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Off-line Signature Verification System using Fusion of Novel Diagonal and Statistical Zone based Features

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Abstract: The aim of off-line signature verification is to decide, whether a signature originates from a given signer based on the scanned image of the signature and a few images of the original signatures of the signer. Although the verification process can be thought to as a monolith component, it is recommended to divide it into loosely coupled phases (like pre-processing, feature extraction, feature matching and classification) allowing us to gain a better control over the precision of different components. This paper will cover all the important phases used in this field by focusing on feature extraction, the third phase in the process. To demonstrate this, fusion of features, named, diagonal and statistical features are extracted from 25 equal zones and are used as input patterns to test the performance of the model. For training and testing feed-forward back propagation neural network and MatLab 7 is used. Results are evaluated on our own database comprising of 400 signature images taken from 10 signers (40 signatures from each signer or person) over a different period of time. The proposed system has specificity as 89% and sensitivity as 95%.

Keywords: Feed- forward Back propagation; Signature Verification; Recognition; Statistical features; Diagonal features; Zone Features.

I. Introduction

In the field of person authentication, signature verification and identification is an important research area. In document authentication, handwritten signatures are publicly and lawfully accepted. Person handwritten signatures provide protected means for validation and authorization in legal and banking documents. Therefore the need of competent off-line signature verification system has been increased. The problem with the signature identification is that the given signature is searched in the database to establish the signer's identity. Signature verification is considered necessary to determine if a particular signature is valid i.e. genuine or forged.

Signatures are divided into online and off-line signatures. Online signatures are captured dynamically and then stored as a function of time. On-line data records the motion of the stylus while the signature is produced, and includes location, and possibly velocity, acceleration and pen pressure, as functions of time [1]. While the off-line signatures are digitized using a flat bed scanner and then stored as 2-D image. In the field of security and prevention of fraud, off-line signature verification is considered as a behavioral characteristic based biometric trait[2], [3]. Off-line systems are needed where only hard copies of signature are available, e.g., in forensic labs for document authentication, in banks for the verification of cheques. Research in this field is unexplored due to limited features available from 2-D signature image. However, researches in on-line signature verification have been reported with high success rates. Signature verification is done by processing the extracted local and global features from the signature images. Outstanding verification results can be achieved by comparing the features of the test signature with that of the user's signature using appropriate classifier. In this paper, statistical and grid features are used as a feature set and Verification is done with back propagation network. One of the main incentives for developing an off-line system is in Forensic Science Labs (FSLs) for detecting the forged and genuine signatures. In signature verification, there are two overall methods that are employed for determining whether a signature is genuine or forged. Much research has already been done and reported in the literature for verifying and recognizing signatures, for instance, a system of two separate phases for signature recognition and verification using a multistage classifier and a combination of global and local features [3]; off-line Persian signature identification and verification based on image registration, Discrete Wavelet Transform (DWT) and image fusion [7], where DWT was used to access details of signature, then several registered instances of each

person's signatures were fused together to generate reference pattern of person's signatures, while in the classification phase, Euclidean distance between the test image and each pattern was used in different sub-bands; different types of pattern recognition schemes, viz., geometric features, moment-based representations, envelope characteristics, tree structured wavelet features, *etc.*, involving individual feature components being weighted by their pattern characterization capability using genetic algorithm [5]; Chinese signature verification using geometric features specific to Chinese handwriting involving four main features for the optimization of the verification of the Chinese signatures, viz., the envelop of the signature, cross-count feature, centre of gravity of sub-region and distance between vectors made of centre of gravity, and area of embedded white space [8]; geometric features based on fixed point arithmetic was also used[16]; a Dynamic Time Warping (DTW) method [6] that works by extracting the vertical projection feature from signature images and by comparing reference and probe feature templates with elastic matching; an Artificial Neural Network (ANN) classifier has been used with geometric feature extraction technique [4]; Support Vector Machine has been used with Off-line signature verification based on Hu's moment invariants and zone features[21]; *etc.*

II. System Description and Data Acquisition

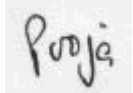
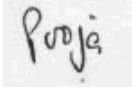
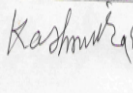
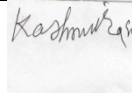
Data set comprising of both genuine and forged signatures collected from different people, over a different period of time used in the proposed work. Genuine signatures are the authentic or real signatures of the person / owner while the forged is the closed imitation of the genuine signature. For correctly classifying the signature class, both genuine and forged signatures are used. Data consisting of signature images is collected from people domain with 400 signature from about 10 different people(given identity $Id_1, Id_2, \dots, Id_{10}$) from different fields and age in 10 days ($10 \times 40 = 400$ images) to account for variations in the signatures with time. Data acquisition is done manually, *i.e.*, data collection for the experiment has been done from different individuals. Signers were provided with plain A4 sheet and each signer has asked to do signature (40 signature images from each signer). Therefore, three-hundred genuine signatures were collected. Also, hundred forged signatures were collected in this work. The signatures of a genuine signer were shown to a new signer and he/she was requested to repeat that genuine signature twenty times after going through a practice session, for collecting the forged signatures. As such, a database of 400 signatures has been created. This database consists of 300 forged signatures (30 signatures each of the 10 signers) and 100 forged signatures (10 signatures each of the 10 users. The collected documents are scanned using HP- scan jet 5400c at 300dpi which is usually low noise and good quality image. The digitized images are stored as JPEG format. This database of signature images has further been divided randomly into training database and testing database by going through different training sessions. This database of signatures has further been divided randomly into training database and testing database as shown in Table-I.

Table I depicts the Training and Testing Database

	Genuine Signatures	Forged Signatures	Total
Training Set	240	80	320
Testing Set	60	20	80
Total	300	100	400

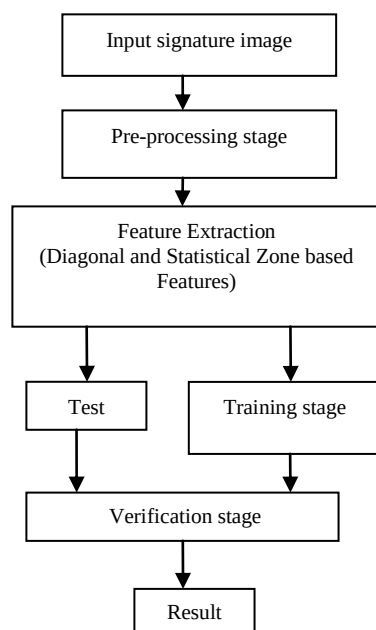
Some raw samples having identity Id_1 and Id_2 of digitized signatures from the dataset is shown in Table-2 and block diagram of the proposed system is shown in Figure 1.

Table II shows the Sample Signatures.

Signature Identity Code	Genuine Signature	Skilled Forgery
Id_1		
Id_2		

Firstly, the 2-Dsignatures images are collected and then they are pre-processed. In third stage, features are extracted from the pre-processed images. The fourth stage describes the training and testing of database. Last stage verifies between train file and test image.

Figure 1 illustrates the block diagram of proposed work.

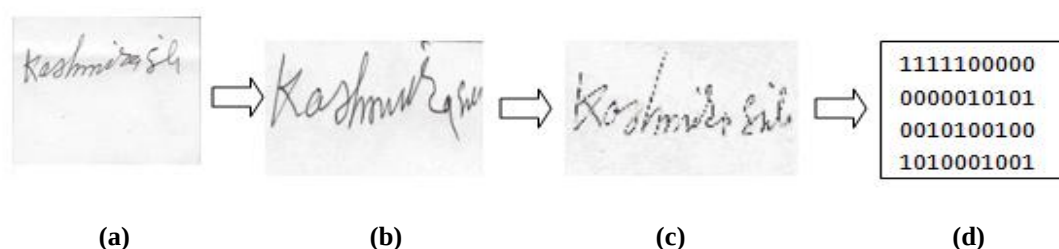


III. Pre-processing of Signature Image

For smoothing, enhancing, filtering, cleaning-up and otherwise massaging a digital image, pre-processing is done [17]. Off-line signature image pre-processing presented here can be broken down into three stages as follows: 1) Resizing 2) Grayscale 3) Skeletonization (Thinning) and 4) Binarization.

The digitized or scanned signature image is resized(100×100)pixels, so that all the collected images will be of same size. Then, it is converted to grayscale as the digitized images were of JPEG format. Then they are thinned to reduce the width of a line like object from many pixels wide to just single pixel [18]. It reduces the memory space required for storing the information about the input characters and no doubt, this process reduces the processing time too. At last, thinned image is binarized (changes into 0 or 1) and is ready for feature extraction. Figure3 below shows the pre-processing stages of the signer having identity ID1.

Figure 3 shows the (a) original; (b) resized; (c) thinned and; (d) binarized signature image.



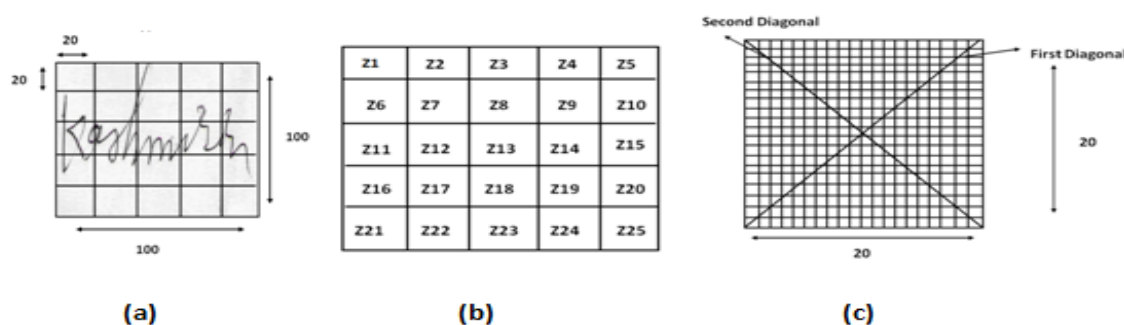
IV. Feature Extraction for Images

For easily classifying the signature features are extracted from the 2-D digitized pre-processed signature images. Features provide the relevant shape information of the image and are the most important stage in the signature verification system. The selection of a stable and representative set of features is the heart of pattern verification system design. In this paper, the combination diagonal features and some strong statistical features are used.

A. Zone based Diagonal Feature

Every image of size (100×100) pixels is divided into 25 equal zones ($Z_1, Z_2 \dots Z_n$), each of size (20×20) pixels. The features that are extracted from each zone, by moving along its two diagonals and taking the sum of 1's are called diagonal features. Each zone has 2 diagonal sub-features values that are summed individually to form two feature values and placed in the corresponding zone. This procedure is sequentially repeated for the all the zones. There could be some zones whose diagonals are empty of foreground pixels. The feature values corresponding to these zones are zero. Finally, fifty ($25 \times 2 = 50$) features are extracted from each signature image. Figure 4 below shows the process of division from original image to zone image.

Figure 4 depicts the (a) Pre-processed signature image with zones; (b) 25 Equal Zones of an image; and (c) Zone (Z_1) depicting two diagonals.



V. Statistical Feature

Statistical features are characteristics, which identify or describe the signature as whole [3] and local features are confined to limited portion (e.g., a zone). In this paper, from each zone, following four strong statistical features are extracted by using the Image Processing Toolbox of Matlab 7.0.

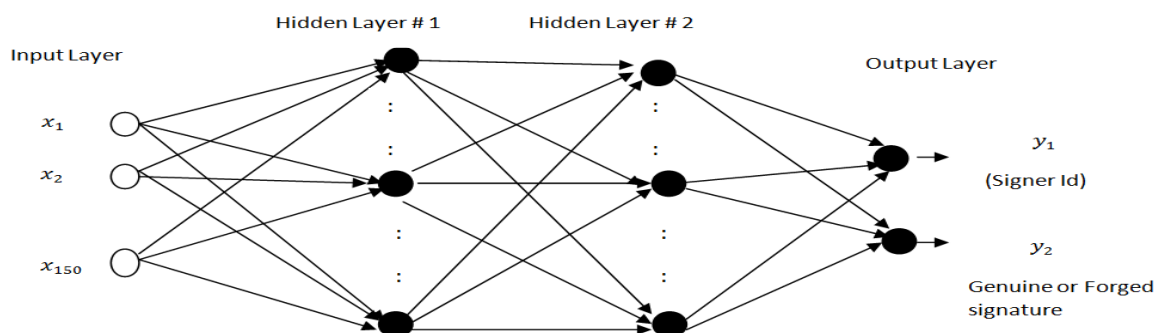
- A. **Mass:** It is the total number of 1's in the thinned binary image [21].
- B. **Normalised Area:** Normalised area [20] of black pixels is found as the ratio of the area of black pixels to the area of signature image ($width \times height$) of the signature. Normalised area of black pixels is calculated from binary and thinned images.
- C. **Euler's Count:** It gives total number of objects in the image minus the total number of holes in those objects. Connectivity of objects can be either 4-connected or 8-connected neighbourhood.
- D. **Number of Local Maxima**

It is the number of regional maxima/peaks in the vertical/horizontal projection.

One hundred fifty features are extracted from the whole signature image, consisting of twenty-five $[(25 \times 4) = 100]$ statistical and fifty $(25 \times 2 = 50)$ zone features. Hence, one hundred fifty features in all are generated from each signature image $(100 + 50 = 150)$. This set of diagonal and statistical features are used as input to the verification system.

VI. Training and Testing of Neural Network

Neural Network model are used to train the model and for verify the signatures. The uniqueness of Neural Network is such that they could be used to categorize the signatures as genuine and forged by retraining the model. Neural Network model is constructed by utilizing the data, as described in the preceding Section-2. The network model was explored with 150 neurons in the input layer, two hidden layers and; an output layer with two neurons. The back-propagation learning algorithm with Bayesian regularisation technique has been used for training the model. The tangent-sigmoid function was used as transfer function for hidden layer(s) and linear function was employed on the output layer. A variety of combinations of several architectural parameters, viz., number of HL(s), epochs, error goal, learning rate, number of neurons in each HL were empirically explored through trial and error approach. The best configuration was found to be the feed-forward network with HL having 11 neurons in first HL and 9neurons in second HL. The error goal was set empirically to 0.0001, while learning rate was initialised to the value, 0.7 and the epochs were set to the value, 10000. Figure 6 shows the pictorial architecture for the proposed model. Table 3 shows the architectural values of the proposed model.

Figure 5 shows the training of network**Table III depicts the best selected architectural values of the proposed model**

Feed-Forward Neural Network (Parameters)	Parameters Values
Output Layer	1
Hidden Layer	2
Neurons in Input Layer	150
Neurons in Hidden Layer #1	11
Neurons in Hidden Layer #2	9
Activation Function	Tan-Sigmoid
Learning Algorithm	Back propagation
Epochs	500
Goal	0.0001

VII. Experiments Results and Discussion

Different proportion of training and testing data is used as input to the classifier. Various experiments have been conducted to evaluate the preferential ability of the features. Best results are empirically found with 320 signatures used for training and 80 signatures for testing. The feature vector comprising 150 features extracted by means of the diagonal and statistical zone based features was used for training the feed-forward back-propagation neural network model. Also, the proposed system was tested based on the same 150 features. The Table-4 depicts the results for analysing proposed system's accuracy in terms of *specificity* (the proportion of forgeries which are correctly identified), *sensitivity* (the proportion of actual genuine signatures, which are correctly identified as positives).

$$Sensitivity = \frac{TP}{TP + FN}.$$

$$Specificity = \frac{TN}{TN + FP}.$$

where TN= True Negatives; TP=True Positives; FN =False Negatives; FP=False Positive

Table IV shows the results in terms of specificity and sensitivity of the signature verification system.

Specificity	Sensitivity
89%	95%

VIII. Conclusion

To verify off-line signature system, a neural network model based on novel diagonal and statistical zone based features has been developed. A database collected at different intervals of time, comprising of genuine and forged signatures of several people of different age groups, was also developed. The signature database was utilised for training the neural network model. The model exhibits specificity of 89% and sensitivity of 95%.

IX. References

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