclidean distance [10], fractional distances [12], and weighted fractional distances.

The feature extraction techniques used are described in section 2.1, and the classification techniques are described in section 2.2.

2.1 Feature Extraction

Feature extraction is performed using Local Directional Pattern[5]. This technique utilizes the 8 orientations of Kirsch masks, as shown in Figure 1, to detect the presence of edges or corners and their orientations. Values of the 8 mask orientations, m_0, m_1, ... , m_7, are obtained by performing a convolution of Kirsch masks with the image at each pixel, followed by a binarization. In other words, given the source image I_{src}, we will compute I_{LDP}, which is a transformed image using Algorithm 1.

In Figure 2, an example of Local Directional Pattern transformation of a source image $I_{src}(x, y)$ into a new image $I_{LDP}(x, y)$ is shown.

A histogram, H_{LDP}, can then be created from the image $I_{LDP}(x, y)$. However, since each 8-bit pixel has exactly three bits with the value 1 and 5 bits with the value 0, this allows for only 56 possibly permutations out of the usual 256. Therefore, the histogram will only account for these 56 possible values.

$$\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \quad \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

East M_0 North East M_1 North M_2 North West M_3

$$\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$$

West M_4 South West M_5 South M_6 South East M_7

Figure 1: The 8 orientations of Kirsch Masks

Further, it is possible to divide the image $I_{LDP}(x, y)$ into blocks by splitting it a specified number of parts vertically ($split_V$) and horizontally ($split_H$) and have a 56-value histogram for each block. The final feature vector, FV_{LDP}, is then obtained by concatenating all of these histograms, $FV = H^1_{LDP} + H^2_{LDP} + ... + H^{split_V \times split_H}_{LDP}$.

Algorithm 1 Local Directional Pattern, I_{LDP}, calculation of an image, I_{src}

Require: I_{src}, ▷ Source Image
Ensure: I_{LDP}, ▷ Image Transformed using Local Directional Pattern

for each pixel (x,y) **do**
  for i=0 to 7 **do**
    for k= - 1 to 1 **do**
      for l = -1 to 1 **do**
        $m_i = m_i + M_i(k+1, l+1) \times I_{src}(x+k, y+l)$
      end for
    end for
    Transform the three highest values m_i into 1s and the rest into 0s
  end for
  $powerof2 = 1$
  $I_{LDP}(x, y) = 0$
  for i = 0 **do** 7
    $I_{LDP}(x, y) = I_{LDP}(x, y) + m_i \times powerof2$
    $powerof2 = 2 \times powerof2$
  end for
end for

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).

The equation for determining the Euclidean distance between vectors $x = (x^i)_{i=1,2,...,m}$ and $y = (y^i)_{i=1,2,...,m}$

85	32	26
53	50	10
60	38	45

Mask index	m_7	m_6	m_5	m_4	m_3	m_2	m_1	m_0
Mask value	-303	97	161	537	313	97	503	-399
Rank	5	7	6	1	4	8	2	3
Code bit	0	0	0	1	0	0	1	1
LDP code	19							

Figure 2: Calcualtion of the LDP code [3]

is computed as defined in equation (1).

$$||x - y||_p = (\Sigma_{i=1}^{m} |(x^i - y^i)|^p)^{1/p} \tag{1}$$

where $p = 2$.

2.2.2 *Weighted Euclidean distance*

The weighted Euclidean distance measure is a technique adapted from [10] to improve the classification accuracy by adding weight. In our case we add weight that has statistical importance, related to the most reliable features from the feature vector.

Given a set of of signatures $S = \{sig_1, sig_2, \ldots, sig_n\}$, represented by their feature vectors spaces as

$$sig_j = (sig_j^1, sig_j^2, \ldots, sig_j^m)$$

where $j = 1, 2, \ldots n$, and sig_i^j is the i^{th} component of the j^{th} signature, with $i = 1, 2, \ldots m$.

We will compute the standard deviation of each component of reference signatures as follows:

The mean μ^i is computed as

$$\mu^i = \frac{1}{n} \sum_{l=1}^{n} sig_l^i \tag{2}$$

and the standard deviation σ^i is defined as

$$\sigma^i = \sqrt{\frac{1}{n} \sum_{l=1}^{n} (sig_j^l - \mu^j)^2} \tag{3}$$

The weighted Euclidean distance between two signature $x = (x^i)_{i=1,2,\ldots,m}$ and $y = (y^i)_{i=1,2,\ldots,m}$ can then be calculated using the standard deviation as shown in Equation 4

$$||x - y||_p = \left(\sum_{j=1}^{m} \frac{|(x^j - y^j)|^p}{\sigma^j} \right)^{1/p} \tag{4}$$

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[2]. This is called the concentration phenomenon. To overcome this limitation of distance-based distance classification, Vivaracho-Pascual et. al. [12] 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 (1) where $0.1 \leq p \leq 2.0$.

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 (4) where $0.1 \leq p \leq 2.0$. The optimal value of p is calculated experimentally for each user.

3. RESULTS AND DISCUSSION

3.1 Data Set

The Grupo de Procesado Digital de Senales (GPDS) signature database is used in the analysis of the techniques. The database consists of authentic and forged signature sets for 300 different individuals. There are 24 authentic signatures and 30 skilled forgeries per each individual. All signatures are stored in black and white.

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 testing random forgeries with each individual, a single authentic signature from each of the other 299 individuals is used.

3.2 Thresholding

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 are equal.

The reference feature vector is created by calculating the mean of each feature in the feature vectors of 10 authentic signatures. The distance between the reference feature vector and each of the remaining 14 authentic signatures is determined using one of the Euclidean, fractional, weighted Euclidean or weighted fractional distance equations. A threshold distance value is determined. All distances below the threshold are regarded as authentic, while all distances about are regarded as forgeries. The FRR is calculated from this. Likewise, the FARS and FARR are obtained from the distance calculated between the reference feature vector and the skilled and random forged signatures respectively.

The optimal threshold distance value is determined locally for each individual as the value that produces the EER. This is the threshold where the FRR and FARS are equal. In Fig. 3, this is represented as the convergence point of the FRR and FARS on the ROC curve. The FARR is then determined using this threshold value.

3.3 Results

Tests are performed using the distance-based classification techniques. These techniques are the Euclidean, fractional, weighted Euclidean and weighted fractional distances. For each classification technique, multiple vertical ($split_V$) and horizontal ($split_H$) split sizes are tested. The number of splits are in the range of 1, i.e. no splits, to 8, providing a total of 49 different combinations of splits which were applied globally to all individuals. This is done to find the best possible global feature vector size per classification technique and investigate the effect of the weighted distances and fractional distances on the concentration phenomenon. The feature vector size is determined by $split_H \times split_V \times H$ where H is the length of the histogram, which is always 56 in the LDP extraction technique. For the best classification technique with the

Table 1: The effect of different $split_H$ and $split_V$ on EER(%) using the Euclidean distance

H \ V	1	2	3	4	5	6	7
1	25.0	23.9	22.6	23.0	22.6	22.8	23.0
2	23.8	22.3	**21.7**	22.0	22.0	22.3	22.4
3	24.0	22.7	21.9	21.9	22.2	22.3	22.6
4	24.1	23.0	22.5	22.5	22.8	23.0	23.1
5	24.3	23.7	23.1	23.2	23.5	23.6	23.9
6	24.8	24.0	23.4	23.7	24.0	24.2	24.5
7	25.2	24.4	24.2	24.1	24.5	25.0	25.3

Table 2: The effect of different $split_H$ and $split_V$ on EER(%) using fractional distances

H \ V	1	2	3	4	5	6	7
1	18.9	17.7	17.0	16.9	16.7	16.6	16.6
2	18.0	16.8	16.2	16.1	16.1	15.9	16.0
3	17.5	16.5	15.6	15.7	15.4	15.2	15.2
4	17.5	16.2	15.9	15.6	15.4	15.3	15.3
5	17.5	16.3	15.3	15.4	15.3	15.2	15.0
6	17.7	16.1	15.7	15.4	15.2	15.0	14.9
7	17.4	16.2	15.4	15.3	15.0	14.8	**14.7**

Table 3: The effect of different $split_H$ and $split_V$ on EER(%) using the weighted Euclidean distance

H \ V	1	2	3	4	5	6	7
1	18.6	17.9	16.8	16.5	16.1	16.0	16.0
2	18.4	16.5	15.8	15.7	15.4	15.3	15.2
3	17.3	16.0	15.5	15.3	14.6	14.8	14.6
4	17.4	15.7	15.2	15.1	**14.5**	14.8	14.8
5	17.3	15.6	14.7	14.8	14.6	14.6	14.7
6	17.0	15.7	14.8	15.0	14.7	14.8	14.7
7	16.9	15.5	14.8	14.9	15.0	14.7	15.0

Table 4: The effect of different $split_H$ and $split_V$ on EER(%)using weighted fractional distances

H \ V	1	2	3	4	5	6	7
1	16.8	16.1	15.1	14.8	14.5	14.4	14.2
2	16.7	14.1	14.2	14.0	13.7	13.4	13.3
3	15.7	14.3	13.6	13.2	12.7	12.6	12.5
4	15.8	14.0	13.3	13.0	12.5	12.7	12.4
5	15.3	14.1	12.8	12.7	12.5	12.3	12.3
6	15.1	13.9	12.9	12.7	12.6	12.5	12.3
7	15.0	13.8	12.9	12.7	12.5	12.3	**12.2**

Table 5: The effect of different $split_H$ and $split_V$ on FARR(%)using weighted fractional distances

H \ V	1	2	3	4	5	6	7
1	1.08	0.70	0.47	0.43	0.52	0.57	0.57
2	0.65	0.48	0.54	0.84	0.81	0.93	1.22
3	0.54	0.42	0.66	0.75	0.75	0.81	1.09
4	0.56	0.53	0.23	0.91	1.00	1.11	1.14
5	0.63	0.79	1.00	1.02	1.20	1.28	1.28
6	0.68	0.76	1.16	1.08	1.34	1.36	1.45
7	0.68	0.88	1.18	1.36	1.44	1.63	1.64

lowest EER, the FARR is also shown.

The first analysis is performed with the Euclidean distance and the results are shown in Table 1. The worst EER when using the Euclidean distance was found to occur with the largest feature vector size, i.e. 7 vertical $\times$ 7 horizontal splits. This EER was 25.3%. Conversely, the best EER occured with one of the smallest feature vector sizes, i.e. 3×2 splits. This EER was 21.66%. The accuracy trend with standard Euclidean distance measuring was that the EER was poor for the smallest feature vectors, it then improved as the feature vectors became larger and more detailed, but then worsened once the feature vectors became too large. This reduction in accuracy confirms that the concentration phenomenon occurs with large feature vectors because the Euclidean distance causes the distance values to cluster. The weighted Euclidean distance and fractional distance discussed below are used to counter this phenomenon.

The second analysis is performed with the fractional distance and the results are shown in Table 2. The classification technique produced a higher accuracy in comparison with the Euclidean distance. The worst EER occurred with the smallest feature vector, i.e. 18.9% with 1×1 splits. This worst EER is still better than the best EER of the Euclidean distance, which was 21.7%. As the feature vectors increase in size, the accuracy of this classification technique gradually improves. The best EER was achieved with the largest feature vector, i.e. 14.7% with 7×7 splits. This shows that the fractional distances overcome the concentration phenomenon that adversely affects larger feature vectors when the Euclidean distance is applied. The best EER of the fractional distance is better than the best Euclidean distance EER by almost 7%. Larger feature vectors were tested, but have been excluded due to subsequent decreasing accuracies and lack of space.

The third analysis is performed with the weighted Euclidean distance and the results are shown in Table 3. This classification technique also produced a higher accuracy in comparison to the Euclidean distance and while also producing a slightly higher accuracy than the fractional distance. Once again, the worst EER occurred with the smallest feature vector, i.e. 18.6% with 1×1 splits. The best EER occurred among one of the largest feature vectors, i.e. 14.5% with 5×4 splits. This is better than both the Euclidean and fractional distances. While the weighted Euclidean distance does not counter the concentration phenomenon completely, it is effective enough to produce a good accuracy.

The fourth and final analysis is performed with the weighted fractional distance, which is a combination of the weighted and fractional distance techniques. The results are shown in Table 4. This combined technique

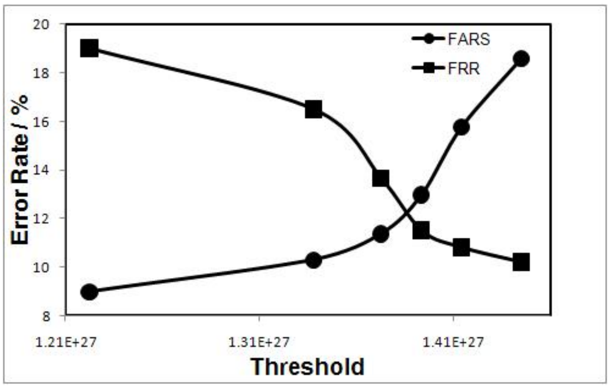

Figure 3: Calculation of EER on applying the weighted fractional distances with 7x7 splitting

provides the best accuracy from all four of the compared techniques.Just like with the fractional and weighted Euclidean distances, the worst EER occurred with the smallest feature vector, i.e. 16.8% with 1×1 splits. Just like with the fractional distance, the best EER was obtained with the largest feature vector, i.e. 12.2% with 7×7 splits. This EER is the best from all the compared techniques. It provides a 9.5% increase in accuracy in comparison with the best Euclidean distance EER. The FARR values for the weighted fractional distance are shown in Table 5. Conversely, it can be seen that increased feature vector sizes cause the undesired effect of an increase in the FARR.

The greatest accuracy was achieved by a combination of weighted and fractional distances with an EER of 12.2%. This is more accurate by almost 10% in comparison to the best standard Euclidean distance measure.

3.4 Literature Comparison

The results in this paper are compared to those of Ferrer et. al. [3], who used the same feature extraction technique, the Local Directional Pattern; and the same signature database, GPDS300. However, they used a different classification technique, namely, Support Vector Machines (SVM) with a Radial Basis Function (RBF) kernel. By using these techniques, they obtained an EER of 17.8% and FARR of 0.68%. In comparison, we obtained a best EER of 12.2% with an FARR of 1.64% by using weighted fractional distance classification instead.

While both systems obtained an FARR of below 2%, the better FARR was obtained by Ferrer et. al. This can be attributed to the use of random forgeries in the training of their classifier, which was not performed 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

An alternative efficient handwritten signature classification technique has been presented. The proposed technique uses a combination of multiple distance-based classification techniques: *weighted Euclidean distance*, *fractional distance* and *weighted fractional distance*, to verify the Local Directional Pattern-based signature features. Experimental results show that the proposed approach obtains an Equal Error Rate (EER) of 12.2% on skilled forgeries. This is comparable to literature results where supervised learning techniques were applied to the same feature extraction techniques, which obtained an EER of 17.8%. Therefore, a combination of multiple distance-based classification techniques is an alternative signature classification technique with an accuracy rate of 87.8%.

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