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# Offline Signature Verification based on Centerline Similarities

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**Digital signatures are becoming increasingly common in author identification. However, handwritten signatures play an important role in different aspects of life like business and the banking sector. Offline signature verification methods analyze the images and shapes of the signatures. Several methods use skeleton that is a frequently used shape descriptor that summarizes the general form of objects.**

**Here, we present an offline signature verification method which is based on similarity measures designed for a comparison of 2D skeleton-like shape features. The proposed method was evaluated on the publicly available SigComp2011 and SigWiComp2013 databases. The results that we obtained are competitive with the systems submitted to two recent signature verification competitions.**

## Introduction

With the spread of digital documents, the digital signature plays an important role in verifying the origin of the documents. However, the handwritten signature as a biometric identifier still cannot be replaced by a digital signature. This is especially true in the case of business, financial, and official documents, where the handwritten signature is mostly accepted.

Forensic handwriting analysis experts investigate many features in a given sample like slant, loops, letter connections, directions and flow of writing movement, where the author raised the pen, and where he stopped during the writing process (Morris and Morris, 2000; Kelly and Lindblom, 2006). There are some applications for analyzing handwritten samples that take into account the features preferred by the handwriting analysis experts (Atanasiu, 2011; Atanasiu et al., 2011). Several methods exist for verifying (Dehgan et al., 1997; Chen and Srihari, 2005; Impedovo et al., 2008; Justino et al., 2005; Lee, 1999; Napoles and Zanchettin, 2012; Plamondon and Srihari, 2000; Kalera et al., 2004; Huang et al., 2002), identify (Kisku et al., 2010; Kalera et al., 2004; Plamondon and Srihari, 2000; Pourshahabi et al., 2009; Lee, 1999), and recognizing (Mandal et al., 2011; Ismail et al., 2000; Frias-Martinez et al., 2006; Lee, 1999) signatures. In spite of the computer aided decision systems the opinion of forensic handwriting analyzer experts are essential in disputed cases.

The aim of the above-mentioned applications is to support the verification of the customer signatures. These algorithms extract some shape features from the original image of the signature, then they apply graph matching or shape descriptors for comparison. The frequently used classification methods are based on the Dynamic Time Warping (DTW) (Shanker et al. 2007, Chen and Srihari 2005, Impedovo et al. 2008), Neural Networks (NN), Hidden Markov Models (HMM), and Support Vector Machine (SVM) (Justino et al. 2005).

There are two kinds of handwriting and signature analysis, namely offline and online. Offline methods investigate the images of the signatures, while online ones analyze the dynamics of the handwriting. Furthermore, online and offline information may be combined and investigated together (Abbas and Chibani 2011).

Skeleton is a shape descriptor that summarizes the general form of objects. 2D thinning algorithms are capable of extracting some skeleton-like shape features (i.e. topological kernels and centerlines) from binary images (Siddiqi and Pizer 2008). Most of the offline signature analysis approaches extract the centerlines from the binarized signature images for a morphological and topological analysis. Two signatures from the same author vary from each other and some strokes may cross the signatures once, while in some other samples these strokes may go under the signature and look like underlines. This also depends on the writer and writing environment; and, moreover, it is influenced by the speed of the writing and tiredness (Impedovo et al., 2012; Plamondon, 2005; Plamondon and Djioua, 2006). Hence a topological analysis may lead to the rejection of genuine signatures as well. Impedovo et al. investigated some stable segments that were quite similar in all reference signatures and applied them in signature verification (Pirlo and Impedovo, 2010; Impedovo et al., 2012).

Several offline signature verification methods apply skeletonization techniques well. Most of them use thinning in a pre-processing step to determine the skeleton image of the signature and extract global features (e.g. width, height, the height-to-width ratio, maximum horizontal or vertical projection, image area, the vertical or horizontal center of the signature) and grid features (pixel densities, distribution, predominant axial slant) for each cell taken from the skeleton of the signature (Rathi et al., 2012; Azzopardi and Camilleri, 2008; Baltzakis and Papamarkos 2001). In addition, Baltzakis and Papamarkos (2001) extracted texture features, that were based on the graylevel image of the signature. In contrast, Justino et al. (2000) used the skeleton of the signature image just to determine the axial slant in each grid cell.

In an evaluation of thinning algorithms, Lee, Lam, and Suen (1994) proposed two similarity measures for centerlines. As a basis of comparison the "ideal" reference skeleton was drawn for the observed object. Here, each centerline provided by thinning algorithms was compared with this reference skeleton. One of the proposed similarity measures $C^k$ has a range of [0,1].

Our verifier applies thinning as a pre-processing step (similar to that described in the abovementioned articles), but we use centerlines as the representation of the signatures and unlike the other methods used they are directly compared based on a distance metric specially developed for skeleton comparison (Lee et al., 1994).

Here we propose an offline method for signature analysis. The similarity measure $C^k$ proposed for 2D centerlines forms the basis of our signature verification method.

The rest of the paper is organized as follows: In Section 2 we describe our algorithm, then in Section 3 we present our experimental results. Lastly in Section 4, we round off this paper with some brief conclusions and remarks.

## Methods and Materials

Next, we will give a detailed description of our verification system.

Signature verification systems are composed of pre-processing, feature extraction and classification tasks. In pre-processing the signature images are segmented to determine the binary image of the signatures, and after binarization the centerlines are extracted as shape features. In the classification phase the signatures are compared pairwise and centerline similarity is applied to decide whether a questioned signature is probably a forged or a genuine one.

### *Segmentation*

The first pre-processing task of our algorithm is segmentation. We require grayscale images for segmentation, hence RGB images are converted to grayscale using just the luminance and avoiding the hue and saturation from the HSL (hue-saturation-lightness) representation of the original RGB image.

Although signature images have a quite high contrast between the background (paper) and foreground (handwriting), we cannot apply a simple global thresholding to the image. Some noise may appear in the image that needs to be suppressed. Here, we choose an averaging filter with a 5×5 window size for noise reduction.

We applied a region growing method for segmentation. Region growing is an iterative segmentation method where the initialized regions are determined as single points or point sets, and for each iteration step regions are expanded to their neighboring pixels satisfying the given homogenity criteria (Gonzalez and Woods, 2008).

Seed points of initialized regions are provided by the result of the Canny edge detector (Canny, 1986). The scale parameter of the Canny edge detector is set to 2 based on previous experiments.

For each iteration step, regions grow to the pixels of lower intensities such that new points joined to the region inherit the highest intensity of the neighboring pixels belonging to the region. This iteration step is repeated until there is no new pixel merged to any region.

Since segmentation is a labeling problem, we should mention that in this process we use just two labels. The foreground is marked by a '1' label and background by a '0' label. We allow the merging of disjoint regions as well.

Lastly, morphological filtering (Gonzalez and Woods, 2008) is applied using a diamond-shape structuring element with radius of 1.

The pseudo code of segmentation process is shown in Algorithm 1. Note that the process can be speeded up only if the pixel coordinates of the current region boundaries are considered for each iteration step.

### *Registration*

From the segmentation procedure, we get binary images of signatures. To compare the signatures, we have to transform them to the same position. Image registration computes the transformation parameters that move the observed object to the reference one. Most of the registration algorithms are iteration-based method whose computational time increases if the amount of feature points is large. We decrease the number of feature points

**Algorithm 1** Region Growing Segmentation

```
INPUT:   I   // grayscale image
OUTPUT:  B   // segmented image
B ← Canny(I)   // Canny edge detection
repeat {// iteration step}
  changed ← false
  for each pixel (x, y) do
    if B[x, y] = 1 then
      for s ∈ {−1, 1} do
        if B[x + s, y] = 0 and I[x, y] ≤ I[x + s, y] then
          B[x + s, y] ← 1
          I[x + s, y] ← I[x, y]
          changed ← true
        end if
        if B[x, y + s] = 0 and I[x, y] ≤ I[x, y + s] then
          B[x, y + s] ← 1
          I[x, y + s] ← I[x, y]
          changed ← true
        end if
      end for
    end if
  end for
until changed = false
return B
```

**Algorithm 2** Iterative Closest Point Registration

```
INPUT:   P        // reference point set
         Q        // observed point set
         δ(P, Q)  // error function
         ε        // acceptable error
OUTPUT:  T, R     // transformation matrices
T ← I   // the identical translation
R ← I   // the identical rotation
repeat
  for each point q ∈ Q do
    Match the closest point p ∈ P to q
  end for
  for each point p ∈ P do
    for each point q ∈ Q do
      if p is matched to q then
        Remove point matching (p, q) with non-minimal distances.
      end if
    end for
  end for
  Compute the transformation T′ and rotation R′ for the matched point pairs with minimal δ(P, Q) error.
  Q′ ← {R′ · T′ · q | q ∈ Q}   // transformation
  if δ(P, Q) > δ(P, Q′) then
    T ← T · T′
    R ← R · R′
    Q ← Q′
  else
    return T, R
  end if
until δ(P, Q) ≤ ε
return T, R
```

that represents the shape of each signature to reduce the computational time. Skeleton is a shape descriptor that summarizes the general form of objects. Thinning is a skeletonization technique in digital images that is capable of extracting both types of skeleton-like shape features (i.e., a topological kernel and centerline) (Siddiqi and Pizer, 2008; Gonzalez and Woods, 2008). Segmented signatures are represented by their centerlines and skeletal points in registration are treated as feature points.

Unfortunately, the topology and the size of two signatures written by the same author may be different, and the centerlines may consist of a different number of skeletal points. Thus, we consider these skeletal point sets as point clouds.

A widely used set of registration methods developed for point clouds is the iterative closest points (ICP) algorithms (Goshtasby, 2012; Besl and McKay, 1992). This concept is an iteration-based method that computes the rotation and translation matrices of the transformation. The general scheme of ICP algorithms is shown in Algorithm 2. As an error function, the root mean square (RMS) error was applied. Here, we used the Matlab implementation[1] of ICP.

The results of pre-processing steps are depicted in Figures 1, 2, and 3. Figures 1 and 2 show the original signature (a), segmented signatures (b), centerline of the signatures (c) and the results of the registration (d) for two writers. Figure 3 shows two examples for registration, (a) shows a registration result of two genuine signatures, while (b) shows a registered forgery and genuine signature. As can be seen, there is a certain difference between the two registered genuine signatures (Figure 3(a)) and the registered genuine signature and forgery (Figure 3(b)). The genuine signatures are quite similar, but the forged one does not match the genuine sample. Figure 4 shows two pairs of registered signatures: Figure 4(a) shows two genuine signature from the same author; Figure 4(b) shows a genuine and a forged one. The signatures are from the SigComp2011 dataset and due to the regarding restriction, the whole image cannot be included in papers, thus only a part of the image is presented here. Similarly, Figure 5 shows two pairs of registered signatures from a Japanese writer.

### *Comparison of Signatures*

Here, we decided to apply the similarity measure $C(P,Q)$ developed by Lee et al. (1994) for the quantitative comparison of skeletonization methods. In their study, the results of several thinning al-

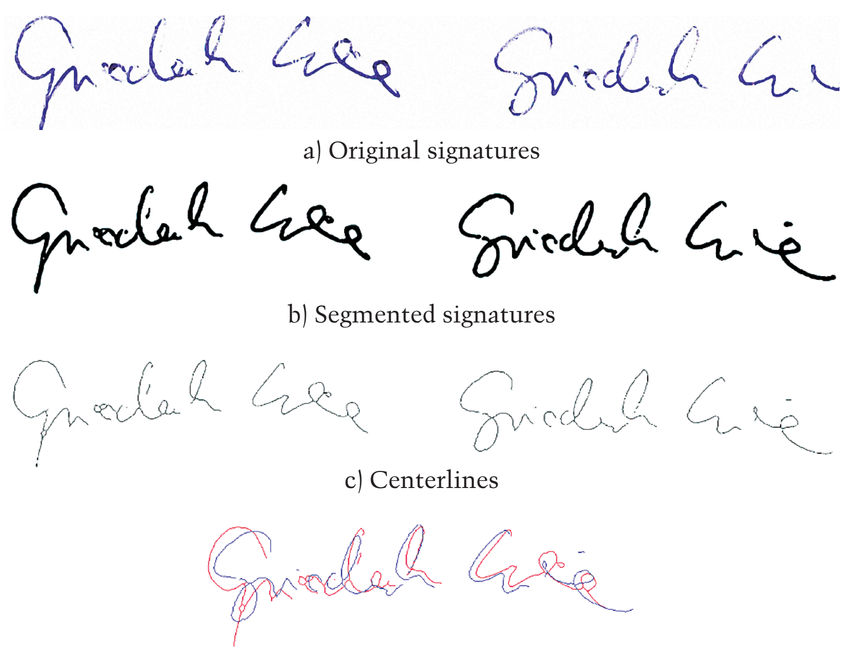


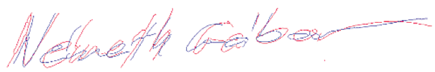

**Figure 1.** Results of preprocessing steps of genuine signatures from first author

[1]http://goo.gl/9UhrQV

a) Original genuine signatures

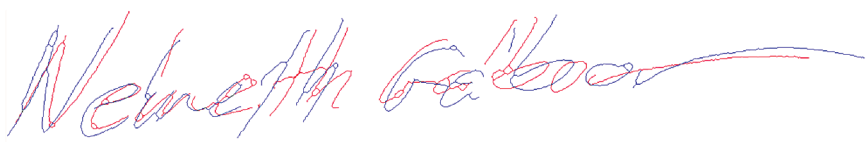
b) Segmented genuine signatures

c) Centerline of genuine

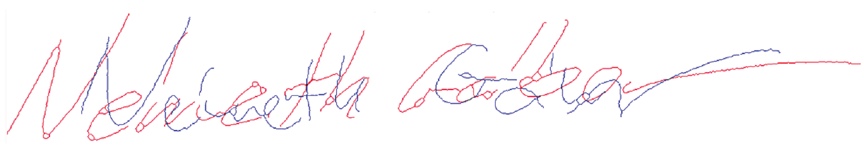


d) Registered centerlines

**Figure 2.** Results of preprocessing steps of genuine signatures from second author



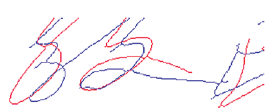
a) Genuine signatures



b) Genuine and forged signatures

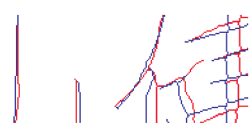
**Figure 3.** Registered signatures

a) Genuine signature parts

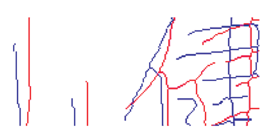


b) Genuine and forged signature parts

**Figure 4.** Part of registered Chinese signatures.



a) Registered genuine signature parts



b) Registered genuine and forged genuine signature parts

**Figure 5.** Part of registered Chinese signatures.

gorithms were compared with the reference centerlines of binary objects.

Next, we will use the $C$ measure for a comparison of the centerlines of two given signatures (denoted by $P$ and $Q$). The distance $d(p,q)$ between two distinct 2D points $p=(p_x, p_y)$ and $q=(q_x, q_y)$ is computed as follows:

$$d(p,q) = \sqrt{(p_x - q_x)^2 + (p_y - q_y)^2}$$

Furthermore, the distance between a 2D point $p$ and a point set $P$ is given by

$$\Delta(p, P) = \min_{q \in P} d(p, q)$$

The similarity measure $C(P, Q)$ between two point sets $P$ and $Q$ is defined as follows:

$$C(P, Q) = \frac{1}{2}\left(\frac{1}{\#P}\sum_{p \in P}\frac{1}{1+\Delta^2(p, Q)} + \frac{1}{\#Q}\sum_{q \in Q}\frac{1}{1+\Delta^2(q, P)}\right)$$

where $\#P$ and $\#Q$ indicate the number of elements of set $P$ and $Q$, respectively.

Here it is clear that $C(P, Q)$ takes values in the range [0,1] and a higher value means a better similarity.

### *Classification*

First, the similarity measures are calculated for the reference signatures for each writer $w$. Each reference signature is compared with every other reference signatures of the same writer; hence if writer $w$ has $n$ reference signatures, then we compute $\binom{n}{2}$ similarity values. As a reference similarity $S_{Rm}$ the minimal, maximal, or average ($m \in$ {min, max, avg}) value is taken into account.

For each writer $w$ the similarity value of a questioned signature is computed in a similar way. Each questioned signature Q is compared with each reference signature.

So if $n$ reference signatures are present, we will calculate $n$ similarity values. The $S_{Qm}$ similarity of the questioned signature $Q$ will be considered the minimal, maximal, or average ($m \in$ {min, max, avg}) value of these similarities.

Based on these statistical values, nine writer-dependent constraints are investigated. Each constraint has a form of $S_{Qm} < k \cdot S_{Rm}$, where $k$ is varied in the range [0,2] and $m \in$ {min, max, avg} denotes the minimal, maximal, and average similarity values. If the similarity of the questioned signatures is above the threshold $k \cdot S_{Rm}$, then it is rejected (i.e., treated as forgery); otherwise it is accepted (i.e., treated as genuine).

In addition, we investigate writer-independent constraints, where the constraints do not take into account the reference similarity. In this case the questioned $Q$ signature is rejected if its similarity value $S_{Qm}$ is less than $k$; otherwise it is accepted as genuine. All together for each dataset twelve constraints are examined.

## Results

Here, we present the results got from applying our approach on three public datasets.

### *Datasets*

In this study we will utilize the SigComp2011 Dutch and Chinese offline (Liwicki et al. 2011) and the SigWiComp2013 Japanese offline (Malik et al. 2013) databases. Only the testing (evaluation) datasets will be used for evaluation purposes because the algorithm does not have any predefined parameter that needs to be trained.

The Dutch evaluation dataset consisted of RGB images with 400 dpi resolution in PNG format, including 12 reference and 24 questioned signatures (12 genuine and 12-20 forged) taken from 54 authors. Altogether, the evaluation dataset consisted of 1933 handwritten signature images.

The Chinese evaluation dataset consisted of grayscale images in PNG format, including 10-12 reference and 46-48 questioned signatures (12 genuine and 34-47 forged) taken from 10 authors. Altogether, the evaluation dataset consisted of 601 handwritten signature images.

The Chinese signature dataset also contained frames around the signatures. These strokes did not belong to the signatures, so the results of further processing steps could have been distorted. These line segments can be easily detected, since they are close to the image border and slant nearly horizontally or vertically. We used the Hough transformation to determine the lines, but several line segments might be present in the picture and some of them might belong to the signature. Hence, we had to rarefy the list of detected lines. After the detection of all line segments we kept just the nearly parallel and perpendicular ones (with a ± 5 degrees tolerance level). If the majority of the object points were located on one side of the line, we kept it;

otherwise it was removed from the list. Lastly, the remaining lines were used as a mask to remove the frame.

The Japanese evaluation dataset is consisted of binary images which were generated from online signatures. The total evaluation set comprised 20 authors, 20 reference and 66-69 questioned signatures (36 genuine and 30-33 forged) per author. In total, the evaluation dataset consisted of 1566 handwritten signature images.

### *Evaluation*

In signature verification the basic goal is to accept the genuine signatures and reject the forged ones; however no system is perfect or foolproof.

In order to evaluate the verification methods, measures can be applied. The False Acceptance Rate (FAR) is the percent of the accepted forged signatures relative to the number of accepted forged and rejected forged samples (i.e., the number of forged samples).

The False Rejection Rate (FRR) is the percent of the rejected genuine signatures relative to the number of rejected genuine and accepted genuine samples (i.e., the number of genuine samples).

The FAR, FRR values are computed the following way:

$$FAR = \frac{FP}{FP + TN} = \frac{FP}{N},$$

$$FRR = \frac{FN}{FN + TP} = \frac{FN}{P}$$

where

- TP (true positive) is the number of genuine signatures recognized as genuine ones,
- FP (false positive) is the number of forged signatures recognized as genuine ones,
- FN (false negative) is the number of genuine signatures recognized as forged ones,
- TN (true negative) is the number of forged signatures recognized as forged ones,
- N (negative) is the number of forged signatures, and
- P (positive) is the number of genuine signatures.

The accuracy, FAR, and FRR values for the three evaluation datasets have been presented in Table 1.

By varying the parameter $k$ (and the threshold value), the FAR and FRR values also change (see Figures 6, 7, and 8). If FAR and FRR attain the same value, then it is referred to as the Equal Error Rate (EER).

For the Dutch dataset, the lowest false rejection and false acceptance rates were 20.83% and 20.81%, respectively, at k=0.86 with an accuracy of 79.18%. It was achieved with the constraint which takes into account the average similarity values; hence a questioned signature Q is rejected if $S_{Qavg} < k \cdot S_{Ravg}$. See the related FRR/FAR curves in Figure 6.

The lowest FRR and FAR values are 24.17% and 24.25% respectively at k=1.16 with and 75.77% accuracy for Chinese evaluation set. It was achieved with the constraint that a questioned signature was rejected if $S_{Qmax} < k \cdot S_{Ravg}$. See the related FRR / FAR curves in Figure 7.

In our experiments the 25.41% / 25.83% is the lowest FRR / FAR with an accuracy 74.36% at $k$=1.02 for the Japanese evaluation set for the same constraint as that for the Chinese, and one when the $S_{Qmax}$ is compared with the $S_{Ravg}$. See the related FRR / FAR curves in Figure 8.

Compared with the reported system for the SigComp2011 and SigWiComp2013 contests, the accuracy lies between 71.02% and 97.67% for the Dutch set, between 51.95% and 80.04% for the Chinese set, and between 66.67% and 90.72% for the Japanese set (see Tables 2, 3, and 4).

The results of our system lies in the midrange of the results for the Dutch and Japanese datasets compared to those got by the systems entered in the two competitions.

For the Chinese dataset, our system outperformed all the systems in the competitions, except for the winner from Sabanci University.

Other results with all the constraints are listed in Table 1.

## Conclusions

In this paper, an offline signature verification systems was proposed and evaluated on public signature datasets. The system is based on the centerlines of the signatures and a similarity measure designed for centerline comparison.

Based on our experimental results (see Table 1), the constraints based on the average reference similarity always outperformed the global

**Table 1.** Summary of results for the twelve constraints and three databases

| CHINESE | | | |
|---|---|---|---|
| **Constraint** | **Best accuracy (k)** | **FAR/FRR (k)** | **Accuracy** |
| $S_{Qmin} < k \cdot S_{Rmin}$ | 72.48% (2.2995) | 42.23% / 42.50% (1.175) | 57.70% |
| $S_{Qavg} < k \cdot S_{Rmin}$ | 64.07% (2.195) | 39.51% / 39.17% (1.745) | 60.57% |
| $S_{Qmax} < k \cdot S_{Rmin}$ | 66.53% (2.995) | 38.69% / 39.17% (2.430) | 61.19% |
| $S_{Qmin} < k \cdot S_{Ravg}$ | 78.44% (0.700) | 40.05% / 40.83% (0.530) | 59.75% |
| $S_{Qavg} < k \cdot S_{Ravg}$ | 83.37% (0960) | 29.97% / 29.17% (0.815) | 70.23% |
| $S_{Qmax} < k \cdot S_{Ravg}$ | 81.52% (1.420) | 24.25% / 24.17% (1.160) | 75.77% |
| $S_{Qmin} < k \cdot S_{Rmax}$ | 77.41% (0.495) | 38.69% / 38.33% (0.330) | 61.40% |
| $S_{Qavg} < k \cdot S_{Rmax}$ | 76.59% (0.685) | 31.06% / 29.17% (0.500) | 69.40% |
| $S_{Qmax} < k \cdot S_{Rmax}$ | 79.06% (0.880) | 27.25% / 25.83% (0.705) | 73.10% |
| $S_{Qmin} < k$ | 77.41% (0.090) | 37.87% / 46.67% (0.065) | 59.96% |
| $S_{Qavg} < k$ | 78.44% (0.140) | 28.88% / 28.33% (0.100) | 71.25% |
| $S_{Qmax} < k$ | 80.90% (0.170) | 25.34% / 24.17% (0.140) | 74.95% |
| **DUTCH** | | | |
| **Constraint** | **Best accuracy (k)** | **FAR/FRR (k)** | **Accuracy** |
| $S_{Qmin} < k \cdot S_{Rmin}$ | 69.31% (0.975) | 31.92% / 32.41% (1.040) | 67.83% |
| $S_{Qavg} < k \cdot S_{Rmin}$ | 73.50% (1.325) | 29.89% / 30.56% (1.435) | 69.77% |
| $S_{Qmax} < k \cdot S_{Rmin}$ | 71.41% (1.580) | 31.14% / 31.33% (1.900) | 68.76% |
| $S_{Qmin} < k \cdot S_{Ravg}$ | 67.52% (0.600) | 32.71% / 32.56% (0.605) | 67.37% |
| $S_{Qavg} < k \cdot S_{Ravg}$ | 79.49% (0.845) | 20.81% / 20.83% (0.860) | 79.18% |
| $S_{Qmax} < k \cdot S_{Ravg}$ | 78.24% (1.120) | 22.54% / 22.69% (1.145) | 77.39% |
| $S_{Qmin} < k \cdot S_{Rmax}$ | 61.93% (0.370) | 38.34% / 37.81% (0.370) | 61.93% |
| $S_{Qavg} < k \cdot S_{Rmax}$ | 71.25% (0.535) | 29.89% / 28.70% (0.515) | 70.71% |
| $S_{Qmax} < k \cdot S_{Rmax}$ | 74.83% (0.715) | 25.04% / 25.77% (0.690) | 74.59% |
| $S_{Qmin} < k$ | 61.62% (0.090) | 42.10% / 39.66% (0.075) | 59.13% |
| $S_{Qavg} < k$ | 69.77% (0.110) | 31.46% / 31.17% (0.105) | 68.69% |
| $S_{Qmax} < k$ | 73.66% (0.140) | 27.54% / 25.15% (0.140) | 73.66% |
| **JAPANESE** | | | |
| **Constraint** | **Best accuracy (k)** | **FAR/FRR (k)** | **Accuracy** |
| $S_{Qmin} < k \cdot S_{Rmin}$ | 63.95% (1.025) | 36.11% / 36.63% (0.990) | 63.65% |
| $S_{Qavg} < k \cdot S_{Rmin}$ | 66.52% (1.345) | 36.61% / 33.83% (1.400) | 66.29% |
| $S_{Qmax} < k \cdot S_{Rmin}$ | 67.57% (1.640) | 32.92% / 33.17% (1.840) | 66.97% |
| $S_{Qmin} < k \cdot S_{Ravg}$ | 68.02% (0.610) | 35.56% / 36.30% (0.545) | 64.10% |
| $S_{Qavg} < k \cdot S_{Ravg}$ | 74.51% (0.830) | 28.47% / 28.38% (0.765) | 71.57% |
| $S_{Qmax} < k \cdot S_{Ravg}$ | 76.55% (1.090) | 25.83% / 25.41% (1.020) | 74.36% |
| $S_{Qmin} < k \cdot S_{Rmax}$ | 67.35% (0.395) | 34.72% / 36.47% (0.340) | 64.48% |
| $S_{Qavg} < k \cdot S_{Rmax}$ | 74.06% (0.545) | 29.31% / 29.87% (0.465) | 70.44% |
| $S_{Qmax} < k \cdot S_{Rmax}$ | 76.92% (0.700) | 25.28% / 26.07% (0.625) | 74.36% |
| $S_{Qmin} < k$ | 66.52% (0.125) | 36.39% / 33.33% (0.110) | 65.01% |
| $S_{Qavg} < k$ | 72.47% (0.160) | 29.72% / 28.38% (1.155) | 70.89% |
| $S_{Qmax} < k$ | 74.36% (0.225) | 25.56% / 25.91% (0.210) | 74.28% |

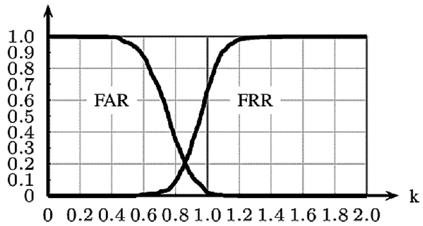



**Figure 6.** False Acceptance Rate (FAR) and False Rejection Rate (FRR) respect to the thresholding parameter k and $S_{Qavg} < k \cdot S_{Ravg}$ (Dutch dataset).

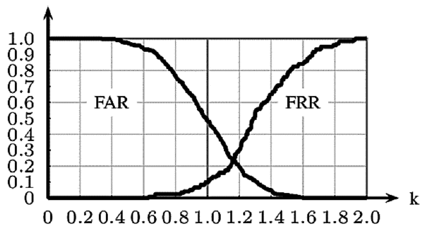



**Figure 7.** False Acceptance Rate (FAR) and False Rejection Rate (FRR) respect to the thresholding parameter k and $S_{Qmax} < k \cdot S_{Ravg}$ (Chinese dataset).

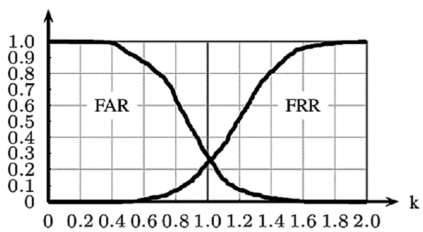



**Figure 8.** False Acceptance Rate (FAR) and False Rejection Rate (FRR) respect to the thresholding parameter k and $S_{Qmax} < k \cdot S_{Ravg}$ (Japanese dataset).

**Table 2.** Comparison of our results with those got from the systems submitted to SigComp2011 for the Dutch dataset

| Author | Accuracy (%) | FRR | FAR |
|---|---|---|---|
| Qatar | 97.67 | 2.47 | 2.19 |
| Qatar | 95.57 | 4.48 | 4.38 |
| HDU | 87.80 | 12.35 | 12.05 |
| Sibanci University | 82.91 | 17.93 | 16.41 |
| **Proposed** | **79.25** | **20.81** | **20.83** |
| Anonymous-1 | 77.89 | 22.22 | 21.75 |
| DFKI | 75.84 | 23.77 | 24.57 |
| Anonymous | 71.02 | 29.17 | 28.79 |

**Table 3.** Comparison of our results with those got from the systems submitted to SigComp2011 for the Chinese dataset.

| Author | Accuracy (%) | FRR | FAR |
|---|---|---|---|
| Sibanci | 80.04 | 21.01 | 19.62 |
| **Proposed** | **75.77** | **24.25** | **24.17** |
| Anonymous1 | 73.10 | 27.50 | 26.70 |
| HDU | 72.90 | 27.50 | 26.98 |
| DFKI | 62.01 | 37.50 | 38.15 |
| Anonymous2 | 61.81 | 38.33 | 38.15 |
| Qatar (Chinese opt) | 56.06 | 45.00 | 43.60 |
| Qatar (Dutch opt) | 51.95 | 50.00 | 47.41 |

**Table 4.** Comparison of our results with those got from the systems submitted to SigWiComp2013 for the Japanese dataset.

| Author | Accuracy (%) | FRR | FAR |
|---|---|---|---|
| Sab1 | 90.72 | 9.74 | 9.72 |
| Sab2 | 89.82 | 10.23 | 10.14 |
| Sab3 | 86.95 | 13.04 | 13.06 |
| Teb1 | 76.70 | 23.60 | 23.06 |
| **Proposed** | **76.55** | **25.83** | **25.41** |
| Teb5 | 74.59 | 25.41 | 25.42 |
| Teb2 | 73.98 | 26.07 | 25.97 |
| Bud | 72.70 | 25.23 | 25.36 |
| Teb4 | 72.10 | 25.89 | 27.92 |
| Teb3 | 68.33 | 31.35 | 31.94 |
| Qatar | 66.67 | 33.33 | 33.33 |

threshold, the minimal and maximal reference similarity, so outliers detrimentally affects the results, which was expected.

Although the system did not outperform all the systems in the recent competitions, the results are robust on different datasets and the system can be applied without the need for pretraining of parameter values.

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## References

Abbas, N. and Chibani, Y. (2011). Combination of off-line and on-line signature verification systems based on SVM and DST. In *Proc. of 11th Int. Conf. on Intelligent Systems Design and Applications (ISDA) 2011*, pp. 855–860.

Atanasiu, V. (2011). Forensic vs. computing writing features as seen by rex, the intuitive document retriever. In *Proc. of Int. Workshop on Automated Forensic Handwriting Analysis (AFHA) 2011*, pp. 16–20.

Atanasiu, V. , Likforman-Sulem, L., and Vincent, N. (2011). Writer retrieval—exploration of a novel biometric scenario using perceptual features derived from script orientation. *Proc. of Int. Conf. on Document Analysis and Recognition*, 0:628–632.

Azzopardi, G. and Camilleri, K. P., (2008). Offline Handwritten Signature Verification using Radial Basis Function Neural Networks, In *Proc. WICT*, Malta.

Baltzakis, H. and Papamarkos, N. (2001). A new signature verification technique based on a two-stage neural network classifier. *Engineering applications of Artificial intelligence*, 14(1):95–103.

Besl, P. J. and McKay, N. D. (1992). Method for registration of 3-D shapes. *Proc. SPIE*, 1611:586–606.

Canny, J. (1986). A computational approach to edge detection. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 8(6):679–698, Nov 1986. ISSN 0162-8828. doi: 10.1109/TPAMI.1986.4767851.

S. Chen and S. Srihari. (2005). Use of exterior contours and shape features in off-line signature verification. In *Proc. of Int. Conf. on Document Analysis and Recognition (ICDAR) 2005*, pp. 1280–1284. IEEE Computer Society, 2005. ISBN 0-7695-2420-6.

de Medeiros Napoles, S.H.L. and Zanchettin, C. (2012). Offline handwritten signature verification through network radial basis functions optimized by differential evolution. In *Proc. of Int. Joint Conference on Neural Networks (IJCNN) 2012*, pp. 1–5.

Dehghan, M., Faez, K., and Fathi, M. (1997). Signature verification using shape descriptors and multiple neural networks. In *Proc. of IEEE Region 10 Annual Conference. Speech and Image Technologies for Computing and Telecommunications*, volume 1, pp. 415–418. IEEE.

Frias-Martinez, E., Sanchez, A., and Velez, J. (2006). Support vector machines versus multi-layer perceptrons for efficient off-line signature recognition. *Engineering Applications of Artificial Intelligence*, 19(6):693 –704, 2006.

Gonzalez, R.C. and Woods, R.E. (2008). *Digital Image Processing*. Pearson/Prentice Hall, 2008. ISBN 9780131687288.

Goshtasby, A. Image Registration—Principles, Tools and Methods. (2012). *Advances in Computer Vision and Pattern Recognition*. Springer. ISBN 978-1-4471-2457-3.

Huang, K. and Yan, H. (2002). Off-line signature verification using structural feature correspondence. *Pattern Recognition*, 35(11):2467 – 2477.

Impedovo, D. and Pirlo, G. (2008). Automatic signature verification: The state of the art. *Systems, Man, and Cybernetics*, *Part C: Applications and Reviews, IEEE Transactions on*, 38(5):609–635.

Impedovo, D., Pirlo, G., Sarcinella, L., Stasolla, E., and Trullo, C.A. (2012). Analysis of stability in static signatures using cosine similarity. In *Proc. of Int. Conf. on Frontiers in Handwriting Recognition (ICFHR) 2012*, pages 231–235.

Ismail, M.A. and Gad, S. (2000). Off-line arabic signature recognition and verification. *Pattern Recognition*, 33(10):1727 – 1740.

Justino, E. JR, Yacoubi, A., Bortolozzi, F., and Sabourin, R. (2000). An off-line signature verification system using hmm and graphometric features. In *Proc. Fourth IAPR International Workshop on Document Analysis Systems (DAS)*, pp 211–222..

Justino, E. J.R., Bortolozzi, F., and Sabourin, R. (2005). A comparison of SVM and HMM classifiers in the off-line signature verification. *Pattern Recognition Letters*, 26(9):1377 – 1385.

Kalera, M. K., Srihari, S., and Xu, A. (2004). Offline signature verification and identification using distance statistics. *International Journal of Pattern Recognition and Artificial Intelligence*, 18(07):1339–1360.

Kelly, J.S. and Lindblom, B.S. (2006). *Scientific Examination of Questioned Documents*, Second Edition. Forensic and Police Science Series. Taylor & Francis, 2006. ISBN 9781420003765.

Kisku, D. R., Gupta, P., and Sing, J. K. (2010). Offline signature identification by fusion of multiple classifiers using statistical learning theory. *International Journal of Security & Its Applications,* Jul 2010, Vol. 4 Issue 3, p35.

Lee, S.-W., Lam, L., and Suen, C.Y. (1994). A systematic evaluation of skeletonization algorithms. *Thinning Methodologies for Pattern Recognition*, 8:239–261.

Lee, S.W. (1999). Advances in Handwriting Recognition. *Series in Machine Perception and Artificial Intelligence*. World Scientific. ISBN 9789810237158.

Liwicki, M., Malik, M.I., van den Heuvel, C.E., Chen, X., Berger, C., Stoel, R., Blumenstein, M., and Found, B. (2011). Signature verification competition for online and offline skilled forgeries (sigcomp2011). In *Proc. of Int. Conf. on Document Analysis and Recognition (ICDAR) 2011*, pp 1480–1484.

Malik, M.I., Liwicki, M., Alewijnse, L., Ohyama, W., Blumenstein, M., and Found, B. (2011). ICDAR 2013 competitions on signature verification and writer identification for on- and offline skilled forgeries (SigWiComp2013). In *Proc. 12th International Conference on Document Analysis and Recognition (ICDAR) 2013*, pp 1477–1483, Aug 2013. doi: 10.1109/ICDAR.2013.220.

Mandal, R., Roy, P. P., and Pal, U. (2011) Signature segmentation from machine printed documents using conditional random field. In *Proc. of Int. Conf. on Document Analysis and Recognition (ICDAR) 2011*, pp. 1170–1174. IEEE.

Morris, R. and Morris, R.N. (2000). Forensic Handwriting Identification: Fundamental Concepts and Principles. Academic. ISBN 9780125076401.

Pirlo, G. and Impedovo, D. (2010). On the measurement of local stability of handwriting: An application to static signature verification. In *IEEE Workshop on Biometric Measurements and Systems for Security and Medical Applications (BIOMS) 2010*, pp. 41–44.

Plamondon, R. (1995). A kinematic theory of rapid human movements: Part I: Movement representation and generation. *Biological Cybernetics*, 72(4):295-307.

Plamondon, R. and Djioua, M. (2006). A multi-level representation paradigm for handwriting stroke generation, *Human Movement Science*, 25(4-5):586-607.

Plamondon, R. and Srihari, S.N. (2000). Online and off-line handwriting recognition: a comprehensive survey. I*EEE Trans. on Pattern Analysis and Machine Intelligence*, 22(1):63–84.

Pourshahabi, M.R., Sigari, M.H., and Pourreza, H.-R. (2009). Offline handwritten signature identification and verification using contourlet transform. In *Proc. of Int. Conf. of Soft Computing and Pattern Recognition (SOCPAR) 2009*, pp. 670–673.

Rathi, A., Rathi, D., and Astya, P. (2012). Offline handwritten signature verification by using pixel based method. *International Journal of Engineering Research and Technology (IJERT)*, 1. ISSN 2278-0181.

Shanker, A.P. and Rajagopalan, A.N. (2007). Off-line signature verification using DTW. *Pattern Recognition Letters*, 28(12):1407 – 1414.

Siddiqi, K. and Pizer, S. (2008). *Medial Representations: Mathematics, Algorithms and Applications.* Springer Publishing Company, Incorporated, 1st edition. ISBN 1402086571, 9781402086571.