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A RELIABLE BINARIZATION METHOD FOR OFFLINE SIGNATURE SYSTEM BASED ON UNIQUE SIGNER'S PROFILE

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Abstract. *Previous studies on offline signature verification are still having a main challenge to propose a robust and accurate binarization technique that supports various types of scanned signatures with different resolutions and additional noise. This paper outlines a reliable binarization technique using background estimation to generate three different grayscale images which are implemented to a robust thresholding technique based on Laplacian zero-crossing concept. The three output binary images will be evaluated using ordinal structure fuzzy module (OSFM) to choose the best one to be an input to the next stages. The proposed offline signature system will use only one master signature to build the signer's profile which will be used in the comparison stage. Comparing the proposed thresholding technique with the other ones proves that the false acceptance rate (FAR) and false rejection rate (FRR) have been improved for different types of collected signatures.*

Keywords: Binarization technique, Laplacian zero-crossing, Ordinal structure fuzzy module (OSFM), Offline signature verification, Profile of signer, Master signature

1. **Introduction.** Signature verification is designed to verify subjects based on the traits of their unique signature. As a result, individuals who do not sign in a consistent manner may cause an issue to the system to verify their signature correctly due to inconsistency. During creating the signer's profile, only one signature sample is targeted to be used for the construction of the template. This stage will be a bit challenging as most literature concerning offline signature verification assumes that there will be a sizeable number of sample signatures available from which a profile of an individual signer can be constructed. The challenge is how to use one sample signature of the signer and to be able to find the variability between signatures provided from the same person [1]. During verification enough characteristics must remain constant to determine with confidence that the authorized person signed. As a result, individuals with muscular illnesses and people who sometimes sign with only their initials might result in a higher false rejection rate (FRR), which measures the likelihood that a system will incorrectly reject an authorized user.

Typical document verification system (DVS) aims at extracting the signature from the scanned document and verifies it as accurately as possible. The full process of the DVS can be summarized as the following stages [2].

- Preprocessing Stage: Many researchers proposed highly computation preprocessing which enhanced the scanned input image effectively, but failed to be implemented practically due to slow performance [3]. The two main parts in the preprocessing stages are noise removal and skewing technique. These steps are highly related to resolution of provided signature, blurred images, noisy backgrounds, and many other factors. Several studies on noise removal and skewing over offline signature were conducted based on different features as projection profile calculation [4], connected-component analysis [5], color distribution [6], gradient levels. However, it is particularly noted that many of the previous techniques have limitation to specific scenarios and highly time consuming [7].
- Binarization Stage: Multiple techniques are proposed to binarize the image since a long time. Signatures in usual cases should consist of two components which are foreground component called objects of interest, and a background component. In practical scenario of gray level image, the intensity values of pixels are not likely to have only two levels, but instead of a range of intensities. This is due to multiple reasons: non-uniform printing or non-uniform scanning, or a result of intensity transitions at the region edges that are located between foreground and background regions. In addition, binarizing the image using a proper thresholding technique is considered as one of the crucial stages in the verification system, as it has a major impact on all the consequence stages [8,9].
- Feature Extraction Stage: The purpose of this stage is to simplify the amount of resources required to describe a large set of data accurately. The challenge is behind finding unique features able to describe a set of signatures with sufficient accuracy and without the need to use multiple signatures to build a signer's profile [10].
- Verification Stage: This stage consists of how to describe and represent the features to be an input to the verification stage. Challenge of feature representation is to decide the proper representation of the extracted features which achieve the fastest performance. Different ways were proposed by the researchers as structural, vector, and trees [11]. In addition to the representation, choosing proper verification algorithms out of the vast techniques in offline signature namely supervised and unsupervised learning, will enhance the whole system [12]. As with all verification problems, the two main issues are the type of similarity measure(s) applied and the calculation of the threshold(s) to determine whether a test signature is accepted or rejected.

Various factors in the offline signature verification like noisy background, similarities of colors between the signature foreground and its background, scanning resolution, illumination, contrast, and many other factors, make the verification process a complicated process [13].

Success of the proposed system depends on accurate verification of signature, which in turn depends on successful binarization. For post gray scaling, a pixel on the image has a value between 0 (absolute black) to 255 (absolute white), for 8 bit images, while for post binarization the pixels have only two values 0 (black) or 1 (white), i.e., suppressing the noise and leaving only the foreground. Success of binarization is very critical since the correct matching with the built profiles of different persons depends on the quality of binarized image. A good binarization decreases the computational load, simplifies further processing and improves overall OSV performance [14].

To achieve the previous mentioned target, a new thresholding technique based on background estimation and OSFM fusion will be defined.

In the end, the work tries to prove the efficiency of the proposed binarization method in the worst-case scenario, where only one sample signature is available to create a signer's profile and highly accurate system can be produced. Such scenarios occur in the banking industry, where a bank only has one hard copy of each customer's signature and aims to implement some form of automatic signature verification without requiring all the customers to attend an enrollment session at a bank branch.

The proposed system is developed based on a collection of signatures which consists of a simple background, noisy background, simple signature, and complicated signature. The first stage of the whole system is pre-processing stage which is performed to remove the noise, rotate and skew the extracted signature, after that three different grayscale signature will be generated based on background estimation concept. Zero-crossing Laplacian concept will be used to generate the binary images for the three inputs. In the end, OSFM will be used to evaluate the inputs and nominate the best image for the classification stage as shown in Figure 1.

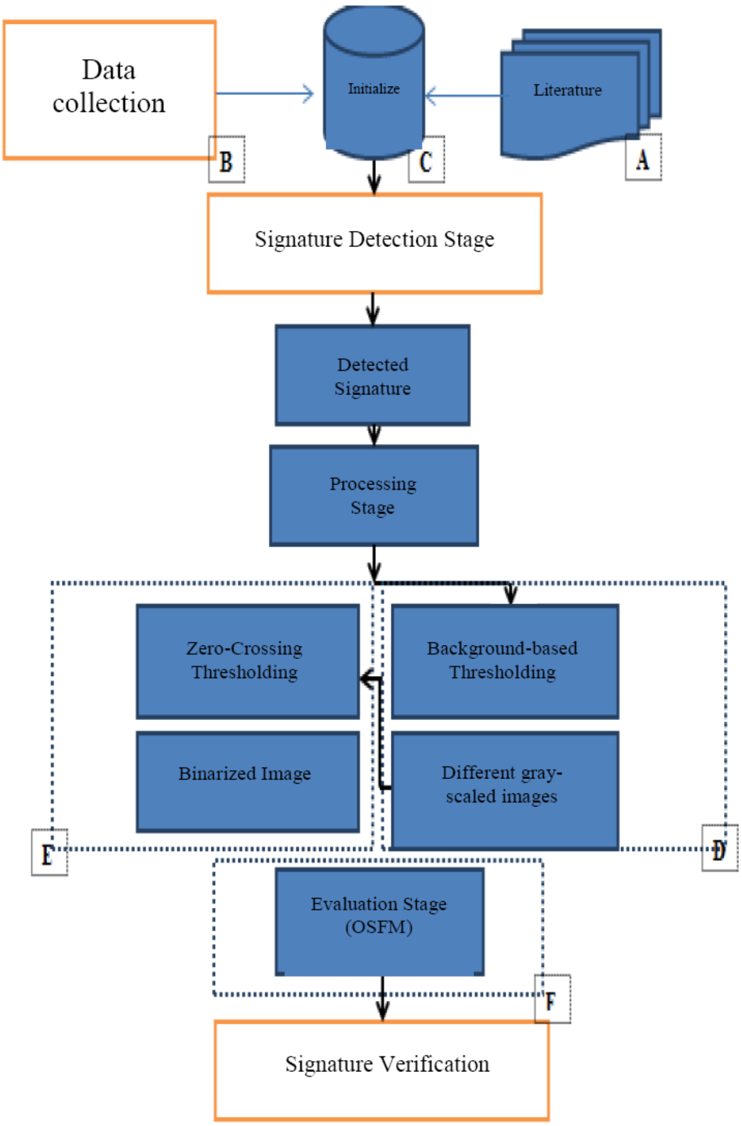

FIGURE 1. DVS process flow

This paper has been organized with the Introduction first. Preprocessing stage is described briefly in the next section, proposed reliable thresholding technique which consists of three stages namely, background estimation, zero-crossing thresholding, and evaluation stage is next described, and experimental results showing the robustness of the proposed thresholding technique and the conclusion are discussed in the last sections.

2. **Preprocessing.** Each signature was scanned into a computer and considered as offline image. This image is converted to grayscale and then to binary by implementing an adaptive thresholding algorithm. After binarization stage, signatures' images usually still need additional preprocessing stages before proceeding to next stages. These steps are required for both noise reduction and skew correction. Noise removal stage tries to eliminate the effects due to the type of pen used (ball, felt-tip, calligraphic), by dilating, thinning and pruning the image to expose the signature's skeleton [15]. Precisely, a single dilation of the image was performed with the intention of removing any breaks in the signature that might have occurred during the thresholding. Next, the image was thinned iteratively until no more pixels are removed. Finally, a number of iterations of a simple pruning algorithm (based on the calculated pen width) were performed to remove unwanted spurs from the signature.

After removing the noise, signature tilting is corrected by finding the proper rotation method. To do this, the best fitting ellipsoid for the signature was found by calculating the eigenvalues and eigenvectors of the covariance matrix formed by the points in the signature. The eigenvector with the largest eigenvalue gives the major axis of the ellipsoid, and so the signature. Note that in signatures where the major axis is not prominent small variations in the signature can lead to large differences in the major axis. Thus, where the ratio of the largest eigenvalue to the smallest eigenvalue fell below a certain threshold, signature rotation was not applied.

After enhancing the scanned images of the offline signatures by implementing different techniques in the preprocessing stage, finding the proper thresholding method in addition to calculating the accuracy is explained next.

3. **Proposed Thresholding Technique.** This section provides full details about the proposed binarization technique based on the background estimation and OSFM evaluation. The work can be split to three different stages named as, background-based estimation (BBE) which stage 'D', zero crossing thresholding (ZCT) which is stage 'E', and evaluation stage (ES) using OSFM which is stage 'F'.

3.1. **BBE stage.** BBE will apply equalized histogram on the input grayscale image to standardizing gray scale intensity distribution of the gray scaled image of the detected plate as the first stage. Calculating the mean and standard deviation of the gray scaled image is done next to be used for grayscale calculation. In yet another aspect, the standard deviation is scaled using three different scaling factors, and wherein by changing the scaling factor, multiple estimated background values are generated to produce three different gray scale images.

The equations used for the calculation are as the following:

$$\text{Mean } (\mu) = \frac{\sum((\text{Gray scale value of the pixel}) \times (\text{Count of the pixel}))}{\text{Count of respective pixels}}$$

$$\text{Variance } (\sigma^2) = \frac{\sum((\text{Gray scale value of the pixel} - \mu)^2 \times (\text{Count of the pixel}))}{\text{Count of respective pixels}}$$

$$\left(\sigma_W^2\right) = \mu + W_f \sigma_f^2 : W_f = -0.5, 0, 0.5$$

FIGURE 2. Three different outputs of BBE stage

Assigning different scales to the variance while generating the grayscale image will assist in generating three different grayscale images as shown in Figure 2.

The generated different grayscale images will be sent to ZCT stage in order to be binarized.

3.2. **ZCT.** In ZCT, the binarization process will not be done by estimating the threshold value using one of the traditional techniques as Fisher's criterion for linear discriminant analysis used by Otsu thresholding method. The traditional Otsu method estimates the threshold reference value by selecting the value that maximizes the inter-class variance and minimizes the intra-class variance [16]. Otsu method is a global common thresholding technique using a unique value to binarize the image and cannot be implemented for different scenarios as proposed in this paper [17-19]. For the previous mentioned reason, thresholding based on Laplacian crossing is proposed as by doing the following.

As width is the distance between 2 zero crossing points in binarized input image, width is calculated horizontally, vertically, and diagonally. After finding the nominated width in different directions, the most common width will be chosen as a target width (TW) based on their histogram distribution (frequency) as shown in Figure 3.

All the width falling into the group of the target width will be chosen over the whole image. Filtration based on applying gradient vector flow (GVF) technique to check the arrows created by over each stroke is applied to filtering out the nominated strokes based on the next condition.

- If the arrows are pointing towards each other, strokes will be kept.

After getting the strokes, the neighbors will be scanned in order to restore the needed parts related to the component.

The generated different binary images will be sent to OSFM in order to choose the best one of them for verification stage.

3.3. **Evaluation stage.** ES is configured to process the candidate binary images and evaluate them based on different rules using OSFM.

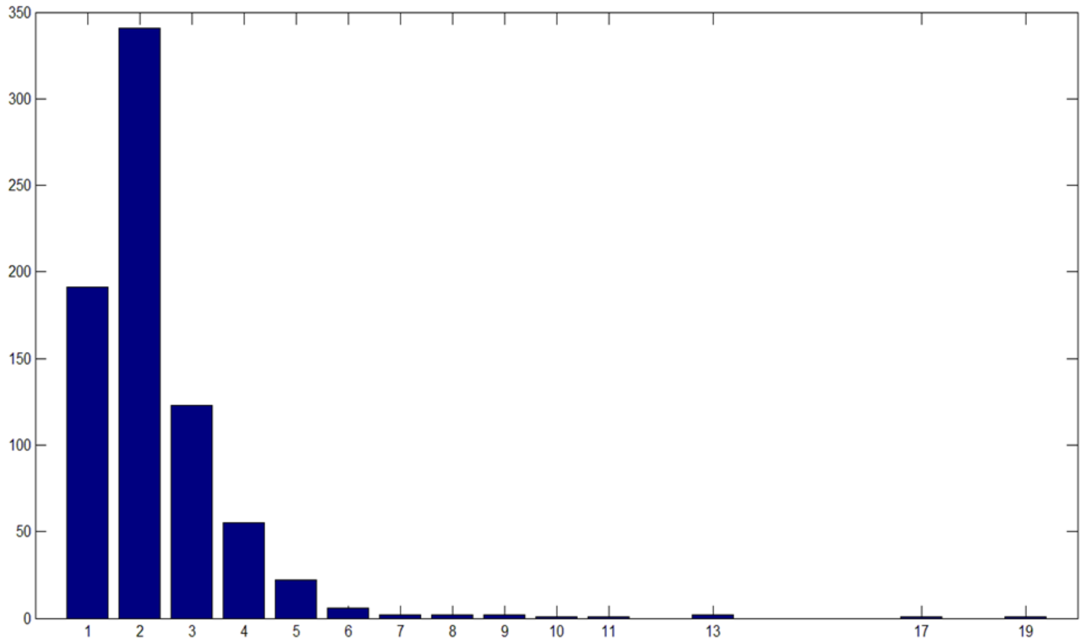

Figure 3. Histogram of the highest frequency width

Figure 4. Three different outputs of ZCT stage

The properties of the ordinal structure model of fuzzy reasoning are based on the conventional fuzzy algorithm [19].

Proposed thresholding technique is considered as a multi-input single-output (MISO) control system. Using the conventional fuzzy reasoning method, the inference rules have to be described in multi-dimensional inputs and single output spaces and this is rather difficult to be configured. Thus, an ordinal structure model of fuzzy reasoning is used in this system. The model well coincides with the human image of fuzzy inference rules in the case where a system has many inputs and many outputs.

The conventional fuzzy logic engine consists of 4 main blocks which are:

- Fuzzifier
- Inference engine
- Knowledge based
- Defuzzifier

Fuzzifier block is involved in the conversion of the input/output values of the fuzzy decision system into a corresponding fuzzy input values. The fuzzy sets of different inputs are as the following.

First rules are based on comparing the height of each isolated blob with whole signature height as Figure 5(a).

Second rules are based on comparing the width of each isolated blob with signature width as Figure 5(b).

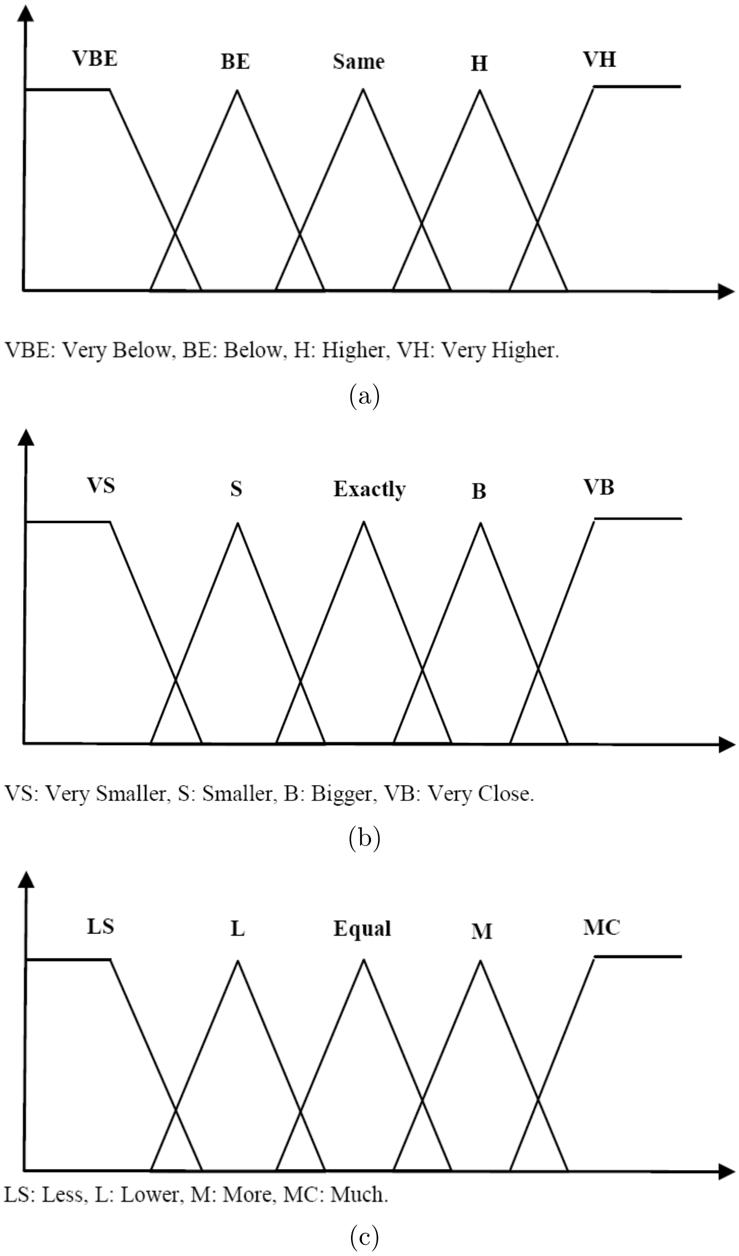

Figure 5. The fuzzy sets of fuzzifier block

Third rules are based on calculating the white density of each detected blob as Figure 5(c).

The input variables of the three different binary images are being translated into the above 3 fuzzy sets. The membership value for each of the inputs ranges from 0 to 1.

Inference engine infers the rules from knowledge of the system to data. Based on the 3 input variables, a set of rules can be developed. Examples of rules are given below in addition to matrix rule (Table 1).

Rule 1: IF (Binary1 = VBE) AND (Binary2 = LS)
THEN – the most likely Decision = Too weak (TW)

Rule 2: IF (Binary1 = VBE) AND (Binary2 = L)
THEN – the most likely decision = Too weak (TW)

Rule 3: IF (Binary1 = BE) AND (Binary2 = L)
THEN – the most likely Decision = Weak (W)

Rule 4: IF (Binary1 = E) AND (Binary2 = S)
THEN – the most likely Decision = Strong (S)

TABLE 1. The fuzzy association matrix rule

	VBE	BE	Same	H	VH
VS	TW	FA	W	TW	TW
S	TW	TW	S	TW	TW
Exactly	W	S	S	W	W
B	TW	TW	S	TW	TW
VB	TW	TW	W	TW	TW

	VBE	BE	Same	H	VH
LS	TW	FA	W	TW	TW
L	TW	TW	S	TW	TW
Equal	W	S	S	W	W
M	TW	TW	S	TW	TW
MC	TW	TW	W	TW	TW

	LS	L	Equal	M	MC
VS	TW	FA	W	TW	TW
S	TW	TW	S	TW	TW
Exactly	W	S	S	W	W
B	TW	TW	S	TW	TW
VB	TW	TW	W	TW	TW

Defuzzification process is process of converting the fuzzy output variables into crisp values. The fuzzy output variable which is the "Similarity Decision" is represented by the fuzzy sets as shown in Figure 6.

Unlike the conventional fuzzy logic, the rules in OSFM are defined as a set of rules weighted individually according to their importance. Ordinal module fuzzy uses the moment method [20] to calculate the inference values, for an n-input, one-output system the inference rules will be as the following:

R_i: If x_1 is A_{i1} then y_i is B_i

R_j: If x_2 is A_{j2} then y_j is B_j $(i = 1, 2, \ldots, n)$
Inference value will be [20]:

$$y = \frac{\sum_{i=1}^{n} w_i \mu_i c_i S_i + \sum_{j=1}^{n} w_j \mu_j c_j S_j}{\sum_{i=1}^{n} w_i \mu_i S_i + \sum_{j=1}^{n} w_j \mu_j S_j}$$

where

- A_i, A_j and B_i are fuzzy variables.
- y_i, y_j are the inferred values.
- μ_i, μ_j are the truth values.
- c_i, S_i, c_j, S_j are central position and area of membership function with the fuzzy variable.
- R_i is the i-th fuzzy rule with the input x_1.
- R_j is the j-th rule with the input x_2.
- w_i is the weight of the rule R_i.
- w_j is the weight of the rule of R_j.

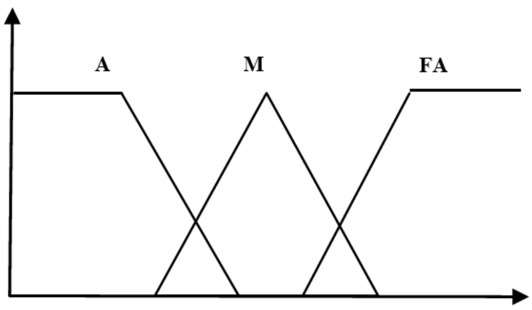

FIGURE 6. The fuzzy set of output value

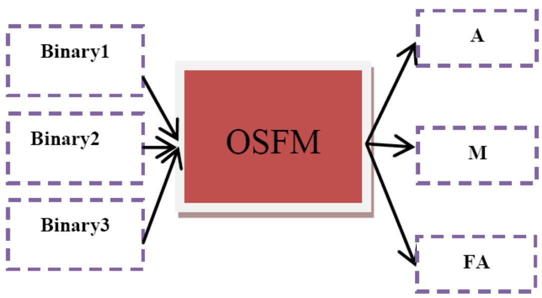

FIGURE 7. Structure ordinal module of fuzzy work

Each rule is weighed according to how well its conditional part matches its importance. As the weighting of the rules will affect the accuracy of the whole system, it is considered as one of the most important stages in the whole method. Usually, the knowledge and experiential rules of experts should be incorporated in the system to define the weights for each rule.

From the inference value equation, the weights of the three binary images (inputs) should be determined. In order to calculate the weights, we should count the following.

V1: the number of the highest values (VH, MU, VB)

V2: number of the second highest values (H, M, B)

V3: number of matching values (Same, Exactly, Equal)
V4: number of low values (BE, L, S)
V5: number of very low values (VBE, LS, VS)
The following weights assigned to values [15]
V1 = 1, V2 = 0.8, V3 = 0.5, V4 = 0.3, V5 = 0.
$W_i = ((V1 * 1) + (V2 * 0.8) + (V3 * 0.5) + (V4 * 0.3) + (V5 * 0))/O_t$
where
W_i = weights of each input i.
O_t = total number of outputs.
The final result of the proposed system depends on the decision of the ordinal structure fuzzy module implemented in the thresholding stage.

The following values are assigned to the decision module (OSFM):
S (Strong) = 1, TW (Too Weak) = 0.3, W (Weak) = 0.6
To obtain the result, initially the value of 0.67 is compared with the output of OSFM to know whether the studied binary image is going to be chosen or not as the following.

If the decision value >= 0.67
Will be chosen.
To prove the efficiency of the proposed system, offline signature's database is collected to conduct the experiment and evaluate the results. The process of building the database is explained in detail in the following section.

4. **Experimental Results.** The OSV will be tested using the dataset mentioned below and will be divided into two categories of testing named, accuracy and timing testing. Both of these categories are required to prove the target of the conducted research to provide a highly accurate system which is able to be implemented practically in the real life. The experiments will evaluate the accuracy of the proposed thresholding technique among different common thresholding techniques.

Table 2. Collected database for evaluation

Set	**Type**	**Number of signs/signer**	**Total signatures of 14 user**
Testing	Genuine	3	42
	Low resolution	7	98
	Noisy background	4	56

Different common global thresholding algorithms consisting of 12 direct-based were applied over the different collected signatures. Their performance was evaluated comparatively depending on the outcome of the verifier. The verifier uses common features among them in order to make a decision whether the signature is genuine or not. This experiment addressed challenges in the binarization which affected quite critically to the performance of the successive steps in the verification. The most important challenge is the value of the FAR and FRR of a signature which is referred to as Type I error or commonly called FAR and Type II error or commonly called FRR.

The results the FRR rates the signature system after implementing direct-based thresholding techniques over signature are demonstrated in Table 3.

FAR results after implementing direct-based thresholding techniques over signature are demonstrated in Table 4 for only seen signatures as they are the most challenging ones.

An experimental testing of all the adapted thresholding techniques was performed over collected signatures in four different categories. These signatures are different in terms of complexity and resolution. The results of the experiments are shown in Tables 3 and

TABLE 3. The FRR rates of OSV after implementing different thresholding techniques

Signatories	False Rejection Rate (FRR)			
	SIS	OTSU	Hou	P-Tile
Signer1	0.24	0.15	0.32	0.22
Signer2	0.27	0.22	0.24	0.19
Signer3	0.23	0.20	0.28	0.38
Signer4	0.1	0.21	0.28	0.45
Signer5	0.42	0.40	0.48	0.58
Signer6	0.18	0.10	0.16	0.12
Signer7	0.3	0.48	0.32	0.42
Signer8	0.12	0.13	0.23	0.33
Signer9	0.21	0.15	0.18	0.36
Signer10	0.35	0.31	0.22	0.44
Average	**0.242**	**0.235**	**0.271**	**0.349**

Signatories	False Rejection Rate (FRR)			
	Renyi	Chang	Prewitt	Rosenfeld
Signer1	0.52	0.28	0.48	0.38
Signer2	0.49	0.28	0.38	0.38
Signer3	0.56	0.18	0.22	0.32
Signer4	0.52	0.45	0.25	0.45
Signer5	0.43	0.28	0.34	0.64
Signer6	0.46	0.22	0.26	0.36
Signer7	0.47	0.44	0.48	0.38
Signer8	0.38	0.36	0.42	0.32
Signer9	0.39	0.44	0.22	0.42
Signer10	0.46	0.36	0.38	0.48
Average	**0.468**	**0.329**	**0.343**	**0.413**

4 using the FRR and FAR criteria over ten different signers. The OTS, SIS, and Hou had the lowest FRR value based on the calculated values. OTSU is a simple binarization method. The resulting binary images are promising in case of simple signatures but unable to properly binarize them in case of complex transition between the foreground and the background. Also the performance of the technique is massively affected by changing the resolution of the scanned signature. In general, this method is time-consuming and fails under the previous mentioned scenarios. The results of applying SIS to the signature are also shown in Table 3. As shown, the results are satisfactory and better than the OTSU, in terms of complicated integrated signatures and noisy background but worse in simple signatures with white homogenous background. Hou as a global thresholding method is also implemented over the dataset. The method transforms the input image values to get better threshold outputs and to solve issues faced such as the case of very simple signature, which has little information located in scattered places. It also successfully separates the background from the foreground. Hou's consumes more time than the previous point-dependent methods.

To prove the efficiency of the proposed ATM technique, the results for both FRR and FAR are discussed and compared below with the other highest thresholding techniques proposed by other researchers as Table 5 and Table 6.

Table 4. The FAR rates of OSV after implementing different thresholding techniques on seen collected samples

Signatories	False Acceptance Rate (FAR)			
	SIS	OTSU	Hou	P-Tile
Signer1	0.43	0.26	0.26	0.38
Signer2	0.25	0.1	0.1	0.4
Signer3	0.37	0.3	0.3	0.33
Signer4	0.13	0.13	0.13	0.37
Signer5	0.12	0.08	0.18	0.38
Signer6	0.24	0.26	0.26	0.49
Signer7	0.23	0.16	0.26	0.32
Signer8	0.55	0.48	0.48	0.44
Signer9	0.27	0.2	0.2	0.33
Signer10	0.18	0.18	0.18	0.36
Average	**0.277**	**0.215**	**0.235**	**0.38**

Signatories	False Acceptance Rate (FAR)			
	Renyi	Chang	Prewitt	Rosenfeld
Signer1	0.38	0.32	0.36	0.33
Signer2	0.33	0.34	0.38	0.35
Signer3	0.36	0.44	0.34	0.42
Signer4	0.24	0.23	0.33	0.32
Signer5	0.32	0.26	0.28	0.32
Signer6	0.36	0.34	0.36	0.44
Signer7	0.26	0.26	0.46	0.26
Signer8	0.46	0.28	0.38	0.48
Signer9	0.4	0.4	0.32	0.28
Signer10	0.48	0.3	0.36	0.28
Average	**0.359**	**0.317**	**0.357**	**0.348**

Table 5. The FRR rates of OSV suggested thresholding method with the other three chosen thresholding methods

Signatories	False Rejection Rate (FRR)			
	SIS	OTSU	Hou	**ATM**
Signer1	0.24	0.15	0.32	0.2
Signer2	0.27	0.22	0.24	0.17
Signer3	0.23	0.20	0.28	0.13
Signer4	0.1	0.21	0.28	0.08
Signer5	0.42	0.40	0.48	0.32
Signer6	0.18	0.10	0.16	0.02
Signer7	0.3	0.48	0.32	0.28
Signer8	0.12	0.13	0.23	0.02
Signer9	0.21	0.15	0.18	0.11
Signer10	0.35	0.31	0.22	0.23
Average	**0.242**	**0.235**	**0.271**	**0.156**

TABLE 6. The FAR rates of OSV suggested thresholding method with the other three chosen thresholding methods

Signatories	False Acceptance Rate (FAR)			
	SIS	OTSU	Hou	**ATM**
Signer1	0.43	0.26	0.26	0.23
Signer2	0.25	0.1	0.1	0.05
Signer3	0.37	0.3	0.3	0.27
Signer4	0.13	0.13	0.13	0.03
Signer5	0.12	0.08	0.18	0.02
Signer6	0.24	0.26	0.26	0.16
Signer7	0.23	0.16	0.26	0.13
Signer8	0.55	0.48	0.48	0.25
Signer9	0.27	0.2	0.2	0.17
Signer10	0.18	0.18	0.18	0.08
Average	**0.277**	**0.215**	**0.235**	**0.139**

5. **Conclusion.** Many research works are done on offline signature verification system, and the previous studies have assumed that there will be at least three sample signatures available from which a profile of an individual signer can be constructed to produce an accurate and reliable system. The purpose of this paper is to present robust thresholding image to be used as an input to the classification stage of OSV with only one signature to build the signer's profile. It has been shown that fusing different binary images by using the background estimation concept decreases the EER and lessens the difference between FAR and FRR values for individual signers. These presented techniques have been implemented in a commercial cheque clearing system for use in banks where only one sample signature is available. In this system, automatic signature verification is used to support manual verification by highlighting possible forgeries. This work can formulate a good start for other researchers who are looking to find a good binarization method to binarize the signature and discussing the other consequent steps that are related to the binary image.

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