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Spatial Analysis of Local Statistics for Handwritten Signature Recognition

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Abstract

Handwritten signature is one of the most popular distinguishing biometric traits which can be used for secure personal authentication. Many challenges rise for handwritten signature recognition which include complexity of writing the signature (writing style, stroke pattern) also feature extraction and representation that give the best result. In this paper, a handwritten signature recognition system is proposed for static images. The system consists of three primary stages (preprocessing, feature extraction and recognition). In preprocessing stage, image processing methods are applied to remove the undesired noise and extract the signature region (ROI). After that, a new set of spatial-statistical features is determined from extracted ROI body, representing the density of the signature in each image block. The set of introduced features is determined from the spatial domain after partitioning it into overlapped blocks. Then, the spatial-statistical features are determined from each block separately and assembled into one feature vector to represent the tested signature sample. The experimental results showed that the developed system could give recognition accuracy of around 99.81%; when tested on a dataset (SigCom2011) consisting of 612 signature images that belong to 102 persons using visual studio as programming environment.

Keywords- Handwritten signature, Density-based features, Noise removal, Rotation compensation, Statistical classifier.

I. INTRODUCTION

INTRODUCTION

Person identification and verification is very substantial in security applications. Now, the biometric approach is an interesting method of identification and verification. Biometric is a measure for verification and identification which have many advantages such as unique for each individual, and cannot be forgotten, and it is together with persons always [1],[2].

Biometric systems are pattern recognition systems, they could assign the authenticity of the person based on a specific physiological or behavioral characteristic that he has (such as: retina, fingerprint, signature, palm etc.) [3]. The signature recognition is a very robust biometric to authenticate the user since the signature for different individuals vary with the variation of individuals [4]. Automatic signature recognition and verification systems have many applications, such as credit card validation, land purchases, legal documents, cheques, and security systems [5].

There are two major approaches for recognizing the signature: offline [6] and online [7]. A special set of instruments and devices are required for online or dynamic method in order to capture the dynamic signature features (like the pen pressure, and speed of signature movements over the paper at the time of the writing) [8]. The dynamic information being available since the signature signal is captured during the writing process [9]. On other hand, offline or static method uses the pictorial handwriting data that obtained using an optical scanner or camera, thus only a static image is available [10]. This approach is based on the static characteristics of the signature which are invariant [11]. Kalera et al. [12] presented Offline Signature Identification and Verification via using Distance Statistics. To extract global, statistical, geometrical and topological features of the signature, they employed the GSC (Structural, Concavity, and Gradient) technique. Every signature sample had a related binary feature vector, and the distance between any given sample and all other samples was determined by utilizing the correlation measure to quantify the similarity between two binary pictures. They employed the KNN (K-Nearest Neighbors) classification in the method they used. The proposed method achieved identification accuracy of 93.18% when using K=3.

Zhang et al. [13] presented Off-line Signature Recognition and Verification via the model of self-regression using the Kernel Principal Component (KPC). For the purpose of ensuring to precisely define each individual's signature, the model of self-regression selects a specific number of the fundamental elements from the kernel space for the input variables, providing strong verification and

recognition performance. In the first experiments, the pattern performed optimally when applied directly to bitmap pictures. The proposed approach achieved 92% and 5% for FRR(false rejection rate) and FAR(false acceptance rate), respectively.
Ghandali et al. [14]. presented an off-line Persian signature system based on combining of image based on feature and Discrete Wavelet Transform (DWT) This method uses a discrete wavelet transform to obtain high frequency channels with signature geometries. The signature patterns are then created by combining up several samples of a person's signature according to high frequency channels. As classifiers, Support Vector Machines (SVM) were employed. The dataset utilized consists of six authentic, one expertly forged, and one easily faked signature from each of the 90 signers. For FAR and FRR, the obtained error rates are 10% and 8.9%, respectively.
Banerjee et al. have developed an approximately suitable dependent and independent writer language invariant offline verification of signatures method. An offline signature is initially gathered as a picture, Singular value decomposition is then used to create a related signal. Following that, four separate sorts of features—statistical, shape-based, similarity-based, and frequency-based features are extracted from the signature image's modified signal. Then, we proposed a new wrapper selection of features technique based on the newly described meta-heuristic Red Deer Algorithm to reduce the feature dimension and keep just the necessary characteristics for use in the authentication and verification of digital signatures. Using a confidence score from the Naive Bayes classifier, authentication and verification have been achieved [15]. Convolutional neural networks (CNN) have also been used in an experiment to compare the outcomes with Recurrent Neural Networks RNN-based results. In this domain, the suggested RNN-based signature verification and recognition system outperforms CNN and the most recent discoveries, according to experimental data [1]. A suggestion for developing compositional synthetic signatures using shape primitives and the synthetic dataset from the Group Decision Support Systems GPDSS. The first two approaches are "on-demand" generators that may be used to create potentially an endless number of synthetic signatures during the training phase. In our method, we first trained Siamese Neural Networks using the GAVAB dataset's signatures and various combinations of synthetic data. Combining real and fake signatures for training led to the best verification outcomes [17].
The paper [18] discusses the critical problem of using handwritten signatures to identify individuals in order to authenticate essential documents. A hybrid deep learning network is proposed in this research as a unique method for offline signature verification, taking into account the difficulties caused by intrapersonal variance, interpersonal similarity, and skillful imitation. This network consists of a Bidirectional Long Short-Term Memory (BiLSTM) network and a Convolutional Neural Network (CNN).
The method's justification stems from the structural similarities that exist between authentic signatures and expertly forged ones, making the identification of minute variations crucial. By utilizing CNNs' deep learning powers to extract important information and minute patterns from picture pixels, the suggested method seeks to accurately discriminate between authentic and fake signatures.
In [19] In biometrics and document authentication, handwritten signature verification is a crucial task with applications in money, legal paperwork, and security. This study tackles this challenge. Even though computer vision and machine learning have made great strides in this area, some dataset properties and model choices may still allow for improvement.
The feature vectors were subjected to a variety of machine learning approaches in order to train models for signature verification, including Support Vector Machines (SVM) with various kernels (rbf, poly, and linear), k-Nearest Neighbors (KNN), Decision Trees (DT), Linear Discriminant Analysis, and Naïve Bayes. The models' performance was assessed by looking at how accurately they classified data. Without using feature selection methods, the proposed offline signature verification obtained 91.3% accuracy. Nevertheless, the accuracy was increased to 97.7% by employing the NCA feature selection method with only 300 features. The advantage of having a self-organized framework and high classification accuracy were proved by the suggested method.

This paper is organized into 4 sections. Beside the introductory section, section 2 illustrates the proposed methodology, and section 3 shows some of the best attained results met during the comprehensive tests applied on the database. Finally, a list of conclusions is given in section 4.

II. PROPOSED SYSTEM

The proposed methodology consists of three important stages, as shown in Figure 1 they are: (a) Pre-processing stage, (b) Feature extraction stage and (c) Signature recognition Stage. The aim of pre-processing stage is to enhance signature image by removing unwanted effects such as light, rotation, and noise effects. Some important image processing methods (like de-noising filters, morphological operations, rotation compensation, Region of Interest Extraction-ROI) were applied to achieve the required improvements. The next stage in the proposed system is the feature extraction stage. A set of density-based features was introduced to represent the attributes of signature body blocks; the calculated relevant density parameters of all blocks are assembled as a feature vector that can distinguish one signature from another. Finally, the identity of the calculated feature vector is assigned by finding the best template matching in the recognition stage.

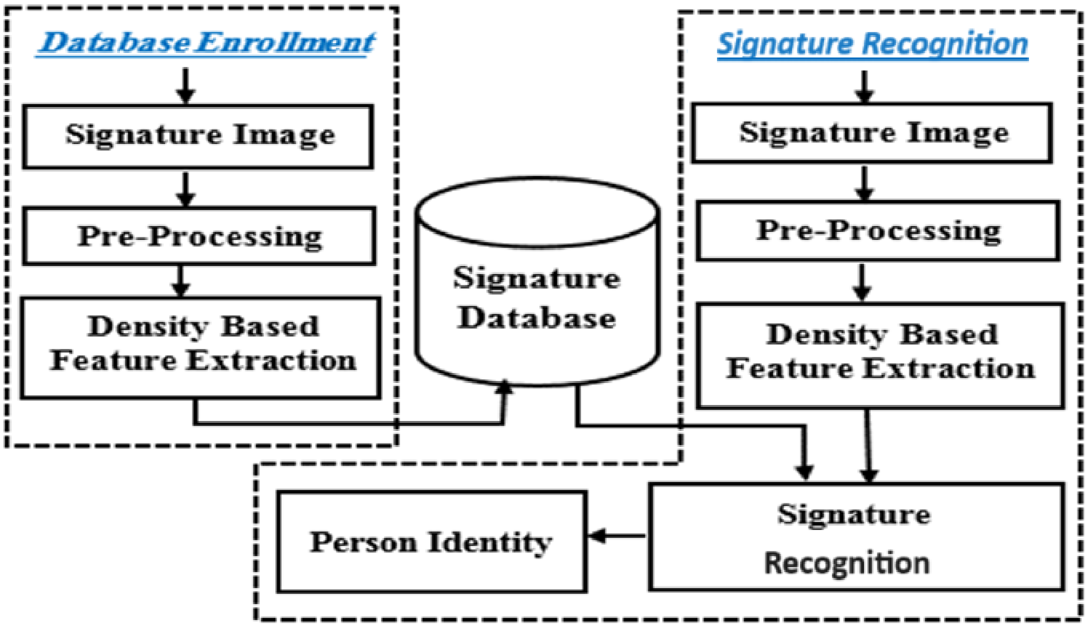

Figure 1. The layout of proposed signature recognition

A. Pre-Processing Stage

The low-level operations applied on input or intermediate versions of images are called pre-processing. Pre-processing is very beneficial in different cases; they may help in suppressing information that is unrelated to a certain analysis task or a given image processing need; or they enforce the appearance of the wanted components. Therefore, the aim of pre-processing is to enhance some important features of the image for further processing or to improve the image data that contains undesired distortions [20]. Preprocessing stage in the proposed system is composed of the following steps:

1- Image Subtraction Step

The light shadow which is produced from bad resolution of the scanner device or from incorrect lighting condition in the place of image capturing, can affect the accuracy of the extracted signature features, so there is a need to apply subtraction step to reduce this effect. The subtraction step is performed by applying the following operation (that clarified in Figure 2):

a. Firstly, the smoothed variant of the image is calculated by applying mean filter of size (5x5),
b. Then, each pixel of the original image is subtracted from the corresponding pixel in the smoothed image and the produced value is then magnified by multiplying it with a certain scaling factor.
c. Finally, the resulted pixels values are clipped (i.e., if pixel value is less than 0 then it is set to zero, while if it is greater than 255 then set its value to 255); this step will ensure that the pixels values of the final subtracted image lay within the dynamic intensity range [0,255].

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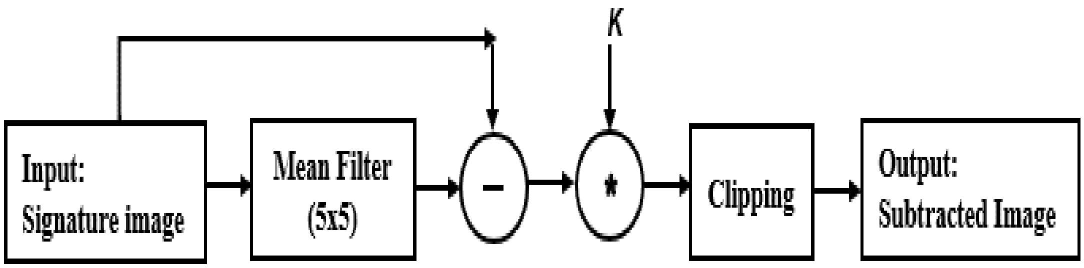

Figure 2. The block diagram of subtraction step

In the proposed system, the subtraction process is performed upon two levels: locally and globally.

i. Local Mean Subtraction: In local subtraction step, the image is, firstly, divided into blocks and the subtraction procedure is applied individually in each block. Local subtraction is effective in reduction the shadow effects depending on the local block conditions.
ii. Global Mean Subtraction: The global subtraction is similar to local one except that all pixels are subtracted from a single mean value that is calculated for the whole image pixel intensities (i.e. overall WxH pixels). With global subtraction the shadow is treated as nearly same overall the signature image.

2- Brightness Gamma Stretching

The light transmission is generally corresponding to the voltage raised to a power called gamma, with symbol γ. For image pixel intensity, I(x, y), the general equation to achieve gamma correction, IG(x, y), value is [21]:

$$I_G(x,y) = 255 \times \left(\frac{I(x,y)}{255}\right)^{\gamma} \qquad (1)$$

In gamma stretching the brightness of signature is corrected to increase signature visibility in order to facilitate the process of distinguishing it from the surrounded background.

3- Image Binarization

To segment the signature image into two regions: background (with black color) and foreground (with white color) then the binarization process can be applied. A threshold value (T) is defined, and each pixel value is compared with it, if the pixel is greater than T then the pixel value is set to 1 otherwise the value set to 0.

4- Gaps & Small Islands Removal

The binary version of produced signature image may hold small gaps and islands which causes dis-connectivity in signature body and then decreasing the discriminating effectiveness of the extracted features. To solve these problems, dilation and erosion morphological operation are applied. One of the most crucial morphological procedures is dilation. Once the test gap shows little pixel counts, it is employed to bridge gaps. The parts included in the binary picture grows due to dilation, which also creates a connection among them. [22]. The operator is applied to provide the basic effect of enlarging the regions boundaries of foreground pixels. Thus, the holes within these regions become smaller and the areas of foreground pixels grow in size. The dilation of image, I, by structuring element S is represented by I ⊕ S. The new value ID(x, y) for pixel I(x, y) is determined by positioning the structuring element S with its origin at (x, y) and counting pixels in S with on values. If the count is greater than or equal to a threshold parameter, then set the pixel value as given by the following rule [23] [24]:

$$I_D(x,y) = \begin{cases} 1 & if\ S\ hits\ I \\ 0 & otherwise \end{cases} \qquad (2)$$

Typically to eliminate the borders of spots of pixels that are in the foreground in a binary picture, erosion provides a reverse result of dilation. Thus, holes within these areas become larger and the areas of foreground pixels shrink in size.

5- ROI Extraction

To eliminate those parts of signature image which do not relate onto the signature rectangle, because they are outside the viewing volume or outside interesting level (i.e., ROI region), the clipping operation is applied. Clipping operation is necessary to enclose the work within the selected area at which the interesting discriminating features is applicable; this step is necessary to minimize the number of required operations and to decrease the processing time. ROI region is extracted by opening four scans upon the four directions (left, right, top, and bottom) of the signature image. In each direction, if a white pixel is met, then the coordinate (x, y) of it is registered and the search is stopped. The four extracted pixel coordinates are used to estimate ROI width, height and starting position; such that from the horizontal scan the lowest and highest x- coordinates are used for left & right bounding, and for vertical scan the lowest and highest y-values are adopted.

6- Cleaning of Noisy Regions

Since, the resulted image may contain small noisy regions. So, the produced image needs to be cleaned. The seed filling algorithm that used as region growing segmentation method is used to assemble the entire signature body as sub regions using the connectivity of white pixels comprising the region body. Small regions (e.g., regions with size less than or equal to m pixels; where m is set 15 in this work) or a region which is laid on the image border and whose thick regions whose width or height is small while the area is greater than a given threshold are removed to produce cleaner binary image. Figure 3 shows the results of applying pre-processing steps on an example signature image. These steps are mentioned in the figure as follows: : (a) Local subtraction step result, (b) Global subtraction step result, (c) Gamma brightness stretching step result, (d) Binarization step result, (e) Gaps & islands removing step result, (f) ROI extraction step result, (g) Noisy region cleaning result

B. Feature Extraction stage

In this step, the last processed picture is used to obtain a collection of distinguishing details. The details that were recovered corresponds to the needed features vector for person identification. In the proposed system, the distribution of local average of signature density is introduced and used.

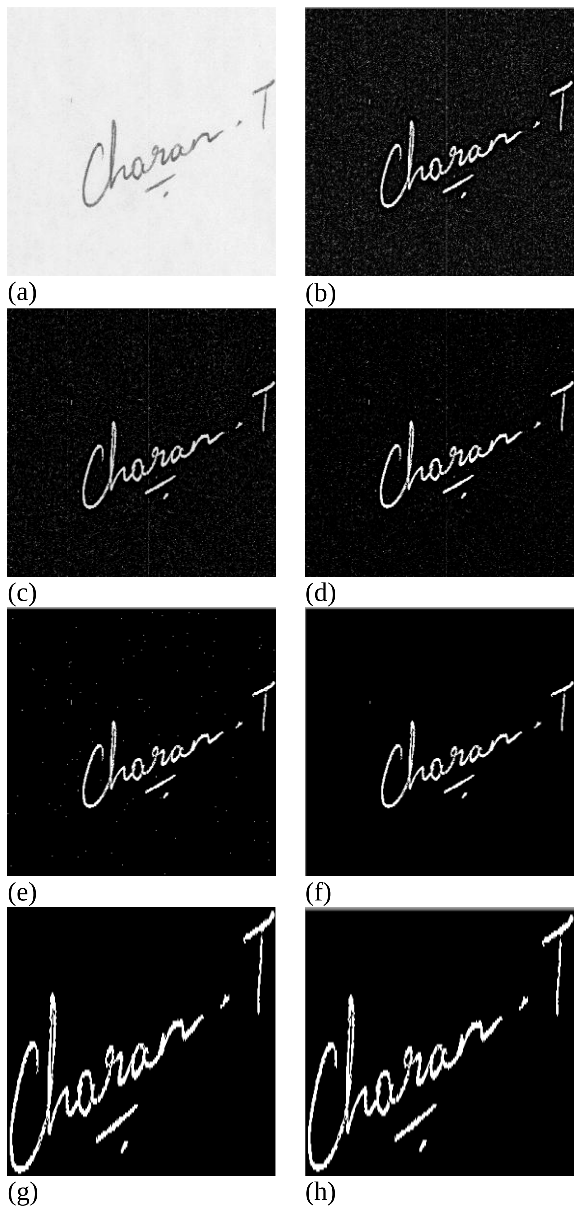

Figure 3. Pre-processing stage results: (a) Local subtraction step result, (b) Global subtraction step result, (c) Gamma brightness stretching step result, (d) Binarization step result, (e) Gaps & islands removing step result, (f) ROI extraction step result, (g) Noisy region cleaning result

1- Rotation Compensation Step

Rotation problem is one of the most difficult problems that facing accurate signature recognition of person signature, the differences in rotation angles between signature image samples cause incorrect feature extraction which is in turn cause low recognition accuracy. In order to solve this problem, the rotation compensation step is applied. For rotation compensation, the Principal Component Analysis (PCA) method is used to calculate the rotation angle based on distribution of data along X-axis and Y-axis. PCA is a method for calculating the directions where the data vary through and the associated significance of each direction in regard to the collection of data points. The direction (θ) at which the diversity of the data is highest is given by the primary principal component, and the direction (θ) of the highest variance in the direction orthogonal to the primary principal component is given by the second principal component and so on as shown in Figure 4. The following equation is used to determine (θ) [25]:

$$\theta = \frac{1}{2} tan^{-1}\left(\frac{2\sum_{y=0}^{H-1}\sum_{x=0}^{W-1}(x-x_c)(y-y_c)Img(x,y)}{\sum_{y=0}^{H-1}\sum_{x=0}^{W-1}Img(x,y)[(y-y_c)^2-(x-x_c)^2]}\right) \quad (3)$$

Where, (H & W) are the signature image width & height, respectively. Img(x,y) is the binary image array such that it value is 1 for pixel belong to signature body, and 0 for the background pixels. (xc,yc) are the coordinates of the center of mass point:

$$x_c = \frac{\sum_{y=0}^{H-1}\sum_{x=0}^{W-1} xImg(x,y)}{\sum_{y=0}^{H-1}\sum_{x=0}^{W-1} Img(x,y)} \ , \ y_c = \frac{\sum_{y=0}^{H-1}\sum_{x=0}^{W-1} yImg(x,y)}{\sum_{y=0}^{H-1}\sum_{x=0}^{W-1} Img(x,y)} \quad (4)$$

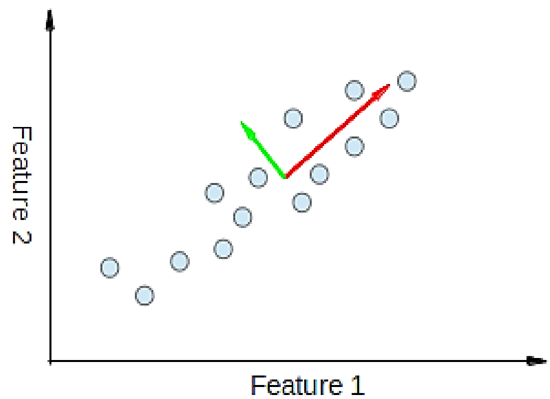

Figure 4. PCA Component Rotation Angle Computation

After applying the rotation compensation step, all signature samples are aligned to be at same direction. Figure 5 shows the sample of the rotation compensation operation when applied on a signature image.

(a) (b)

Figure 5. Rotation Compensation Step Results :(a) The Image Before Applying Rotation Compensation, (b) The Image After Applying Rotation Compensation

2- Density Based Feature Extraction Step

The procedures below were used to obtain this collection of features from the signature picture:

a. The extracted signature image from rotation compensation step blocks that overlay each other. The purpose of overlap partitioning is to prepare for any signature shifting that may occur during signature writing where there may be different overshoots in the signature body which may occur at the signature writing time. Figure 6 illustrates how the image is divided to overlapped blocks.

b. By dividing the total amount of calculated signature points (i.e., the total number of not a zero values points) by the block dimension, the mean energy value of every single block is determined.
c. Determine the mean number of signature points for every block, and then put the mean number list into a feature vector, also the following features are used:
  1. The relative average ($\bar{d}_v$) and standard deviation (σ_v) of vertical projection of the signature segment lay within the block.
  2. The relative average ($\bar{d}_h$) and standard deviation (σ_h) of horizontal projection of the signature segment lay within the block.

The involved equations of the above-mentioned parameters are [26]:

i. $$Density: Den \frac{1}{w_b h_b} \sum_{x=x_s}^{x_e} \sum_{y=y_s}^{y_e} Img(x, y) \quad (5)$$

Where (xs, ys) are the coordinates of top left corner of the block, (xe,ye) are the coordinates of bottom-right corner; wb is the block width (xe-xs+1), hb is the block height (ye-ys+1).

ii. $$d_v \frac{1}{w_b h_b} \sum_{x=x_s}^{x_e} xProj(y) \quad (6)$$

iii. $$d_h \frac{1}{w_b h_b} \sum_{y=y_s}^{y_e} yProj(x) \quad (7)$$

iv. $$\sigma_v \frac{1}{w_b h_b} \sum_{x=x_s}^{x_e} (xd_v)^2 ProjV(y) \quad (8)$$

v. $$\sigma_h \frac{1}{w_b h_b} \sum_{y=y_s}^{y_e} (yd_h)^2 ProjH(x) \quad (9)$$

vi. $$ProjV = \sum_{y=y_s}^{y_e} Img(x, y)\,, \quad ProjH = \sum_{x=x_s}^{x_e} Img(x, y) \quad (10)$$

C. Signature Recognition Stage

In recognition step, the identity of a given signature is recognized by finding the best matching class of the extracted feature vector. This stage implies two phases: (1) the database enrolment step and (2) the signature identification step as follows:

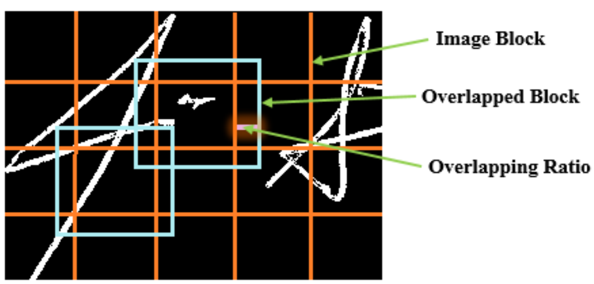

Figure. 6. Overlapped block idea

1- Database Enrollment Step

The samples of each class were divided into two sets: training set and testing set. The training set was selected randomly by choosing 75% of the samples belong to each class while the remaining samples are treated as testing set. The feature vectors of training set are used to construct the single template feature vector that representing each class which is used as decision boundary for that class.

2- Signature Identification Step

The effectiveness of the extracted features are checked through testing the samples of the testing set by measuring the distance of their feature vector from the template feature vector of each class, the degree of similarity was assessed using traditional Euclidean distance metrics [27]:

a. Mean Absolute Differences (MAD):

$$MAD(S_i, T_j) \sum_{k=1}^{\#features} \left| s_i(k) t_j(k) \right| \quad (11)$$

b. Mean Square Differences (MSD):

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$$MSD\left(S_i, T_j\right) \sum_{k=1}^{\#features} \left(s_i(k) t_j(k)\right)^2 \tag{12}$$

c. Normalized Mean Absolute Differences (nMAD):

$$nMAD\left(S_i, T_j\right) \sum_{k=1}^{\#features} \frac{\left|s_i(k) - t_j(k)\right|}{\sigma_j(k)} \tag{13}$$

d. Normalized Mean Square Differences:

$$nMSD\left(S_i, T_j\right) \sum_{k=1}^{\#features} \left(\frac{(s_i(k) - t_j(k))^2}{\sigma_j(k)}\right) \tag{14}$$

Where, tj() is the mean of jth template, σj() is the corresponding standard deviation vector; si() is the feature vector of of jth template.

III. RESULTS AND DISCUSSIONS

The dataset used in the conducted tests consists of 612 signature images belong to 102 persons. A part of the persons (i.e., 64 persons) were taken from a publicly published database, while the remaining belong to people working at different places; each person was asked to draw his signature for 6 times and these signatures were used as class samples for that person. Figure 7 shows the signature image samples for two different persons (person1 and person2). For the established handwritten signature recognition system, the tests results indicated that each of the parameters " The quantity of blocks and the rate of overlap" has significant effect on the attained recognition rate. The recognition rate was calculated using the four considered distance measures. Table 1 lists the attained recognition values for different values of the quantity of blocks and the rate of overlap of 0.1. Since the rate of overlap (0.1) led to high recognition rate so the test stopped at this value and using it as the optimal value for overlapping parameter. The table shows that the use of nMSD (i.e., the 4th distance measure) led to recognition rates higher than those obtained when using other distance measures. So, for this reason the 4th distance measure is adopted in the system. The best desired recognition rate (i.e., 99.81%) is achieved when the number of blocks is set (9x9).

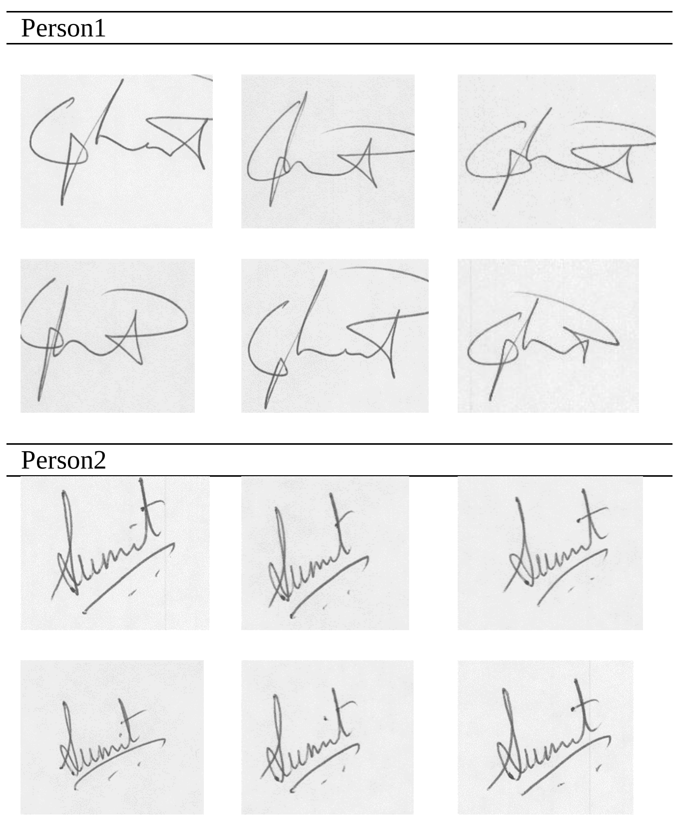

Figure 7. An Example Images for the Dataset Used in the Experiments

TABLE 1. RR FOR DIFFERENT NUMBERS OF BLOCKS WITH ROTATION COMPENSATION STEP

Over Ratio	RR for different numbers of blocks								
	1x1	2x2	3x3	4x4	5x5	6x6	7x7	8x8	9x9
0.1	60.95%	69.44%	86.11%	88.4%	91.34%	92.81%	94.02%	97.22%	99.81%

Table 2 shows the recognition ability of the proposed system without applying rotation compensation step, where Figure 8 shows the effectiveness of the proposed system with and without applying rotation compensation step for different number of blocks and over rate ration=0.1. The results approved the effectiveness of this step in increasing the accuracy of the computed features.

TABLE 2. RR FOR DIFFERENT NUMBERS OF BLOCKS WITHOUT ROTATION COMPENSATION STEP

Over Ratio	RR for different numbers of blocks								
	1x1	2x2	3x3	4x4	5x5	6x6	7x7	8x8	9x9
0.1	50.34%	56.03%	76.75%	82.09%	88.55%	90.14%	92.67%	93.14%	95.30%

Table 3 shows the recognition ability of the proposed system with other research, and it shows the system's performance as proposed. The results approved the effectiveness and the accuracy of the computed features

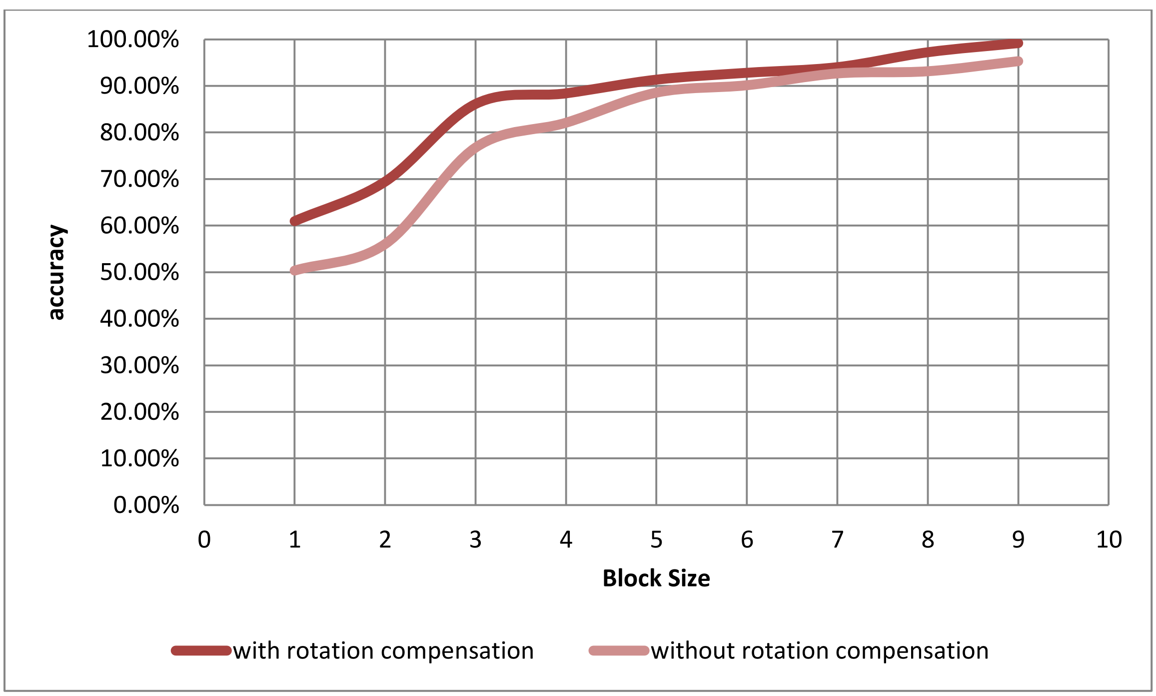

Figure 8. The Effect of Rotation Compensation Step on The Recognition Results for Different Number Of Blocks And Over Rate Ratio=0.1

Both Equal Error Rate (EER) and accuracy are evaluation metrics commonly used in comparsion for system performance and give further distinct interpretation of the output results from the proposed system. The following equation were used for evaluation[28]:

$$FAR = \frac{Falsd\ Acceptances}{Total\ true\ samples} \tag{15}$$

$$FRR = \frac{False\ Rejections}{Totalr\ False\ samples} \tag{16}$$

The EER is founf by solving the equation $FAR = FRR$. In other words, it is the point at which the likelihood of mistakenly accepting a real sample equals the likelihood of mistakenly rejecting a fake sample.

TABLE 3. COMPARISION OF PROPOSED SYSTEM WITH OTHER RESEARCH

Method	Feature Extraction	Classifier	EER	Accuracy
Ghosh (2021) [24]	Structural and directional	RNN	0.01	99.94
Souza et al. (2020) [27]	White-box analysis	Dichotomy transformation	0.22	99.78
Ruiz et al. (2020) [29]	Data Augmentation	CNN	0.05	99.95
Masoudnia et al. (2019) [30]	Multi-loss snapshot	Ensemble of SVMs	0.28	99.72
Abdel-Basset et al. (2020) [31]	Haar like features	Haar Cascade Classifier	8.0	92
F. Özyurt et al. (2024) [19]	MobileNetV2	KNN, DT and Naïve Bayes	0.03	97.7
Proposed Method	PCA and DBFE	Euclidean and MD Classifier	0.82	99.81

IV. CONCLUSION

In this paper, an offline handwritten recognition system is proposed. In preprocessing stage some effective processing steps are applied to reduce the image defects. The rotation compensation step was applied to effectively reduce the handwriting rotation effects among the signature images for same person. A feature vector with writing density features is introduced; it is determined by dividing the signature image into overlapped blocks and calculating density of signature part in that block. The proposed system gave accuracy around 99.81% when it was tested using the testing dataset. As a future work density feature can be calculated in frequency domain through using some transformation methods like wavelet transform, DCT, etc.

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