Off-Line Hand Written Signature Verification using Neural Network

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ABSTRACT

The signature of a person is an important biometric attribute of a human being which can be used to authenticate human identity. A number of biometric techniques have been proposed for personal identification in the past. Among the vision-based ones are voice recognition, face recognition, fingerprint recognition, iris scanning and retina scanning. Voice recognition or signature verification are the most widely known among the non-vision based ones. As signatures continue to play a very important role in financial, commercial and legal transactions, truly secured authentication becomes more and more crucial. Handwritten signatures are considered as the most natural method of authenticating a person's identity. A signature by an authorized person is considered to be the "seal of approval" and remains the most preferred means of authentication. However human signatures can be handled as an image and recognized using computer vision and neural network techniques. With modern computers, there is need to develop fast algorithms for signature recognition. There are various approaches to signature recognition with a lot of scope of research. The method presented in this paper consists of image prepossessing, geometric feature extraction, neural network training with extracted features and verification. A verification stage includes applying the extracted features of test signature to a trained neural network which will classify it as a genuine or forged. In this paper, off-line signature recognition & verification using neural network is proposed, where the signature is captured and presented to the user in an image format. Signatures are verified based on parameters extracted from the signature using various image processing techniques. The Off-line Signature Recognition and Verification is implemented using MATLAB. This work has been tested and found suitable for its purpose.

Keywords: Biometrics, error back propagation algorithm, center of mass, neural network, normalized area of signature, Signature, Biometric, Neural Networks, Off-line Signature Recognition and Verification

1. INTRODUCTION

In our society, traditional and accepted means for a person to identify and authenticate himself either to another human being or to a computer system is based on one or more of these three (3) general principles:

- What the person knows
- What he possesses or
- What he is

The hand written signature is regarded as the primary means of identifying the signer of a written document based on the implicit assumption that a person's normal signature changes slowly and is very difficult to erase, alter or forge without detection. The handwritten signature is one of the ways to authorize transactions and authenticate the human identity compared with other electronic identification methods such as fingerprints scanning, face recognition and retinal vascular pattern screening. It is easier for people to migrate from using the popular pen-and-paper signature to one where the handwritten signature is captured and verified electronically. The signature of a person is an important biometric attribute of a human being and is used for authorization purpose. Various approaches are possible for signature recognition with a lot of scope of research. Here, we deal with an off-line signature recognition technique. Signatures are composed of special characters and flourishes and therefore most of the time they can be unreadable. Also intrapersonal variations and interpersonal differences make it necessary to analyze them as complete images and not as letters and words put together [6]. Signature recognition is the process of verifying the writer's identity by checking the signature against samples kept in the database. The result of this process is usually between 0 and 1 which represents a fit ratio (1 for match and 0 for mismatch). Signature recognition is used most often to describe the ability of a computer to translate human writing into text. This may take place in one of two ways either by scanning of written text (off-line method) or by writing directly on to a peripheral input device. The first of these recognition techniques, known as Optical Character Recognition (OCR) is the most successful in the main stream. Most scanning suites offer some form of OCR, allowing user to scan handwritten documents and have them translated into basic text documents. OCR is also used by some archivist as a method of converting massive quantities of handwritten historical documents into searchable, easily-accessible digital forms.

As signature is the primary mechanism both for authentication and authorization in legal transactions, the need for efficient auto-mated solutions for signature verification has increased [1].Unlike a password, PIN, PKI or key cards –

identification data that can be forgotten, lost, stolen or shared – the captured values of the handwritten signature are unique to an individual and virtually impossible to duplicate. Signature verification is natural and intuitive. The technology is easy to explain and trust. The primary advantage that signature verification systems have over other type's technologies is that signatures are already accepted as the common method of identity verification [2].
A signature verification system and the techniques used to solve this problem can be divided into two classes Online and Off-line [3].On-line approach uses an electronic tablet and a stylus connected to a computer to extract information about a signature and takes dynamic information like pressure, velocity, speed of writing etc. for verification purpose. Off-line signature verification involves less electronic control and uses signature images captured by scanner or camera. An off-line signature verification system uses features extracted from scanned signature image. The features used for offline signature verification are much simpler. In this only the pixel image needs to be evaluated. But, the off-line systems are difficult to design as many desirable characteristics such as the order of strokes, the velocity and other dynamic information are not available in the off-line case [4, 5]. The verification process has to wholly rely on the features that can be extracted from the trace of the static signature images only. Vigorous research has been pursued in handwriting analysis and pattern matching for a number of years. In the area of Handwritten Signature Verification (HSV), especially offline HSV, different technologies have been used and still the area is being explored. In this section we review some of the recent papers on offline HSV. The approaches used by different researchers differ in the type of features extracted, the training method, and the classification and verification model used.

2. OVERVIEW OF SIGNATURE RECOGNITION

A problem of personal verification and identification is an actively growing area of research. The methods are numerous and are based on different personal characteristics; voice, lip movement, hand geometry, face, odor, gait, iris, retina and fingerprint are the most commonly used authentication methods. All these psychological and behavioral characteristics are called biometrics. The driving force of the progress in this field is above all, the growing role of the internet and electronic transfers in modern society. Therefore considerable number of applications is concentrated in the area of electronic commerce and electronic banking systems [9]. The biometrics have a significant advantage over traditional authentication techniques due to the fact that biometric characteristics of the individual are not easily transferable are unique of every person and cannot be lost, stolen or broken. The choice of one of the biometric solutions depends on several factors which include [3]:

- User acceptance
- Level of security required
- Accuracy
- Cost and implementation time

The method of signature verification reviewed in this paper benefits the advantage of being highly accepted by potential customers. The use of the signature has a long history which goes back to the appearance of writing itself [9]. Utilization of the signature as an authentication method has already become a tradition in the western civilization and is respected among the others. The signature is an accepted proof of identity of the person in a transaction taken on his or her behalf. Thus the users are more likely to approve this kind of computerized authentication method [10]. Signature verification systems differ in both their feature selection and their decision methodologies. More than 40 different feature types have been used for signature verification [8]. Features can be classified into two major types: local and global [4]. Global features are features related to the signature as a whole, for instance the average signing speed, the signature bounding box and Fourier descriptors of the signatures trajectory. Local features correspond to a specific sample point along the trajectory of the signature. Examples of local features include distance and curvature change between successive points on the signature trajectory [4]. Most commonly used online signatures acquisition devices are pressure sensitive tablets capable of measuring forces exerted at the pen-tip, in addition to the coordinate of the pen. The pressure information at each point along the signature trajectory is another example of commonly used local feature. Some of these features are compared in order to find the more robust ones for signature verification purposes. Other systems have used genetic algorithms to find the most useful features. Due to the high sampling rate of the tablet, some consecutive sample points may mark the same trajectory point especially when the pen movement is slow. Most verification systems resample the input so as to obtain a trajectory consisting of equidistant points. This is often done in order to remove redundant points to speed up the comparisons and to obtain a shape-based representation, removing the time dependencies, separately keep track of the local velocity values and use them in aligning two signatures. Signature recognition and verification involves two separate but strongly related tasks: one of them is identification of the signature owner, and the other is the decision about whether the signature is genuine or forged. Also, depending on the need, signature recognition and verification problem is put into two major classes: (i) On-line signature recognition and verification systems (SRVS) and (ii) Off-line SRVS. On-line SRVS requires some special peripheral units for measuring hand speed and pressure on the human hand when it creates the signature. On the other hand, almost all Off-line SRVS systems rely on image processing and feature extraction techniques [1].

Biometric security is a computerised method of verifying a person's identity based on his/her body and/or physical attributes. Various forms of biometric security exist including fingerprinting, iris recognition [10], speech recognition [17], heart sound recognition [7], and keystroke recognition [12]. However, dispite the novelty and perceived security of the aforemention techniques, the longest standing and most natural method for verifying one's identity is through the use of a handwritten signature. Handwritten Signature Verification (HSV) is an automated method of verifying a signature by capturing features about a signature's shape (i.e., static features) and the charactertics of how the person signs his/her name in real-time (i.e., dynamic features). HSV is more generally accepted by the public and is less intrusive than other biometric authentication techniques. Neural networks (NNs) have been a fundamental part of computerized pattern recognition tasks for more than half a century, and continue to be used in a very broad range of problem domains. The two main reasons for their widespread usage are: 1) power (the sophisticated techniques used in NNs allow a capability of modeling quite complex functions); and 2) ease of use (as NNs learn by example it is only necessary for a user to gather a highly representative data set and then invoke training algorithms to learn the underlying structure of the data). The HSV process parallels this learning mechanism.
There are many ways to structure the NN training, but a very simple approach is to firstly extract a feature set representing the signature (details like length, height, duration, etc.), with several samples from different signers. The second step is for the NN to learn the relationship between a signature and its class (either "genuine" or "forgery"). Once this relationship has been learned, the network can be presented with test signatures that can be classified as belonging to a particular signer. NNs therefore are highly suited to modeling *global* aspects of handwritten signatures. Concentrated efforts at applying NNs to HSV have been undertaken for over a decade with varying degrees of success (e.g., see [9], [16]). The main attractions include:
1) *Expressiveness*: NNs are an attribute-based representation and are well-suited for continuous inputs and outputs. The class of multi-layer networks as a whole can represent any desired function of a set of attributes, and signatures can be readily modeled as a function of a set of attributes.
2) *Ability to generalize*: NNs are an excellent generalization tool (under normal conditions) and are a useful means of coping with the diversity and variations inherent in handwritten signatures.
3) *Sensitivity to noise*: NNs are designed to simply find the best fit through the input points within the constraints of the network topology (using nonlinear regression). As a result, NNs are very tolerant of noise in the input data.
4) *Graceful degradation*: NNs tend to display graceful degradation rather than a sharp drop-off in performance as conditions worsen.
5) *Execution speed*: The NN training phase can take a large amount of time. In HSV this training is a oneoff cost undertaken off-line (i.e., rarely performed while a user waits for verification results).
This paper presents a method for HSV by using NN architecture. Various static (e.g., height, slant, etc.) and dynamic (e.g., velocity, pen tip pressure, etc.) signature features are extracted and used to train the NN. Several Network topologies are tested and their accuracy is compared. The resulting system performs reasonably well with an overall error rate of 2.3% being reported for the best case.

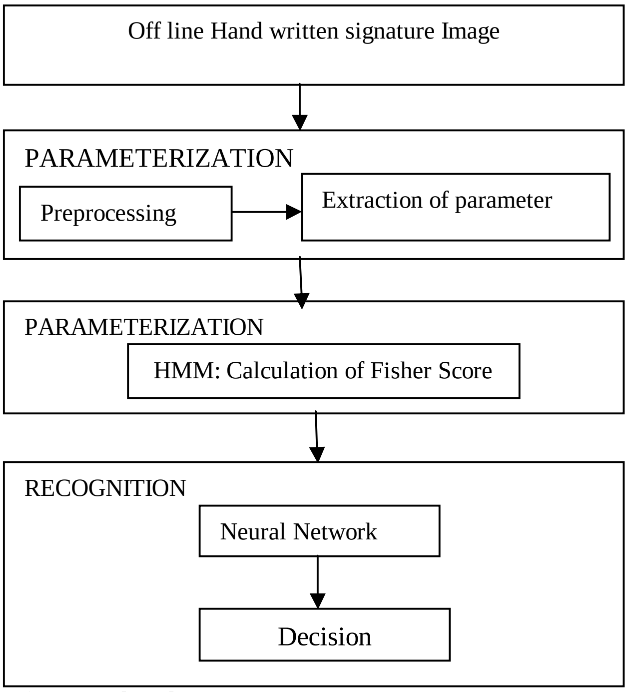

Figure 1: hand written signature recognition

3. METHODOLOGY

In this section, block diagram of system is discussed. Fig. 1 gives the block diagram of proposed signature verification system which verifies the authenticity of given signature of a person. The design of a system is divided into two stages:
1. Training stage
2. Testing stage

A training stage consist of four major steps
1) Retrieval of a signature image from a database
2) Image pre-processing
3) Feature extraction
4) Neural network training

A testing stage consists of five major steps
1) Retrieval of a signature to be tested from a database
2) Image pre-processing
3) Feature extraction
4) Application of extracted features to a trained neural network
5) Checking output generated from a neural network.

Fig. 2 shows one of the original signature image taken from a database and all the subsequent figures show the resultant signature image obtained after performing the steps mentioned in an algorithm.

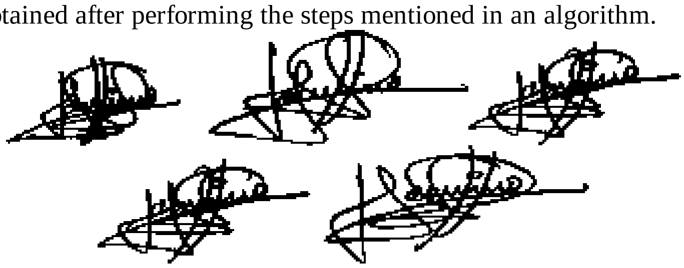

Figure 2: Signature Image

3.1 Pre-processing

The pre processing step is applied both in training and testing phases. Signatures are scanned in gray. The purpose in this phase is to make signature standard and ready for feature extraction. The pre-processing stage improves quality of the image and makes it suitable for feature extraction [11]. The prepossessing stage includes

3.1.1 Converting image to binary

A gray scale signature image is converted to binary to make feature extraction simpler.

3.1.2 Image resizing

The signatures obtained from signatory are in different sizes so, to bring them in standard size, resizing is performed, which will bring the signatures to standard size 256*256 as shown in Fig. 2.

3.1.3 Thinning

Thinning makes the extracted features invariant to image characteristics like quality of pen and paper. Thinning means reducing binary objects or shapes to strokes that are single pixel wide.

3.1.4 Bounding box of the signature:

In the signature image, construct a rectangle encompassing the signature. This reduces the area of the signature to be used for further processing and saves time.

3.2 Feature Extraction

The choice of a powerful set of features is crucial in signature verification systems. The features that are extracted in this phase are used to create a feature vector. A feature vector of dimension 24 has been used to uniquely characterize a candidate signature. These features are extracted as follows:

Maximum horizontal and vertical histogram:

Horizontal histogram is calculated by going through each row of the signature image and counting number of black pixels. A row with maximum number of black pixels is recorded as maximum horizontal histogram. Similarly, a vertical histogram is calculated by going through each column of the signature image and finding a column with maximum number of black pixels.

Center of mass:

Split the signature image in two equal parts and find center of mass for individual parts.

Normalized area of signature:

It is the ratio of area of signature image to the area of signature enclosed in a bounding box. Area of a signature is the number of pixels comprising it.

Aspect Ratio:

It is the ratio of width of signature image to the height of the image. This is done because width or height of person's signature may vary but its ratio remains approximately equal.

Tri surface feature:

Two different signatures may have same area .so; to increase the accuracy of the features three surface feature has been used. In this, a signature is divided into three equal parts and area for each part is calculated. Eq. (1) is then used to calculate normalized area of each part. Figure (6) shows tri surface feature

The six fold surface feature:

Divide a signature in three equal parts and find bounding box for each part. Then calculate centre of mass for each part. Draw a horizontal line passing through centre of mass of each part and calculate area of signature above and below centre of mass within a bounding box. This provides six features.

Transition feature:

Traverse a signature image in left to right direction and each time there is a transition from 1 to 0 or 0 to 1, calculate a ratio between the position of transition and the width of image traversed and record it as a feature. Repeat a same process in right to left, top to bottom and bottom to top direction. Also calculate total number of 0 to 1 and 1 to 0 transitions. This provides ten features.

3.3 Creation of feature vector

A feature vector of size 24 is formed by combining all the extracted features as discussed in section 2.2.

3.4 Training a neural network

Extracted 24 feature points are normalized to bring them in the range of 0 to 1.These normalized features are applied as input to the neural network.

3.5 Verification.

In the verification stage, a signature to be tested is pre-processed and feature extraction is performed on pre processed test signature image as explained in section 2.2 to obtain feature vector of size 24. After normalizing a feature vector it is fed to the trained neural network which will classify a signature as a genuine or forged.

4. OVERVIEW OF NEURAL NETWORK

The objective of this study is to classifying hand written signature using feed forward back propagation neural network and Levenberg-Marquardt (LM) as the training algorithm. In this paper, LM training algorithm is adopted for updating each connection weights of units. LM algorithm has been used in this study due to the reason that the training process converges quickly as the solution is approached. For this study, sigmoid, hyperbolic tangent functions are applied in the learning process. Feed forward back propagation neural network use to classify signature according to feature vector characteristic. Feed forward back propagation neural network is created by generalizing the gradient descent with momentum weight and bias learning rule to multiple layer networks and nonlinear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train feed forward back propagation neural network. Neural network train until it can classify the defined pattern. The training algorithms use the gradient of the performance function to determine how to adjust the weights to minimize performance. The gradient is determined using a technique called back propagation, which involves performing computations backwards through the network. The back propagation computation is derived using the chain rule of calculus. In addition, the transfer functions of hidden and output layers are tan-sigmoid and tan-sigmoid, respectively.

4.1 Training and Testing Result

The proposed network was trained with feature vector data cases. When the training process is completed for the training data, the last weights of the network were saved to be ready for the testing procedure. The time needed to train the training datasets was approximately 20.60 minutes. The testing process is done for 300 cases. These 300 cases are fed to the proposed network and their output is recorded.

Performance plot: Performance plot show the training errors, validation errors, and test errors appears, as shown in the training process. Training errors, validation errors, and test errors appears, as shown in the following figure 3.

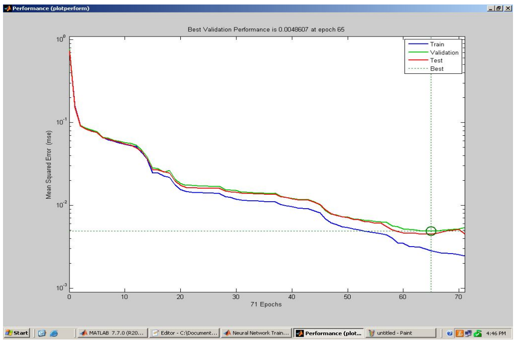

Figure 3: Performance plot

Receiver Operator Characteristic Measure (ROC) Plot: The colored lines in each axis represent the ROC curves. The *ROC curve* is a plot of the true positive rate (sensitivity) versus the false positive rate (1 -specificity) as the threshold is varied. A perfect test would show points in the upper-left corner, with 100% sensitivity and 100% specificity. For this problem, the network performs very well. The results show very good quality in the following figure 4.

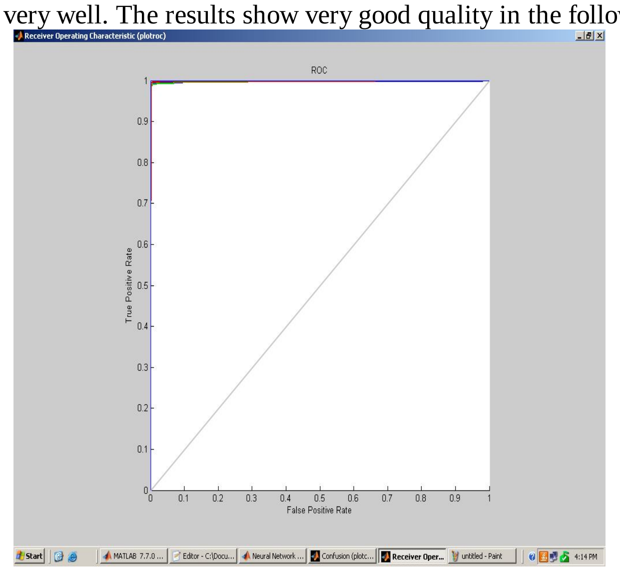

Figure 4: ROC Plot

Regression plots: This is used to validate the network performance. The following regression plots display the network outputs with respect to targets for training, validation, and test sets. For a perfect fit, the data should fall along a 45 degree line, where the network outputs are equal to the targets. For this problem the fit is reasonably good for all data sets, with R values in each case of 0.93 or above. The results show in the following figure 5.

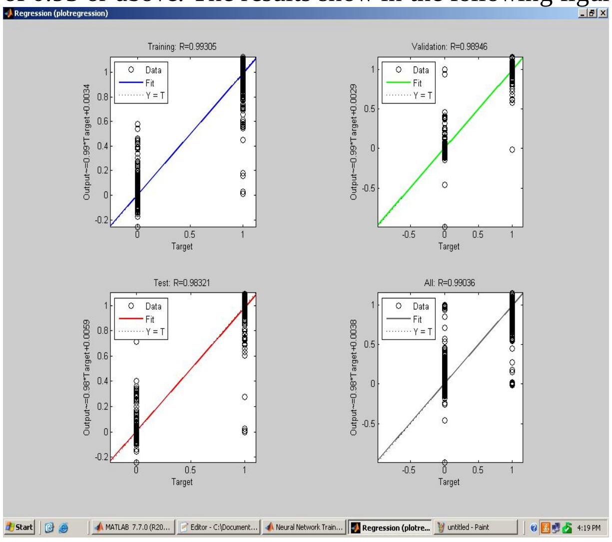

Figure 5: Regression Plots

Training State Plot: Training state plot show the deferent training state in training process and validation check graph. These plots also show the momentum and gradient graph and state in training process. The results show in the following figure 6.

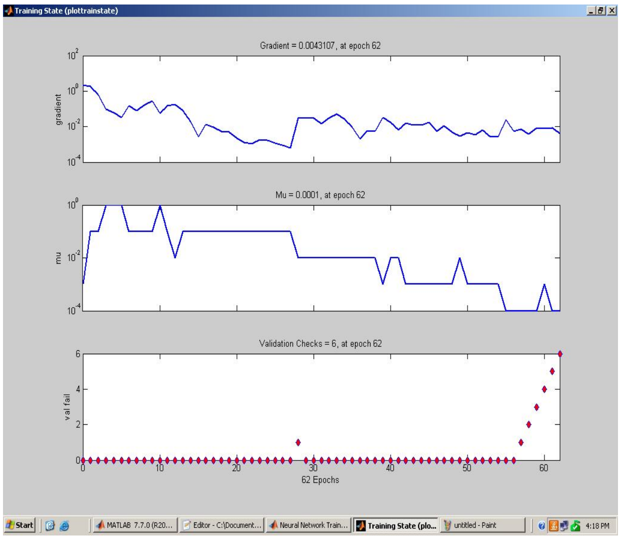

Figure 6: Training State Plot

5. RESULTS AND DISCUSSION

For training and testing of the system many signatures are used. The results given in this paper are obtained using the “Grupo de Procesado Digital de Senales” (GPDS) signature database [12]. The results provided in this research used a total of 2000 signatures. Those 2000 signatures are comprised of 50 sets (i.e. from 50 different people) and, for each person there are 32 samples of genuine signatures and 32 samples of forgeries. Figure 6 shows some of the signatures in the GPDS database. To train the system, a subset of this database was taken comprising of 32 genuine samples taken from each of the 30 different individuals and 32 forgeries made by different person for one signature. The features extracted from 32 genuine signatures and 32 forged signatures for each person were used to train a neural network. The architecture of neural network used has input layer, hidden layer and output layer [13]. Number of neurons in the input layer are 24, 24 neurons in the hidden layer and one neuron in the output layer.

After applying a feature vector of test signature if the output neuron generates value close to +1 test signature is declared as genuine or if it generates value close to -1 it is declared as forged.Fig.3 shows performance graph of the training a two layer feed forward neural network using Error Back Propagation Algorithm (EBPTA). When verification begins, the application updates the user of the current state of events. For instance, at the first stage, settings are initialized, indicated by “Initializing settings...” and “initializing settings...Done”, when completed. At the second stage, the training set for the inputs is generated, indicated by the output “Generating training set...” and “Generating training set...Done”, when completed. At third stage, when training on the images begins, the program notifies with “Began training process...” and when done, the final notification states “Completed training process successfully.” After the entire process of training, a file is generated and stored in the files system. This file contains the network details of the training process in binary.

5. CONCLUSION

This paper presents a method of off line handwritten signature verification using neural network approach. The method uses features extracted from preprocessed signature images. The extracted features are used to train a neural network using error back propagation training algorithm. The network could classify all genuine and forged signatures correctly. When the network was presented with signature samples from database different than the ones used in training phase, out of 600 such signatures (300 genuine and 300 forged) it could recognize 596 signatures correctly. Hence, the correct classification rate of the system is 98.66% in generalization. Our recognition system exhibited 100% success rate by identifying correctly all the signatures that it was trained for. However, it exhibited poor performance when it was presented with signatures that it was not trained for earlier. We did not consider this a “high risk” case because recognition step is always followed by verification step and these kinds of false positives can be easily caught by the verification system. Generally the failure to recognize/verify a signature was due to poor image quality and high similarity between two signatures. Recognition and verification ability of the system can be increased by using additional features in the input data set. This study aims to reduce to a minimum the cases of forgery in business transactions.

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