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An Offline Handwritten Signature Verification Using Low Level Stroke with Feature Extraction and Hybrid Classifiers

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ABSTRACT

Biometrics can be classified into two types, namely, physiological (fingerprint, Iris, face recognition etc) and behavioural (signature verification, keystroke dynamics etc.). In an authentication system, signature identification and verification plays an important role. Signature identification is again classified into two types, that is, static signature recognition (offline) and dynamic signature recognition (online).Online signature verification system uses a special sensor for capturing the image whereas in offline signature identification, no special sensor is required. Offline signature system needs only a pen and paper. Signature authentication is accepted as a legal mark of identification and authorization and finds an application in different fields like finance, bank and in jurisdictional documents. In this research work, we have proposed an offline signature verification system. Signature verification is a process in which a genuine person has been recognized on the basis of their signature. In the proposed work, signatures are executed by three processes like pre-processing, feature extraction and classification. In pre-processing, Binarization and color conversion has been performed. For extracting features, Low-level stroke feature technique along with SIFT method has been used. In the proposed work, we have used the combination of SVM and ANN as a classifier to classify the test data according to the training set. Initially, the features are trained using SVM, after that, the output of SVM act as the input of ANN and creates a better training structure to achieve better accuracy of proposed signature recognition system. The simulation is being performed in image processing toolbox under the MATLAB software. The performance metrics like FAR, FRR and Accuracy has been measured and comparison of proposed with existing technique has been provided.

Keywords : Biometrics, offline handwritten signature verification, Scale feature Transform (SIFT), Low level stroke, Support Vector Machine (SVM), Artificial Neural Network (ANN)

I. INTRODUCTION

For identifying the identity of a person, different techniques such as face recognition, fingerprint, and iris analysis are there because of their distinctive characteristics. Identification of an individual is necessary in the places where we require security like at border, offices, Shopping Malls banks etc [1]. Biometric is a technique that is used for identifying an individual on the basis of their physical characteristics and behavioral characteristics. By means of physical characteristics, a person is identified on the basis of face, fingerprint, DNA etc whereas in behavioral recognition system, a person is recognized on the basis of voice, signature and keystroke. In the proposed work, offline handwritten signature recognition is used for identifying an individual [2]. A number of researchers have been proved that handwritten signature recognition has provided good biometric feature with small changes in percentage. Some signatures may be identical but they can be differentiated by using some techniques [3]. The main aim of the research is to identify handwritten signature that the written signature is genuine or forgery. Here, the term forgery means, false or copy of genuine signature. The forgery signature is classified into three types: (1) random forgery (2) Simple forgery (3) skilled forgery [4].

In random forgery, the forger has no knowledge about the name and signature shape. In Simple forgeries, the forger knows the name of the person but not the style of signatures [5]. In skilled forgeries, the forger knows the signature names as well as the signature style of the person. Signature verification is a technique of identifying a person on the basis of his/her hand written signature [6]. Signature identification system is mainly classified into two types [7]:

1. Online signature verification system

In this system, signature is written on an electronic device like on tablet by using a special device such as digital pen, digitizer [8]. The verification is done in real time basis and uses dynamic properties of signature such as pen movement. Dynamic information like position, pen pressure, velocity, speed and coordinate of signature are generated [9].

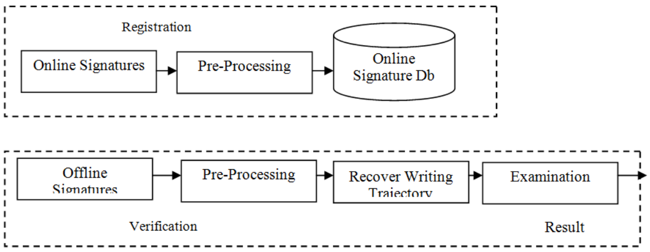

Figure 1: Signature Verification Model

2. Offline signature verification system

In this system, the handwritten signature is written on a paper such as in bank cheque [10]. Then, the signature images are scanned by using optical scanner to convert the signature written on the paper into digital form and then scanned images are processed by using different processes like pre-processing, feature extraction, and classification [11].

Off line signature verification is more complex than online signature verification as it is difficult to collect information from the offline images [12]. But the requirement of special devices to scan or to write on the digital device makes online system unsuitable for many practical uses. Offline system used by many companies of finance systems because of its simplicity as it is similar to the existing manual verification system. Offline recognition goes through a number of processes mentioned below [13]:

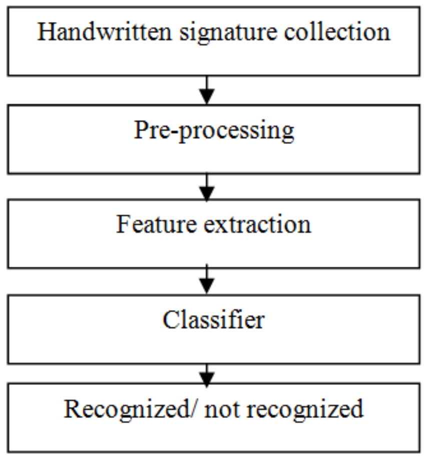

Figure 2: Phases of offline handwritten signature verification system

i. **Pre-processing:** After scanning the handwritten signature using an optical device, pre-processing is applied. This helps to remove the unwanted data and convert the scanned image into binary form.

ii. **Feature extraction:** The required features of the signatures are extracted by using feature extraction techniques. In the proposed work, Scale invariant transform (SIFT) and Low Level Stroke techniques are used.

iii. **Classifier:** In the proposed work, we have use the combination of SVM and ANN as a classifier to classify the test data according to the training set. Firstly, the features using the SVM are trained after that, the output of SVM act as the input of ANN and create a better training structure to achieve better accuracy of proposed signature recognition system.

2.1 Feature Extraction Techniques Used In the Proposed Work

In the proposed work, Scale invariant transform (SIFT) and Low Level Stroke (LLS) techniques are used. Both are described below:

Scale invariant feature Transform (SIFT)

In the proposed research, Scale invariant feature technique (SIFT) has been used to extract the features from the signature image [14]. When the images are different in terms of scale, orientation etc. recognizes the images Feature descriptor that works effectively. The phases used to generate SIFT features are shown in figure below:

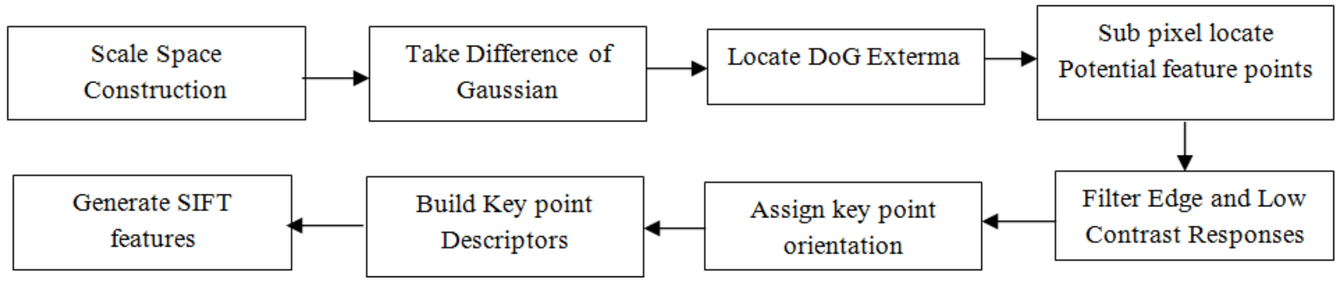

Figure 2. Flow diagram of SIFT algorithm

Low level stroke (LLS)

S.K. mitra and M.M Goswami used Low Level feature extraction for extracting the features of Guajarati character. Types of low level features are listed below [15]:

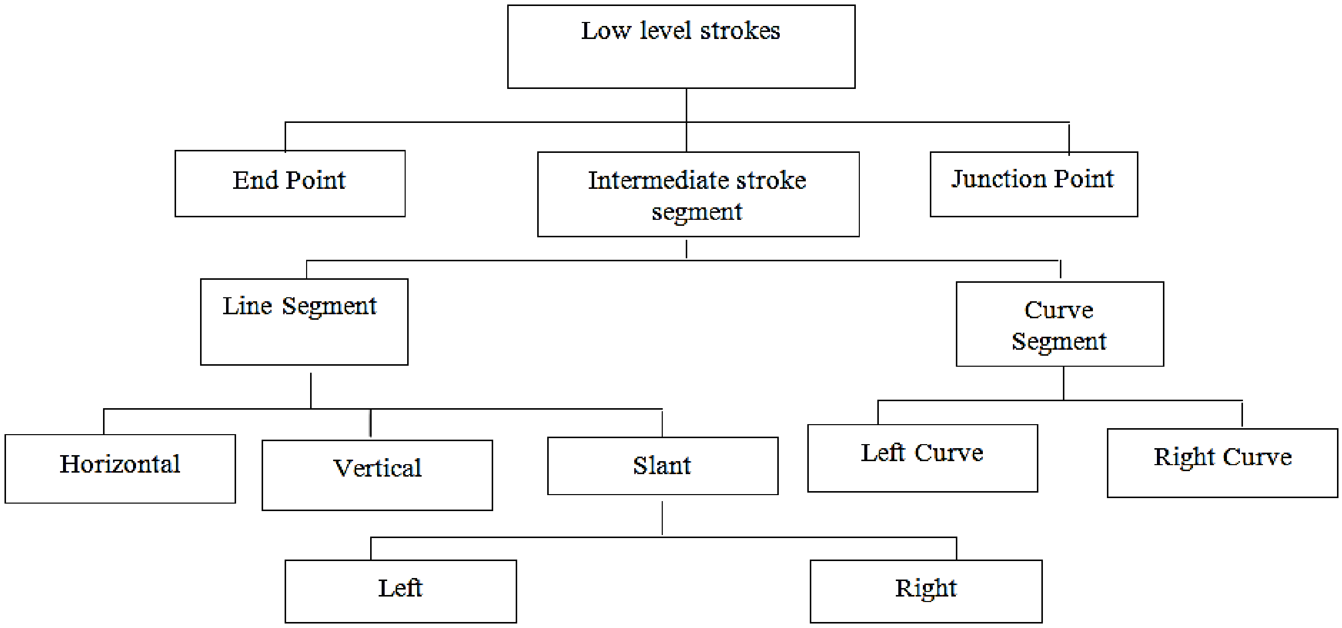

Figure 3. Types of low level stroke

In the proposed work, signature is recognized on the basis of start point/ end point, junction point, curves and line element.

1.1 Classification techniques used in the proposed work

In the proposed work, a combination of two classification techniques Support Vector machine (SVM) and Artificial Neural Network (ANN) have been used. The description of these techniques is provided below:

i. Support vector machine (SVM)

A Support vector machine is a tool used for classification, for return predictions and maximizes the prediction accuracy using machine learning approach. The classifiers are mainly divided into two categories named as linear classifier and non linear classifier. SVM comes under linear classifier category. If the available information is non- linear then SVM used one kernel function out of the four functions to make the data in linear form. A SVM normally generate a large margin hyper plane means that the perpendicular distance between the neighboring point and the hyper-planes should be maximum. Practically, the data is available in overlapped form and thus, SVM relies on loss function. These loss functions are used to ignore the error and present the information within the true value range.

ii. Artificial neural network (ANN)

The extensive use of ANN has been increased in signature verification and recognition because of its power and comfort of use. An artificial neural network is an analytical model that prompted by biological neural networks [8]. It is a combination of artificial neurons and has complicated relationships to know the pattern of signature. The ANN method firstly extracts the features and represents the signature details such as height, width, length, and span and so on with several samples from individual signers. In the second step, it determines the relationship among the signature and its class to verify the genuine or forgery signature. After producing the relationship, the neural network tests the signature and classifies according to an appropriate signer. Therefore, the ANN is extremely adapted for offline signature verification.

II. Related Work

A.Hamadene and Y. Chibani [2016] proposed a single class independent system and has used FDM (Feature dissimilarity measures) as a classifier. The dataset consists of 1320 genuine signature and forgery signature. The performance of the system has been evaluated by calculating three parameters, False rejection rate (FAR), False rejection rate (FRR) and Average Error rate (AER). Ali Karouni et al. [2011] presented a technique for offline verification of signature by using a group of simple shape based geometric features. . The performance parameters like FAR and FRR has been measured. FAR of about 1.6% and FRR of 3% has been obtained. Igor V. Anikin and Ellina S. Anisimova [2016] proposed an approach for recognizing signature using fuzzy logic as a classifier. The database has been collected from MCYT signature and experiment has been performed on 100 users along with 25 genuine and 25 fake signatures. The performance parameters like FAR, FRR has been measured. The FRR value of 0.03 and FAR value of 0.01 has been measured. J. B. Fasquel et al. [2002] proposed one offline signature verification system which integrates some statistical classifiers. The signature verification system is consisted of three steps, in which the first step transforms the original signatures using the identity and Gabor transforms, the second step was to inter-correlate the computed signature with the alike transformed signatures of the learning database and then, in the third step, verification of the genuineness of signatures by merging the decisions is being related to each transform. The proposed system also allowed the refusal of 62.4% of the fabrication used for the experiments when 99% of genuine signatures were correctly recognized. FAR and FRR were 2.56 and 1.43 respectively. Julio Martínez-R et al. [2013] Introduced on-line signature verification based on optimal feature representation and neural-network-driven fuzzy reasoning. The proposed work has created a positional signing model of a person consisting of shape features and dynamic features are also extracted from a set of original signatures. Afterward, for each typical feature, an averaged prototype and evenness function were calculated using genetic optimization, this procedure is derived from the concept of optimal feature representation in which FRR was 1.05% and FAR was 0.27%. Ashwini Pansare et al. [2012] extracted set of geometric features from a signature image which includes centre of mass, area of signature, tri surface features, six fold surface features etc .FAR and FRR were reported to be 14.66% and 20% respectively.

III. Simulation Model

The signatures of an individual are an established proof of identity and any work say transaction performed by a person needs proper security. Hence, the users are more expected to support such computerized authentication and validated method. This research has dealt with the development of offline handwritten signature verification system with the usage of range independent and distributed images. Utilization of low level stroke features is considered for signature recognition system matching. Parameters, namely, FAR (false acceptance rate), FRR (false rejection rate) and accuracy has been used for calculating the performance of the proposed work. This section explains the steps by which the simulation works has been implemented and are explained below:

- Step 1. Design a GUI for the simulation of proposed work.
- Step 2. Develop a code for uploading the signature data for training and testing of proposed work.
- Step 3. Apply pre-processing on the uploaded image to make sure that the uploaded image must be compatible with software.
- Step 4. After that develop a code for the extraction of low level strokes from the pre-processed image.
- Step 5. Develop a code for extracting features from the strokes.
- Step 6. Initialize the SVM and ANN for training of data according to feature.
- Step 7. After the training of data we have tested the signature image to verify the proposed work,

Step 8. At last, calculate the performance metrics like FRR, FAR and accuracy.

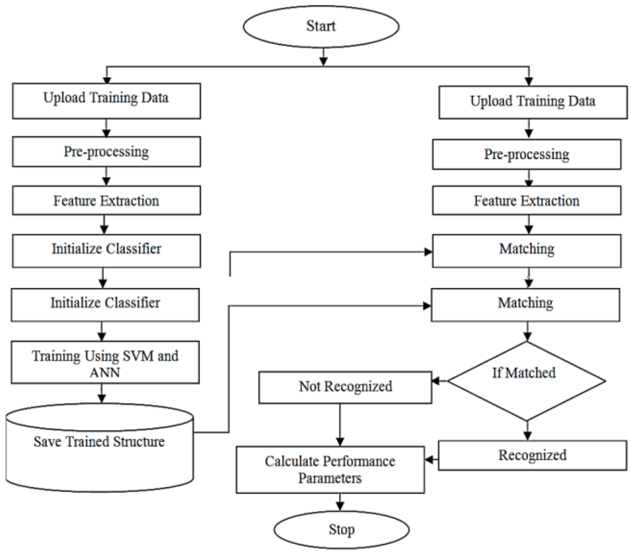

Figure 4. Proposed Work Methodology

IV. Simulation Results

This section explains the result obtained after the simulation of the whole process. The proposed research work, An Offline handwritten signature verification using low level stroke and SIFT as a feature extraction techniques along with hybrid classifiers named as ANN & SVM has been designed.

Table 1: Performance parameters of the proposed work

Number of samples	FAR	FRR	Accuracy
1	0.097	0.097	98.55
2	0.089	0.098	97.57
3	0.094	0.097	96.45
4	0.092	0.098	95.27
5	0.090	0.096	92.18
6	0.097	0.096	97.75
7	0.096	0.095	96.97
8	0.092	0.094	94.35
9	0.088	0.097	95.15
10	0.087	0.092	98.17

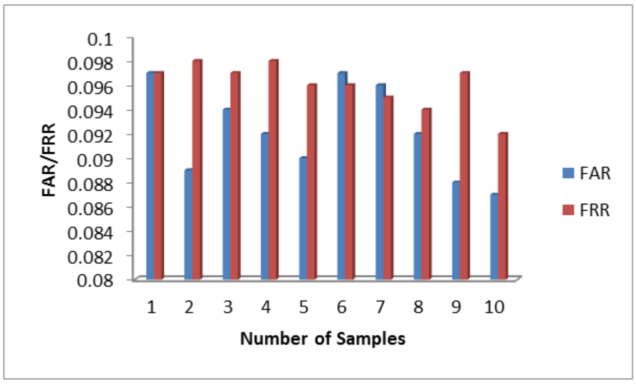

Figure Error! No text of specified style in document.. FAR/FRR values of the proposed work

In the above figure, x-axis represents the number of samples and y-axis represents FAR and FRR values obtained for the proposed work. Red bar line indicates the FRR values whereas blue bar line indicates the FAR values of the proposed handwritten signature recognition system. The average value of FAR and FRR obtained are 0.092 and 0.096 respectively.

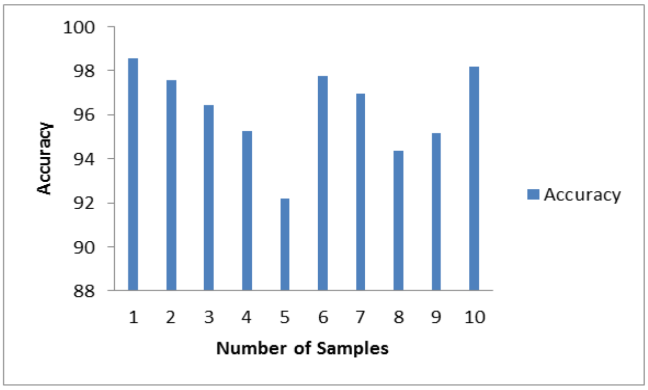

Figure 6. Accuracy of the proposed work

In the above figure, x-axis represents the number of samples and y-axis represents the FAR and FRR values obtained for the proposed work. The average value of accuracy obtained for 10 numbers of samples is 96.24.

Comparison of Existing Work With Proposed Work

In this section, comparison of proposed with existing work has been explained in detail. In the existing work Guajarati handwritten signature has been recognized by using Low level stroke as feature extractor and SVM as a classification technique. The performance parameters like FAR, FRR and Equal error rate have been measured. In the proposed work, for extracting features Low level stroke along with SIFT technique has been used. The extracted features are classified by using two classifiers named as SVM and ANN. The values are compared as shown in table below:

Table 2: Comparison of existing with proposed work

Number of samples	FAR		FRR	
	Proposed	**Existing**	**Proposed**	**Existing**
1	0.097	0.0480	0.097	0.36
2	0.089	0.0913	0.098	0.31
3	0.094	0.0576	0.097	0.27
4	0.092	0.0336	0.098	0.24
5	0.090	0.0961	0.096	0.20
6	0.097	0.1298	0.096	0.18
7	0.096	0.0961	0.095	0.16
8	0.092	0.0288	0.094	0.14
9	0.088	0.1538	0.097	0.10
10	0.087	0.2355	0.092	0.08

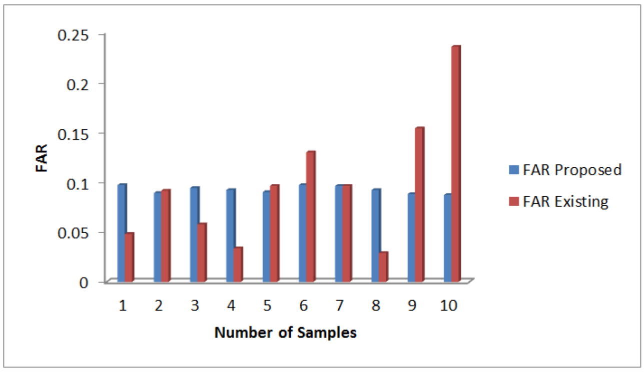

Figure 7. Comparison of Proposed FAR values with the existing FAR values

In the figure above, x-axis represents the number of samples whereas y axis represents the FAR obtained for proposed as well as existing work. Blue bar line indicates the FAR values obtained or the proposed work whereas red bar line indicates the FAR values obtained for the existing work. The average value obtained for existing and proposed work are 0.0922 and .097 respectively.

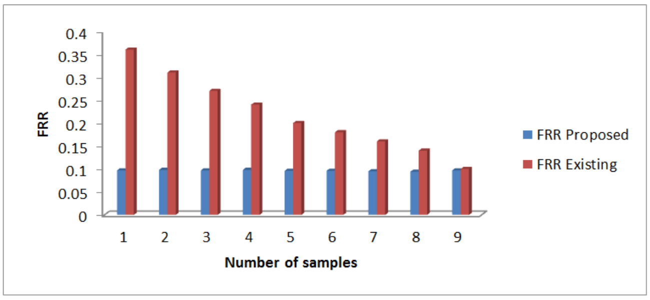

Figure 8. Comparison of FRR values for existing and proposed work

In the figure above, the average of FRR values obtained for ten numbers of samples for the existing work and the proposed work are 0.096 and 0.204 respectively. 3.759 is the average value obtained for the equal error rate (EER) of the proposed work. In the proposed work, we have measured accuracy. EER can be calculated form accuracy by using the formula below:

$$EER = 100 - Accuracy$$

By using the above formula, the EER average value obtained for the proposed work is 3.759 whereas for the existing work the average value of EER is 15.59.

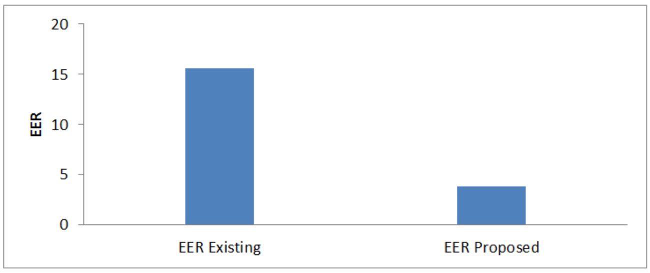

Figure 9. Accuracy of proposed with existing work

From the above figure, it is clear that the error rate of existing work is more than the proposed work. Hence, it is clear that by using two classifiers named as SVM and ANN, the accuracy of the signature recognition system has been increased.

V. CONCLUSION

The basic advantage of implementing artificial neural networks is that it can train the most discriminative and representative set of features to improve the classification efficiency. We have presented a classifier with the combination of artificial neural network and support vector machine to achieve the better reorganization accuracy of proposed work. In the proposed work, low-level strokes based feature are extracted using the SIFT feature descriptor and for verification of system, a hybrid classifier has been used. The hybrid classifier is obtained from artificial neural network along with the support vector machine. By using the hybrid classifier, the accuracy of proposed work is better as compared to the existing work. The experimental results are far better than the signature reorganization system using single classifier. The proposed algorithm is implemented as a practical and helpful for signature verification and recognition system. The false rejection rate (FRR) can further be improved by using enhanced feature extraction techniques. The average value of FAR obtained for existing and proposed work are 0.0922 and .097 respectively. The average of FRR values obtained for ten numbers of samples for the existing work and the proposed work is 0.096 and 0.204 respectively. In the proposed work, we aimed to achieve better Equal Error Rate (EER).The average EER of 3.759 has been obtained for the proposed work.

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