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An Application of the 2D Gaussian Filter for Enhancing Feature Extraction in Off-line Signature Verification

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***Abstract*—Similar to many other pattern recognition problems, feature extraction contributes significantly to the overall performance of an off-line signature verification system. To be successful, a feature extraction technique must be tolerant to different types of variation whilst preserving essential information of input patterns. In this paper, we describe a grid-based feature extraction technique that utilises directional information extracted from the signature contour, i.e. the chain code histogram. Our experimental results for signature verification indicated that, by applying a suitable 2D Gaussian filter on the matrices containing the chain code histograms, an average error rate (AER) of 13.90% can be obtained whilst maintaining the false acceptance rate (FAR) for random forgeries as low as 0.02%. These figures are comparable or better than those reported by other state of the art feature extraction techniques such as the Modified Direction Feature (MDF) and the Gradient feature.**

***Keywords*-Off-line signature verification; Support Vector Machines; Gaussian filter; Modified Direction Feature; Gradient feature; Gaussian Grid feature**

I. INTRODUCTION

Signatures have been widely accepted by society as a convenient certificate of consent and authorisation. Unlike other authentication schemes using PIN or password, smartcard or fingerprints, signatures cannot be forgotten, stolen, or lost. On the one hand, a conscious individual must be capable of producing his own signature as a proof of his identity. On the other hand, a genuine signature can only be produced while this subject is conscious. A person can forget his PIN or password but is unlikely to forget how to sign his own signature. Fingerprints can be obtained and used when a person is unconscious but this is not the case with a signature.

Besides the above characteristics, forging a signature deceptively appears to be easy. Forging signatures does not require any special facilities or knowledge. All one needs is a pen, some genuine specimens and plenty of time for practising. Through practising, a forger becomes more skilled and his forgeries are more difficult to be distinguished. These facts make signature forgery an attractive means of conducting fraudulent activities, and signature verification a challenging problem.

The verification of handwritten signatures can be performed automatically either on-line, off-line, or a hybrid of the two. Whenever a special instrument such as a tablet, stylus, or digitizer is involved, the verification system is considered on-line. Off-line verification employs the signature's static image solely. The availability of dynamic information such as stroke order, local velocity, and even pressure in some advanced devices, provides on-line verification systems with a significant advantage over their off-line counterparts. As a consequence, some researchers [1] attempted to utilise local grey levels as an indication of dynamic information to improve the overall accuracy of automatic signature verification systems. Conversely, an off-line verification system has potentially more applications as it does not require any special devices and off-line signatures are already popular. In the hybrid approach, the verification of a questioned signature image is performed with reference to on-line information registered earlier. The verification procedure often includes the estimation or recovery of the writing trajectory from the scanned image prior to comparing the properties of the recovered trajectory against the established profile. Notable researchers following this approach include Qiao *et al.* [2] and Zimmer and Lee Luan [3].

In this research, the application of the 2D Gaussian filter for enhancing a grid-based feature extraction technique for the off-line signature verification problem was investigated. Experimental results showed that the proposed technique produces better results than the Modified Direction Feature (MDF) and the Gradient feature under the same experimental settings.

The remainder of this paper is organized as follows: The next section introduces the background of the proposed feature extraction technique. After that, Section II details the technique itself. The experimental settings are described in Section III and this is followed by results in Section IV. Finally, Section V concludes and proposes directions for future research.

II. BACKGROUND

Feature extraction is a crucial process not only in signature verification but also in pattern recognition. In this process, essential information is extracted from the preprocessed input pattern and is represented in a suitable form for the classifier to undertake further processing (Fig. 1). Most importantly, a successful feature extraction technique must be the one that produces good results. It should also tolerate different kinds of

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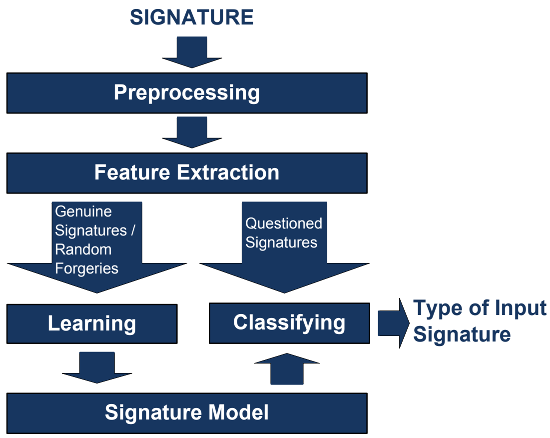


Fig. 1: Automatic Off-line Signature Verification System

variation such as shift, rotation, or dilation [4]. Nevertheless, the dimensions of the feature vector should be minimized to enable computational feasibility.

A feature extraction technique can be categorised to be global or local. A global technique is usually computed from the whole input signature without partitioning it. This is different from local features where one or more processes are applied to every section/zone. Amongst the zoning-based techniques, the grid approach appears to be the more popular.

In our recent investigation [5], the performance of the Modified Direction Feature (MDF) and the Gradient feature have been compared using the same settings for experimentation. The experimental results showed that the Gradient feature outperformed the MDF. Interestingly, both techniques employ local and directional information of signature contours but represent it differently. The MDF extracts directional information from the normalized contour whilst in the Gradient feature this information is extracted in more detail using 32 quantized directions. The location information wherefrom directional information has been sampled, has also been utilised by both techniques. The Gradient feature encoded this information in the row and column id of each element of the gradient matrix. MDF recorded the location of the transition as LT values. To reduce feature vector dimensions, the MDF employed local averaging whilst the Gradient feature employed a Gaussian filter.

One major difference between the two feature extraction techniques, as we noticed, is the blurring process employed by the Gradient feature. This operation was performed by applying a 2×2 mean filter on the input image 5 times. Blurring not only helps smoothing/repairing broken contour segments but it also emitted information, i.e. a high frequency signal, from one point to its surrounding area. By doing this, further image manipulations can benefit from more generalized input and the stability against small variations can be maintained. It is hypothesised that the blurring process had a significant impact on the performance of the Gradient feature and largely contributed to its enhanced performance compared to the MDF. The above observations lead us to the development of the Gaussian Grid feature extraction technique.

A. Gaussian Grid Feature Extraction Technqiue

The Gaussian Grid feature employs signature contours as its input. From the contour representation of a signature image, the Gaussian Grid feature extraction technique performs the following steps:

Step 1: The input signature contour image is divided into $m \times n$ zones.

Step 2: By tracing the contours in each block the 4-direction chain code histogram of each block is created. Every step from a pixel to its adjacent one of the four directions (horizontal, vertical, left-diagonal, and right-diagonal) are counted. There are four matrices of size $m \times n$ for each direction, namely H, V, L, and R.

Step 3: Apply a Gaussian smoothing filter to each directional $m \times n$ matrix A obtained in the previous step.

$$A^*_{ij} = \sum_{di=-\infty}^{\infty} \sum_{dj=-\infty}^{\infty} A_{i+di,j+dj} \frac{1}{2\pi\sigma^2} e^{-\frac{di^2+dj^2}{2\sigma^2}} \quad (1)$$

Step 4: The value of each element of each matrix obtained in the previous step is adjusted by dividing its value by the maximum value of the four matrices.

$$A_{ij} = \frac{A_{ij}}{\max(H_{xy}, V_{xy}, L_{xy}, R_{xy})} \quad (2)$$

Figure 2c illustrates the combined matrix after being filtered and normalised in this step. In this figure as well as Fig. 2b, each group of four colours red, blue, green, black and their luminance represent the directions and the accumulated chain code value after normalization.

Step 5: From the two-matrix pairs horizontal (H) and vertical (V) matrices, left-diagonal (L) and right-diagonal (R) matrices, two new matrices $\oplus$ and $\otimes$ are established using the following two equations:

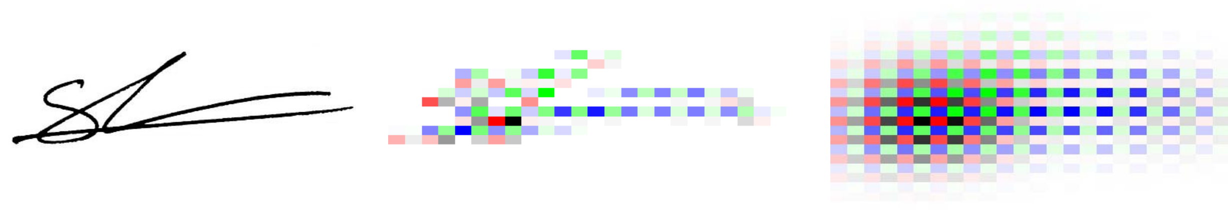
$$\oplus_{ij} = \begin{cases} \dfrac{\max(H_{ij}, V_{ij})}{\min(H_{ij}, V_{ij})} & \text{if } \max(H_{ij}, V_{ij}) \neq 0 \quad (3) \\ 0 & \text{if } \max(H_{ij}, V_{ij}) = 0 \quad (4) \end{cases}$$

$$\otimes_{ij} = \begin{cases} \dfrac{min(L_{ij}, R_{ij})}{max(L_{ij}, R_{ij})} & \text{if } max(L_{ij}, R_{ij}) \neq 0 \quad (5) \\ 0 & \text{if } \max(L_{ij}, R_{ij}) = 0 \quad (6) \end{cases}$$

From our previous research [6] using the energy feature, we learnt that the proportions between perpendicular directions are relatively stable features which produce better verification accuracies. It was decided to employ this global feature as a local feature in this newly proposed technique.

Step 6: The feature vector is formed by merging the six matrices H, V, L, R, $\oplus$, and $\otimes$. The dimension of the output feature vector is $m \times n \times 6$.

In a number of preliminary experiments with the 9x9 grid configuration, it was observed that $\sigma = 1.2$ produced acceptable results and this value was adopted for later experiments.



(a) Original signature

(b) Colour map representation of the chain code histogram

(c) Colour map of the chain code histogram after applying the Gaussian filter with $\sigma = 1.2$

Fig. 2: Illustration of (a) an input signature and its chain code histogram (b) before and (c) after applying the Gaussian filter. The colours red, green, blue, and black represent the intensity of directions vertical, right diagonal, horizontal, left diagonal respectively

Besides this, the dimensions of the grid (m and n) were set to be equal.

III. Experimental Settings

Research in automatic signature verification has long been constrained by the unavailability of a standard database. As a result, many researchers employ a proprietary corpus rather than a publicly available one. The quality of available databases also varies as there has been no standard collection protocol. Besides, it is very costly to create a large corpus with different types of forgeries, especially skilled forgeries. A forger must possess a certain degree of forging experience to produce forgeries of this type. Forgers with such skill are unlikely to reveal themselves.

In this work, we employed a subset of the publicly available GPDS-960 corpus so that the results are more comparable. This signature corpus is available for download once requested from the following website: http://www.gpds.ulpgc.es/download/index.htm. The subset we employed consists of 160 sets whereby the writer number ranges from 001 to 160. Each signature set includes 24 genuine signatures and 30 simulated forgeries or relatively high skilled ones. In total, this research employed 3840 genuine signatures and 4800 simulated forgeries. The signature images were scanned at the resolution of 600dpi before being down-sampled to 150dpi and converted into black and white images by the owner. Details of the collection protocol of this corpus can be found in [7].

TABLE I: Sample Configuration for the Training and Testing of a Classifier

Phase	Genuine	Random Forgery	Simulated Forgery
Training	12	400	0
Testing	12	59	15

The learning and classifying processes were performed using the well-known support vector machine (SVM) [8] with the Gaussian kernel. Among the parameters, the capacity (C) was fixed at 1000 whilst σ was varied in order to plot the ROC curve. For each value of σ, the reported false rejection rate (FRR) and false acceptance rate (FAR) are calculated by averaging corresponding results obtained from every signature set after 30 runs. For convenience in comparison, the lowest average error rate (AER) value of FRR and FAR for simulated forgeries (FAR^2) is also reported. The FAR for random forgeries (FAR^1) is reported at the same value of σ at which the best AER was reported.

For every experiment with each signature the classifier was trained using 12 genuine signatures and 400 random forgeries. The random forgeries are the genuine signatures of 100 randomly chosen individuals. No simulated forgeries were used in the training process. A system requiring simulated forgeries for the establishment of a writer profile rather than for general system parameters determination, would require simulated forgeries for every additional writer in the future and tends to be less practical.

In the testing process, the performance of the classifier for each writer was evaluated using the remaining 12 genuine signatures, 59 random forgeries, and 15 randomly chosen simulated forgeries. The random forgeries employed in the testing process are genuine signatures of the remaining 59 individuals who were not involved in the training process. The sample configuration of the training and testing processes is summarised in Table I.

Another set of experiments has been conducted to test the hypothesis that the application of the Gaussian filter improves the performance of the proposed technique. In those experiments, Step 3 of the proposed technique has been removed.

IV. Results and Discussion

As reported in Table II, the proposed technique produced an AER of 13.93% when the 12×12 grid configuration was employed. This result is comparable to both the MDF and the Gradient feature whose AER values are 17.25% and 15.03% respectively [5]. Even in a smaller dimension configuration ($9 \times 9 \times 6 = 486$) the proposed technique produces a better AER of 14.40%. These figures are depicted in Fig. 3. Apart from that, the FAR rate for random forgeries (FAR^1) was also kept as low as 0.02% (i.e., 56 out of $30 \times 160 \times 59 = 283200$ tests). It is believed that this error rate could be reduced further and easily by employing more random forgeries in the training process.

TABLE II: Experimental Results Obtained Using the Proposed Technique

Grid Size	Filter	FRR	FAR^1	FAR^2	AER
$9 \times 9_{\sigma=1.2}$	Yes	14.37%	0.04%	14.42%	14.40%
$12 \times 12_{\sigma=1.2}$	Yes	14.18%	0.02%	13.68%	**13.93%**
$9 \times 9_{\sigma=1.2}$	No	17.97%	0.04%	18.08%	18.03%
$12 \times 12_{\sigma=1.2}$	No	19.48%	0.06%	19.84%	19.66%

Without the Gaussian filter, the lowest average error rates increased significantly as expected. In these experiments, the AER for the 9×9 and 12×12 grids are 18.03% and 19.66% respectively (See Tab. II).

Unlike the Gradient feature in which the Gaussian filter was employed to reduce the dimensions of the feature vector, the proposed technique uses the Gaussian filter to spread and preserve information. As a low-pass filter, the Gaussian filter attenuates and preserves high frequency signals/information in the neighbourhood. It is noticed, though unintentionally, that information had also been preserved in overlapping-zone techniques such as the Flexible Grid feature [9] or the overlapping window [10]. The main difference is that, in the proposed technique, information from the whole cell was preserved and transmitted to a larger number of surrounding zones.

Apart from the Gradient and the MDF feature extraction techniques, it is difficult to compare the performance of the proposed technique with other techniques directly, especially those that were not tested using the GPDS corpus. Each database was created using different collection protocols. Signature collection protocols have a significant impact on the characteristics of a database, and subsequently the performance of feature extraction techniques. For example, the verification system proposed by Wen *et al.* [4] produced an EER of 11.4% with their own corpus, which consisted of 55 signature sets, and 15.02% for the MCYT corpus [11]. In that work, 16 genuine specimens were employed to establish each writer profile. Similarly, Vargas *et al.* [1] reported that their grey-level based feature extraction technique produced better results with the MCYT corpus than the GPDS. These researchers explained that the difference was due to the employment of various pens in the production of the GPDS corpus.

The best AER of the proposed technique is comparable to the AER rates reported by Ferrer *et al.* [7] (14.26% and 13.35% for SVM and HMM respectively) with a note that the FAR for random forgeries of the proposed technique is very much lower (0.02% vs. 2.65%). It should be noted that in order to establish the decision threshold, Ferrer *et al.*'s technique employed 3 simulated forgeries for each writer.

Despite the encouraging results, the proposed feature extraction technique produced a relatively large feature vector. In the 12×12 grid configuration, the number of dimensions is 864 which is 7-fold more than the size of the MDF feature vector. Compared to the 9×9-grid configuration, the size of

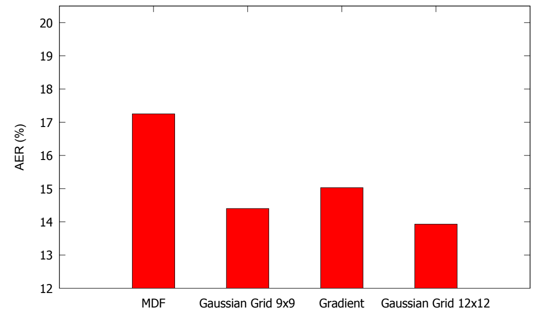


Fig. 3: Performance comparison of feature extraction techniques

the feature vector of the 12×12 configuration is nearly 2-fold whilst the accuracy is only improved by merely 0.5%. σ has not been exhaustively tuned for the best accuracy in our experiments. Fig. 4 depicts the ROC curves of different experimental settings investigated in this research.

V. Conclusions and Future Work

We have demonstrated that the performance of a particular grid-based feature extraction technique can be improved using a 2D Gaussian filter. Although the features and the extraction process appeared to be much less sophisticated compared to other techniques, its performance is comparable or better than other state-of-the-art techniques. Nevertheless, the Gaussian filter can be easily applied to other zone-based feature extraction techniques in which the accumulation of information occurs. This is an advantage of information preservation using a Gaussian filter over blurring a pattern directly.

As the proposed technique employs the signature contour as its input, its performance is affected by the quality of the input contour which again heavily relies on preprocessing techniques. Future investigations will employ more robust techniques to extract directional information. Apart from that, more local features can be employed in Step 5 of the proposed feature extraction technique to provide the classifier with additional information. Other parameters of the technique

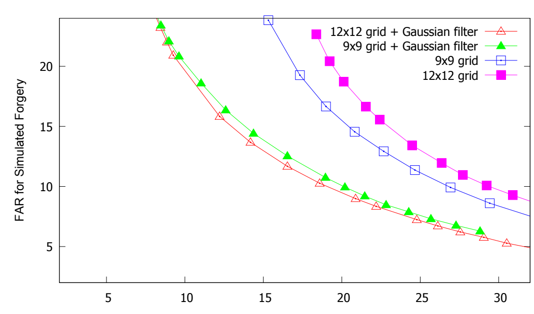


Fig. 4: ROC curves obtained using different experimental settings

including σ and the dimensions of the grid could also be tuned to achieve better verification accuracies.

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