Classifications of signatures by radial basis neural network

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ABSTRACT

The personal signature can be considered one of the most common behavioral biometrics. In this study, signatures are classified according to their specifications. The statistical calculation is considered for the specifications of each signature. Then, a radial basis neural network (RBNN) is adapted to apply multiple classifications for the employed signatures. A big number of signatures are utilized; they are obtained from the database called biometric ideal test (BIT). The total number of collected signatures is equally divided between the testing and training phases, where it is partitioned into 50% for the training and 50% for the testing. The proposed technique could achieve attractive performance, where each of the mean square error (MSE) and mean absolute error (MAE) attained a small value of 0.028. In addition, the proposed approach using the RBNN is compared with the different neural networks of the state-of-the-art techniques in order to demonstrate that the outcomes are acceptable and successful.

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1. INTRODUCTION

The word 'biometric' can be used for referring to pattern recognition based on a certain trait. In general, there are two types of biometrics (or characteristics), these are physiological and behavioral. Physiological characteristic refers to a trait that can be found within the human body. Whereas, behavioral characteristic refers to a certain manner or style of an individual [1]. Behavioral biometrics are expectedly more challenging than physiological biometrics. This is because they are affected by feelings and situations during their acquirements. Instances of physiological biometrics are palmprint [2], fingerprint [3], earprint [4], [5], and deoxyribonucleic acid (DNA) print [6]. On the other hand, Instances of behavioral biometrics are voice [7], [8], signature [9], and keystroke [10]. Signature characteristic is so famous, common, and popular. It is a behavioral biometric, so, it is a challenging trait. It can have the parameters of coordination points, synthetic timestamps, pen ups and pen downs, and pen pressures [11]. Each person has a certain signature shape and drawing style. From this point, various signatures can be observed. Examples of different signature shapes and drawing styles are shown in Figure 1.

Kaur and Kumar [12] provides a comprehensive, systematic overview of signature identification and verification strategies used online and offline. Surveys concerning two approaches, that is writer-independent and writer-dependent methods, are offered in offline signature verification. In addition, the outcomes of a comprehensive analysis of extraction of the features and algorithms for classification utilized in the procedure of both identification and verification of the signature have been included. Several datasets from the literature are used to test various signature identification and verification procedures, and the findings are presented in this paper. For signature identification and verification tasks, a review is provided in terms of the pre-processing, classification, as well as feature extraction strategies [13]. Moreover, a comparison of systems is employed in the literature for verification and identification methods in offline and online systems, taking into consideration the datasets utilized and the outcomes for each system.

A signature identification system based on the camera is presented in [14]. Irrespective of alterations in the camera's location relative to the surface of writing has been emphasized that the necessity of signature parameterization so as to produce satisfying classification consequences. The work shows that the parameterization for affine arc-length is outperformed Euclidean arc-length parameterizations and has better traditional time. The study also discovered that the performance of the verification system has superior to 1% on random forgeries and 4% on skilled forgeries. In addition, the achieved recognition rate is better than 1%, whereas this rate is similar to the best biometrics based on the camera.

An offline signature recognition based on discrete wavelet transform (DWT) is applied [15]. Three processes were utilized pre-processing, feature extraction, and image registration. To improve the accuracy and save processing time, pre-processing actions were accomplished. Furthermore, from the signature picture, the useful features are extracted by employing many layers of DWT. From the suggested technique used, the outcome of the recognition rate is 100%.

An artificial neural network (ANN) is created in [16] for an offline system for authenticating signatures after they have been recognized. The training of the system is critical, as the success rate is computed by the appropriate training sample. The percentage rate of success of the signature recognition system is estimated to be around 95%. Image quality is crucial for a bad signature image might lead to a signature not being recognized or verified. Increases in signature attributes/features will improve the system's verification capabilities, but they may also raise computational complexity.

In order to improve the recognition accuracy of the handwritten signature tasks, Hirunyawanakul *et al.* [17] proposes a deep convolutional neural networks (DCNN) approach. The DCNN has employed two techniques: transferring the learning utilizing features from a model that has been pre-trained on a bigger dataset, and generating a model of the CNN from the scratch. A total of 600 images of handwritten signatures were collected from 30 persons for the collection. The accuracy of the suggested technique is compared to the results produced from different machine learning algorithms in order to assess its efficacy. The comparison demonstrates extremely satisfied recognition results, with both approaches achieving a 100% recognition rate.

A hear cascade classifier (HCC) is exploited in [18], as one of the machine learning algorithms that is employed to recognize and verify handwritten signatures. The UTSig collection for Persian writers was utilized, which involves 8,280 pictures collected from 115 writers. The synthetic signature database called the GPDS database is provided data from 4,000 synthetic persons having a left-to-right writing style with respect to English writers. After the pre-processing step is achieved, then a classifier is generated for each signature from the signatures of the writers. A massive number of signatures are employed for training and then testing each classifier by adding artificial noises to the signature pictures. The performance system was evaluated on real signature pictures and the accuracies attended were: 92%, and 92.42% for the GPDS, and UTSig datasets, respectively.

Image processing strategies as well as the back propagation neuron network system (BPNNS) were applied for recognizing the offline signature system in [19]. The image processing approaches were exploited for signature pre-processing purposes, which include: conversion from red, green, blue (RGB) to grayscale, filtering, modifying, and establishing a threshold, after that, detection by the canny edge is used, and finally, picture scaling is employed to minimize processing time. To extract the processed picture features, BPNNS with a predetermined number of hidden layers and neurons is utilized. Likewise, the pictures existing in the dataset are also preprocessed and their features are extracted in the same way. A higher performance accuracy can be obtained depending on the number of hidden layers and neurons. The proposed technique demonstrates that the experimental outcome has a higher rate of success.

The paper in [20] presents a technique for pre-processing signatures so as to make verification easier. In addition, a new method is also suggested for detecting forgeries and recognizing signatures with verification by employing CNN. Furthermore, different methods and algorithms were utilized such as speeded up robust features (SURF), crest-trough, and Harris corner detection algorithms. The system has achieved a range of accuracies (90%-94%), and (85%-89%) for recognizing signatures and detecting forgeries, respectively.0

To cope with the large-scale training challenge, [21] presents a batch normalization large-scale signature network (LS2Net) which represents a new framework of the CNN. In addition, the LS2Net_v2 is a new network structure that was established. Furthermore, based on the classifier a class center (C3) approach was also suggested. The system uses the dataset called GPDS-4000 and employed 96,000 signatures collected from 4,000 signers for recognizing offline signatures. Moreover, CEDAR and MCYT datasets are selected as well as the GPDS-4000 in order to provide a realistic comparison. The LS2Net approach accomplished a recognition rate of 98.30%, and 96.41% for CEDAR and MCYT datasets, respectively. However, the highest outcomes were obtained by the LS2Net.v2 method using the GPDS-4000 dataset with a performance accuracy equal to 96.91%. In addition, the paper shows that the batch normalization and the C3 method have a considerable impact on performance. This paper aims to provide a study about applying multiple classifications for signatures by using radial basis neural network (RBNN). Subsequent to this introduction, the rest sections have been distributed according follows: section 2 explains the proposed approach, section 3 shows the outcomes with discussions and section 4 illustrates the summary of this paper including the conclusions.

Figure 1. Examples of different signature shapes and drawing styles [22]

2. PROPOSED METHOD

First of all, signatures are analyzed to obtain their main features. The analysis consists of three main processes for each signature. These processes are: computing the discrete fourier transform (DFT) technique to produce the frequency domain coordination, creating the function of pressure to describe the trajectory signal, and displaying completely the acquired signals in the time domain [11]. Figure 2 shows the main framework for creating the synthetic signature algorithm. It is significant to clarify that the pressure function is compromised of two parameters. The first parameter is to binary represent the pen up and pen down as '0' and '1', respectively. The second parameter is for the pressure on a writing surface. Furthermore, to obtain more precise information from a signature, some improvement operations are applied. Examples of these are translation, rotation, scaling, flourishing, and smoothing [11]. Hence, each signature will have 5 descriptions: x coordinates, y coordinates, synthetic timestamps, pen ups and pen downs, and pressure function [11], [22]. Consequently, a statistical calculation of the standard deviation (STD) is considered for each 5 described values. STD calculation can be expressed as (1) [23]:

$$STD = \sqrt{\frac{1}{q-1}\sum_{k=1}^{q}(p_k - \bar{p})^2} \tag{1}$$

where STD is the calculated standard deviation, q is the number for each block's pixel values, p_k is the intensity of kth pixel for each block, and $\bar{p}$ is the average of the block pixels values. Subsequently, the RBNN, which is a supervised network, is adapted for the multiple classifications of signatures. The composition of the RBNN is from three main layers: the input and output layers, as well as the hidden layer. Figure 3 depicts the network in its general structure. In the hidden layer of the RBNN, the transfer function is termed the radial basis function (RBF) [24]. In (2) and (3) are used in such a hidden layer [25]:

$$h_j = x^T w_j \ , j = 1,2, \ldots , n \tag{2}$$

$$z_j = \exp\left[\frac{h_j - 1}{\sigma^2}\right] \tag{3}$$

where h_j is the prior calculated hidden value, x is the input vector, T is the transpose parameter, w is the weights vector between the input and hidden layers, n is the number of neurons in the hidden layer, z_j is the hidden value of the calculated output, and σ is a smoothing parameter of the transfer function. Consequently, a linear function is utilized in the output layer [26]. Thus, (4) can be exploited directly [27]:

$$y_j = \sum_{j=1}^{p} z_j w_j \qquad (4)$$

where y_j represents an output value for the output layer. Like other neural networks, the RBNN works in two phases: train and test. Each phase will deal with certain patterns of signatures. After the training phase, it provides the required weights. On the other hand, after the testing phase, intelligent outputs can be produced.

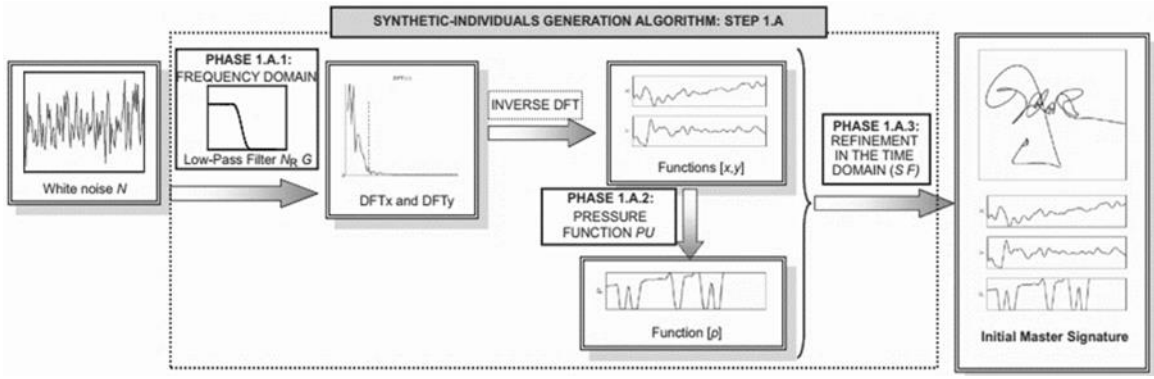

Figure 2. The main framework for creating the synthetic signature algorithm [11]

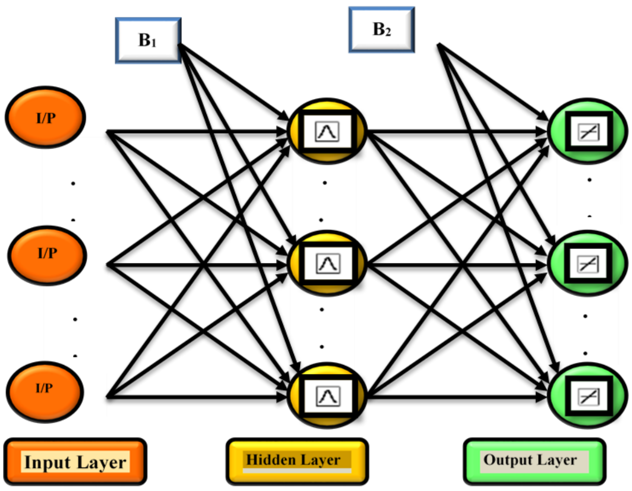

Figure 3. The general structure of the RBNN approach

3. RESULTS AND DISCUSSION

First of all, a database from the biometric ideal test (BIT) [28] is utilized. It has a very big number of signatures composed of 8,750 signatures collected from 350 persons, where each person participates with 25 patterns of signatures. The first 5 patterns follow the variability of an intra-session. Whilst, the rest patterns follow the variability of an inter-session. Duplicated samples are produced by developing the lognormal parameters of the main signature as illustrated in [11].

As mentioned, every signature pattern has 5 descriptions of x coordinates, y coordinates, synthetic timestamps, pen ups and pen downs, and pressure function as clarified in [11], [22]. Each one of these descriptions has many values. However, they have been resized to only 65 values as this are the smallest number of values in the shortest signature descriptions.

Consequently, the statistical STD calculation is computed for each 5 described values. Therefore, the number of RBNN inputs is 65. As mentioned, the RBNN is adapted for the multiple classifications of signatures. The outcomes are chosen to be multiple classifications for 70 persons. The number of hidden nodes or units here is 875 nodes. Overall, 1,750 patterns are exploited and partitioned into 50% out of the total patterns are used for the training phase, while the remaining 50% for the testing phase.

Figure 4 depicts the suggested RBNN's training curve. This figure shows how the training curve is successfully graduated to the goal of zero value with the performance of mean square error (MSE) equal to 0.0002. The required number of iterations here is 850 epochs. For comparison purposes, various neural networks are investigated with exact RBNN parameters.

According to Table 1, it can be investigated that the classical cascade-forward neural network, backpropagation with momentum in training. A standard backpropagation neural network has been reported with small values of the MSE, mean absolute error (MAE), and accuracy (100-(MAE×100)). On the other hand, it is apparent that the suggested approach attained remarkable outstanding. That is, the MSE and MAE are each recorded at a small value of 0.028. Also, the accuracy for the multiple classifications of signatures in this paper achieves 97.2, which is obviously a high value. Different state-of-the-art neural network techniques might be used in various applications as in [29], [30].

Additional comparisons with state-of-the-art papers are considered, specifically with [31], [32]. Both of these papers concentrated on writer identification. An end-to-end framework was suggested with the recurrent neural network (RNN) in [31]. The reported accuracies in this study were benchmarked as 100% and 99.46% for English handwriting and Chinese handwriting, respectively [31]. Whereas, an end-to-end system namely the DEEP writer ID was proposed with a deep CNN in [32]. The reported accuracies in this study were benchmarked as 98.51% and 95.72% for English text and Chinese text, respectively [32]. It seems that recorded accuracies in [31], [32] are more than our achieved accuracy.

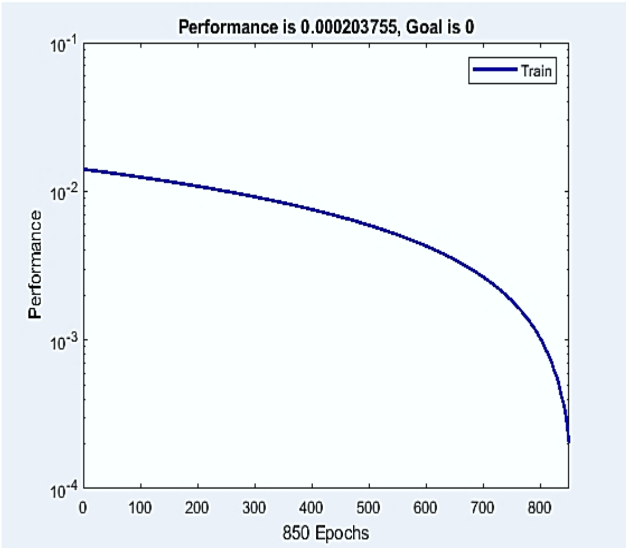

Figure 4. The suggested RBNN method's training curve

Table 1. Comparisons of the performance accuracy for different neural networks techniques

Neural network method	MSE	MAE	Accuracy
Cascade-forward	0.046	0.151	84.87
Backpropagation with momentum in training	0.043	0.143	85.68
Backpropagation	0.040	0.133	86.71
Proposed RBNN	0.028	0.028	97.18

4. CONCLUSION

In this study, the classification method of signatures was suggested. It consisted of the signature analysis, statistical computation, and suggested RBNN. The RBNN model is the technique that was suggested and adapted for performing the multiple classifications between various signatures. A big number of signatures was exploited in this study where 1,750 patterns were used. The number of employed signatures was split into two halves for both the testing and training phases. Interesting and remarkable results were obtained. That is, a low error value of 0.028 has been recorded for the MSE and exactly a similar value has been reported for the MAE. Furthermore, the highest accuracy of 97.182% was attained. These performances were confirmed to be successful and acceptable after comparing the suggested RBNN with other neural networks.

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