Non-English and Non-Latin Signature Verification Systems: A Survey

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Abstract - **Signatures continue to be an important biometric because they remain widely used as a means of personal verification and therefore an automatic verification system is needed. Manual signature-based authentication of a large number of documents is a difficult and time consuming task. Consequently for many years, in the field of protected communication and financial applications, we have observed an explosive growth in biometric personal authentication systems that are closely connected with measurable unique physical characteristics (e.g. hand geometry, iris scan, finger prints or DNA) or behavioural features. Many works are done in the field of signature verification involving English signatures but to the best of our knowledge very few works are considered regarding non-English signatures such as Chinese, Japanese, Arabic etc. In order to convey the state-of-the-art in the field to researchers, in this paper we present a survey of non-English signature verification systems**.

Key Words: Off-line and On-line signature verification, Biometrics, Authentication systems, Forgeries.

I. INTRODUCTION

The handwritten signature has always been one of the most simple and accepted way to authenticate an official document. Research into signature verification has been vigorously pursued for a number of years and it is being explored especially in the off-line mode [1, 2]. The recognition of human signatures is significantly concerned with the improvement of the interface between human-beings and computers [3, 4]. A signature verification system and the associated techniques used to solve the inherent problems of authentication can be divided into two classes: (a) on-line methods [7, 8] to measure the sequential data such as order of stroke, and writing speed, pen pressure and other temporal information by utilizing intelligent algorithms [9, 10], and (b) off-line methods [11, 12] that use an optical scanner to obtain handwriting data written on paper. On-line signature verification has been shown to achieve much higher verification rates than off-line verification [11] as a considerable amount of dynamic information is lost in the off-line mode.

Signatures are not considered as a collection of letters and words [14]. It is often difficult for a human to instantly verify two signatures of the same person because signature samples from the same person are similar but not identical and signatures can change depending on elements such as mood, fatigue, time etc. Great inconsistency can even be observed in signatures according to country, habits, psychological or mental state, physical and practical conditions [15].

Many pieces of works are done in the field of signature verification involving English signatures but to the best of our knowledge only little attention has been given towards non-English signatures such as Chinese, Japanese, Arabic etc. In order to convey the state-of-the-art of non-English signature verification, in this paper we present a survey of non-English signature verification systems.

II. SIGNATURE VERIFICATION CONCEPT

In general to deal with the problem of off-line/on-line signature verification, researchers have investigated a commonly used approach which is based on two different patterns of classes: class1 and class 2. Here class1 represents the genuine signature set, and class2 represents the forged signature set.

Usually two types of errors are considered in signature verification system. The False Rejection, which is called a Type-1 error and the False Acceptance, which is called a Type-2 error. So there are two common types of error rates: False Rejection Rate (FRR) which is the percentage of genuine signatures treated as forgeries, and False Acceptance Rate (FAR) which is the percentage of forged signatures treated as genuine.

III. TYPES OF FORGERIES

There are usually three different types of forgeries to take into account. According to Coetzer et al. [16], the three basic types of forged signatures are indicated below:

1. Random forgery. The forger has no access to the genuine signature (not even the author's name) and reproduces a random one.
2. Simple forgery. The forger knows the author's name, but has no access to a sample of the signature.
3. Skilled forgery. The forger has access to one or more samples of the genuine signature and is able to reproduce it.

But based on the various skilled levels of forgeries, it can also be divided into six different subsets. The paper [17] shows various skill levels of forgeries and these are shown below.

1. A forged signature can be another person's genuine signature. Justino et al. [18] categorized this type of forgery as a Random Forgery.
2. A forged signature is produced with the knowledge about the genuine writer's name only. Hanmandlu et al. [19] categorized this type as a Random Forgery whereas Justino et al. [18] categorized this type as a Simple Forgery. Weiping et al. categorized this type as a Casual Forgery [20].
3. A forged signature imitating a genuine signature's model reasonably well is categorized as a Simulated Forgery by Justino et al. [18].

4. Signatures produced by inexperienced forgers without the knowledge of their spelling after having observed the genuine specimens closely for some time are categorized as Unskilled Forgeries by Hanmandlu et al. [19].
5. Signatures produced by forgers after unrestricted practice by non-professional forgers are categorized as Simple Forgery/Simulated Simple Forgery by Ferrer et al. [21], and a Targeted Forgery by Huang and Yan [22].
6. Forgeries which are produced by a professional imposter or person who has experience in copying Signatures are categorized as Skilled Forgeries by Hanmandlu et al. [19].

IV. NON-ENGLISH SIGNATURE VERIFICATION TECHNIQUES

We think that the shape of non-English signatures and writing styles are different to English signatures. Arabic script is written from left to right. Most of the Japanese signatures consist of two to six kanji, hiragana and/or katakana component characters and they are spaced appropriately from each other. Persian signatures are also different from other signature types because people usually do not use text in it and they draw a shape as their signature. Hence in this work, non-English signature verification systems are reported and they are described below.

A. Chinese Signature Verification Systems

Chinese signature consists of many strokes and these strokes can be taken into consideration for signature authentication. Liu [23] discussed this issue, but he discussed it from the point of view of identifying a signature manually.

Off-line Chinese Signature Verification Systems

Lv et al. [24] developed a Chinese off-line signature verification system. A database of 1100 signatures was developed for experimentation. Support Vector Machines (SVM) are used as a classifier. Four different types of features such as moment feature, direction feature, grey distribution and stroke width distribution are used here. Based on each feature, the accuracies are calculated separately and an average accuracy was also calculated based on all combined feature sets. An average error rate 5.10% is found using the combined feature sets. SVM based techniques are also proposed by Chen et al. [25] and Meng et al. [26] for Chinese signature verification. Shen et al. [27] proposed an off-line Chinese signature verification system based on geometric features. A database of 800 signatures was used for experimentation and obtained 96.8% accuracy. Four main features such as: (a) Envelope of the signature (b) Cross-count feature (c) Centre of gravity feature and distance between vectors made from the centre of gravity (d) Embedded white area and position are used to optimise the verification scheme. Some similar works are also proposed by Bajaj et al. [28] and Huang et al. [29].

Lin and Li [30] proposed a Chinese signature verification scheme using normalized Zernike moment invariants (NZMI). A total of 210 signature samples were collected from 35 writers. The average accuracies of 8% and 12% are obtained for FRR and FAR, respectively. Belkasim et al. [31] introduced a new recursive formula to derive Zernike moments.

In another work of Lin and Li [32], they utilized a set of shape features based on special characteristics of Chinese signatures along with high pressure feature. Their features includes: (a) Ratio of a signature's height to its width. (b) Ratio of a signature's height to its packed width (c) Slant (d) Stroke width. To define the global high-pressure features (GHP) they use Ammar et al's [33] dynamic threshold selecting method. A database of 100 genuine Chinese signatures and 50 forged signatures are collected for the experiment. Reported FRR and FAR rates are 1.0% and 4.0%, respectively.

Chang et al. [34] presented a dynamic handwritten Chinese signature verification system based upon a Bayesian neural network. Features such as: timing features, average velocity feature, average length in the eight directions, width/height ratio, left-part/right-part density ratio, upper-part/lower-part density ratio etc are utilize in the work. Similar works are proposed by Brault and Plamondon [35] and Lorette [36]. A database of 1200 signature samples is collected. The experimental results show the type I error is about 2% and the type II error rates are approximately 0.1% and 2.5% for "simple" and "skilled" forgeries, respectively.

Ji et al. [37] developed an off-line Chinese signature verification system based on a weighting factor of similarity computation. Their earlier paper introduces an improved approach to verify off-line Chinese signatures and it is described in [38]. In their proposed scheme, seven features such as (a) Relative horizontal centre (b) Relative vertical centre (c) The number of points having horizontal neighbours (d) The number of points having vertical neighbours, (e) The number of points having positive diagonal neighbours (f) The number of points having negative diagonal neighbours and (g) Stroke thickness of the segments are used. This technique for off-line Chinese signature verification based on different weighting factors is compared with an expert on questioned documents used to verify a signature sample [39]. The experimental results are generated differently using different data sets. The average ERR is 3.30% and the average EAR is 16.50% for simple forgeries when the weighting factor is 0.04.

Ji and Chen [40] proposed an off-line Chinese signature verification System. A method to solve the problem for random forgeries and simple forgeries is presented in their paper. The pre-processing techniques used here are described in detail in [41]. The features are extracted in seven steps as discussed in the paper [33]. A database of 4800 handwriting samples from 32 participants is used in this method to obtain a verification accuracy rate of 91%.

Zuo et al. [42] proposed an off-line Chinese signature verification scheme using Pseudo-Zernike invariant moments as for static features due to scale and translation invariance. High-density factors, relative gravity centre and Wavelet Transform are used as dynamic features. A database of 290 signatures was collected. As a result of their experiments, the FAR and FRR was 7.84% and 6.89%, respectively.

Cheng et al. [43] presented a handwritten Chinese signature verification scheme. An attributed string matching approach based on the writing sequences of an input signature is proposed. In order to obtain an attributed string that is used in the string matching similarity calculation, the input signatures are split into several segments. The stroke attributed feature is used in their proposed technique. A large database is used to obtain 1.5% and 3.6% for type1 and type2 error rates respectively. A similar matching method is performed by Chen et al. [44].

Ye et al. [45] developed an off-line handwritten Chinese signature verifier with an inflection feature. Different scale wavelet transforms are used in the curvature signature signals transformation. The signature curves are divided into several parts, i.e. the strokes, according to the inflections. The distance between two corresponding strokes is measured with a Dynamic Time Warping algorithm. A database of 3120 signatures was collected for the experiments. The rate of FRR and FAR (skilled forgery) are 1.33 % and 6.72%, respectively.

On-Line Chinese Signature Verification Systems

Xiao and Dai [46] introduced a hierarchical on-line Chinese signature verification system. First, global features are applied to obtain a statistical decision through comparing their weighted distance. Secondly, the input primitive string is matched with its reference primitive string by attributed automaton. In their paper an attributed automaton [47] which has four edit operations (insertion, deletion etc.) are applied to solve the problem of inconsistency of signature segmentation.

Tseng and Huang [48] presented an on-line Chinese signature verification scheme based on the ART Neural Network. The verification method based on one bit quantized pressure patterns, which constitute time domain information. The timing information contained in the on/off motions of handwriting is analysed by Zimmermann and Varady [49]. Carpenter and Grossberg [50] also proposed a method based on the ART Neural Network. The error rates 4.5% and 5% are obtained for type1 and type 2, respectively. Techniques based on neural network expert systems to identify Chinese signature are proposed by Ng and He [51] and He et al. [52].

Cheng et al. [53] presented an on-line Chinese signature verification system using a voting scheme. Global feature, line segment feature, 8-directional chain code feature, Spectral information, similarity of position sequences, similarity of velocity sequence, similarity of attribute strings, segment correlation, Tremor feature are used in these nine expert steps. A database of 600 genuine signatures and 12000 forge signatures is used. Some similar types of works are conducted by Suen et al. [54] and Jeng et al. [55] based on neural networks and wavelet transforms respectively. Y. Mizukami [56)] developed a handwritten Chinese character recognition system using hierarchical displacement extraction based on directional features. Other techniques involving on-line signature verification can be obtained in [57-64].

B. Japanese Signature Verification Systems

The Japanese handwritten signature verification is difficult due to the lack of stability and individuality. Only a few articles are available on Japanese handwritten verification and they are discussed as follows. Ueda et al. [65] presented an off-line Japanese signature verification system using a pattern matching technique. The similarity between two signatures obtained by pattern matching is affected by stroke widths. Stroke widths vary with the pen used for signing, and even if signatures are written with the same pen, the stroke width may also vary. In their modified pattern matching method, the strokes of the signatures are first thinned and then the thinned signatures are blurred by a fixed point-spread function. A database of 2000 signatures including 100 genuine signatures from 10 writers and 100 forged signatures from 10 writers are used. An average error rate 9.10% is obtained. Some techniques for verification of Japanese handwritten signatures have been proposed in [66-68].

Yoshimura and Yoshimura [69] presented off-line verification of Japanese signatures after elimination of background patterns. Some preprocessing techniques to eliminate the background pattern are performed as follows: position adjustment, filtering, clipping of random noise and smoothing for noise elimination etc. The verification stage following the preprocessing stage is based on the Arc Pattern Method. A small data set is used to obtain an error rate of approximately 14%. Mizukami et al. [70] proposed an off-line Japanese signature verification system using an extracted displacement function.

C. Persian Signature Verification Systems

Ghandali et al. [71] proposed an off-line Persian signature identification and verification system based on Discrete Wavelet Transform and image fusion. In this method, DWT is employed to access high-frequency bands of signature shape. Then, different samples of a person's signature are fused together based on high frequency bands to generate the signature patterns. This pattern is saved in the learning phase. SVMs are used here as classifiers. A database consists of 6 genuine, 1 simple forgery and 1 skilled forgery signatures from each of the 90 signers is used. The error rates, 8.9% and 10% are obtained for FRR and FAR, respectively. Chalechale and Mertins [72], Chalechale et al. [73] proposed a Persian signature recognition system using line segment distribution. Zoghi et al. [74] introduced a Persian signature verification system using Improved Dynamic Time Warping-based Segmentation and Multivariate Autoregressive Modelling. A database including 1250 genuine signatures and 750 forged signatures was used to obtain an accuracy of 88.8% for the testing of skilled forgery signatures. The statistical spectral estimate for each signature segment is obtained via the use of an Auto-Regressive model [75]. The verification process is carried out using an Artificial Neural Network with a multilayer perceptron architecture described in [76].

D. Arabic Signature Verification Systems

Ismail et al. [77] proposed an off-line Arabic signature recognition and verification technique. In the first phase (Identification phase) some features are extracted and there features are: area filtering, translation, extraction of the circularity feature, normalization, image enhancement, partial histogram (Vertical projection, Horizontal projection), Centres of gravity, extraction of the global baseline (BSL), extraction of the upper limit (UL) and lower limit (LL), thinning, calculation of the global slant etc. In this phase, the features are classified into two main groups: global features and local features. In the second phase (Verification phase) some other features are also extracted such as central line features, corner line features, central circle features, corner curve features and critical point features. A set of signature data consisting of 220 genuine samples and 110 forged samples is used for experimentation. Their system obtained a 95.0% recognition rate and a 98% verification rate. Other techniques of Arabic handwritten word recognition systems are described in [78-87].

V. OUR INSIGHTS AND FUTURE WORK

As we could observe among the pieces of non-English signature verification work, maximum work has been done for Chinese. For Japanese, Arabic and Persian only a few pieces of work have been done. Despite of many works in this area, from this survey, we can observe that there are still many challenges in this research area. Signatures may be written in different languages and we need to undertake a systematic study on this. To the best of our knowledge there is no published work on signatures written in Indian languages. India is a multi-lingual and multi-script country and except for English, many people write signatures in local state languages such as Hindi, Bangla, Telugu, Tamil, etc. Thus there is a need to work on signatures written in Indian languages. Researchers have used different features for signature verification. Combination of different classifiers as well as novel and hybrid classifiers should be explored in future work to enhance performance. Accordingly in this survey we noted that all the published work is based on foreground information. A combination of background and foreground information may be considered for obtaining better results in the future.

VI. CONCLUSION

To highlight the state-of-the-art to researchers in the field, this paper presents a survey of the works on non-English signature verification. Different existing approaches are discussed and compared along with their FAR, FRR and associated accuracies. The accuracy rates obtained so far from the available systems is not sufficiently high and more research on off-line signature verification as well as on-line signature verification is required.

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The effect of training data selection and sampling time intervals on signature verification

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***Abstract*—Based on an earlier proposed procedure and data, we extended our signature database and examined the differences between signature samples recorded at different times and the relevance of training data selection. We found that the false accept and false reject rates strongly depend on the selection of the training data, but samples taken during different time intervals hardly affect the error rates.**

***Index Terms*—online signature; signature verification**

I. Introduction

In our earlier study [1], we investigated a procedure for signature verification which is based on acceleration signals. The necessary details about the method – applied in the earlier study and recent study – are explained in Section II. Previously we created a database with genuine and unskilled forgeries and used the dynamic time warping method to solve a two-class pattern recognition problem.

In our recent study we extended the database with fresh recordings of the signatures from former signature suppliers, thus we were able to compare signature samples recorded in different time periods. In addition, we examined how the selection of training data can affect the results of the verification process.

Several types of biometric authentication exist. Some of them have appeared in the last few decades, such as DNA and iris recognition and they provide more accurate results than the earlier methods did (e.g. fingerprint, signature). Hence they are more difficult to forge. However, a signature is still the most widely accepted method for identification (in contracts, bank transfers, etc.). This is why studies tackle the problem of signature verification and examine the process in detail. Usually their aim is to study the mechanics of the process and learn what features are hard to counterfeit.

There are two basic ways of recognizing signatures, namely the offline and the online. Offline signature recognition is based on the image of the signature, while the online case uses data related to the dynamics of the signing process (pressure, velocity, etc.). The main problem with the offline approach is that it gives higher false accept and false reject errors, but the dynamic approach requires more sophisticated techniques.

The online signature recognition systems differ in their feature selection and decision methods. Some studies analyze the consistency of the features [2], while others concentrate on the template feature selection [3]; some combine local and global features [4].

A key step in signature recognition was provided in the First International Signature Verification Competition [5], and reviews about the automatic signature verification process were written by Leclerc and Plamondon [6], [7], Gupta [8], Dimauro et al. [9] and Sayeed et al. [10].

Many signals and therefore many different devices can be used in signature verification. Different types of pen tablets have been used in several studies, as in [11], [12]; the F-Tablet was described in [13] and the Genius 4x3 PenWizard was used in [14]. In several studies (like ours), a special device (pen) was designed to measure the dynamic characteristics of the signing process.

In [15], the authors considered the problem of measuring the acceleration produced by signing with a device fitted with 4 small embedded accelerometers and a pressure transducer. It mainly focused on the technical background of signal recording. In [16], they described the mathematical background of motion recovery techniques for a special pen with an embedded accelerometer.

Bashir and Kempf in [17] used a Novel Pen Device and DTW for handwriting recognition and compared the acceleration, grip pressure, longitudinal and vertical axis of the pen. Their main purpose was to recognize characters and PIN words, not signatures. Rohlik et al. [18], [19] employed a similar device to ours to measure acceleration. Theirs was able to measure 2-axis accelerations, in contrast to ours which can measure 3-axis accelerations. However, our pen cannot measure pressure like theirs. The other difference is the method of data processing. In [18] they had two aims, namely signature verification and author identification, while in [19] the aim was just signature verification. Both made use of neural networks.

Many studies have their own database [12], [13], but generally they are unavailable for testing purposes. However some large databases are available, like the MCYT biometric database [20] and the database of the SVC2004 competition[1] [5].

[1]Available at http://www.cse.ust.hk/svc2004/download.html

II. Proposed method

A. Technical background

We used a ballpoint pen fitted with a three-axis accelerometer to follow the movements of handwriting sessions. Accelerometers can be placed at multiple positions of the pen, such as close to the bottom and/or close to the top of the pen [15], [17]. Sometimes grip pressure sensors are also included to get a comprehensive set of signals describing the movements of the pen, finger forces and gesture movements. In our study we focused on the signature-writing task, so we placed the accelerometer very close to the tip of the pen to track the movements as accurately as possible (see Figure 1).

In our design we chose the LIS352AX accelerometer chip because of its signal range, high accuracy, impressively low noise and ease-of-use. The accelerometer was soldered onto a very small printed circuit board (PCB) and this board was glued about 10mm from the writing tip of the pen. Only the accelerometer, the decoupling and filtering chip capacitors were placed on the assembled PCB. A thin five-wire thin ribbon cable was used to power the circuit and carry the three acceleration signals from the accelerometer to the data acquisition unit. The cable was thin and long enough so as not to disturb the subject when s/he provided a handwriting sample. Our tiny general purpose three-channel data acquisition unit served as a sensor-to-USB interface [21].

The unit has three unipolar inputs with signal range of 0 to 3.3V, and it also supplied the necessary 3.3V to power it. The heart of the unit is a mixed-signal microcontroller called C8051F530A that incorporates a precision multichannel 12-bit analogue-to-digital converter. The microcontroller runs a data logging program that allows easy communication with the host computer via an FT232RL-based USB-to-UART interface. The general purpose data acquisition program running on the PC was written in C#, and it allowed the real-time monitoring of signals. Both the hardware and software developments are fully open-source [22]. A block diagram of the measurement setup is shown in Figure 2.

The bandwidth of the signals was set to 10Hz in order to remove unwanted high frequency components and prevent aliasing. Moreover, the sample rate was set to 1000Hz. The signal range was closely matched to the input range of the data acquisition unit, hence a clean, low noise output was obtained. The acquired signals were then saved to a file for offline processing and analysis.

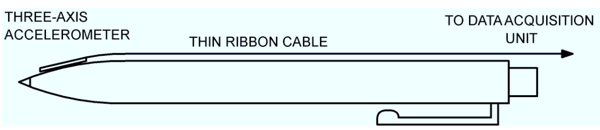


Fig. 1: The three-axis accelerometer is mounted close to the tip of the pen

B. Database

The signature samples were collected from 40 subjects. Each subject supplied 10 genuine signatures and 5 unskilled forgeries, and 8-10 weeks later the recording was repeated with 20 subjects, so we had a total of $40 \times 15 + 20 \times 15 = 900$ signatures. The signature forgers were asked each time to produce 5 signatures of another person participating in the study.

In order to make the signing process as natural as possible, there were no constraints on how the person should sign. This led to some problems in the analysis because it was hard to compare the 3 pairs of curves (two signatures). During a signing session, the orientation of the pen can vary somewhat (e.g. a rotation with a small angle causes big differences for each axis). This was why we chose to reduce the 3 dimensional signals to 1 dimensional signals and we only compared the magnitudes of the acceleration vector data.

Figure 3 shows the acceleration signals of 2 genuine signatures and 2 forged signature. Figures 3a and 3b show samples from the same author, and they appear quite similar. Figures 3c and 3d are the corresponding forged signatures, which differ significantly from the first two.

C. Distance between time series

An elastic distance measure was applied to determine dissimilarities between the data. The dynamic time warping (DTW) approach is a commonly used method to compare time series. The DTW algorithm finds the best non-linear alignment of two vectors such that the overall distance between them is minimized. The DTW distance between the $u = (u_1, \ldots, u_n)$ and $v = (v_1, \ldots, v_m)$ vectors (in our case, the acceleration vector data of the signatures) can be calculated in $\mathcal{O}(n \cdot m)$ time.

We can construct, iteratively, a $C \in \mathbb{R}^{(n+1)\times(m+1)}$ matrix in the following way:

$$\begin{aligned} C_{0,0} &= 0 \\ C_{i,0} &= +\infty, i = 1, \ldots, n \\ ,C_{0,j} &= +\infty, j = 1, \ldots, m \\ C_{i,j} &= |u_i - v_j| + \min\left(C_{i-1,j}, C_{i,j-1}, C_{i-1,j-1}\right), \\ & \qquad i = 1, \ldots, n, j = 1, \ldots, m. \end{aligned}$$

After we get the $C_{n,m}$ which tells us the DTW distance between the vectors u and v. Thus

$$\mathrm{d}_{\mathrm{DTW}}(u, v) = C_{n,m}.$$

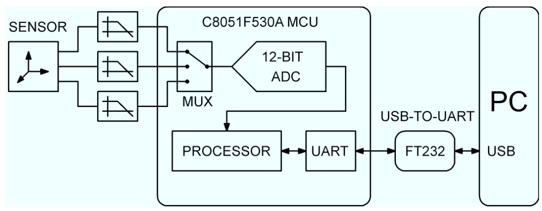
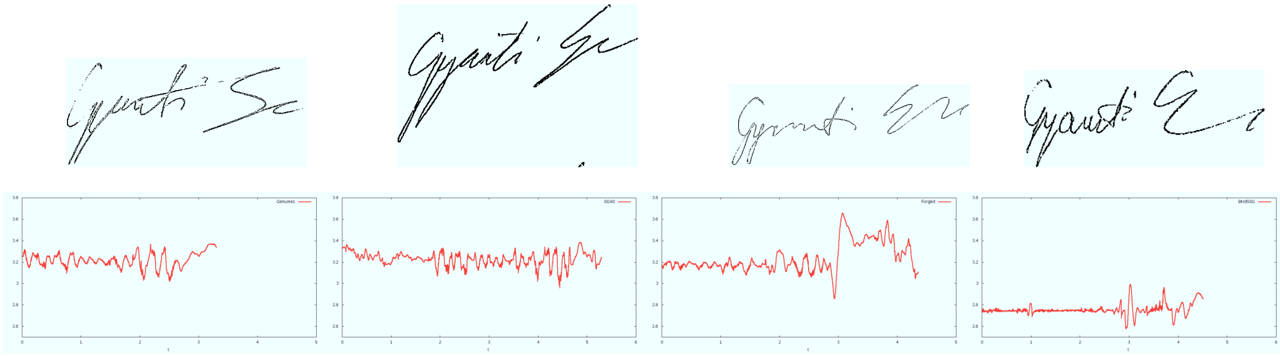


Fig. 2: Block diagram of the data acquisition system



(a) Genuine - 1st time period (b) Genuine - 2nd time period (c) Forgery - 1st time period (d) Forgery - 2nd time period

Fig. 3: The images and corresponding acceleration signals of two genuine signatures and two forged signatures

The DTW algorithm has several versions (e.g. weighted DTW and bounded DTW), but we decided to use the simple version above, where $|u_i - v_j|$ denotes the absolute difference between the coordinate i of vector u and coordinate j of vector v.

Since the order of the sizes of n and m are around $10^3 - 10^4$, our implementation does not store the whole C matrix, whose size is about $n \times m \approx 10^6 - 10^8$. Instead, for each iteration, just the last two rows of the matrix were stored.

III. Selection of reference signatures

First, we examined the $40 \cdot 15 = 600$ signatures from the first time period. For each person, 5 genuine signatures were chosen first randomly as references, and included in the training set. All the other signatures of this person and unskilled forgeries of their signature were used for testing. Thus the test set contained 5 genuine and 5 unskilled forged signatures for each person.

We first computed the minimum distance between the five elements of the training set ($D_{\mathbf{min}}$). Then, for each signature in the test set, the minimum distance of the signature from the training set's five signatures was found ($D_{\mathbf{dis}}$). Now, if for some t in the set

$$D_{\text{dis}} < m \cdot D_{\text{min}}$$

then t was accepted as a true signature; otherwise it was rejected.

Besides the minimum we also used two other metrics, namely the maximum and average distances, but the minimum produced the lowest error rates.

The performance of a signature verification algorithm can be measured by the Type I error rate (false reject), when a genuine signature is labelled as a forgery and Type II error rate (false accept), when a forged signature is marked as genuine. After we analyzed the results, we observed that the Type I and II errors depend on how we choose the reference signatures, so we checked all the possible choices of reference signatures and compared error rates. For each person there were $\binom{10}{5} = 252$ possible ways of how to choose the 5 reference signatures from the 10 genuine signatures.

False acceptance/rejection rates		
Type I	Type II	No of cases
0%	0%	39
20%	0%	135
40%	0%	68
60%	0%	7
80%	0%	3
	Total	252
24.13%	0%	

TABLE I: A typical distribution of error rates

False acceptance/rejection rates		
Type I	Type II	No of cases
0%	0%	13
0%	20%	52
0%	60%	45
20%	0%	8
20%	60%	58
20%	20%	45
40%	20%	8
40%	60%	22
60%	60%	1
	Total	252
13.81%	38.33%	

TABLE II: A different distribution of error rates

Based on our earlier studies [1], we set the multiplier m at 2.16 because we got the highest overall accuracy ratio (88.5%) with this value.

A typical distribution of Type I and Type II error rates is shown in Table I. The first two columns show the error rates, while the third one shows certain cases with the corresponding error rates. The last row shows the average error rate.

According this table, in 39 cases (out of 252) the Type I and Type II error rates are equal to 0. The average type error rate of 252 possibilities is 24.13%, while the average Type error rate is 0. For 27 authors (out of 40) and for each case, the false reject rates were 0%. A much worse, but very rare case is shown in Table II.

The average false accept rate was 14.34%, with a standard deviation of 13.62%; the average false reject rate was 12.89%,

DTW	AE50	AE51	AE52	AE53	AE54	AE55	AE56	AE57	AE58	AE59	ME60	ME61	ME62	ME63	ME64
AE50	0														
AE51	63	0													
AE52	98	64	0												
AE53	125	71	105	0											
AE54	116	65	67	101	0										
AE55	63	113	136	167	157	0									
AE56	114	80	76	127	67	155	0								
AE57	104	68	76	115	73	147	63	0							
AE58	74	66	63	111	59	105	37	49	0						
AE59	233	173	86	177	82	317	165	152	122	0					
ME60	344	239	254	281	386	532	333	202	234	372	0				
ME61	274	232	252	285	441	450	402	239	246	501	135	0			
ME62	237	177	175	231	255	350	222	179	158	316	70	107	0		
ME63	318	259	260	304	410	494	334	221	227	372	50	83	67	0	
ME64	710	677	697	716	875	854	796	670	684	977	260	198	395	269	0

TABLE III: Sample distance matrix – First time period

DTW2	AE80	AE81	AE82	AE83	AE84	AE85	AE86	AE87	AE88	AE89	ME90	ME91	ME92	ME93	ME94
AE80	0														
AE81	34	0													
AE82	34	41	0												
AE83	50	63	47	0											
AE84	52	58	43	49	0										
AE85	217	213	179	227	206	0									
AE86	139	130	152	150	145	325	0								
AE87	117	103	144	154	147	339	81	0							
AE88	55	52	52	91	82	140	154	121	0						
AE89	65	63	60	71	65	233	105	125	92	0					
ME90	293	245	270	355	310	236	336	302	228	328	0				
ME91	227	198	208	295	252	245	275	262	165	259	54	0			
ME92	339	298	322	419	387	288	393	348	273	413	45	106	0		
ME93	617	625	569	617	699	473	518	415	473	770	202	260	117	0	
ME94	388	425	492	540	582	293	469	376	395	582	67	150	40	100	0

TABLE IV: Sample distance matrix – Second time period

DTW	AE50	AE51	AE52	AE53	AE54	AE55	AE56	AE57	AE58	AE59	AE80	AE81	AE82	AE83	AE84	AE85	AE86	AE87	AE88	AE89
AE50	0																			
AE51	63	0																		
AE52	98	64	0																	
AE53	125	71	105	0																
AE54	116	65	67	101	0															
AE55	63	113	136	167	157	0														
AE56	114	80	76	127	67	155	0													
AE57	104	68	76	115	73	147	63	0												
AE58	74	66	63	111	59	105	37	49	0											
AE59	233	173	86	177	82	317	165	152	122	0										
AE80	74	51	47	95	75	112	65	67	50	168	0									
AE81	75	51	50	102	69	119	64	59	47	179	34	0								
AE82	67	40	48	96	54	104	74	66	57	179	34	41	0							
AE83	94	63	58	94	58	121	78	75	68	129	50	63	47	0						
AE84	90	54	57	87	44	120	65	53	49	124	52	58	43	49	0					
AE85	84	238	265	259	251	147	352	303	268	453	217	213	179	227	206	0				
AE86	223	145	111	192	141	306	128	145	110	92	139	130	152	150	145	325	0			
AE87	179	126	126	190	170	252	84	108	96	203	117	103	144	154	147	339	81	0		
AE88	45	63	77	132	105	82	87	83	64	217	55	52	52	91	82	140	154	121	0	
AE89	133	70	55	120	52	185	67	77	65	109	65	63	60	71	65	233	105	125	92	0

TABLE V: Distances between genuine signatures from both time periods

with a standard deviation of 24.33%.

IV. Different time period

Since a signature can change over time, we decided to examine how this affects the DTW distances of the acceleration signals of signatures. We recorded genuine and forged signatures from 20 authors in two time periods this year: between January and April and between May and June.

Table III and IV are two (DTW) distance matrices calculated for the same subject in the two time periods.

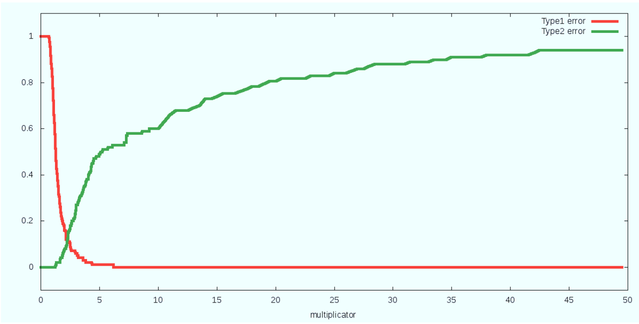
The intersection of the first 10 columns and 10 rows shows the distance values between the genuine signatures (obtained from the same person). The intersection of the first 10 rows and the last 5 columns tells us the distances between genuine and the corresponding forged signatures. The rest (the intersection of the last 5 rows and last 5 columns) shows the distances between the corresponding forged signatures.

In Table III [Table IV] the distance between the genuine signatures varies from 60 to 317 with an average of 108 and a standard deviation 53 [from 34 to 334 with an average value of 117 and a standard deviation 73], but between a genuine and a forged signature it varies from 158 to 977 with an average of 393 and a standard deviation of 211 [from 165 to 770 with an average value of 382 and a standard deviation of 142]. The distance matrices for other persons are similar to those given above.

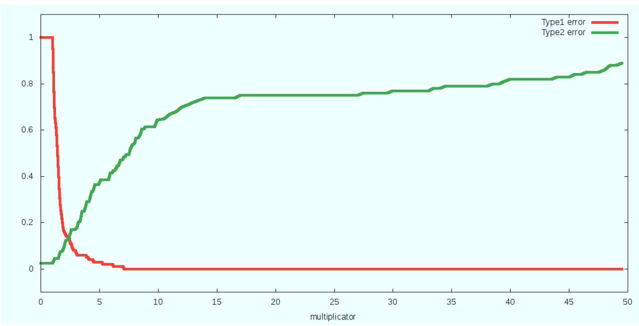
In most cases there were no significant differences between distance matrices calculated for different time periods (and from the same author). Table V shows the DTW distance between genuine signatures taken from the same author for the different time periods. AE50-59 are from the first period, while AE80-89 are from the second. The average distance is 114, the minimum is 34, the maximum is 453 and the standard deviation of the distances is 70.3.

Figures 4a and 4b show the false reject and false accept rates as a function of the constant multiplier m of the minimum distance got from the training dataset.

We can see that in both time intervals we get a zero false accept rate when $m = 7$. The curves decrease quite quickly, while the increase of the false reject rate is less marked. The main difference between the two time intervals and the false reject rate curves is that in the first time interval it increases faster than in the second. The reason is probably that in the second time interval the acceleration signals were quite similar (see tables III and IV).



(a) 1st time period



(b) 2nd time period

Fig. 4: False acceptance and false rejection rates

V. Conclusions

In this paper an online signature verification method was proposed for verifying human signatures. The new procedure was implemented and then tested. First, a test dataset was created using a special device fitted with an accelerometer. The dataset contained $600 + 300 = 900$ signatures, where 600 signatures were genuine and 300 were forged. By applying a time series approach and various metrics we were able to place signature samples into two classes, namely those that are probably genuine and those that are probably forged.

Based on our earlier experiments, we examined how the training set selection varies over a period of weeks (in most cases it was a few months) and how time influences the false acceptance and false rejection rates. We found that a person's signature does not vary much over a period of weeks or months, but it could vary more over longer periods.

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Classification of Features into Strong and Weak Features for an Intelligent Online Signature Verification System

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Abstract—**This paper presents an efficient algorithm for the classification of features into strong and weak features for every distinct subject to create an intelligent online signature verification system. Whereas Euclidean distance classifier is used for validation processes and low error rates obtained illustrate the feasibility of the algorithm for an online signature verification system.**

Keywords-Signature Biometrics; intellegient signature verification ; online signature verification; classification of features; strong features; weak features; dynamic signature verification; euclidean distance classifer

I. Introduction

Today, with the astonishing growth of the Internet and Intranet, E-commerce and E-finance become the hottest topics on this planet. Doing business through the public network makes personal identification data security more and more crucial as well. How to protect the private identification from being pirated is the key issue that the Internet and intranet clients would be concerned with before such E-business could be widely accepted since authentication has become an essential part of highly computerized services and/or security-sensitive installations in modern society.

Signature verification fulfills all the above described circumstances and can play a vital role in protection and personal identification as it is a popular means of endorsement historically. Although such signatures are never the same for the same person at diverse times, there appears to be no practical problem for human beings to discriminate visually the real signature from the forged one. It will be extremely useful when an electronic device can display at least the same virtuosity.

Signature verification systems are usually built following either on-line or off-line approaches, depending on the kind of data and application involved. On-line systems generally present a better performance than the off-line system but require the necessary presence of the author during both the acquisition of the reference data and the verification process limiting its use. In online signature verification systems, additional features such as pen pressure, pen speed and pen tilt angle have made the process of forging online signatures more difficult. Equal error rate of available online signature verification systems lies between 1 to 10%.

Still a lot of work is needed to be done to reduce Equal error rate (EER) to make online signature verification the most secure way of personal identification.

II. Feature Extraction

Feature extraction phase is one of the crucial phases of an on-line signature verification system. The discriminative power of the features and their flexibility to the variation within the reference signatures of a writer, play one of the major roles in the whole verification process. While features related to the signature shape are not dependent on the data acquisition device, presence of dynamic features, such as pressure at the pen-tip or pen-tilt, depends on the hardware used.

Features may be classified as global or local, where global features identify signature's properties as a whole and local ones correspond to properties specific to a sampling point. For example, signature bounding box, average signing speed, trajectory length or are global features, and Local features include curvature change between consecutive points on the signature trajectory or distance are local features. Features may also be classified as temporal (related to the dynamics) and spatial (related to the shape).

These features can be referred as human traits, as they can vary from person to person and can be classified as strong or weak for every distinct individual. If we make a list of these features, more than 100 features are present and even new features can be derived depending on their discriminative power.

III. Database & Compilation

A. System

For the purpose of signature verification we made an experimental setup in which a person is enrolled in the database by taking some of his/her signatures and a template is created and stored against the name and ID of the specified person. A new signature from that person can then be checked against the enrolled template to validate the person. Furthermore we will discuss about the technique used in our system, database and how we optimized features as strong and weak features.

B. Database Completion

A comprehensive database was created by obtaining the signatures from the students. Signatures were gathered from a total of hundred subjects with ten signatures from each subject. So a total of thousand signatures were collected to create the original signature database. WACOM INtuous4 tablet with a sampling rate of 200 samples per seconds was used for this purpose.

To form the forgeries database we performed a total 10 forgeries per person, among which were five zero-effort forgeries and five skilled forgeries. The forgeries that are performed by first training the counterfeiter to copy the precise dynamics of the original signer are skilled forgeries. A forger is trained by showing him plots of the original signature being performed or by training the original signer himself.

IV. Signature Verification Technique

In the first phase, a signature verification technique was successfully put into operation for the classification of original and forged signatures using Euclidean Classifier. The technique is previously implemented by H. Dullink, B. Van Daalen, J. Nijhuis, L. Spaanenburg, and H. Zuuidhof [1].

A. No Pre-Processing

The technique we implemented did not use any preprocessing because the tablet used had a sampling rate of 200 samples per second. Therefore it was not essential to smooth or normalize the signature datasets, which were required if we had used the signatures collected from a tablets with low resolution. Re-sampling and resizing was also skipped considering the fact that valuable data is lost while pre-processing the data.

B. Feature Extraction

Among the list of features that can be extracted a total of 26 features were extracted. The features extracted were **standard deviation of x-acceleration, standard deviation of y-acceleration, average pressure, standard deviation of x-velocity, standard deviation of y-velocity, number of pen-up samples, pen down time/total time taken, standard deviation of y / change in y, pen down time, RMS velocity / maximum velocity, average jerk, jerk RMS, maximum sample point x-coordinate, maximum sample point of y-coordinate, zeros of x-velocity, standard deviation of x-coordinates, standard deviation of y-coordinates, total number of samples, time taken, length, zero crossings of x-velocity, zero crossings of y-velocity, zero crossings of x-acceleration, zero crossings of y-acceleration, zeros in x-acceleration, zeros in y-acceleration.**

A pressure sensitive tablet was used that records pressure at every sample taken, providing with a very strong local feature of pressure.

C. Optimization & Experimental Setup

Here is an important discussion that how we opted only 9 features out of those 26 features for our system. As we know that a large number of features have been proposed by researchers for online signature verification [2], [3], [4]. However, a little work has been done in measuring the consistency and discriminative power of these features [5], [6]. On the basis of consistency and discriminative power features can be divided into strong and weak features, where presence of the strong features decreases the FRR while on the other hand presence of some weak features also decreases FRR but increases FAR. Thus there is a need to select the best features set.

The approach we used for classification of strong and weak features is by using difference between mean to standard deviation ratio of each feature from the feature vector and from the forgeries features vector set. Thus the mean/standard-deviation difference of each feature from the template of 100 subjects was taken. The standard deviation of a feature shows how large a deviation from the enrolled template can be tolerated (i.e. large deviated signature could be classified as true for large standard deviation).

$$C = \sqrt{\left(\left(\frac{Mo}{STDo}\right) - \left(\frac{Mf}{STDf}\right)\right)^2} \quad (1)$$

In (1), Mo/STDo is the mean/standard-deviation ratio of the feature of original signatures and Mf/STDf is the mean/standard-deviation ratio of the feature of forgery signature. The features with large value of mean/standard-deviation difference as compared to others were taken as strong features and others as weak features eliminating which results in considerable good results.

A number of original signature's features have a large mean/standard-deviation ratio and of course it will decrease FRR but contrary to it forgery signature's features having a large mean/standard-deviation will decrease FAR. So therefore to obtain best results we took the difference between the original signature and forgery signature.

D. Optimization Results

As computed using (1) nearly 14 features have greater C than other 16 features. As researchers have discussed earlier that too many features may decrease FRR but increase FAR

[7] therefore we have to choose between the best of them. The 14 features with greater C are **standard deviation in y-velocity, total samples, number of zeros in y-acceleration, number of zeros in x-acceleration, zero crossings in x-acceleration, zero crossings in y-acceleration, zero crossings in x-velocity, zero crossings in y-velocity, length, average pressure, total time, number of zeros in y-velocity, number of zeros in x-velocity and pen-down time.**

TABLE I. CALCULATIONS OF EQUATION (1)

Feature	Mo/STDo	Mf/STDf	C
Std Dev y/Δy	-4.8766	-1.9296	2.9
T(pen-down)/T(total)	23.3710	17.6752	5.4
N (pen-ups)	3.8719	0.8551	2.95
Standard Deviation vy	25.2692	13.9054	12.3
Standard Deviation vx	2.8116	1.9122	0.9
N(vy=0)	5.8355	1.2074	4.6
Average v/v(max.)	5.7595	3.3267	2.45
(x1-xmin)/average x	4.5197	2.8109	1.7
Total Samples	15.9329	2.1116	13.79
(x1-xmax)/average x	-7.4158	-8.2712	0.8
N(max. y)	15.9590	17.7610	1.81
Standard Deviation of ay	3.1448	4.0654	0.92
Standard Deviation of ax	1.6747	2.1500	0.48
Number of zeros in ay	7.7817	1.0288	6.78
Number of zeros in ax	8.5880	1.2653	7.30
Zero cross. X-acceleration	9.0654	1.3230	7.68
Zero cross. Y-acceleration	9.6669	1.2263	8.44
Zero cross. X-velocity	12.8354	1.5204	11.31
Zero cross. Y-velocity	13.5760	1.2228	12.35
Length	7.5981	1.7094	5.89
rms jerk	2.6554	1.9491	0.71
average jerk	2.7470	2.4410	0.26
N(max. x)	15.4440	13.6379	1.81
Average Pressure	12.1289	2.2516	9.87
Total Time	15.9329	2.1116	13.82
Number of zeros in vy	8.8355	1.2074	7.63
Number of zeros in vx	8.5746	1.2781	7.30
(y1-ymax)/average y	-3.9525	-3.1871	0.77
(x1-xmin)/average x	8.0218	5.4126	2.62
Pen-down Time	29.7766	2.9390	26.87

Highlighted features are with greater results

Features such as total time, pen-down time and total samples are all time dependent features so therefore for a versatile verification engine we opted total time to be the best among them. Moreover standard deviation of y-velocity is another feature having a greater result but on the standard deviation of x-velocity has a very small difference, therefore this ambiguous result made us step down with these features too.

V. INTELLIGENT ONLINE SIGNATUARE VERIFICATION

The experimental setup and optimization proposed above gave very good results but still as we have discussed earlier that signature and its features are personal traits and they may vary person to person. Thus to make this system efficient and intelligent we made it route person to person. As we had a list of 9 most efficient features, we decided to choose 5 out it but based on subject itself. These 5 features may vary person to person. While recording a template from a subject all these features were stored in the template but at the time of verification we proposed a system in which only 5 features were compared against its template based on the following results.

$$\mathbf{X = C/\ Vx\ \ - STDf} \qquad (2)$$

Where C is the difference between the **mean/standard-deviation** ratio of the feature of original signatures and the **mean/standard-deviation** ratio of the feature of forgery signature from (1) which is already calculated and Vx is current value of the sample and STDf is the standard deviation of the forgery signature already stored. So among the 9 features, only 5 features are opted which have a greater value of X from (2).

A. Comparison

For comparison we need a reference. So for the enrollment process we selected 5 original signatures from each signature extracted the 9 features described above to create a reference template. The template contains the mean, standard deviations and their difference stored in 3 vectors R, S and C respectively. If we want to compare a signature (original or forged) with the template we will first compute the feature vector of that signature and corresponding vector X using (2). Then the greater 5 features depending on the value of X will be stored in a vector T. To compare the signature we will simply opt out those 5 features from R and S and a distance vector D will be computed using Euclidean classifier.

$$\mathbf{D = R - T} \qquad (3)$$

Then the distance vector V will be normalized by dividing each value by the corresponding standard deviation in the vector S to obtain a vector Z whose mean is then computed and finally the computed norm is compared to a pre-defined threshold.

B. Results

Results for FRR, FAR of the template of 5 signatures of 100 subjects were computed with threshold from 4 to 9 for this intelligent online signature verification system and best results were obtained.

TABLE II. CALCULATIONS OF FFR AND FAR (1)

Threshold	FRR	FAR
4	**11.57%**	**0.72%**
5	**11.20%**	**3.92%**
6	**4.53%**	**8.02%**
7	**2.06%**	**13.62%**
8	**1.13%**	**19.89%**
9	**0.66%**	**27.02%**

Results obtained from our implementation are very better than a number of techniques implemented because we used very strong features and an intelligent system to classify them person to person. Anyways more work can be done on this system to make it more efficient by using other classifiers and updating signature over time with tablets with better sampling rates.

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Forensic vs. Computing writing features as seen by Rex, the intuitive document retriever

Vlad Atanasiu

Abstract—The paper reveals the superficial matching between script features as understood by forensic experts and computer scientists and advocates the development of computational instruments tailored to fit the features traditionally used by the forensic community. In particular, and including other areas of graphonomics and the general public, there exists a demand for software for the analysis of intuitive features, think "slant" or "roundness," as opposed to analytical features, like "Fourier transform" or "entropy." Rex, a software with such a capability, is introduced and used to explore the potentialities of this approach for script forensics. An investigation of properties of the script contour orientation, the feature used by Rex, is also presented.

***Index Terms*—script features, contour orientation, computational graphonomics, handwriting forensics,**

I. Introduction

In this paper I wish to discuss the distinction between the typical forensic and computer science writing features (section II), introduce a software that takes into account their specifics (section III) and investigate the behavior of the feature used by the said software (section IV). The overall goal of the paper, beside the immediate benefits derived from the individual topics, is to provide thinking material about the challenges building software adapted to forensic applications.

II. Forensic vs. Computing writing features

Semiotics — That much forensic handwriting expertise is subjective and would profit from mathematics and computing in its quest for objectivity and replicability is publicly admitted [1], but the less advertised side of reality is that of software insisting to treat the users on feasts of mathematics and technology without actually meeting their needs [2]. At the root of this dialogue of the deaf lies, among other interesting factors of the sociology of science, the very words "writing feature." For forensic experts the "feature" is usually intuitively comprehensible, such as "slant" [3], while for computer scientists the most powerful "features" are mathematical concepts, like "Fourier components" or "fractal dimension," which need specialized knowledge for their properties to be understood. Developing measurement software for intuitive features not only gives forensic professionals tools which they know how to handle, but also allows them to communicate about their work — an essential aspect in respect to testimony in court. Intuitive features additionally benefit the design of computer systems, improving the ergonomy of user interfaces as exemplified in section III.

Table I
Divergence in use of writing features across graphonomics areas

intuitive ◄	**Writing features**	► analytical
pen pressure, stroke width, character slant, allographs, line justification, baseline shape, regularity, aesthetic quality...		Fourier components, wavelet coefficients, entropy, fractal dimension, hidden Markov model...
▼ primary use	**Graphonomics areas**	▼ primary use
×	forensics, paleography, typography, art, education, medicine	·
·	writing recognition, digital libraries, biometrics, neurocognitive sciences	×

Cognition — An interesting viewpoint on the debate over intuitive and analytic features is to consider mathematics as an evolutionary outcrop of the neural computing capacities of the brain. Intuition is evolutionary unconscious learning by interaction with the environment to which conscious analysis supplements when novelties arise. Thus the two can be envisioned as a continuum, mathematics progressively becoming intuitive.

Sociology — To think that the divergence of the two feature types is a function of mathematical educational level is overlooking a fundamental distinction. Writer identification and verification are main mobiles of computational handwriting forensics, and because here only results count, it can use any method without even the need of thorough understanding insofar as it is better. This evolutionary mindset of a goal-focused black box approach is faced by the knowledge-oriented crystal ball attitude seen in the traditional graphonomical research, which adds to the control tasks mentioned above a considerable interest in the handwriting ecosystem, i.e. the structures and dynamics of handwriting features across populations and the underlying factors: material, cognitive, biomechanical, sociocultural.

Linguistics — The issues with the term "feature" extend to a further worldview cloaking inconspicuously its users. The proposition "This font is Roman" is considered in philosophy either as an expression on a property owned by the font (objectivism) or attributed to the font by an observer (subjectivism) [4], [5]. The difference is one of lifestyle: the world is there for

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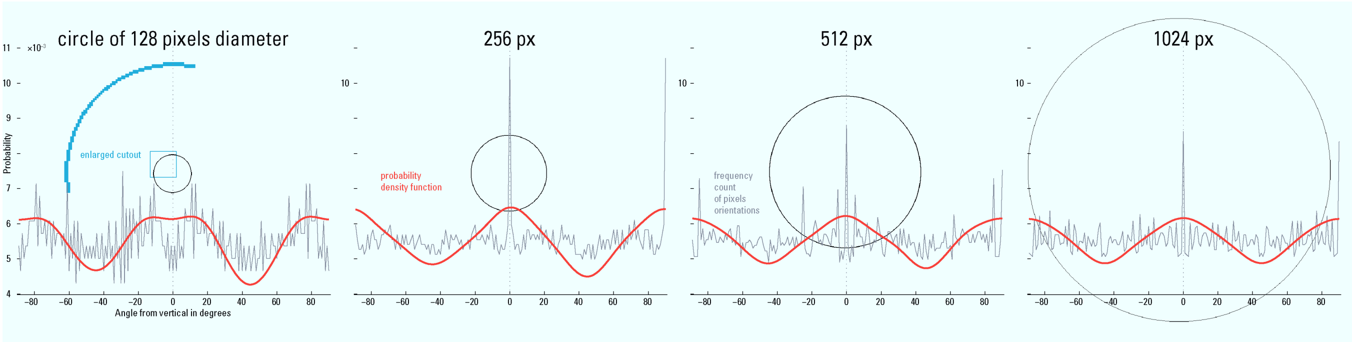

Fig. 1. Contour orientation profiles — Look carefully at the enlargement of the 128 pixels diameter circle and you'll see four horizontal and vertical pixels in a row: a bitmap shape representation has more pixels in these directions than warranted by the ideatic shape. The distortion decreases with object size. The ordinate values reveal that bias is small: its amplitude is ~0.002, while for a typical written document the mean is ~0.025 and the maximum ~0.04 (see Fig. 3 and [16]–[18]).

truth to be discovered or for models to be invented. Translated at lexical level this is what defines the terms "feature" and "descriptor," among their numerous handwriting related synonyms [3]. To this author "descriptor" seems more appropriate since it doesn't presuppose anything about the object (it just is) and it's easier and more fun to be critical about a model than a truth. Incidentally, while "feature" prevails in graphonomics, "descriptor" has a foothold in the wider pattern recognition community, as witnessed in a wording like "shape descriptor."

Implications — Computer scientists have to consider in common intelligence with forensic experts three issues worth mentioning because they bear an influence on how the software presented later in the paper is to be used. The issues are the desired precision of the analysis, the definition of the features and the affordability to analyze them in the current state of the art. I will illustrate this through two visual examples.

Precision — Fig. 1 presents three bitmap circles of various sizes for which the orientation along their contour is measured (details in section III). Being circles, we would expect that all orientations be equally well represented, but due to the discrete nature of the underlying raster in which the shapes live the distribution is biased towards the orthogonal direction — the distribution will peak at 0 and 90 degrees ([6], [7], for hexagonal grids see [8]). Making a model of the distortion and applying it to arbitrary orientation profiles should solve the issue, but it turns out that the distortion is shape specific. For example, a vertical line has no distortion at all, so there is no need for correction. A somewhat better choice is to increase the image resolution at capture time or after, with the drawback of generating voluminous files and knowing that often only low resolution images are available. This digital geometry problem is compounded upstream by the design of discrete Gaussian filters for orientation measurement [9], and downstream by digitization, the same physical document producing at pixel level different shapes depending on its alignment with the digital grid of the imaging system, hence affecting the replicability of results [10], [11]. A number of techniques address these issues [12]–[15] but the implications for handwriting analysis have yet to be fully explored, starting with the question of how much precision is needed for which application. High accuracy graphonomics is therefore an area open to investigation.

Definition — I discuss now the slant of three Roman script characters as perceived by a human and raise the question of how this simple feature should be defined. In the case of **l** the slant is vertical and corresponds to the shape's axis of equilibrium through its center of gravity — here the slant is a physical property of the object. For an **o** there is no way to tell how the character is oriented would the baseline be unknown — slant is here a property of the object relative to the surrounding. The slant of **y** can be considered as upright only if we are able to identify the shape as character "y" and be aware of the convention that this lower case letter has to be considered vertical despite its physical right-leaning — this is a case of semantic slant. A deeper examination might reveal even more criteria. In conclusion, a slant analysis algorithm implementing human expert behavior appears to be more challenging than suspected, given first the very difficulty to define the feature, and secondly due to the mix of perceptual and cultural considerations to model.

Afordability — The last sentence leads to the issue of affordability: do we have the technological means to perform comprehensive slant analysis since we need to recognize unconstrained handwritten characters? This task not being presently solved, a positive answer can be given only if we are happy with a certain degree of imprecision, its exact amount having to be determined. Some of the fine computational forensic expertise that we would wish to attain is thus yet out of reach.

III. Rex, the intuitive document retriever

Rationale — Written documents in databases can be retrieved by appearance by one of the following methods: visual (using a reference document), semantic (describing script features), haptic (by drawing) and exogenous (from document ecosystem metadata). Semantic retrieval is convenient because it is intuitive (it takes place via a graphical and natural-language interface), free of any preexisting model (not always available) and can describe aspects of a script (contrary to the holistic approach of visual retrieval). The software that grew out of these considerations, called Rex, suits the demand for tools supporting forensic specific features as described above (Fig. 2) [16]–[18].

Technicalities — The software measures the local orientation along the writing contour, a popular computational graphonomics feature [19]. This is done by applying on the binary image

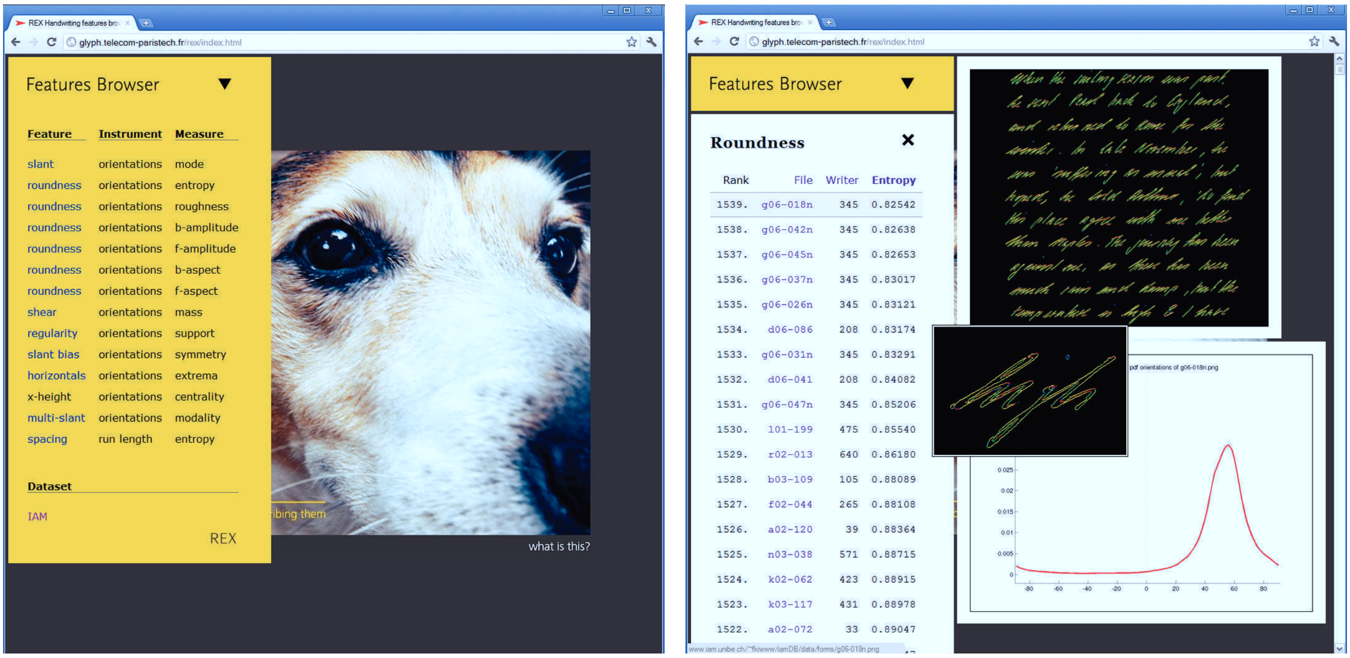

Fig. 2. Rex screenshot — After selecting an intuitive script feature (left picture, showing also the underlying mathematical measurements and instruments), users obtain a list of documents ranked according to the quantitative value of the feature, in this case "roundness" (right picture, giving the file and writer id too). The document and a mouse-over zoom with pixels colorcoded by orientation is presented, as well as the orientation profile and a hyperlink to the original document.

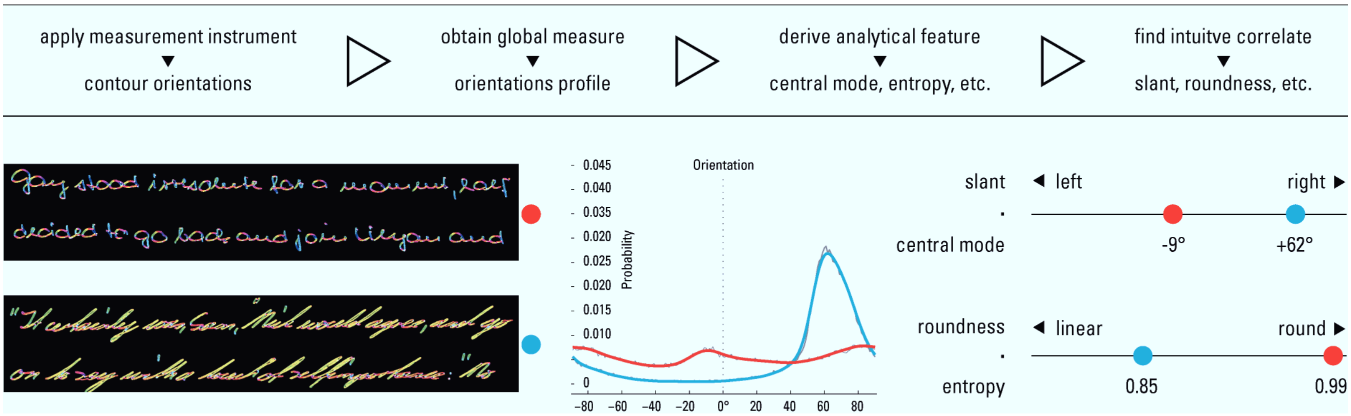

Fig. 3. Pixels to vectors to scalars to concepts — Prospecting for intuitive writing descriptors by extracting various statistical parameters of a global measurement. The colormap of the script samples (P02-081 and L01-199 of [8]) encodes the contour orientation at each pixel location — red for example being horizontal.

of the contour an anisotropic Gaussian filter bank with one degree of radial displacement. At this stage of this well-known approach two innovations are introduced, in addition to the fine grained resolution. First, after deriving the probability density function from the orientations' frequency count, statistical properties of the distribution are obtained. Second, it was discovered that these statistics correlate with various script features of the intuitive type, perceived as distinct one from another, such as "slant," "roundness" or "density" (Fig. 3). To sum up, Rex behaves like a handy, multipurpose Swiss army knife.

Applications — The Swiss reference is not fortuitous, since the handwriting documents presently used by Rex originate in that country (IAM Handwriting Database 3.0 [20]). This shows again the surprising versatility of the tool in that it is not only a document browser, but also a teaching tool about handwriting. In addition to learning about individual documents, Rex provides an insight in the make-up of a population of writers — that of the canton of Bern from where most of the dataset writers hail (Fig. 4). The question that immediately springs to mind — "Do writers from other parts of the world have similar characteristics?" — is typical of the richness of research and pedagogical possibilities opened by such an instrument (indeed, the few Greek, Chinese and other foreigners among the contributors show scriptural characteristics apart form the Swiss majority). If the present usage of Rex is rather limited to a browser of a specific dataset and much development can be imagined, it is nevertheless also an intriguing tool to experiment with as a testbed for other computational forensic applications.

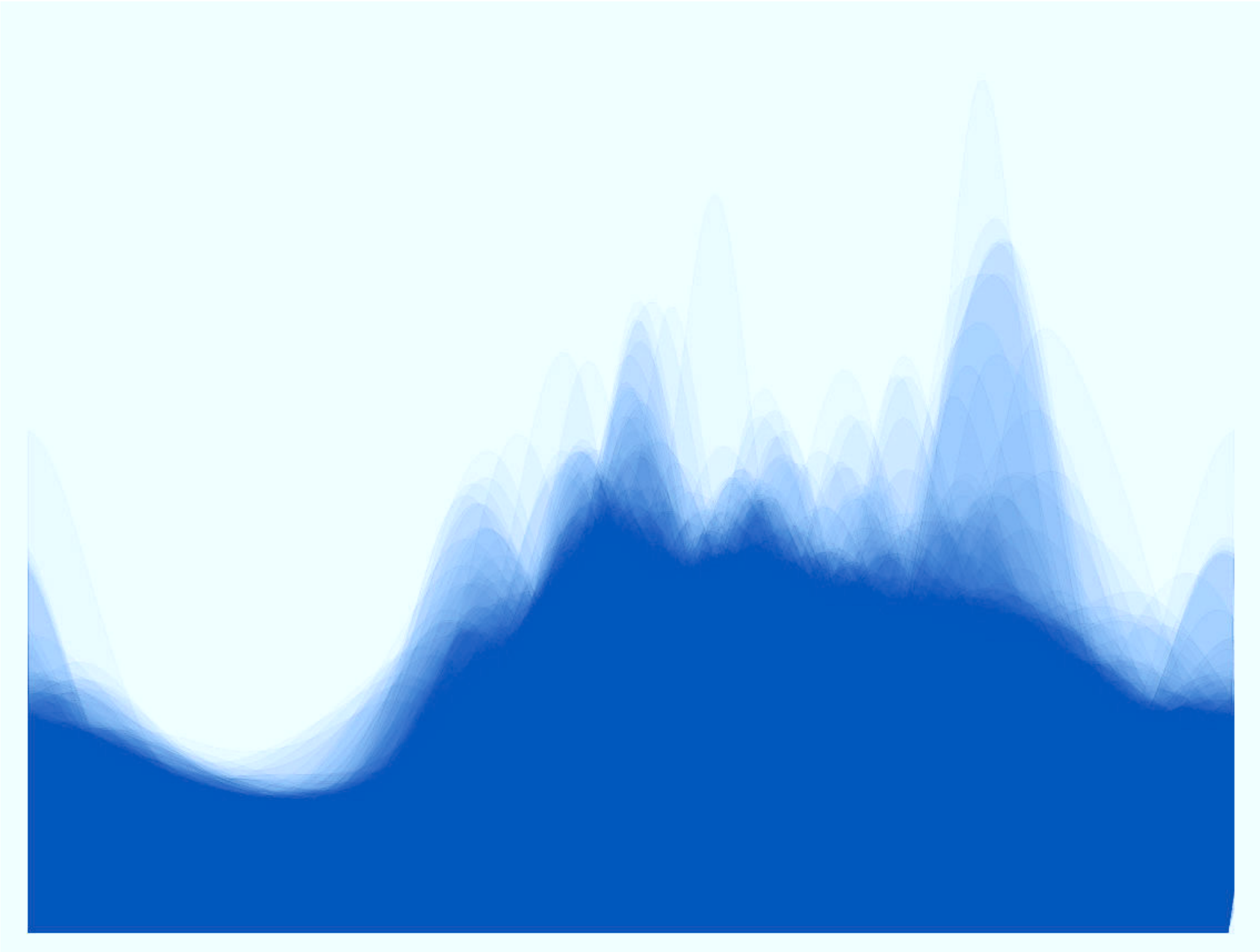

Fig. 4. “1539 Swiss Mountains” — Superpositon of all orientation profiles of the Swiss IAM Offline Database 3.0. We might be aware that few people have a left-slanted handwriting, but this visualization makes the phenomenon visible and measurable: there are few and only small peaks on the left-hand side of the image. It is also apparent that peaks on the right are narrower, hence slanting a handwriting reduces its roundness, making it more linear: a shear transform takes place.

IV. Properties of the orientation feature

While contour orientation is a concept easy enough to grasp, it has a number of less apparent properties with implications for the expertise work. They reveal why studies find orientation not the best performing biometric instrument [19].

Rotation — The feature is evidently not rotation invariant, meaning that the same document will have different measurement profiles depending on, for example, the skew of the paper in a scanner (Fig. 5.1–2). However the difference is only a translation of the profile, thus the bias can be corrected.

Organization — Contour orientation exhibits some unusual cases of shape invariance, all deriving from its low sensitivity to the spatial organization of pixels, due to the fact that, by definition, the measure is done locally. It is thus possible to have perceptually different shapes with the same orientation profile. Fig. 5.5 demonstrates scrambling invariance.

Localization — The various informations that can be read in the global orientation profile can’t be traced to specific locations in the written document. If there is, say slant variation in a particular line, we see it in the profile, but can’t localize the given line and even not know if the variation is concentrated in one line or spread over the entire document.

Convexity — For 180° shape rotations the profiles are identical, leading to shape confusion (Fig. 5.3–4).

Neighborhood — Fig. 5.6 shows that lines and circles in certain configurations can look the same to the orientation instrument: it is unaware about the neighborhood.

Additivity — Shapes contribute linearly to profiles, facilitating combinatorial pattern simulations from primitives.

V. Conclusions

I conclude by reminding that forensic and computational script features are usually not identical, that they need to be thoroughly explored to be safely used, and that public software, like Rex, introduced here, are excellent learning opportunities.

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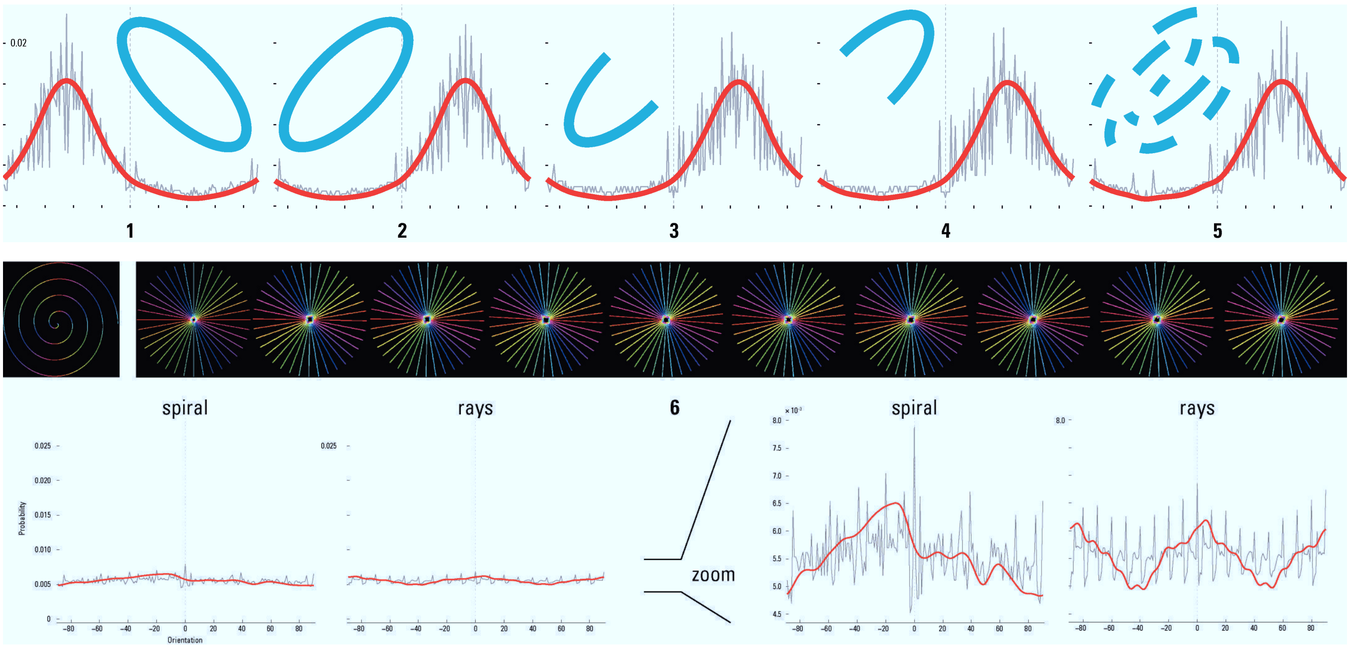

Fig. 5. Cases of confusion — (1, 2) A rotation of shapes (in blue) is equivalent of a translation of the orientation profile (in red). (3, 4) Rotation by 180° or (5) breaking up a shape doesn't affect the orientation profile beyond quantization errors. (6) The bitmaps row shows a spiral and 10 ray bundles, each bundle being rotated by 1° in respect to its neighbor, covering the entire angular sensitivity spectrum of the measurement instrument. Despite the perceptual pattern difference — one linear, the other curly — the orientation profiles are similar, especially when seen at the scale of the writing of Fig. 3 (the differences become visible when zooming in).

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Automated Off-Line Writer Verification Using Short Sentences and Grid Features

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***Abstract*—This work presents a feature extraction method for writer verification based on their handwriting. Motivation for this work comes from the need of enchancing modern eras security applications, mainly focused towards real or near to real time processing, by implementing methods similar to those used in signature verification. In this context, we have employed a full sentence written in two languages with stable and predefined content. The novelty of this paper focuses to the feature extraction algorithm which models the connected pixel distribution along predetermined curvature and line paths of a handwritten image. The efficiency of the proposed method is evaluated with a combination of a first stage similarity score and a continuous SVM output distribution. The experimental benchmarking of the new method along with others, state of the art techniques found in the literature, relies on the ROC curves and the Equal Error Rate estimation. The produced results support a first hand proof of concept that our proposed feature extraction method has a powerful discriminative nature.**

***Index Terms*—Writer Verification, Handwritten Sentences, Grid Features, ROC, EER**

I. Introduction

BIOMETRICS recognition is an appealing method for keeping numerous situations, including defense and economic transactions secured. Thus, access to important resources is granted by reducing potential vulnerability. Among other biometric features, online and offline handwriting, which is a subset of behavioral biometrics, has been frequently used for resolving the problem of recognizing writers either for security or forensic applications [1], [2]. In recent years, writer identification and verification tasks have received considerable attention among the scientific community. A special case of writer verification uses context based handwriting. So, the answer to the question: is this person who he claims to be? shall be provided by examining a predetermined text of known transcription. As stated by Siddiqi and Vincent [3] this kind of writer verification problem is similar to signature verification.

Although content dependent approaches using well defined semantics have been used at the early years of writer recognition there are at least three important reasons that justify the continuous study of handwriting patterns other than signatures. Firstly, biometric verification schemes based on handwritten words or small sentences can be potentialy used to real world security applications which are quickly emerging in a modern and continuous evolving mobile and Internet based environment. Secondly, content based retrieval systems could also benefit since their users could query handwriting images from various corpuses with similar handwriting styles [4]. Finally, an important reason emerges from the field of continuous verification [5]. By this, we mean that we could use the handwritten patterns, to grant access to resources not only to a person's initial entrance, but also within a cyclic and continuously verification loop, throughout the entire use of the application. In order to explore writer verification tasks, we can test a number of algorithms in a number of well established databases in the literature like IAM [6], Firemaker [7], CEDAR [8] and Brazilian Forensic letter database [9]. These databases carry rich handwriting information since they have a large sample size like 156 words and/or paragraphs. The use of these databases might bring around awkward circumstances if issues like those described in the continuous verification schemes need to be raised. This can be easily seen using the following example: Imagine the case that a person has to verify him/her by writing a entire letter in a relative small amount of time. In order to cope with this situation, an alternative idea would be either to use a portion of the afore-mentioned databases or to employ one small sentence content like the one provided by database like the HIFCD1 [10].

In this work, we are presenting a novel feature extraction method for writer verification based on the structured exploitation of the statistical pixel directionality of handwriting. This is achieved by counting, in a probabilistic way, the occurrence of specific pixel transitions along predefined paths within two pre-confined chessboard distances. Then, the handwritten elements described by their strokes, angles and arcs are modelled by fusing, in the feature level, two and three step transitional probabilities. This is an extension of the work proposed in [11] for signature verification.

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A two stage classification scheme based on similarity measures and an SVM has been enabled in the HIFCD1 corpus. The verification efficiency is evaluated by measuring the Equal Error Rate on the ROC curves, which is the point were the probability of misclassifying genuine samples is equal to the probability of misclassifying forgery samples. The EER is evaluated as a function of the word population. This is achieved by plotting the ROC curves each time we append a word for verification.

Finally, in order to benchmark our proposed method, comparisons are provided against recently described, state of the art methodologies for, off-line signature verification pre-processing and feature extraction, as well as writer verification and feature extraction approaches. Within this context, we are providing a feasibility study of the discriminative power of our method. This "feature benchmarking" concept can be justified by the fact that an ideal feature extraction method would make the classifier's job trivial whereas an ideal classifier would not need a feature extractor [12]. Thus, by keeping the classifier stage fixed, feature benchmarking could be rated in a comparative way.

The rest of this work is organized as follows: Section 2 provides the database details and the description of the feature extraction algorithm. Section 3 presents the experimental verification protocol which has been applied. Section 4 presents the comparative evaluation results while section 5 draws the conclusions.

II. Database and Feature Extraction Procedure

A. Database Description and Pre-Processing

In order to provide a confirmation of the proposed method and evaluate our approach, we have employed the HIFCD1 handwritten corpus which has been used formerly in the literature [10]. This corpus is under re-enlistment and enrichment since its initial appearance in 2000. The developed database consists of two different small sentences, one written in Greek and the other one in English. Additionally to the first twenty persons who have been enrolled in the past, another twenty persons have been enrolled later on creating a total temporary set of forty persons. This database is under restructuring in order to increase its size and diversity (e.g. include iris, fingerprints, gait, signatures, face, large scale handwritten text etc.) of biometric samples equivalent to these provided by modern databases like IAM [6] and BioSecure [13]. Each sentence was written by each writer 120 times. Consequently, 9600 sentences were recorded in our database containing a total of 48000 words. Both linguistic forms of the sentences are presented in Fig.1. The Greek language, being our native language, was used in order to maintain constant handwriting characteristics. The Greek sentence is made up of two small words of three letters, two medium length words of seven letters and a lengthy word of eleven letters. Each word has been created in its own cell thus making segmentation procedures trivial. For every word image of the corpus, pre-processing steps are applied in order to provide an enhanced image version with maximized amount of utilized information. The pre-processing stage includes thresholding of the original handwritten image using Otsu's method [14] and thinning in order to provide a one pixel wide handwritten trace, which is considered to be insensitive to pen parameters changes like size, colour and style. Finally, the bounding rectangle of the image is produced. It must be pointed out that we treat the handwritten image as a whole and we do not perform any character segmentation. Next, an alignment is carried out for every bounded image.

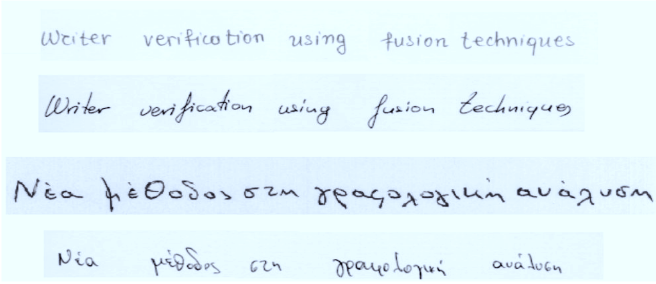

Fig. 1. HIFCD samples

This stage gathers the intrapersonal useful information from all the samples of a writer inside a region that is considered to be the one that contains the most useful handwriting information [9], [11]. In this work, we have used the estimated coordinates of the centre of mass $\overline{x}$ and $\overline{y}$ for each image. Fig. 2 presents in a graphical way the above discussion. In this work the term 'most informative window' (MIW) of the handwritten pattern is presented by considering the processed handwritten word sub-region, inside the bounded image, centred at $\overline{x}$ and $\overline{y}$ parameters while its length and width are determined empirical with trial an error method.

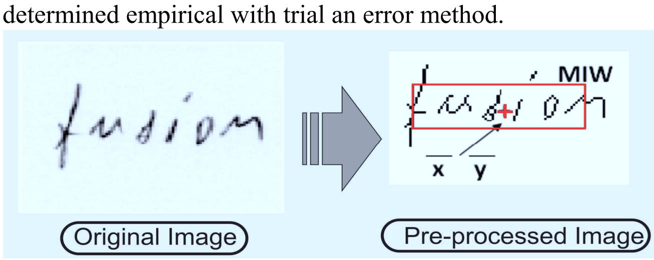

Fig. 2. Original and pre-processed handwritten image with MIW

B. Feature Extraction

The feature extraction method maps the handwriting information, represented by the sequence of MIW words, to a feature vector which models handwriting by estimating the distribution of local features like orientation and curvature. The idea behind this originates from the simplest form of chain code. Analytically, chain code describes an eight set of sequences of two pixels and codes the succession of different orientations on the image grid. When sequences of three successive pixels are examined, line, convex and concave curvature features are generated. Since we do not utilize the features' order of appearance, the corresponding features which can be defined uniquely, beginning from a central pixel to another one, inside a chess-board distance equal to 2 are twenty-two (22). The enforcement of the symmetry condition limits the number of independent convex and concave features to 11. This subset is enriched with the use of four line-features describing the fundamental line segments of slope 0, 45, 90, 135. This 15-dimensional feature space defines the new embedding space. Furthermore we have partitioned the MIW image to a 2×2 sub-window grid, and the respective outputs have been fused in feature level by simple appending.

Following the above idea, we explore an additional feature set by measuring the pixels paths which are obeying the following statement. Find the four pixel connected paths, while restraining the chess-board distance among the first and the fourth pixel equal to three and co instantaneously restraining the chess-board distance among the first and the third pixel equal to two, by ignoring the prior path selection that has taken place in the inner two-step transition. This provides a feature with dimensionality of 28 since we do not partition the image. The final feature vector is generated by appending, in a feature fusion way, the aforementioned two and three step features. Its dimensionality equals to 88 (*four sub-images x 15 features + one image x 28 features*) and it is depicted graphically in Fig. 3. Algorithmically, a rectangular grid of 4 × 7 dimension scans every input of MIW words sequence. This mask aligns each aforementioned pixel with the {5, 3} coordinate, thus enabling 15 potential 2-step paths and 28 3-step paths from the central pixel according to the previous discussion. Then, the paths which are included in the feature set are marked and a counter updates the corresponding features found. Finally, the feature components are normalized by their total sum in order to provide a probabilistic expression.

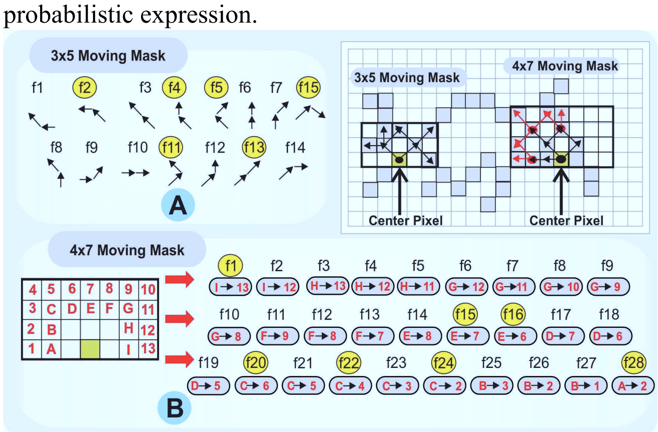

Fig. 3. Feature extraction methodology. Example with activated feature components (represented in yellow circles). a) Basic feature generating mask within chessboard distance of two. b) The feature mask within chessboard distance of three, irrespective of the inner, two-step path.

III. Classification Protocol

As described in section II, the input to the classification system are the training and testing feature vectors denoted hereafter as $\{v_{Tw}, v_{TSw}\}$. The training set v_{Tw} is composed of the genuine and forgery vectors $\{G_{TW}, F_{TW}\}$ of each writer W_i, $i = 1,2,...,40$. The G_{TW} vectors are modeling the genuine class population by means of their average value $\bar{\mu}_{v_{GTW}}$ and standard deviation $\hat{\sigma}_{v_{GTW}}$. Next, the similarity scores of the genuine training vectors are evaluated by using the weighted distance as eq. (1) provides [12] and their pdf $S\left(v_{G_{TW}} \mid W_i\right)$ is stored. A similar procedure, described by eq. (2), has been applied in order to derive the distribution of the similarity scores $S\left(v_{F_{TW}} \mid W_i\right)$ for the case of the false train samples $\{F_W\}$.

$$S\left(v_{G_{TW}} \mid W_i\right) = \left(\sum_{j=1}^{88} \hat{\sigma}(j)^{-2}_{v_{GTW}} \left(G(j)_{TW} - \bar{\mu}(j)_{v_{GTW}}\right)^2\right)^{-0.5} \qquad (1)$$

$$S\left(v_{F_{TW}} \mid W_i\right) = \left(\sum_{j=1}^{88} \hat{\sigma}(j)^{-2}_{v_{FTW}} \left(F(j)_{TW} - \bar{\mu}(j)_{v_{FTW}}\right)^2\right)^{-0.5} \qquad (2)$$

Following the first stage, a two-class support vector machine is employed in order to provide a mapping of the training similarity scores to another distance space, induced by the SVM. Accordingly, inputs to the second stage are the genuine and impostor distribution scores $S\left(v_{G_{TW}} \mid W_i\right)$, $S\left(v_{F_{TW}} \mid W_i\right)$. The output of the SVM is a continuous-valued distance of the optimal separating hyper-plane from the unknown test input sample vector [24]. The mapping function has been represented by a Gaussian Radial Base kernel function after a number of trials.

The testing phase uses the remaining samples of the genuine and forgery sets $\{v_{TSw}\} = \{G_{TSW}, F_{TSW}\}$. Thus, for each writer, the similarity scores, evaluated from the samples of the testing set, are presented as an input to the second stage SVM mapping function. A negative value from the SVM output indicates that the unknown feature vector is below the optimal separating hyper plane and near the hyper-plane which corresponds to the genuine class. On the other, a positive value denotes that the unknown input vector tends to fall towards the impostor hyper-plane class [15]. Finally, the continuous SVM output models both the overall distribution of the genuine writers along with the impostor ones. The selection of the training samples for the genuine class is accomplished using random samples with the hold-out validation method.

Evaluation of the verification efficiency of the system is accomplished with the use of a global threshold on the overall SVM output distribution. This is achieved by providing the system's False Acceptance Rate (FAR: samples not belonging to genuine writers, yet assigned to them) and the False Rejection Rate (FRR: samples belonging to genuine writers, yet not classified) functions. With these two rates, the receiver operator characteristics (ROC) are drawn by means of their FAR / FRR plot. Then, classification performance is measured with the utilization of the system Equal Error Rate (EER: the point which FAR equals FRR).

IV. Results

A. *Benchmarking With Relative Feature Algorithms*

We have benchmarked the proposed methodology against three other feature extraction methods for signature verification and writer identification, which can be found in the literature. The first is a signature verification texture based approach, which is provided by Vargas, Ferrer, Travieso and Alonso [16]. Secondly, we are examining the performance of a shape descriptor proposed by Aguilar, Hermira, Marquez and Garcia, which is based on the use of predetermined shape masks [17]. In all cases, the pre-processing as well as the feature extraction steps have been realized according to the description described by the authors. The third method uses the *f1* contour direction pdf features and the *f2* contour hinge features which are a part of the work proposed by Bulaku and Schomaker [18]. It is of great interest that the *f2* feature is one of the most powerful descriptors for modelling the handwriting. It must be noted that, an appropriate pre-processing step has been carried out in order to provide the contours of the handwritten images.

B. Verification Results

According to the material exposed in section III, representation of the genuine class has been realized with various schemes by utilizing 5, 10, 15, 20, 25, *30* samples for the $\{G_{TW}\}$ training and 115, 110, 105, 100, 95 and *90* samples for the $\{G_{TSW}\}$ testing. On the other, the $\{F_{TW}\}$ training set for the forgery class has been formed using one sample of all the remaining writers which results to a number of 39 samples. The $\{F_{TSW}\}$ samples are formed by employing the remaining $119\left(samples/writer\right)\times 39\ writers$, resulting to a total number of 4641. The ROC curves, which are drawn as a function of the number of words and presented to figs, 4-8, illustrate the classification efficiency of our method against to those mentioned to the previous section. These curves have been evaluated for the last training scheme, i.e 30 and 90 training samples for $\{G_{TW}\}$ and $\{G_{TW}\}$ population. Similar results regarding the evaluation taxonomy have been obtained.

Commenting on the results, it can be easily inferred that our method provides a challenging, first hand proof of concept of its enhanced writer verification capabilities. Another interesting issue is that the verification efficiency is enhanced when the number of the inserted words to the feature stage increases, which is intuitively correct. An Additional comment is that the English sentence provides a boosted EER when compared to the Greek sentence, even though Greek is our native language. This might be due to the fact that the text used in the English sentence incorporates lengthier words when compared to the Greek one. Another standpoint for the enhanced Latin EER measure could be that when Greeks or individuals which are not having English as their native language are forced to write in Latin, their response provides less spontaneous handwritten samples. This may have introduced less writer specificity in the data which in its turn provides higher verification rates. Although the results are quite encouraging however; they must be further tested in larger databases and under a number of different feature and classifications schemes. The best EER rates corresponding to figures 4-8 are presented in tabular form in table 1.

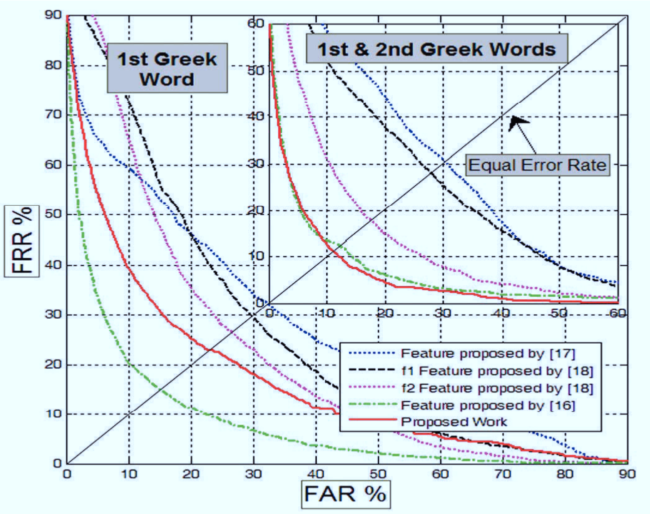

Fig. 4. ROC curves and EER of the proposed and the competitive methods. The lower left part presents the results from one Greek word while the upper right uses a sequence of the first and second words.

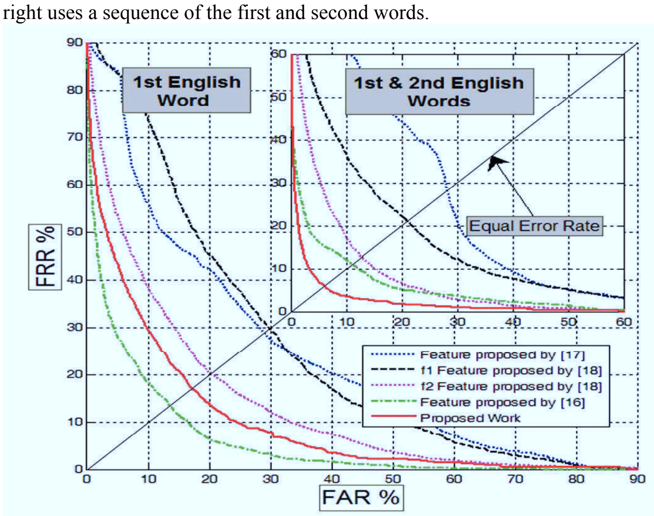

Fig. 5. ROC curves and EER of the proposed and the competitive methods. The lower left part presents the results from one English word while the upper right uses a sequence of the first and second Enlish words.

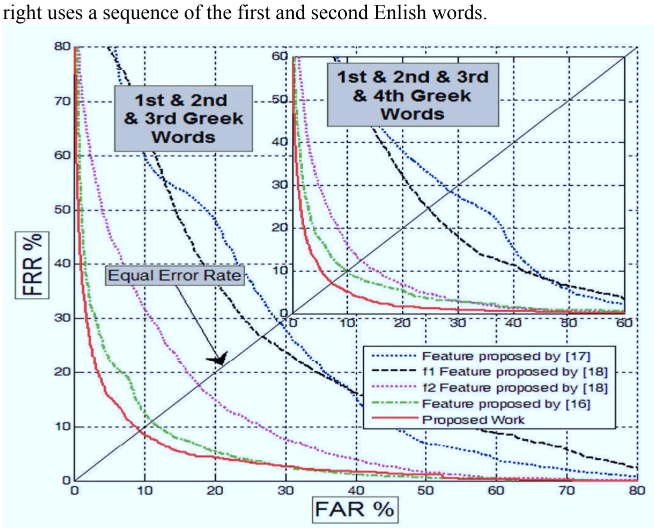

Fig. 6. ROC curves and EER of the proposed and the competitive methods. The lower left part presents the results by employing a sequence of the first three words of the Greek sentence while the upper right uses a sequence of the first four Greek words.

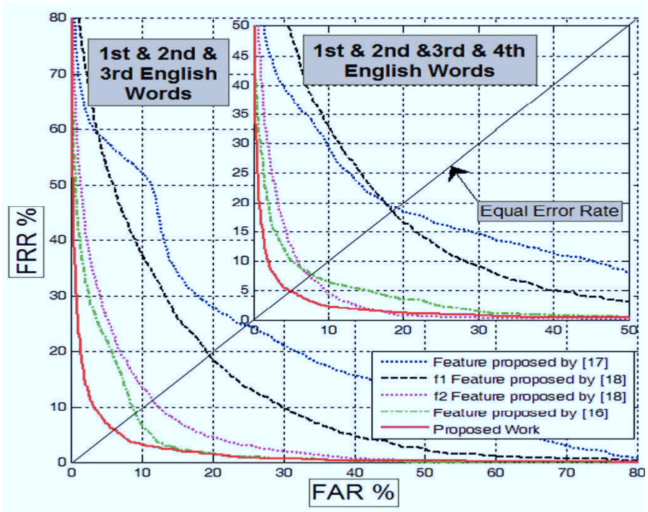

Fig. 7. ROC curves and EER of the proposed and the competitive methods. The lower left part presents the results by employing a sequence of the first three words of the English sentence while the upper right uses a sequence of the first four English words.

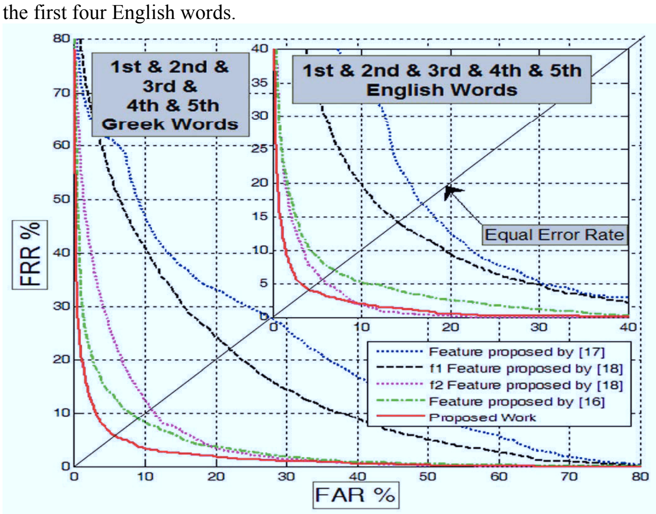

Fig. 8. ROC curves and EER of the proposed and the competitive methods. The lower left part presents the results by employing a sequence of the five words of the Greek sentence while the upper right uses a sequence of the five words of the English sentence.

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TABLE I
CLASSIFICATION EFFICIENCY (%) BASED ON THE EQUAL ERROR RATE DERIVED FROM FIGS. 4-8

Feature Extraction Method	Sequences of Words (1^{st} / {1^{st} & 2^{nd} } / {1^{st}& 2^{nd}&3^{rd}} / {1^{st}& 2^{nd}&3^{rd}&4^{th}} / {all}	
	English Sentence	Greek Sentence
Proposed work	15.53 / 6.05 / 5.92 / 4.90 / 4.08	22.78 / 11.13 / 9.21 / 7.14 / 5.71
Feature proposed by [16]	13.54 / 11.10 / 9.08 / 7.69 / 6.92	15.04 / 12.29 / 10.99 / 9.76 / 8.96
f1 Feature proposed by [18]	29.81 / 21.06 / 19.46 / 18.41 / 14.12	29.78 / 28.08 / 26.49 / 23.85 / 21.98
f2 Feature proposed by [18]	20.22 / 12.72 / 11.36 / 7.48 / 5.58	26.55 / 17.72 / 17.57 / 12.41 / 10.82
Feature proposed by [17]	28.95 / 28.19 / 24.64 / 19.07 / 16.90	32.30 / 30.44 / 29.18 / 28.47 / 27.63

Evaluation of Local and Global Features for Offline Signature Verification

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***Abstract*—In this paper we evaluate the impact of two state-of-the-art offline signature verification systems which are based on local and global features, respectively. It is important to take into account the real world needs of Forensic Handwriting Examiners (FHEs). In forensic scenarios, the FHEs have to make decisions not only about forged and genuine signatures but also about disguised signatures, i.e., signatures where the authentic author deliberately tries to hide his/her identity with the purpose of denial at a later stage. The disguised signatures play an important role in real forensic cases but are usually neglected in recent literaure. This is the novelty of our study and the topic of this paper, i.e., investigating the performance of automated systems on disguised signatures. Two robust offline signature verification systems are slightly improved and evaluated on publicly available data sets from previous signature verification competitions. The ICDAR 2009 offline signature verification competition dataset and the ICFHR 2010 4NSigComp signatures dataset. In our experiments we observed that global features are capable of providing good results if only a detection of genuine and forged signatures is needed. Local features, however, are much better suited to solve the forensic signature verification cases when disguised signatures are also involved. Noteworthy, the system based on local features could outperform all other participants at the ICFHR 4NSigComp 2010.**

***Keywords*-signature verification, mixture models, forgeries, disguised signatures, forensic handwriting analysis**

I. Introduction

Signature verification is in focus of research for decades. Traditionally, automated signature verification is divided into two broad categories, online and offline signature verification, depending on the mode of the handwritten input. If both the spatial as well as temporal information regarding signatures are available to the systems, verification is performed on online data. In the case where temporal information is not available and the systems must utilize only the spatial information gleaned through scanned or even camera captured documents, verification is performed on offline data [1], [2], [3].

The main motivation of this paper is to study the forensic relevance of signature features and their influence on verification. Until now online signature verification is not a common type of criminal casework for a forensic expert because the questioned signatures and the collected reference signatures (known) are commonly supplied offline [4]. Therefore, we focused explicitly on the offline signature verification.

In many recent works signature verification has been considered as a two-class pattern classification problem [1]. Here an automated system has to decide whether or not a given signature belongs to a referenced authentic author. If the system could not find enough evidence of a forgery from the questioned signature feature vector, it simply considers the signature as genuine belonging to the referenced authentic author, otherwise it declares the signature as forged. However, when talk about the forensic aspect, there is another equally important class of signatures that also needs to be identified, i.e., the disguised signatures.

A disguised signature is a signature that is originally written by the authentic reference author. However, it differs from the genuine signatures in the authors intent when it was written. A genuine signature is written by an author with the intention of being positively identified by some automated system or by an FHE. A disguised signature, on the other hand, is written by the genuine author with the intension of denial, that he/she has written that particular signature, later. The purpose of making such disguised signatures can be hundreds, e.g., a person trying to withdraw money from his/her own bank account via offline signatures on bank check and trying to deny the signatures after some time, or even making a false copy of his/her will etc. Potentially whatever the reason is, disguised signatures appear in real world and FHEs have to face them.

The category of disguised signatures has been addressed during the ICFHR 4NsigComp 2010 [5]. This was the first attempt to include disguised signatures into a signature verification competition. The systems had to decide whether the author wrote a signature in a natural way, with an intension of a disguise, or whether it has been forged by another writer.

In this paper we investigate two methods on two benchmark data sets. The first method is based on global features, i.e., a fixed number of features is extracted from signature images. In contrast, the second method uses a local approach, i.e., the number of features might vary - depending on the size of the signature. The two datasets are taken from previous signature verification competitions, i.e., the SigComp09 data set from the ICDAR 2009 [6] and the 4NSigComp10 data set from the ICFHR 2010 [5].

The rest of this paper is organized as follows. Section II summarizes the two datasets used for this study. Section III describes the two robust offline signature verification systems we applied. Section IV reports on the experimental results and provides a comparative analysis of the results. Section V concludes the paper and gives some ideas for our future work.

II. Data sets

A. ICDAR 2009 Signature Verification Competition

The first data set is the training set of the SigComp09 competition [6]. This dataset contains $1,898$ signature samples in all. There are 12 genuine authors – each one of whom wrote 5 of his/her genuine signatures, thereby yielding 60 genuine signatures. 31 forgers were had to forge the genuine signatures. Each forger contributed 5 forgeries for one writer resulting in 155 forged signatures per writer.[1]. Note that this dataset had no disguised signatures.

It is important to note that the said data were collected at a forensic institute where real forensic casework is performed. During dataset generation a special focus was given to the provision of more and more skilled forgeries since automated systems performance could vary significantly with how the forgeries were produced [4].

B. ICFHR 2010 Signature Verification Competition

These signatures were originally collected for evaluating the knowledge of FHEs under supervision of Bryan Found and Doug Rogers in the years 2002 and 2006, respectively. The images were scanned at 600dpi resolution and cropped at the Netherlands Forensic Institute.

The signature collection we used in our evaluation is the original test set of the ICFHR competition. It contains 125 signatures for one reference author. Out of this collection, 25 were the genuine signatures of reference author and remaining 100 were the questioned signatures. These 100 questioned signatures comprised 3 genuine signatures; 90 simulated signatures (written by 34 forgers freehand copying the signature characteristics of the referenced author after training); and 7 disguised signatures written by the reference author himself/herself with the intention of disguise. Note the huge difference between authentic data (3 genuine + 7 disguised signatures) vs. simulations (90 signatures). This did not affect our evaluation since we used the Equal Error Rate (EER) and relied on the Receiver Operating Characteristic curves (ROC-curves).

[1]22 of these forged signatures were not available so they have been ignored (this results in 1,838 forged signatures in all instead of 1860)

III. Automated signature Verification Systems

In this section we provide a short description of two state of the art offline signature verification systems we used in this study.

A. Local Features combined with GMM

This system was originally designed by the authors of this paper. A prior version of this system participated already in the ICDAR 2009 signature verification competition and achieved good results. It was not considered for participation during the 4NSigComp 2010 since the authors of this papers were among the organizers of this event. Our system uses Gaussian Mixture Models (GMMs) for the classification of the feature vector sequences. For the purpose of completeness, a short presentation of the system will be given here. For more details refer to [7].

Given a scanned image as an input, first of all binarization is performed. Second, the image is normalized with respect to skew, writing width and baseline location. Normalization of the baseline location means that the body of the text line (the part which is located between the upper and the lower baselines), the ascender part (located above the upper baseline), and the descender part (below the lower baseline) is vertically scaled to a predefined size each. Writing width normalization is performed by a horizontal scaling operation, and its purpose is to scale the characters so that they have a predefined average width.

To extract the feature vectors from the normalized images, a sliding window approach is used. The width of the window is generally one pixel and nine geometrical features are computed at each window position. Thus an input text line is converted into a sequence of feature vectors in a 9-dimensional feature space. The nine features correspond to the following geometric quantities. The first three features are concerned with the overall distribution of the pixels in the sliding window. These are the average gray value of the pixels in the window, the center of gravity, and the second order moment in vertical direction. In addition to these global features, six local features describing specific points in the sliding window are used. These include the locations of the uppermost and lowermost black pixel and their positions and gradients, determined by using the neighboring windows. Feature number seven is the black to white transitions present within the entire window. Feature number eight is the number of black-white transitions between the uppermost and the lowermost pixel in an image column. Finally, the proportion of black pixels to the number of pixels between uppermost and lowermost pixels is used. For a detailed description of the features see [8].

Gaussian Mixture Models [9] have been used to model the handwriting of each person. More specifically, the distribution of feature vectors extracted from a persons handwriting is modeled by a Gaussian mixture density. For a D-dimensional feature vector denoted as x, the mixture density for a given writer (with the corresponding model A) is defined as:

$$p(x\|A) = \sum_{i=1}^{m} w_i p_i(x)$$

In other words, the density is a weighted linear combination of M uni-modal Gaussian densities, $p_i(x)$, each parameterized by a $D \times 1$ mean vector, and D*D covariance matrix. For further details refer to [10].

B. Global Features combined with kNN

Our system is based on the methods introduced in [11]. However, we have modified/optimized it in order to fit in the scenarios presented in the datasets of the two mentioned signature verification competitions. A short summary of the system is given here, for further details consult [11].

First, the signature image is spatially smoothed followed by binarization. In the optimized version of this approach we used various combinations of local and global binarization techniques. After these preprocessing steps following operations were performed.

- Locating the signature image through its bounding box
- Centralizing the signature image to its center of gravity.
- Partitioning the image horizontally and vertically starting at center of gravity until it is divided into 64 cells.
- Finding the size of each cell of the image and normalizing it with the total number of black pixels it has. This constitutes the first feature vector.
- Calculating the angle that is made by the center point of each cell of the image with its lower right corner to obtain the second feature vector.
- Obtaining a third feature vector by calculating the angle of inclination of each black pixel in a cell to the lower right corner of its corresponding part of the image.

Note that the approach divides the signature into 64 small parts, which can be seen as a local feature extraction technique. However, since this division is based on a global analysis and the number of extracted features is fixed, disregarding the length of the signature, this approach is considered as a global approach. Therefore note that a simple disguise attempt would be to add a random character at the end of the signature and the global approach would fail while the local feature extraction would still find many similarities.

After computing these feature vectors, thresholds are computed using means and variances. Following that, nearest neighbor approach is applied to decide on the result of each feature vector and finally a voting based classification is made. In the optimized version different voting strategies have been applied that improved the overall performance.

IV. Evaluation

For reporting the results we primarily use the ROC-curves according to the evaluation procedure of the ICFHR 4NSigComp 2010. ROC-curves are a standard procedure of assessing the performance of signature verification systems. They are especially suited if there are unequal numbers of forged and genuine signatures in the dataset as in the case of both the ICDAR 2009 and ICFHR 2010 datasets. Results depict that, if only accuracy is used to evaluate signature verification systems, a system that votes by chance may show higher accuracy that in fact is false in context of a biometric system.

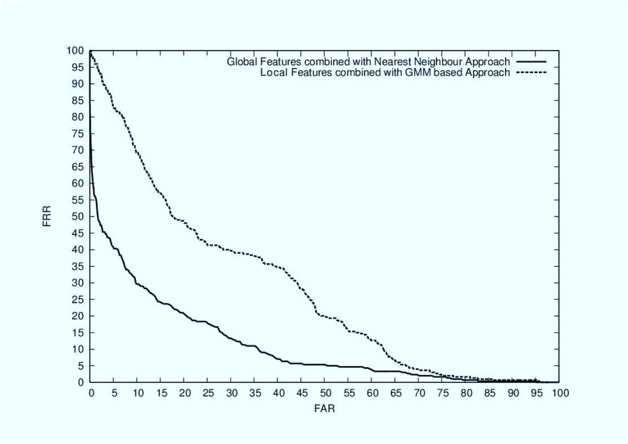

Figure 1: ROC on the ICDAR 2009 data

On the ICDAR 2009 dataset we performed 5-fold cross validation for each of the systems and generated ROC-curves. Furthermore, we evaluated both the systems on the ICFHR 2010 dataset again using the ROC-curves. The details of these evaluations are presented in the following sections.

A. Results on the ICDAR 2009 Dataset

We did 5-fold cross validation in the same way as in [6] and [7], i.e., for each genuine author we used only four of his/her genuine signatures to train and then tested the classifiers. The training set was rotated 5 times.

Figure 1 shows the results of both the systems on the ICDAR 2009 data set. It depicts the average results on all signatures by all writers. As shown in Fig. 1 the global features based system outperforms the local features based system. The Equal Error Rate (EER) for the global features based system is as low as 20 % whereas for the local features based system it is nearly 36 %. Note that the local features based system also participated in the ICDAR SigComp 2009. On the test data it provided an EER of 16 % [6] and was among the best classifiers. Since the test set is not publicly available, therefore we evaluated our system on the training data.

B. Results on the ICFHR 2010 Dataset

We evaluated both of the systems described in Section III according to the scenario posed by the ICFHR 4NSigComp 2010.There, the systems had to present their opinion by

Table I: Interpretation of the output

Decision Value (D)	Probability $P > t$	$P < t$	$P = t$
1	authentic	misleading	inconcl.
2	disguise	simulation	inconcl.
3	inconcl.	inconcl.	inconcl.

Table II: Assessment of the output

True Answer	Probability $P > t$	$P < t$	$P = t$
authentic	correct	incorr.	incorr./ignored
disguise	correct	incorr.	incorr./ignored
simulation	incorr.	correct	incorr./ignored

means of the following two output values for each of the questioned signatures.

- A Probability Value P between 0 and 1.
- A Decision Value D that could be either 1, 2 or 3.

The Probability Value P was compared to a predefined threshold t. A higher value ($P > t$) indicated that the questioned signature was most likely a genuine one. A lower value ($P \leq t$) indicated that the questioned signature was not genuine, meaning that it was not written by the reference author. A probability value of ($P = t$) was considered as inconclusive. The decision value D represents the system's decision about the process by which the questioned signature was most likely generated. A decision value of 1 means that the underlying writing is natural: there is no or not enough evidence of any simulation or disguise attempt and the signature is written by the reference author. The decision value 2 represents that the underlying writing process is unnatural: there is evidence of either a simulation or disguise attempt. Finally, a decision value 3 shows that the system is unable to decide if the underlying writing process is natural or unnatural: no decision could be made whether the signature is genuine, simulated, or disguised.

The output reference showing the various output possibilities is provided as Table I. Here a value of P greater than t with output 1 means correct genuine authorship, with output 2, on the other hand, means that the author has made an attempt to disguise her/his identity. If the Decision Value is 3, then with any value of probability it is simply inconclusive. Any value of P less than t with decision value 2 indicates that the questioned signature is a result of a simulation or disguise process. The final assessment of the output values is given in Table II.

As mentioned already, the novel feature of this dataset is the inclusion of disguised signatures. Various state-of-the-art systems participated in the competition and aimed at correctly classifying these disguised signatures. All of these systems failed to correctly detect the disguised signatures. The EER of the best system was larger than 50 %. More details of these results are provided in [5]. When these systems were evaluated without considering the disguised

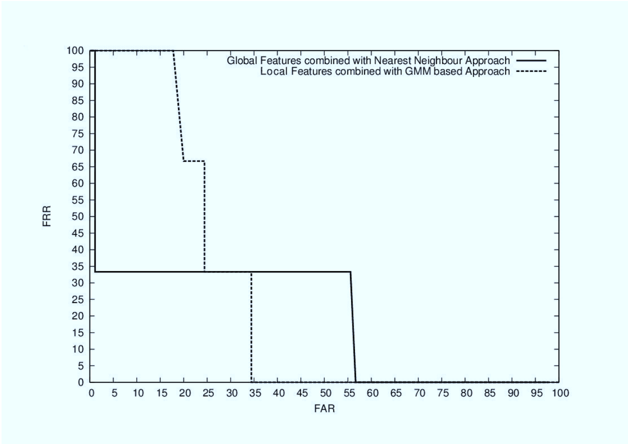

Figure 2: ICFHR 2010 results without disguised signatures

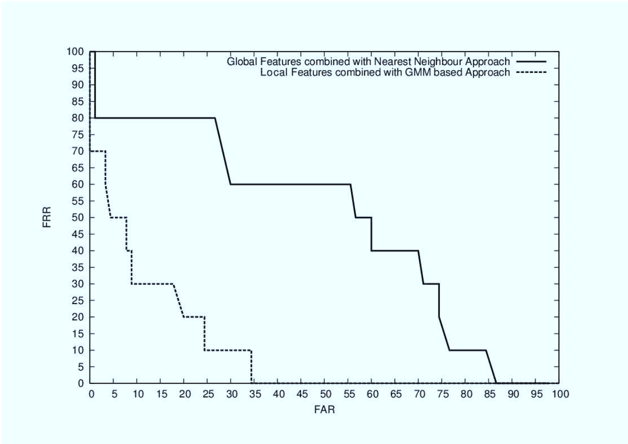

Figure 3: ICFHR 2010 results with disguised signatures

signatures the results of one participant were nearly perfect. In order to make our systems' performance comparable to those from the ICDAR competition, we present our results in the same manner, i.e., first without considering the disguised signatures and then taking the disguised signatures into account as well.

Figure 2 shows the results when we disregard the disguised signatures and consider only the case of forged vs. genuine signatures. The EER of both systems is the same. However, when considering the area under the curve, the local feature based system is slightly better.

The most important aspect of our study is the investigation of the influence of disguised signatures. The results are depicted in Figure 3. As shown, the local features based GMM system performs significantly better than the global features based system. It has an EER of 20% whereas the global feature based system has an EER of nearly 56%. Our point here is that, our GMM classifier performed well because it was relying exclusively on local features. To consolidate our thinking we also performed experimentation with the GMM classifier by feeding it with the global features (the same global features that are used by our NN Classifier). The results were worse in this case. The accuracy went below 50% and the EER was above 70%. Actually the nature of global features is to have a fixed amount of features while local features are not fixed. As such our GMM based system also outperforms all the participants of ICFHR 4NsigComp 2010 in this scenario as well. An important point to mention here is that our GMM based system was not even optimized to work with disguised signatures explicitly. In contrast, it was initially developed as a general-purpose offline writer identification system. We strongly believe that this better performance of our system is attributed to the fact that it relies on the local features.

V. Conclusion and Future Work

In this paper we have reported on the experiments conducted to evaluate the impact of local and global features on automated signature verification for off-line signatures collected by the FHEs. Two state of the art offline signature verification systems were applied on the datasets of the last two signature verification competitions.

Our experimental results show that the global features could produce acceptable results when the traditional paradigm of forged vs. genuine authorship is under consideration. The actual power of local features is revealed when considering the more realistic scenario which involves the presence of disguised signatures among the questioned signatures. This has been shown by using the equal error rates achieved by a GMM based offline signature verification system that heavily relies on the local features of offline signature samples. We strongly believe that the main reason for the good performance of this system is due to the difference that this system is relying on local features.

In future we plan to investigate more local features approaches for signature verification. Using novel image analysis methods like scale-invariant Speeded Up Robust Features (SURF) [12] might be an interesting idea as well. We also plan to combine various offline signature verification systems based on different global and local features through voting strategies to produce even better results.

Furthermore, we plan to perform analyses on data which contains signatures from more reference writers and skilled forgers. Regarding genuine signatures, large and diverse test sets where signatures are produced by different authors under various different psychological and physical conditions may also yield interesting results.

Acknowledgment

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Static Signature Verification by Optical Flow Analysis

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***Abstract*—This paper presents a new approach for static signature verification based on optical flow. In the first part of the paper, optical flow is used for estimating local stability of static signatures. In the second part, signature verification is performed by the analysis of optical flow, using an alternating decision tree. The experimental tests, carried out on signature of the GPDS database, demonstrate the validity of this approach and highlight some direction for further research.**

***Index Terms*—Static Signature Verification, Local Stability, Optical Flow.**

I. Introduction

HANDWRITTEN signatures occupy a very special place in biometrics. Unlike other biometric traits, handwritten signatures have long been established as the most widespread means of personal verification. Signatures are generally recognized as a legal means of verifying an individual's identity by administrative and financial institutions. Moreover, verification by signature analysis requires no invasive measurements and people are familiar with the use of signatures in their daily life [1, 2, 3].

Unfortunately, a handwritten signature is the result of a complex generation process. The rapid writing movement underlying signing is determined by a motor program stored into the brain of the signer and realized though his/her writing system (arm, hand, etc.) and writing devices (paper, pen, etc.). Therefore, a signature image strongly depends on the psychophysical state of the signer and the conditions under which the signature apposition process occurs [4, 5].

The net result is that signature variability is one of the most relevant issues that must be faced to develop accurate signature verification systems. In general, two types of variability can be distinguished in signing: short-term variability and long-term variability. Short-term modifications depend on the psychological condition of the writer and on the writing conditions. Long-term modifications depend on the alteration of the physical writing system of the signer (arm and hand, etc.) as well as on the modification of the motor program in his/her brain [5, 6]

In literature, the approaches proposed for the analysis of local stability are mainly devoted to dynamic signatures. A local stability function can be obtained by using DTW to match a genuine signature against other authentic specimens. Each matching is used to identify the Direct Matching Points (DMPs), that are unambiguously matched points of the genuine signature. Thus, a DMP can indicate the presence of a small stable region of the signature, since no significant distortion has been locally detected. The local stability of a point of a signature is determined as the average number of time it is a DMP, when the signature is matched against other genuine signatures. Following this procedure low- and high-stability regions are identified [7, 8, 9] in the selection of reference signatures [10, 11] and verification strategies [12, 13].

A client-entropy measure has been also proposed to group and characterize signatures in categories that can be related to signature variability and complexity. The measure, that is based on local density estimation by a HMM, can be used to access whether a signature contains or not enough information to be successfully processed by any verification system [14, 15, 16].

Other types of approaches estimate the stability of a set of common features and the physical characteristics of signatures which they are most related to, in order to obtain global information on signature repeatability which can be used to improve the verification systems [17, 18]. In general, these approaches have shown that there is a set of features that remain stable over long time periods, while there are other features which change significantly in time [19, 20]. Of course, since intersession variability is one of the most important causes of the deterioration of verification performances, specific parameter-updating approaches have been considered [18, 19, 20].

Concerning static signatures, a multiple pattern-matching strategy has been recently proposed to determine - at local level - the degree of stability of each region of a signature [21, 22, 23]. In this paper the optical flow is used to estimate the local stability of the signature images. In addition, the optical flow is also considered for signature verification, using an alternate decision tree classifier. The experimental results, carried out on signatures of the GPDS database, demonstrate the validity of the approach with respect to other techniques in literature.

II. Static Signature Analysis by Optical Flow

Two categories of signature verification systems can be

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identified, depending on the data acquisition method [1]: static (off-line) systems and dynamic (on-line) systems. Static systems perform data acquisition after the writing process has been completed. In this case, the signature is represented as a grey level image I(x,y), where I(x,y) denotes the grey level at the position (x,y) of the image. The results is that static systems involve the treatment of the spatio-luminance representation of a signature image. Therefore, no dynamic information is available on the signing process when static signatures are considered [1, 2]. Notwithstanding, static signature verification is very important for many application fields, like automatic bank-check processing, insurance form processing, document validation and so on. When static signatures are considered, information on local stability is an important parameters for verification aims. In this paper local stability is analyzed by optical flow. Optical flow can be defined as the distribution of apparent velocities of movement of brightness patterns in an image I. As discussed in the excellent paper of O'Donovan [24], optical flow has been used for a variety of computer vision applications like autonomous navigation, object tracking, traffic analysis, image segmentation and stabilization.

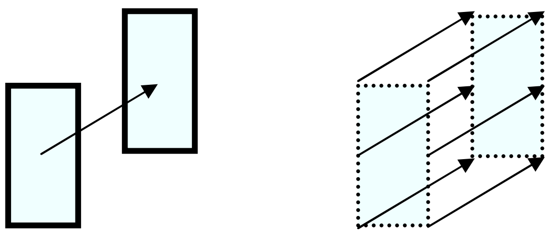
In this paper we consider the approach of Horn and Shunck for optical flow estimation [25]. In this case optical flow is determined through the minimization of the energy functional [25]:

$$E = \iint \left[(I_x u + I_y v + I_t)^2 + \alpha^2 (\|\nabla u\|^2 + \|\nabla v\|^2) \right] \mathrm{d}x\mathrm{d}y$$

where

- I_x, I_y and I_t are the derivatives of the image intensity values along the x, y and time dimensions, respectively;
- $[u_{ij}(x,y), v_{ij}(x,y)]^T$ is the optical flow vector;
- α is the regularization parameter.

In other words, the functional E consists of two terms: the first term is the optical flow constraint equation and the second is the smoothness constraint which is multiplied by the regularization parameter α.



(a) (b)

Fig. 1. Example of Optical Flow.

Horn and Schunk work out the previous minimization problem using a digital estimation of the Laplacian for the optical flow gradients, to get a large system with two equations for each pixel that can be solved by the Jacobi method [25]. Figure 1 shows an example of Optical Flow: in (a) the movement of a rectangle over two frames is shown; in (b) the optical flow vectors is reported.

III. Analysis of Stability of Static Signatures

In the next section, optical flow analysis is applied to the analysis of regional stability of static signatures. For this purpose, after the preprocessing phase, in which each signature is binarized and normalized to a fixed rectangular area, the identification of the stable regions starts.

In particular, let be:

- I^g_i the set of N genuine signatures of a writer, i=1,2,,…N;
- $[u_{ij}(x,y), v_{ij}(x,y)]^T$ the optical flow between I^g_i and I^g_j.

Now, if we consider the i-th signature I^g_i of a signer, for each pixel $I^g_i(x,y)$ we can consider the sets of optical flow vectors defined as:

$$U_i = \{u_{ij}(x,y) \mid j=1,2,\ldots,N;\ j\neq i\}$$

$$V_i = \{v_{ij}(x,y) \mid j=1,2,\ldots,N;\ j\neq i\}.$$

The stability (S) of $I^g_i(x,y)$ can be estimated as:

$$S(I_i^g(x,y)) = \sqrt{\sigma_u^2 + \sigma_v^2}$$

being σ_u and σ_v the standard deviation of U_i and V_i, respectively.

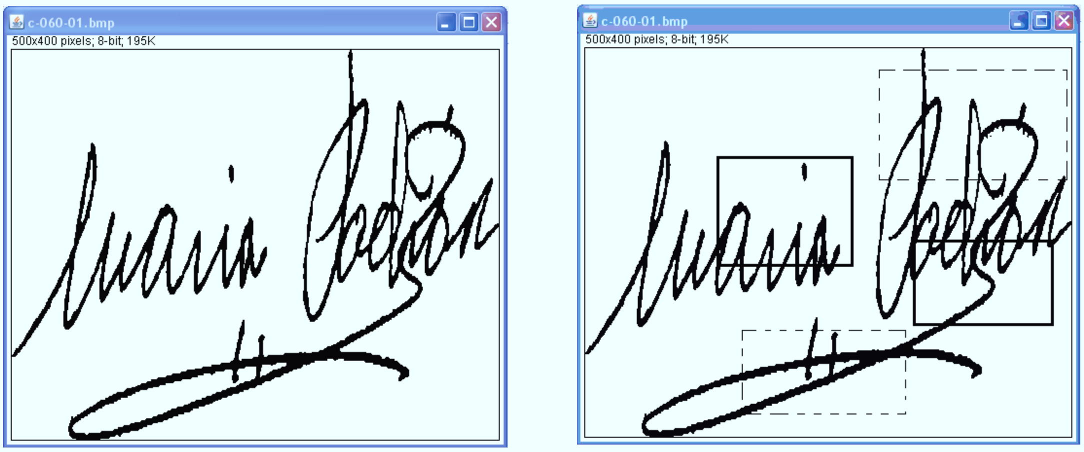
IV. Signature Stability by Optical Flow

Optical flow provides useful information on local dissimilarity among signature images. In this paper this information is used for signature verification aims. In particular, signature verification is performed by an alternating decision tree (ADT). ADT, that was first introduced by Freund and Mason [26], consists of decision nodes and prediction nodes. Decision nodes specifies a predicate condition, prediction nodes contain a single number. Classification by an ADT is performed by following all paths for which all decision nodes are true and summing any prediction nodes that are traversed. More precisely, in our approach, let be:

- I^g_i the set of N genuine signatures of a writer, i=1,2,,…N;
- I^f_p the set of M forgery signatures of a writer, p=1,2,…,M.

In the enrollment stage the ADT is trained by using the optical flow vectors concerning intra-class and inter-class variability:

- $[u_{ij}(x,y), v_{ij}(x,y)]^T$ the optical flow between I^g_i and I^g_j, i,j=1,2,…,N, i≠j (intra-class variability);
- $[u_{ik}(x,y), v_{ik}(x,y)]^T$ the optical flow between I^g_i and I^g_k, i=1,2,…,N, k=1,2,…,M (inter-class variability).



(a) (b)

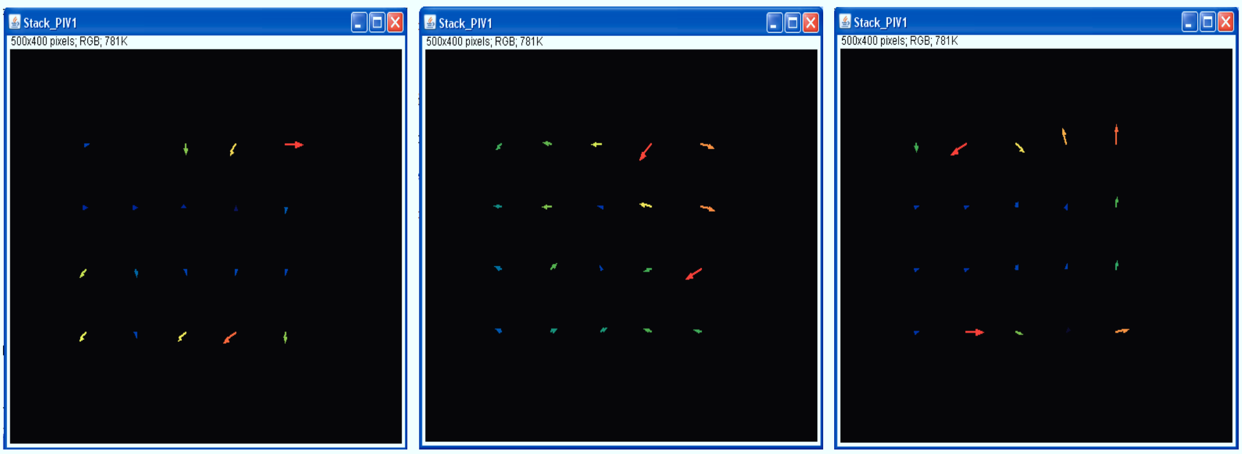
Fig. 2. Example Analysis of Local Stability.

V. EXPERIMENTAL RESULTS

The experimental results have been carried out using static signatures of the GPDS database. The database contains 16200 signatures from 300 individuals: 24 genuine signatures and 30 forgeries for each individual [27]. The result here reported concerns only twenty-five signers since other experiments are still in progress. For each signer the stability analysis is performed, according to the approaches described in Section III. Figure 2 shows a genuine specimen (a) and the result of the stability analysis obtained by optical flow (b). High stability regions are marked by continuous-line rectangles, low stability regions are marked by dotted-line rectangles. In this case the stability analysis has been achieved by considering the three optical flows in Figure 3, obtained by computing the optical flows between the signature in Figure 2a and other three genuine specimens.

Signature verification has been carried out by considering, for each signer, N=5 genuine signatures (I^g_i, i=1,…,5) and M=4 forgeries (I^f_i, i=1,..,4) for training the ADT. Therefore, $\binom{N}{2}=10$ optical flows between genuine signatures and N·M=20 optical flows between genuine signatures and forgeries are used for training. For testing, fourteen genuine and fourteen forged signatures are considered. In the testing stage, the optical fields $[u_{ti}(x,y),\ v_{ti}(x,y)]^T$ between the test signature I^t and each genuine signature I^g_i, i=1,2,…,N, are computed. Each one of the N optical flows is provided to the ADT that returns a verification results r_{ti}. The N results are combined according to the majority vote strategy, in order to define the final verification result for the test signature I^t.

The results, in terms of Type I - False Rejection Rate (FRR) and Type II - False Acceptance Rate (FAR) are reported in Table 1. On average we register a Type I error rate equal to 23% and a Type II error rate equal to 20%. Figure 4 shows an example of optical flow between two genuine specimens. Figure 5 shows the optical flow between a genuine specimen and a forgery. The great amount of deformation is clearly visible when the optical flow is performed between a genuine signature and a forgery.



(a) (b) (c)

Fig. 3. Optical Flows between genuine signatures

TABLE I
Experimental Results

Author n.	PERFORMANCE	
	FRR	FAR
1	14%	36%
2	0%	0%
3	29%	0%
4	43%	57%
5	29%	14%
6	29%	43%
7	0%	0%
8	57%	14%
9	29%	57%
10	0%	0%
11	21%	29%
12	14%	0%
13	29%	50%
14	21%	14%
15	0%	7%
16	14%	14%
17	57%	29%
18	43%	36%
19	0%	0%
20	21%	7%
21	14%	0%
22	14%	14%
23	57%	36%
24	36%	43%
25	14%	7%

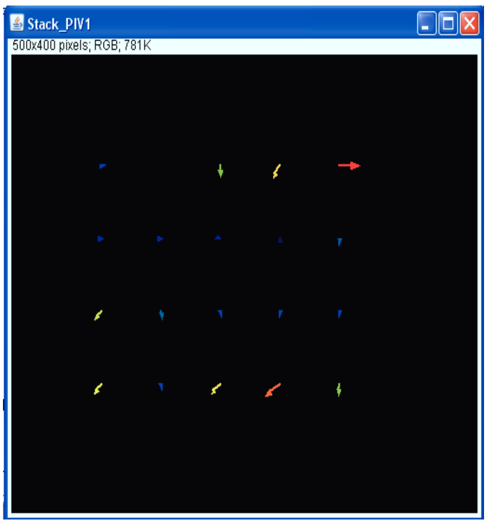


Fig. 4. Optical Flow: genuine vs genuine

Fig. 5. Optical Flow: genuine vs false

VI. CONCLUSION

In this paper optical flow is considered as a tool for static signature analysis. In the first part of the paper local stability in static signatures is analyzed by optical flow analysis. In the second part, optical flow vectors between test signature and genuine specimens are considered to verify the authenticity of a test signature, using an alternate decision tree. Some results carried out on static signatures extracted from the GPDS database demonstrate the new approach is worth consideration for further research. Of course, more experimental results are necessary to verify the effectiveness of the proposed approach and - in particular - to determine the capability of the Optical Flow in recognizing short-term and long-term variability as well as for evaluating the extent to which stability depends on the signature type and signer characteristics.

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A Co-training based Framework for Writer Identification in Offline Handwriting

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***Abstract*—Traditional forensic document analysis methods have focused on feature-classification paradigm where a machine learning based classifier is used to learn discrimination among multiple writers. However, usage of such techniques is restricted to availability of a large labeled dataset which is not always feasible. In this paper, we propose a Co-training based approach that overcomes this limitation by exploiting independence between multiple views (features) of data. Two learners are initially trained on different views of a smaller labeled training data and their initial hypothesis is used to predict labels on larger unlabeled dataset. Confident predictions from each learner are used to add such data points back to the training data with predicted label as the ground truth label, thereby effectively increasing the size of labeled dataset and improving the overall classification performance. We conduct experiments on publicly available IAM dataset and illustrate the efficacy of proposed approach.**

***Keywords*-Writer Identification, Co-training, Classifier, Views, Labeled and Unlabeled data**

I. Introduction

Writer Identification is a well studied problem in forensic document analysis where the goal is to correctly label the writer of an unknown handwriting sample. Existing research in this area has sought to address this problem using Machine Learning techniques, where a large labeled dataset is used to learn a model (supervised learning) that efficiently discriminates between various different writer classes. The key advantage of such learning approaches is their ability to generalize well over unknown test data distributions. However, such generalization provides greater performance only when used with a large labeled data. In real-world scenarios, generating large labeled datasets requires manual annotation which is not always practical. The absence of such datasets also leads to inefficient usage of available unlabeled data that can be exploited to provide a greater classification performance. To address these issues, we propose a Co-training based learning framework that learns multiple classifiers on different views (features) of smaller labeled data and uses them to predict labels for unlabeled dataset which are further bootstrapped to the labeled data for enhancing the prediction performance.

Existing literature on writer identification can be broadly classified into two categories. First category is of text dependent features which capture properties of writer based on the text written. In this writer identification is done by modeling similar content written by different writers. This reliance on text dependent features poses challenges of scalability. In real world application such data is seldom available which limits the usability of these techniques for practical purposes. said et al. [14] extracted text dependent features using Gabor filters but the main limitation was to have a full page of document written by different writers for identification. Second category is based on text independent features. They capture writer specific properties such as slant and loops which are independent of any text written. These techniques are better suited for real life scenarios as they directly model writers as opposed to previous category. Feature selection plays an important role in such techniques. Several features capturing different aspects of handwriting has been tried. zois et al. [15] used morphological features and needed only single word for identification and niels et al. [17] used allographic features to compare using Dynamic Time Warping(DTW). All of this work was focused on better feature selection which would result in better accuracy. They did not lay stress on the techniques used and made an assumption that sufficient amount of such data is available for the system to learn

Likewise, writer identification can also be divided under two major approaches. First is statistical analysis of several features such as edge hinge distribution. Edge hinge distribution captures the change in the direction of writing samples. Second approach is model based writer identification. In this predefined models of strokes of handwriting are used. Prime focus of these techniques was on making a better system for identification using different techniques for modeling and analysis. Various techniques such as Latent Dirichlet Allocation(LDA) were proposed for higher accuracy for identification[12] but it was based on the assumption that sufficient training data is available.

Existing techniques and methods did not make use of unlabeled data for the identification. Information tapped in the unlabeled data can make a significant improvement in

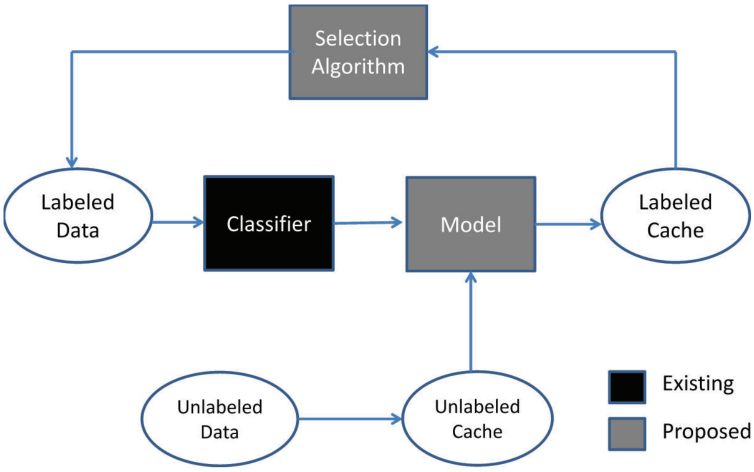

Figure 1. Schematic of Proposed Co-training Based Labeling Approach

the performance of the system. This information can be extracted using different techniques such as transductive SVMs[11] or graph based methods using EM algorithm. They are used to label unlabeled data in a semi supervised framework. nigam et al. [7] later proved that Co-training performs better than these methods in semi supervised framework. It uses small snippet of labeled data and iteratively labels some part of unlabeled data. System retrains itself after every iteration which results in better accuracy. Co-training has been successfully used for semi supervised learning in different areas but never been used for labeling data for writer identification to the best of our knowledge. Co-training has been used for web page classification[1], object detection[5] and for visual trackers[4] . It has been used extensively in NLP for tasks like named entity recognition[6].

The organization of the paper is as follows. Section 2 provides an overview of Co-training based framework. Multiple data views in form of writer features are described in Section 3. Section 4 illustrates the proposed approach. Experimental results are described in Section 5. Section 6 outlines the conclusion.

II. Co-training

Co-training is a semi supervised learning algorithm which needs small amount of training data to start. It reiteratively labels some unlabeled data points and again learns from it. blum et al. [1] proposed co-training to classify web pages on the internet into faculty web pages and non-faculty web pages. Initially they used small amount of web pages of faculty members to train a classifier and were able to correctly classify most of the unlabeled pages correctly in the end. Co-training requires two separate views of the data and two learners. blum et al. [1] proved that co-training works best if the two views are orthogonal to each other and each of them is capable of classification independently. They showed that if the two views are conditionally independent then the accuracy of classifiers can be increased significantly. This is because system is using more information to classify data points. Since both views are sufficient for classification, this brings redundancy which in turns gives more information. nigam et al. [8] later proved that completely independent views are not required for co-training. It works well even if two views are not completely uncorrelated.

Co-training is an iterative bootstrapping method which increases the confidence of the learner in each round. It boosts the confidence of score like Expectation Maximization method but it works better than EM[7]. In EM all the data points are labeled in each round while in Co-training few of the data points are labeled each round and then classifiers are retrained. This helps building a better learner in each iteration which in take would make better decision and hence the overall accuracy of system will increase.

A. Selection Algorithm

Selection of data points is crucial in the performance of the algorithm. New points added in each round should make learner more confident in making decisions about the labels. Hence, several selection algorithms have been tried to make a better system as system's performance can vary if selection method is changed. Different methods out performs each other depending on the kind of data and application. One approach to select points was based on performance[2]. In this method, some points were selected randomly and added to the labeled set. System was retrained and its performance was tested on the unlabeled data. This process was repeated for some iterations and performance of every set of points was recorded. Set of points resulting in best performance were selected to be added in the labeled set and rest were discarded. This method was based on the degree of agreement of both learners over unlabeled data in each round.

Some other methods has also been employed like choosing the top *k* elements from the newly labeled cache. This is an intuitive approach as those points were labeled with the highest confidence by the learner. However, hwa et al. [9] in their work showed that adding samples with best confidence score not necessarily results in better performance of classifiers. So, wang et al. [10] used a different approach in which some data points with lowest scores were also added along with the data points with highest confidence scores. This method was called *max-t, min-s* method and *t* and *s* were optimized for the best performance. So, several different selection methods have been employed as selecting data point in each round is key to the performance of Co-training.

III. Feature Selection

Selection of uncorrelated views is important in the working of Co-training. blum et al. [1] proposed that both views should be sufficient for classification. Each learner trained on the views should be a low error classifier. They proved that error rates of both the classifiers decreases during Co-training because of the extra information added to the system. This extra information directly depends on the degree of uncorrelation. However, abney et al. [3] later reformulated the explanation given by [1] for the working of Co-training in terms of measure of agreement between learners over unlabeled data. abney et al. [3] gave an upper bound on the error rates of learners based on the measure of their disagreement. Hence, independence of both views is crucial for the performance of the system. We chose contour angle features[13] as a first view and we combined structural and concavity features (SC)[18] as a second view. These features can be considered independent as both captures different properties of style of writing.

IV. Proposed Method

Co-training fits naturally for the task of writer identification as any piece of writing can have different views. Contour angle features and structural and concavity features are two such different views for any handwritten text. They can be considered uncorrelated enough to fit the task of writer identification in Co-training framework. Co-training also needs to have two learners to learn over two views. We used two different instances of Random Forest as learners to normalize the effect of learner over views.

Angle features were used to train first classifier and SC were used to train the other one. Then in each round a cache will be extracted from unlabeled data. This cache would be labeled by both learners and some data points will be picked from newly labeled cache by selection algorithm. Selected data points will be added to the training set and the learners are retrained while remaining data points in the cache are discarded. This process is repeated unless the unlabeled set is empty. Below is the pseudo code for the Co-training algorithm.

Algorithm 1 $Co-trainingAlgo$

Require:
$L1 \leftarrow$ Labeled View One
$L2 \leftarrow$ Labeled View Two
$U \leftarrow$ Unlabeled Data
$H1 \leftarrow$ First Classifier
$H2 \leftarrow$ Second Classifier
Train $H1$ with $L1$
Train $H2$ with $L2$
repeat
  Extract cache C from U
  $U \leftarrow U - C$
  Label C using $H1$ and $H2$
  $d \leftarrow$ selection_algo(C) where $d \subset C$
  add_labels(d,$H1$,$H2$)
  $L1 \leftarrow L1 \cup$ view one of d
  $L2 \leftarrow L2 \cup$ view two of d
  Retrain $H1$ on $L1$
  Retrain $H2$ on $L2$
until U is empty

A. Selection Algorithm

Selection algorithm used for selecting data points was based on agreement of both learners over data points. Points on which the confidence of both learners was above certain threshold were selected. In case of documents accuracy of classifier would be high if two different views will indicate same label for any data point. Selection method based on randomly selecting data points and checking their performance as used in [2] was not good as randomly checking takes time. The approach is not scalable as there are several rounds of processing of subset of cache every time a new cache is retrieved. Below is the pseudo code for the selection algorithm. Score function in the algorithm gives the highest value of the confidence scores of the learner for one data point over all writers.

Table I
ACCURACY OF CLASSISIERS WITH BASELINE SYSTEM AND CO-TRAINING

Methods	Full Data	Half Data	One Fourth Data	One Tenth Data
Experiment 1 Baseline	83.73	79.64	74.48	59.00
Co-training	85.58	80.91	75.55	61.24
Experiment 2 Baseline	80.42	76.72	70.59	52.28
Co-training	82.47	77.31	72.15	53.94

Algorithm 2 $SelectionAlgo$

Require:
  $C \leftarrow$ cache
  $t \leftarrow$ threshold
  $d \leftarrow \Phi$
  for each data point c in C **do**
    if score(c,$H1$) $> t$ & score(c,$H1$) $> t$ **then**
      $d \leftarrow d \cup c$
      $C \leftarrow C$ - c
    else
      $C \leftarrow C$ - c
    end if
  end for
  return d

V. EXPERIMENTS

We used IAM dataset which has total of 4075 line images written by 93 unique writers. We conducted two experiments to test the performance of Co-training against the baseline systems. In first we compared the accuracy of classifiers after Co-training against baseline methods by adding the scores of both learners. In this scores of the class distribution of the two learners were added for each data point and a joint class distribution score was generated. Class label with the highest score was assigned to that data point. Second experiment was based on the maximum of the confidence score of the label assigned by each learner. In this each classifier assigns a class label to the data point. This assignment is based on the highest value of the confidence score distribution over all classes. Class label with the higher score between the two is assigned to the data point.

Our goal is to show that Co-training can be used to label unlabeled data even if a small amount of labeled data is present in the beginning. Therefore experiments were run on dataset of different sizes. We conducted experiments with four different settings of data. System was initially trained over full, half, one fourth and one tenth of the total training data. In one tenth training data only three samples per class were present. Table shows that after Co-training accuracy of classifiers is better than the baseline system with all sizes of datasets in both experimental settings.

VI. CONCLUSION

In this paper we presented a Co-training based framework for labeling a large dataset of unlabeled document with the correct writer identities. Previous work in writer identification was focused on either on developing a better feature selection algorithm or to use different techniques for modeling the text of the document. All the work was based on a assumption that sufficient amount of labeled data is available for training a system. In our work we address the problem of limited amount of labeled data present in real life applications. Our method tries to iteratively generate more labeled data from unlabeled data. Experimental studies show that accuracy of learners on the dataset labeled by Co-training was better than the baseline system. This proves the effectiveness of Co-training for labeling a large dataset of unlabeled documents. In future we would like to address this problem of limited data by using other semi supervised learning methods.

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