International Journal of Image Processing and Vision Science

Volume 2 | Issue 1 Article 6

October 2013

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Recommended Citation

RAMESH, P. and RAO, P. NAGESWARA (2013) "HANDWRITTEN SIGNATURE VERIFICATION BASED ON THE USE OF GRAY LEVEL VALUES," *International Journal of Image Processing and Vision Science*: Vol. 2 : Iss. 1 , Article 6.
DOI: 10.47893/IJIPVS.2013.1064
Available at: https://www.interscience.in/ijipvs/vol2/iss1/6

HANDWRITTEN SIGNATURE VERIFICATION BASED ON THE USE OF GRAY LEVEL VALUES

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Abstract: Recently several papers have appeared in the literature which propose pseudo-dynamic features for automatic static handwritten signature verification based on the use of gray level values from signature stroke pixels. Good results have been obtained using rotation invariant uniform local binary patterns LBP plus LBP and statistical measures from gray level co-occurrence matrices (GLCM) with MCYT and GPDS offline signature corpuses. In these studies the corpuses contain signatures written on a uniform white "nondistorting" background, however the gray level distribution of signature strokes changes when it is written on a complex background, such as a check or an invoice. The aim of this paper is to measure gray level features robustness when it is distorted by a complex background and also to propose more stable features. A set of different checks and invoices with varying background complexity is blended with the MCYT and GPDS signatures. The blending model is based on multiplication. The signature models are trained with genuine signatures on white background and tested with other genuine and forgeries mixed with different backgrounds. Results show that a basic version of local binary patterns (LBP) or local derivative and directional patterns are more robust than rotation invariant uniform LBP or GLCM features to the gray level distortion when using a support vector machine with histogram oriented kernels as a classifier.

Index Terms: *Application of support vector machine (SVM), biometrics, histogram SVM kernels, local binary patterns, local directional patterns, offline signature verification, texture features.*

INTRODUCTION:

BIOMETRICS is playing an increasingly important role in personal identification and authentication systems. Several technologies that have been developed in this area are based on fingerprints, iris, face, voice, the handwritten signature, hand,etc.Handwritten signatures occupy a very special place in this wide set of biometric traits. The main reason is tradition: handwritten signatures have long been established as the most widespread means of personal verification. Signatures are generally accepted by governments and financial institutions as a legal means of verifying identity.Moreover, verification by signature analysis requires no invasive measurements and people are used to this event in their day to day activities A handwritten signature is the result of a complex process depending on the psychophysical state of the signer and the conditions under which the signing process occurs.

Although complex theories have been proposed to model the psychophysical mechanisms underlying handwriting and the ink processes, signature verification is still an open challenge since a signature is usually judged to be genuine or a forgery on the basis of only a few reference specimens Two methods of signature verification stand out. One is an offline method that uses an optical scanner to obtain handwriting data from a signature written on paper. The other, which is generally more successful, is an online method, which, with a special device, measures the sequential data, such as handwriting speed and pen pressure. Although less successful than the online method, offline systems do have a significant advantage because they do not require access to special processing systems when the signatures are produced There are two main approaches for offline signature verification: static approaches and pseudo-dynamic approaches. The static one involves geometric measures of the signature while the pseudo-dynamic one tries to estimate dynamic information from the static image.

In off-line systems, a signature is digitised using a flat bed scanner and then stored as an image. These images arecalled statistical or off-line signatures. Off-line data is a 2-D image of the signature. Off-line signature verification is considered as a behavioural characteristic based biometric trait in the field of security and the prevention of fraud.

Off-line systems are of interest especially in scenarios where only hard copies of a signature are available,e.g., where a large number of documents need to be authenticated. Research in the field of off-line signature verification is relatively unexplored; this apathy can be attributed to the inherent limitation of available features from a statistical image of signatures. However, several research studies in on-line signature verification have been reported with high success rates.

Verification decision is usually based on local features extracted from signature under processing. Excellent verification results can be achieved by comparing the robust features of the test signature with that of the user's signature using an appropriate classifier.

SIGNATURE DATABASE

The signature database contains both genuine and skilled forgeries of ten different people. Genuine signature means the original/ authentic signature of the owner/signer whereas a skilled forgery is done by closely imitating the genuine signature of the signer by practising through various time sessions. For correctly categorising the signature class, testing is done with both genuine and forged signature. Three hundred genuine signatures from ten different signers (given identity codes as) have been collected in this study. These signers are of different age groups and from different fields. The signatures are collected during ten days so as to account for the variations in the signatures with interval of time. The A4 size sheet of paper is given to the signers and each signer was requested to give their signature (30 signature images from each signer). Therefore, three-hundred genuine signatures were collected. Also, two hundred forged signatures were collected in this work. The genuine signatures were shown to a new signer and were requested to repeat that genuine signature ten times after going through a practice session, for collecting the forged signatures. Overall, database of 500 signatures has been created.

This database consists of 300 signatures (30 signatures each of the 10 signers) and 200 forged signatures (20 signatures each of the 10 users). This database of signatures has further been divided randomly into training database and testing database as shown in Table-1.

Table 1. Training and Testing Databases.

	Genuine Signatures	Forged Signatures	Total
Training Set	240	160	400
Testing Set	60	40	100
Total	300	200	500

These signatures are scanned using HP-scan jet 5400c at 300dpi, which are usually a good quality and a low noise images. The digitised images are stored as JPEG format. A sample of the signatures from the database is shown in Table-2.The block diagram of the proposed recognition system is shown in Fig. 1.

Table .Sample Signatures

EXISTING SYSTEM:
The verification by signature analysis requires no invasive measurements and people are used to this event in their day to day activities.

Two methods of signature verification stand out. One is an offline method that uses an optical scanner to obtain handwriting data from a signature written on paper. The other, which is generally more successful, is an online method, which, with a special device, measures the sequential data, such as handwriting speed and pen pressure. Although less successful than the online method, offline systems do have a significant advantage because they do not require access to special processing systems when the signatures are produced

DISADVANTAGES OF EXISTING SYSTEM:
The corpuses contain signatures written on a uniform white “nondistorting” background; however the gray level distribution of signature strokes changes when it is written on a complex background, such as a check or an invoice.

PROPOSED SYSTEM:
Among the techniques that analyze the stroke thickness or stroke intensity variations, we highlight those that focus on the gray level distribution in the signature stroke.

The aim of this paper is to evaluate the dependence of the gray level based features and propose strategies to improve their robustness to gray level distortion and segmentation errors due to complex backgrounds.

ADVANTAGES OF PROPOSED SYSTEM:
The proposed system measure gray level features robustness when it is distorted by a complex background and also to propose more stable features. A set of different checks and invoices with varying background complexity is blended

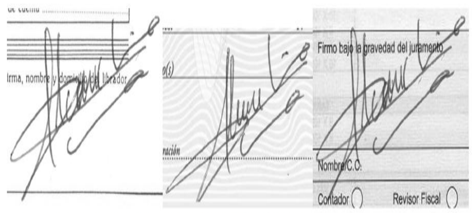


Fig. 2. $I_D(x, y)$ signature and check images blended with different background complexity. Low distortion at left, medium distortion at center, and high distortion at right.

Given that the checks vary in background complexity, the MCYT and GPDS960GraySignature databases were tripled in three databases, depending on the background complexity. In total, eight databases are used and are listed in Table II. The Gray level distortion Gd of each signature was calculated as follows:

$$\mathrm{Gd} = \frac{1}{255 \cdot N \cdot M} \sum_{x=1}^{N} \sum_{y=1}^{M} |I(x, y) - I_D(x, y)| \cdot I_{\mathrm{bin}}(x, y). \quad (3)$$

The distribution of Gd forMCYT database with low, mediumand high gray level distortion

TABLE II
NAME OF DATABASES USED IN TERMS OF GRAY LEVEL DISTORTION

Database names	Gray level distortion			
	No distortion	low	Medium	high
Off-line MCYT	MCYT	MCYT1	MCYT2	MCYT3
GPDS960GraySignature	GPDS	GPDS1	GPDS2	GPDS3

III. PRE-PROCESSING OF SIGNATURE IMAGE

A. Background Removal in Databases With No Gray Level Distortion

The background of the scanned signatures in MCYT and GPDS databases is well contrasted with the darker signature strokes so the signature images were binarized by posterization as suggested in [14]. Let be a 256-level, gray scale signature image of the database, the gray level posterized image is then defined as

$$I_p(x,y) = \text{round}\left(\text{round}\left(\frac{I(x,y)\cdot n_L}{255}\right)\cdot\frac{255}{n_L}\right) \quad (4)$$

where round(.) rounds the elements to the nearest integer. The authors in [14] suggested $n_L=3$.To obtain the binarized signature (white strokes and black background) we apply a simple thresholding operation, as follows:

$$I_{\text{bw}}(x,y) = \begin{cases} 0, & \text{if } I_p(x,y) = 255 \\ 255, & \text{otherwise.} \end{cases} \quad (5)$$

The binarized image displays hair-like artifacts which emerge from signature strokes, as seen in Fig. 4. These artifacts are eliminated as seen in (6), shown at the bottom of the next page, which correspond to or-exclusive operations. The previously specified operation converts the white pixels to black if the left and right pixels are black or if the upper and lower pixels are black.

$$I_A(x,y), = \begin{cases} 0, & \begin{array}{l}\text{if } I_{\text{bw}}(x-1,y)=0 \\ \text{and } I_{\text{bw}}(x,y)=255 \\ \text{and } I_{\text{bw}}(x+1,y)=0\end{array} \quad \begin{array}{l} 2\le x\le N-1 \\ 1\le y\le M\end{array} \\ I_{\text{bw}}(x,y), & \text{otherwise} \end{cases}$$

$$I_{\text{NR}}(x,y), = \begin{cases} 0, & \begin{array}{l}\text{if } I_A(x,y-1)=0 \\ \text{and } I_A(x,y)=255 \\ \text{and } I_A(x,y+1)=0\end{array} \quad \begin{array}{l} 1\le x\le N \\ 2\le y\le M-1\end{array} \\ I_A(x,y), & \text{otherwise} \end{cases} \quad (6)$$

Fig. 4 shows an example of the above-mentioned operation on a signature stroke.

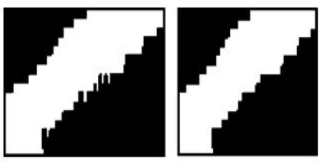


Fig. 4. Eliminating hair-like noise from signature strokes. (Left) signature stroke detail of $I_{\text{bw}}(x,y)$ with noise. (right) Same signature stroke detail of $I_{\text{NR}}(x,y)$ without noise.

The black and white image $I_{\text{NR}}(x,y)$ is used as amask to segmentthe original signature. The segmented signature $I_G(x,y)$ is obtained as

$$I_G(x,y) = \begin{cases} I(x,y), & \text{if } I_{\text{NR}}(x,y) = 255 \\ 255, & \text{otherwise.} \end{cases} \quad (7)$$

An example of the previously described procedure is shown in Fig. 5.

(a) (b) (c)

Fig. 5. Segmentation procedure. Details of (a) original image $I(x,y)$ with 256 gray levels, (b) binarized and noise reduced signature $I_{\text{NR}}(x,y)$, (c) segmented signature $I_G(x,y)$ with white background.

B. Background Removal in Databases With Gray Level Distortion

The posterization procedure is not useful with the databases of the signatures blended with the check images, because the background does not contain uniform character, lines and gray level textures. In this case, we used different background removal algorithms.

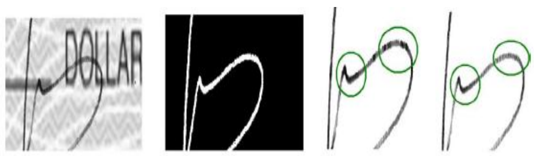
Two methods for signature segmentation were considered: 1) segmentation of the database using the information from the original signature which allows the influence of the gray level distortion to be measured without segmentation error and 2) The use of automatic procedures to eliminate the ackground which includes segmentation error.

1) Signature Segmentation Using Original Signature: Let $I(x,y)$ be a 256-level, gray scale signature image of the database without gray level distortion (MCYT or GPDS) and $I_{\text{NR}}(x,y)$be the same signature converted to black and white as in (6). Let $I_D(x,y)$ be the same signature as $I(x,y)$ except belonging to a database with gray level distortion [see (2)]. The signature $I_D(x,y)$ of is segmented as

$$I_{\text{GD1}}(x,y) = \begin{cases} I_D(x,y), & \text{if } I_{\text{NR}}(x,y) = 255 \\ 255, & \text{otherwise} \end{cases} \quad (8)$$

with the segmented signature $I_{\text{GD1}}(x,y)$.

An example of the procedure can be seen in Fig. 6.



(a) (b) (c) (d)

Fig. 6. Segmentation procedure. Details of (a) original image $I_D(x,y)$ with 256 gray levels, (b) binarized signature $I_{\text{NR}}(x,y)$, (c) segmented signature $I_{GD1}(x,y)$ with gray level distortion, (d) segmented signature $I_G(x,y)$ without gray level distortion. Circles identify some gray level differences.

The circles identify the major gray level distortion in the example.

2) Automatic Signature Segmentation on Complex Backgrounds:

The second method for removing a complex background requires that the signature is segmented from the signed check without using the original signature. The chosen procedure binarizes the check by means of Otsu's threshold. The resulting image contains the signatures strokes plus several lines and text from the check with noise. The binarized image is cleaned by removing the smaller objects. Two additional procedures follow: the first one eliminates the lines while the second one reduces the amount of residual text. The beginning and end of each line is detected by means of the Hough transform and, once the line width is detected, its pixels are turned to white except when the line crosses another object. Text reduction is performed by obtaining the centroids of all the objects and selecting those that are lined up: elimination occurs when at least four objects are aligned to a similar height. A minimum height is required so that low pressure signatures strokes which are similar to dotted lines are not erased. The result is shown in Fig. 7.

Fig. 7. Binarized signed area of a check $I_D(x, y)$ (left), result of line removing procedure (middle), after reducing the amount of residual text $I_{GD2}(x, y)$ (right).

The resulting signature is called $I_{NRD}(x,y)$ and the signature automatically segmented with the gray level distorted is called $I_{GD2}(x,y)$ obtained in a similar way as in (8). Let $I(x,y)$ be a 256-level, gray scale signature image of the database without gray level distortion (MCYT or GPDS database) and $I_{NR}(x,y)$ the same signature converted to black and white. Let $I_D(x,y)$ be the same signature as $I(x,y)$ but belonging to database with gray level distortion and $I_{NRD}(x,y)$ be the black and white signature automatically segmented. The segmentation error Se is measured as

$$\mathrm{Se} = \frac{1}{N \cdot M} \sum_{x=1}^{N} \sum_{y=1}^{M} \mathrm{xor}\{I_{\mathrm{NR}}(x, y), I_{\mathrm{NR}D}(x, y)\} \qquad (9)$$

with xor the or-exclusive operator. The averaged distribution of Se for all the databases is seen in Fig. .

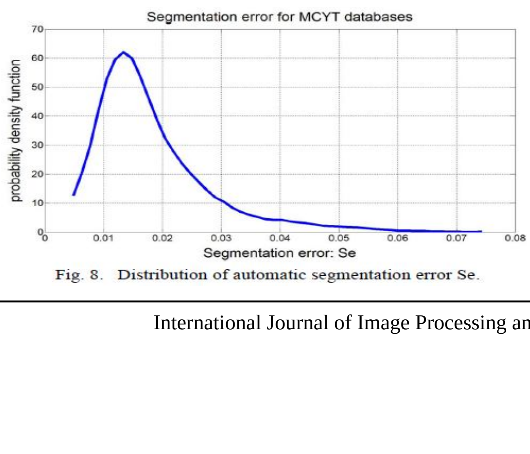


Fig. 8. Distribution of automatic segmentation error Se.

Observe that the average of Se is 0.016. An example of automatically segmented signatures with different Se can be seen in Fig. 9.

Fig. 9. Examples of signatures automatically segmented with Se equal to 0.01, 0.015, 0.02 and 0.03 from left to right.

IV. GRAY LEVEL BASED SIGNATURE FEATURES

A. Local Patterns

The local binary pattern (LBP) operator is defined as a gray level invariant texture measure in a local neighborhood. The original LBP operator labels the pixel of an image by thresholding the 3 3 neighborhood of each pixel and concatenating the results binomially to form a number. Assume that a given image is defined asI(Z)=I(x,y) .The LBP operator transforms the input image LBP(Z) to as follows:

$$\mathrm{LBP}(Z_c) = \sum_{p=0}^{7} s(I(Z_p) - I(Z_c)) \cdot 2^p \qquad (10)$$

where $s(l) = \begin{cases} 1 & l \geq 0 \\ 0 & l < 0 \end{cases}$

The LBP can be extended to a generalized LBP by defining I(ZP)as the gray level of with equally spaced pixels on the circumference of a circle with radius R

$$I(Z_p) = I\left(x + R \cdot \sin\frac{2\pi p}{P}, y - R \cdot \cos\frac{2\pi p}{P}\right) \qquad (11)$$

$$\mathrm{LBP}_{P,R}(Z_c) = \sum^{P-1} s(I(Z_p) - I(Z_c)) \cdot 2^p. \qquad (12)$$

Ojala et al. [25] also observed that in significant image areas certain local binary patterns appear frequently. These patterns are named as uniform LBP since they contain very few transitions from 0 to 1 or 1 to 0 in circular bit sequences. Therefore, they defined the uniform LBP as

$$\mathrm{LBP}^{u2}_{P,R}(Z_c) = \sum_{p=1}^{P} |s(I(Z_p) - I(Z_c)) - s(I(Z_{p-1}) - I(Z_c))|, \quad \text{with } Z_P = Z_0 \qquad (13)$$

$$\mathrm{LBP}^{riu2}_{P,R}(Z_c) = \begin{cases} \sum_{p=0}^{P-1} s(I(Z_p) - I(Z_c)), & \text{if } \mathrm{LBP}^{u2}_{P,R}(Z_c) \leq 2 \\ P+1, & \text{otherwise.} \end{cases} \qquad (14)$$

and the rotation invariant uniform LBP operator as seen in (14), shown at the bottom of the page. An LBP can be considered as the concatenation of the binary gradient directions and is called a micropattern. The histogram of these micropatterns contains information on the distribution of the edges, spots, and other local figures in an image. Nevertheless, these variations of LBPs are still sensitive to random noise and nonmonotonic illumination variation. References [16] and [17] investigated the effectiveness of using high-order local patterns in which the $(n-1)$ th-order derivative direction variations are coded based on binary coding function. Zhang et al. provided calculations for the first order derivatives in [16] along $\alpha = 0°, 45°, 90°$ or $135°$ as

$$\begin{aligned} I'_0(Z_c) &= I(Z_c) - I(Z_3) \\ I'_{45}(Z_c) &= I(Z_c) - I(Z_2) \\ I'_{90}(Z_c) &= I(Z_c) - I(Z_1) \\ I'_{135}(Z_c) &= I(Z_c) - I(Z_0) \end{aligned} \tag{15}$$

with I(Z3),I(Z2),I(Z1),I(Z0) as in Fig. 10. The local derivative pattern is defined as

$$\text{LDerivP}(Z_c) = \{\text{LDerivP}_\alpha(Z_c) | \alpha = 0°, 45°, 90°, 135°\} \tag{16}$$

with $\text{LDerivP}_\alpha(Z_c)$ the local derivative pattern in α direction

$$\text{LDerivP}_\alpha(Z_c) = \{s(I'_\alpha(Z_i) \cdot I'_\alpha(Z_c)) | i = 0, 1, \ldots, 7\}. \tag{17}$$

In a similar way, Jabid et al. [17] proposed a pattern calledthe local directional pattern (LDP) which is based on the eightdirectional edge response values computed by the Kirsh masks.

$\{M_p\}, 0 \leq p \leq 7$. The edge responses $\{m_p\}, 0 \leq p \leq 7$ are worked out as

$$m_p = \sum_{l=0}^{8} I(Z_l) \cdot M_p(Z_l), \quad 0 \leq p \leq 7. \tag{18}$$

Given that the response values are not equally important in all directions, the LDP focuses on the most prominent directions.The LDP code is generated as

$$\text{LDP}(Z_c) = \sum_{p=0}^{P-1} s(m_p - m_k) \cdot 2^p \tag{19}$$

Where mk is the Kth most significant directional response of the sequence . Since in our case K=3 , only 3 bits are on in the LDP code which corresponds to 56 possible values. Since edge responses change less and are more stable than intensity values, LDerivP and LDP patterns are expected to provide more stable values in the presence of gray level distortion.

B. Histogram of Local Patterns

The gray level image IG(Z) is transformed to LBP(Z) LDP(Z) or LderivP(Z) code matrices. Each code matrix contains information about the structure to which the pixel belongs: the stroke edge, stroke corners, stroke ends, inside the stroke or background, etc. We model the distribution of the local pattern by spatial histogram to avoid losing the location of the different structures inside the image. Therefore, the image is divided into a number of adjacent regions [18]. After conducting several experiments and testing a range of smaller and greater region sizes, the best equal error ratio performance was obtained when dividing the image into four equal vertical blocks and three equal horizontal blocks which overlapped by 60% [19]. Consequently, there are 12 blocks and for each block, we calculate the histograms.The histogram of LBP(Z) and LderivP(Z) contains 255 bins while the histogram of LDP(Z) contains 55 bins. Note that the bin corresponding to the code of the background was not considered. An example of histogram is seen in Fig. 11.

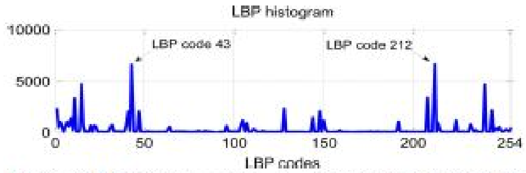


Fig. 11. LBP histogram $h_{LBP}(l), 0 \leq l \leq 254$ of a signature from GPDS960GraySignature corpus. Codes 43 and 212 corresponds to edges structures orientated North West.

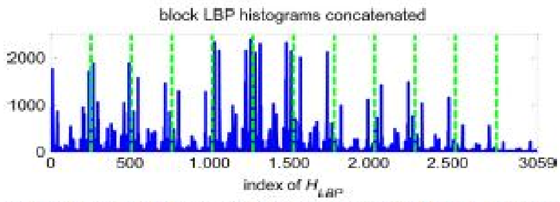


Fig. 12. Example of $H_{LBP}(l)$ vector of the same signature as in Fig. 11. LBP histograms of each block are separated by vertical dashed lines.

The histograms of all the blocks are concatenated to avoid losing the spatial information obtaining the next vectors (nevertheless, experiments accumulating the histograms were also carried out with discouraging results).

1) $H_{LBP} = \{h^i_{LBP} | i = 1, 2, \ldots, 12\}$ of dimension $12 \cdot 255 = 3060$. An example of H_{LBP} can be seen in Fig. 12.
2) $H_{LDerivP} = \{H_{LDerivp_\alpha} | \alpha = 0°, 45°, 90°, 135°\}$ being $H_{LDerivP_\alpha} = \{h^i_{LDerivP_\alpha} | i = 1, 2, \ldots, 12\}$ of dimension $12 \cdot 255 \cdot 4 = 12240$.
3) $H_{LDP} = \{h^i_{LDP} | i = 1, 2, \ldots, 12\}$ of dimension $12 \cdot 56 = 672$.

V. VERIFIERS DESIGN

A. Histogram Similarity Measures

Many similarity measures for histogram matching have been proposed. The simplest one used to measure the similarity between two histograms is given in [26]

$$S_{\mathrm{HI}}(H,S)=\sum_{i=1}^{B}\min(H_i,S_i) \quad (20)$$

Where SHI(H,S) is the histogram intersection statistic between histograms H and S . This measure is intuitively appealing because it calculates the common parts of two histograms. Its computational complexity is very low as it requires only simple operations [16].

It is also possible to use other measures for similarity, such as the chi-square distance defined as

$$\chi^2=\sum_{i=1}^{B}\frac{(H_i-S_i)^2}{H_i+S_i}. \quad (21)$$

B. Classifiers

The previously mentioned measures are used for the nearest neighbor classifier, with the test sample or questioned histogram and the template histogram feature or unquestioned reference.

Alternatively, we have also used a support vector machine (SVM) as a classifier. An SVM is a popular supervised machine learning technique which performs an implicit mapping into a higher dimensional feature space. This is the so-called kernel trick. After themapping is completed it finds a linear separating hyperplane with maximal margin to separate data from this higher dimensional space.

Least squares support vector machines (LS-SVM) are reformulations to standard SVMs which solve the indefinite linear systems generated within them. Robustness, sparseness, and weightings can be imposed to LS-SVMs where needed and a Bayesian framework with three levels of inference is then applied [27].

Though new kernels are being proposed, the most frequently used kernel functions are linear, polynomial, and radial basis function (RBF). This study tested the linear and RBF kernel. In the case of the RBF kernel, the concatenated histogram vector produces a very long feature vector for training a classifier with a few genuine samples. Discrete cosine transform (DCT) or principal component analysis (PCA) are two methods that were tested to reduce dimensionality.

Another classical kernel that is used in computer vision and in this study is the kernel [28]. Several authors define the additive kernel as the negative of the distance. As such a kernel is only conditionally positive definite, here we have used as kernel:

$$\chi^2_{\mathrm{PD}}=\sum_{i=1}^{B}\frac{2H_iS_i}{H_i+S_i} \quad (22)$$

which makes the additive X^2 kernel positive definite [28].Finally, we also tested a generalized version of the histogram intersection (GHI) as a kernel [29], which has already been used in face biometrics [30] and is defined as

$$S_{\mathrm{GHI}}(H,S)=\sum_{i=1}^{B}\min\left(H_i^{\beta},S_i^{\beta}\right) \quad (23)$$

with β a real number greater than 0.

SVM or LS-SVM makes binary decision and multiclass classification possible by adopting the one-against-one or one-against all techniques. In our study we adopted the second technique. We carried out grid-search on the hyperparameters in the ten-fold cross validation for selecting the parameters on the training sequence. The parameters setting that produce the best cross-validation accuracy were picked.

VI. EXPERIMENTAL RESULTS

An automatic signature verifier should assess whether a questionedsignature is an authentic signature normally used by the reference writer. A failure in this case is referred to as type I error (false rejection or miss). The system should also avoid the acceptance of questioned signatures which are the product of a forgery process. The second error is referred to as type II error (false acceptance or false alarm). Commonly, forgeries are divided into three different types: a fictitious signature which is usually a genuine signature belonging to a different writer, a simple forgery for which the forger knows the writer's name,and finally the simulated forgery which is a reasonable imitation of the genuine signature model [31]. In this paper, fictitious signatures and simulated forgery types were used. The signature model will be trained only with genuine and fictitious signatures.

For experiment we took 8 original signatures from each person and selected 3 for training. These original signatures are taken in different days. Forgeries taken by three persons and 10 from each. Total 50 originals and 30 forgeries for each person signature are going to be tested. There are two thresholds (one based on vertical splitting and another based on horizontal splitting) for each person signature.

5.1 Training:

Let n signatures are taking for training from each person. There are 60 feature points from each original signature, 30 are taken by vertical splitting (Section2.2) and 30 are taken by horizontal splitting (Section2.3). Individual thresholds and patterns are calculated for vertical splitting and horizontal splitting. Pattern points based on vertical splitting are shown below.

5.2 Testing:
When new signature comes for testing we have to calculate features of vertical splitting and horizontal splitting. Feature points based vertical splitting are vnew;1, vnew;2, vnew;3, vnew;4,…….. vnew;29, vnew;30. Distances between new signature features and pattern feature points based on vertical splitting are shown below:

5.3 Results
False Acceptance Rate (FAR) and False Rejection Rate (FRR) are the two parameters using for measuring performance of any signature verification method. FAR is calculated by equation 3.14 and FRR is calculated by equation 3.15.

VII. CONCLUSION

Histograms of local binary, local directional and local derivative patterns used for texture measures are proposed for offline automatic signature verification. These parameters were evaluated with different classifiers such as nearest neighbor and SVM. SVM was evaluated with different kernels such as the classical RBF and the histogram-oriented kernels GHI and kernels. The results show that the kernel provides the best results with local derivative patterns.

These results improve those reported in [14]. The SVM with kernel has proved to be more robust against the gray level distortion when the signatures are mixed with bank checks. With this configuration, the robustness against gray level distortion is very similar with the basic LBP, LDP and LDerivP features.

The proposed configuration is evaluated under different circumstances: changing the number of training signatures, multiple signing sessions, database with different inks, increasing the number of signers and combining different features at score level. Results have also been provided when looking for the signature in the check and segmenting it automatically. In all the cases, the best results were obtained with the LDerivP parameters, which improve the results claimed in the established baseline, revealing very significant improvements with fictitious signatures.

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