Forensic Science International 282 (2018) 101–110

Contents lists available at ScienceDirect

Forensic Science International

journal homepage: www.elsevier.com/locate/forsciint

# Assessment of signature handwriting evidence via score-based likelihood ratio based on comparative measurement of relevant dynamic features

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ARTICLE INFO

*Article history:*
Received 22 May 2017
Received in revised form 10 November 2017
Accepted 13 November 2017
Available online 21 November 2017

*Keywords:*
Signature
Comparative measurement
Relevant dynamic feature
Offline handwriting
Evidence evaluation

ABSTRACT

This paper extends on previous research on the extraction and statistical analysis on relevant dynamic features (width, grayscale and radian combined with writing sequence information) in forensic handwriting examinations. In this paper, a larger signature database was gathered, including genuine signatures, freehand imitation signatures, random forgeries and tracing imitation signatures, which are often encountered in casework. After applying Principle Component Analysis (PCA) of the variables describing the proximity between specimens, a two-dimensional kernel density estimation was used to describe the variability of within-genuine comparisons and genuine–forgery comparisons. We show that the overlap between the within-genuine comparisons and the genuine–forgery comparisons depends on the imitated writer and on the forger as well. Then, in order to simulate casework conditions, cases were simulated by random sampling based on the collected signature dataset. Three-dimensional normal density estimation was used to estimate the numerator and denominator probability distribution used to compute a likelihood ratio (LR). The comparisons between the performance of the systems in SigComp2011 (based on static features) and the method presented in this paper (based on relevant dynamic features) showed that relevant dynamic features are better than static features in terms of accuracy, false acceptance rate, false rejection rate and calibration of likelihood ratios.


## 1. Introduction

Despite the advances of digitalization and the move towards paperless offices, forensic handwriting examinations involving signatures are still common in cases. For instance, 1017 forensic handwriting cases were examined in our institute, in 2014: 963 cases referred to signatures, comprising about 95% in all submitted handwriting cases. Such a high percentage of signature handwriting submissions continued in 2015 and 2016.

While comparing questioned and reference handwriting samples, forensic handwriting examiners (FHEs) observe and evaluate similarities and differences. Then they provide an opinions as to the authorship of the questioned handwriting based on their training and experience [1]. The process of comparison and follow-up assessment of the observations are highly dependent on the experts. In the National Research Council's report to the US Congress, the committee said that the scientific basis for handwriting comparisons and assessment in forensic handwriting examinations should be strengthened [2]. This paper focuses on operator independent techniques. In that area, the weighing of the observed similarities and differences in handwriting examination is not straightforward and has not been submitted to a lot of systematic research.

In order to evaluate the authorship based on the similarities and differences observed on questioned and reference handwriting, previous studies on automatically extracted features [3–5] have already contributed to help FHEs to quantitatively measure the features of handwriting and assess the value of handwriting evidence. The application of a likelihood ratio framework for handwriting evidence evaluation received particular attention [6–10]. In this paper, we will build on this framework. Previous research [3,4] was rather limited in terms of features used (loops), was focused essentially on handwriting and with a limited set of

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https://doi.org/10.1016/j.forsciint.2017.11.022
0379-0738/

imitations used as genuine forgeries to test the system. This contribution aims at studying signatures, on a large corpus involving genuine and skilled imitated signatures.

Handwriting, including the production of signatures, is the effect of a dynamic behaviour. This behaviour materialises on paper in the form of static traces that are submitted to FHEs. FHEs then reconstruct the dynamic writing sequence based on the analysis of the traced images. It means that the operator-independent features used to characterise the handwriting should capture the dynamic nature of the behaviour and not rest only on static measures such as relative proportions, sizes and shapes of letters. Most of the past research focused on the static features, such as contour, gradient, direction of slopes, etc. The sequence of handwriting was neglected. The writing sequence is a new measured feature in forensic science. This paper will take advantage dynamic time wrapping techniques to capture all features while maintaining the writing sequence.

In this paper, we follow the process of features detection and analysis in forensic handwriting examination described in Ref. [5]. In summary, it takes the following steps: following image capture of signatures, a threshold is applied to the image to obtain binarized images. The skeleton and the signature edges are extracted by digital image processing. The skeletonized signatures are submitted to a programme allowing the extraction of the writing sequence. The width, grayscale and radian were automatically extracted from the writing sequence. Thus, the features of width, grayscale and radian combined with writing sequence are automatically extracted. Next, a dynamic time warping method is applied to cope with the difference writing speeds. The pairwise correlation coefficient was used to characterize and express the similarities between signatures.

The extracted features, namely width, grayscale and radian, are fully described in Ref. [5]. They are measured at every pixel following the skeleton of the whole signature. The skeleton is constructed to reflect the writing sequence of the signature, acquired at 400 dpi.

They are qualified as “dynamic features” because they are extracted accounting for the writing order. They are not extracted at the time of capture, but acquired after the writing act on the images itself. Because these features are different from dynamic features extracted from on-line handwriting, but still reflect the writing sequence, we called them “relevant dynamic features”.

This paper presents three major improvements compared to previous work in [5]: (1) the signature database was enlarged to twenty groups and 1654 signatures; (2) Probability density distributions were estimated to show the variability of within-genuine comparisons and genuine–forgery comparisons; (3) Likelihood ratios (LRs) were calculated based on the relevant dynamic features.

Finally, the comparisons between the performance of the systems in Signature Verification Competition for Online and Offline Skilled Forgeries [10] (SigComp2011, based on static features) and the system presented in this paper (based on relevant dynamic features) assess the performance of the methodology presented in this paper.

## 2. Material and method

### 2.1. Signature database

A signature database (20 groups, 1654 signatures) was acquired based on a previous signature database, including genuine signatures, freehand imitation signatures, tracing imitation signatures and random forgeries without any model.

That was done to reflect situations often encountered in casework. Chinese signatures were written by 20 volunteers using a ballpoint pen with black ink on A4 paper (for genuine signatures, random forgeries and freehand imitation forgeries) printed with 12 squares and 195 mm–271 mm, and highly transparent paper (for tracing imitation forgeries), with the signatories sitting while signing. Twenty volunteers who could produce skilled imitation forgeries were also recruited. The skilled imitations were produced by trained forensic document examiners who have developed skills in producing imitations. The Chinese signature database was composed of 1654 signatures of 20 groups produced by 20 groups of volunteers (each composed of one writer and a set of forgers); every group contained 20–24 genuine signatures (denoted as GE), 30–36 freehand imitation forgeries with a genuine model by three volunteers (denoted as FF), 10–12 random forgeries without any model by one volunteer (denoted as RF) and 10–12 tracing imitation forgeries by one volunteer (denoted as TF). For the production of forgeries, one genuine signature was chosen as the model at random. The freehand imitation forgeries, tracing imitation forgeries and forgeries without any model were all called “forgeries” in this paper.

Our signature database is summarized in Table 1. We have grouped the forgeries in two categories:

**Table 1**
Chinese signature database.

| Group ID | Genuine signature (GE) | Freehand imitation forgery (FF) | Tracing imitation forgery (TF) | Random forgery (RF) |
|---|---|---|---|---|
| G1 | 24 | 35 | 12 | 12 |
| G2 | 24 | 36 | 12 | 12 |
| G3 | 24 | 34 | 12 | 12 |
| G4 | 24 | 36 | 12 | 12 |
| G5 | 24 | 35 | 12 | 12 |
| G6 | 23 | 36 | 12 | 12 |
| G7 | 24 | 36 | 12 | 12 |
| G8 | 22 | 34 | 12 | 12 |
| G9 | 21 | 34 | 12 | 12 |
| G10 | 23 | 35 | 12 | 12 |
| G11 | 24 | 34 | 12 | 12 |
| G12 | 24 | 35 | 12 | 12 |
| G13 | 24 | 36 | 12 | 12 |
| G14 | 24 | 36 | 12 | 12 |
| G15 | 22 | 35 | 12 | 12 |
| G16 | 24 | 36 | 12 | 12 |
| G17 | 24 | 36 | 12 | 12 |
| G18 | 24 | 33 | 12 | 12 |
| G19 | 24 | 36 | 12 | 12 |
| G20 | 24 | 35 | 12 | 12 |