Offline Handwritten Signature Recognition

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***Abstract*—**Biometrics, which refers to identifying an individual based on his or her physiological or behavioral characteristics, has the capability to reliably distinguish between an authorized person and an imposter. Signature verification systems can be categorized as offline (static) and online (dynamic). This paper presents a neural network based recognition of offline handwritten signatures system that is trained with low-resolution scanned signature images.

***Keywords*—**Pattern Recognition, Computer Vision, Adaptive Classification, Handwritten Signature Recognition.

I. Introduction

PATTERN recognition is concerned with the automatic detection and classification of objects or events. Emerging new applications resulted in increasing interest in pattern recognition. The interest in pattern recognition is so diverse that pattern recognition applications attract researchers belonging to all possible disciplines ranging from business to the most sophisticated industries [1]. Accurate automatic personal identification is now needed in a wide range of civilian applications [2-3] involving the use of passports, cellular phones, automatic teller machines, and driver licenses [4].

A biometric can be classified as physiological or behavioral. Common physiological biometric include face, facial characteristics, fingerprints, hand or palm geometry, and retina or iris. Behavioral characters include signature, voice, keystroke pattern, walking style, and gait [5]. Most physiological features remain relatively stable over time, while behavioral characteristics are in control of the subject and tend to change over the short and long terms due to health, physiological state and aging. While physiological biometrics may be adequately represented by a single sample, behavioral biometrics generally require several samples due to their inherent variability, for example, signatures vary depending on fatigue, mental and physical state, and writing position [6].

Of all the biometric, handwritten signature recognition is simple, inexpensive, non-intrusive, and acceptable in society for confirming transactions, civil law contracts, acts of volition, and one's identity [7]. This is primarily due to the age old usage of handwritten signatures as a means of human identification and its freedom from association with any privacy intrusion related issues [8]. Hence research in developing biometrics systems that can improve the accuracy of handwritten signature verification continues to be of prime interest to date [9-10]. However, it also has the disadvantages of lower identification and verification precision in comparison with other biometrics, non-linear changes with size changing, and dependency on time and emotion [11]. Even though the handwritten signature verification has been extensively studied in the past decades and with the best methodologies functioning at high accuracy rates, there are a lot of open questions [12] to be answered.

Overall, signature verification systems can be categorized as offline (static) and online (dynamic) [13]. Offline signature verification is obtained from a piece of writing paper which is scanned as an input image. It is mostly found on bank checks and documents signature. On the other hand, online signature verification uses the dynamic properties of the signature (signature trajectory, pen pressure, pen downs and pen ups, time stamping, etc) which are captured by a pen based tablet. Online signature verification is more robust, reliable, and accurate than offline signature verification as its dynamic properties make the process of forging an online signature more difficult [14]. However in the most common real-world scenarios, this information is not available, because it requires the observation and recording of the signing process. This is the main reason, why static signature analysis is still in focus of many researchers. Offline methods do not require special acquisition hardware, just a pen and a paper, they are therefore less invasive and more user friendly [12].

Edson et al. proposed an off-line signature verification system using Hidden Markov Model [15]. Zhang et al. proposed handwritten signature verification system based on neural 'Gas' based vector quantization [16]. Vélez et al. proposed robust off-line signature verification system using compression networks and positional cuttings [17]. Arif and Vincent concerned data fusion and its methods for an off-line signature verification problem which are Dempster-Shafer evidence theory, Possibility theory and Borda count method [18]. Chalechale and Mertins used line segment distribution of sketches for Persian signature recognition [19]. Jain et al. [20] proposed more than 70 different feature types to be used for online signature verification.

The reemergence of interest in neural networks in recent years has caught the attention of those involved in pattern detection and classification as they begin to recognize the potential advantages of a neural network approach. Neural networks are data processing structures that are constructed in analogy to neurobiological models. Their elements are neurons and they learn by example. The networks are comprised of processing elements, each of which has set of inputs, a set of weights, and one output. Inputs are multiplied by their weights and summed. The output is computed as a nonlinear function of the summation. They offer fine-grained

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parallelism, and exhibit fault-tolerance. One advantage of any neural network, which performs classification task, is that it will learn its own coarse-grained features, thus precise locations do not form any part of an input set [21].

In this paper, we present a neural network based recognition of offline handwritten signatures system that is trained with low-resolution scanned signature images. The objective is to eliminate bulk storage requirements. We used neural networks because of their adaptive nature of
learning by example in solving problems. This feature makes such computational models very appealing for a wide variety of application domains including pattern recognition. The neural network approach has long been in use for pattern recognition. The classifier performance is evaluated using a locally developed database comprising Arabic and English handwritten signatures. The handwritten signatures are recognized based on features extracted with an adaptive learning vector quantization (LVQ) neural network compact architecture [22]. The images are scanned for this purpose using a resolution of 200 dpi (see Fig. 1).

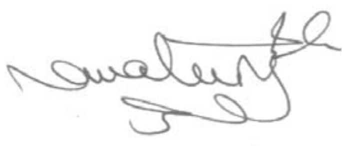

Fig. 1 A 256 gray level 450×200 pixels handwritten signature

II. LVQ CLASSIFIER

LVQ (learning vector quantization) is a supervised classifier that was first studied by Kohonen [23]. To classify an input vector, it must be compared with all prototypes. The Euclidean distance metric is used to select the closest vector to the input vector. And the input vector is classified to the same class as the nearest prototype.

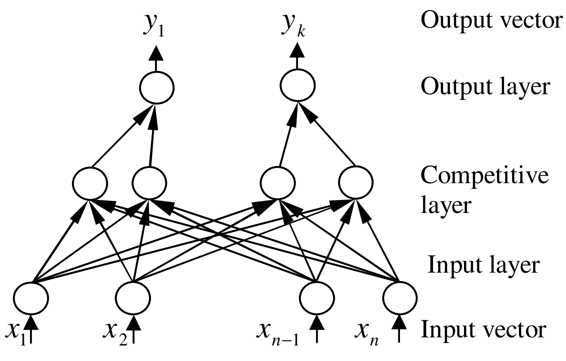

Fig. 2 Architecture of the LVQ classifier

The LVQ classifier (Fig. 2) consists of an input layer, a hidden competitive layer, which learns to classify input vectors into subclasses and an output layer, which transforms the competitive layer's classes into target classifications defined by the user. Only the winning neuron of the hidden layer has an output of one and other neurons have outputs of zero. The weight vectors of the hidden layer neurons are the prototypes, the number of which is usually fixed before training begins. The number of hidden neurons depends upon the complexity of the input-output relationship and significantly affects the results of classifier testing. Selection of the number of hidden neurons must be carefully made, as it highly depends on the encompassed variability in the input patterns. Extensive experiments are performed to conduct the suitable number.

For a training set containing *n* input signatures, each of these images is labeled as being one of *k* classes. The learning phase starts by initiating the weight vectors of neurons in the hidden layer. Then, the input vectors are presented randomly to the network. For each input vector X_j, a winner neuron W_i is chosen to adjust its weight vector:

$$\|X_j - W_i\| \le \|X_j - W_k\|, \text{for all } k \ne i \tag{1}$$

The weight vector $W_i(t)$ is updated to the next step t+1 as follows:

$$W_i(t+1) = W_i(t) + \alpha(X_j - W_i(t)) \tag{2}$$

if X_j and W_i belong to the same class

$$W_i(t+1) = W_i(t) - \quad (X_j - W_i(t)) \tag{3}$$

if X_j and W_i belong to different classes.

where $0 \le \alpha \le 1$ is the learning rate, which may be kept constant during training or may be decreasing monotonically with time for better convergence [23]. Otherwise, do not change the weights. The training algorithm is stopped after reaching a pre-specified error limit. During the test phase, the distance of an input vector to each processing element of the hidden layer is computed and again the nearest element is declared as the winner. This in turn fires one output neuron, signifying a particular class.

III. SIGNATURE DATABASE PREPROCESSING

A typical biometric system has three distinct phases. These are biometric data acquisition, feature extraction, and decision-making. The first step, the acquisition phase, is extremely important. If high quality images are not obtained, the next phase cannot operate reliably. In fact, most difficulties in accurately identifying an individual can be traced back to the image acquisition phase.

In our database, we collected 945 signatures from 35 persons (27 signatures each person). Signatures were collected using an A4 sized paper having drawn 3 rectangles of varying sizes. Each rectangle was further divided equally in 9 small boxes and the participants were asked to sign within the available space of boxes. The purpose of this exercise was to get signatures of varying covered areas. Among the participants, 20 were males and 15 were females. The signatures were scanned into the computer as color images of sizes 450×200, 400×185, and 350×170 pixels bmp (bitmap image file) format without any compression with a resolution of 200 dpi. The database has considerable variability in that as it is built over a period of time. This is crucial because signing characteristics can be very dependent on an individual's emotion, health, state of mind, writing posture, available space, fatigue, etc. The whole set of scanned handwritten signatures is re-sampled as 200×100 pixels and converted to 8-bit 256 gray level images. To reduce the image size, a low pass filter is applied to the image before interpolation using the nearest (Euclidean distance) neighbor interpolation method.

IV. Algorithm

The most challenging step in the design of a pattern recognition system is the selection of a suitable base model that constitutes its building blocks. The next step is the features selection and extraction method.

A. Neural Classifiers

In machine-based detection, a gallery of patterns is first enrolled in the system and coded for subsequent searching. A probe pattern is then obtained and compared with each coded image in the gallery, detection is noted down when a suitable match occurs. The challenge of such a system is to perform detection of the pattern despite transformations; area of the image, changes in lighting conditions, common problems of machine vision, and changes due to an individual's emotion, health, state of mind, writing posture, fatigue, etc. The need is, thus, to find appropriate codings for signatures which can be derived from a number of images and to determine in what way, and how well, two such codings shall match before the signatures are declared the same.

B. LVQ Models

A generic learning vector quantization neural network consists of three layers. The first layer is the input layer, which consists of as many neurons as the number of input samples of the image to be recognized. The hidden layer size is problem dependent. The number of hidden layer neurons (HN) should be suitable to capture the knowledge of the problem domain. For example, training a neural network to recognize signatures which belong to number of classes (NC), at least NC hidden layer neurons are required. To capture a large range of input pattern variability, a large number of hidden layer neurons is necessary. But, the problem is how large should it be.

Visualizing the learned pattern of the hidden layer neurons, it is found that there are neurons with completely blurred patterns, blind neurons [22], as these neurons did not see the images which are clamped to the neurons of the input layer. Eliminating the blind neurons enhances the classifier performance. The algorithm based on efficient LVQ model parameters is as follows:

1. Select the network parameters:
   - ✓ Input layer size = Image size (200 × 100 = 20,000 neurons).
   - ✓ Training set size = S (10 or 20 subjects) × X (12 signatures).
   - ✓ Number of classes (NC) = S (number of subjects).
   - ✓ Hidden layer neurons (HN) = S × (1 or 2).
   - ✓ Learning rate (α) = 0.1.
   - ✓ Set up the target vector which specifies the target class of each pattern in the training set.
   - ✓ Display update rate =100.
   - ✓ Arrange the input patterns of the training set as one-dimensional columns in an array (P).
   - ✓ Number of training epochs (EP) = 1500 or 2500.
2. Initialize an LVQ classifier: Initialization of the weight matrix for competitive layer w_1 and linear layer w_2.
3. Start training of an LVQ classifier based on selected efficient model parameters.
4. Test the trained classifier on both training and test sets and compute percentage of correct classification (pcc) for training and test sets respectively.
5. Get the best accuracy rate of signature recognition and calculate the average and standard deviation of the 50 best networks.
6. Exit.

V. Experimental Results

Many experiments are performed to explore the possibility of the best parameters selection for handwritten signature recognition neural network classifier. Table 1 shows various experimental results of the networks trained for the recognition of signatures. As shown, the recognition rate of the best network architecture is 98.7% for a random test subset #1 of 10 subjects with 150 handwritten signatures, i.e., 15 signatures of varying covered areas for each person, while for the subset #2, it is 94.7%. This infers that not all handwritten signatures have the same recognition rate, on average, as some signatures are similar in shape to the others in the second subset.

The system is trained with a training set of 120 signatures of varying covered areas of same subjects. The efficiency of the proposed architecture is evaluated on both the time and the space scale. By setting the number of hidden layer units (NH) equal to the subjects (S) or twice of subjects (2 × S) has condensed not only the network memory requirements for the internal representation of target signature images, but also it has enhanced the processing speed, both training time of the network and recognition time of the signature image are reduced. This makes the proposed architecture feasible for large data training and test samples in real-time application domains.

TABLE I
BEST, AVERAGE, AND STANDARD DEVIATION (Σ) OF PERCENTAGE OF CORRECT CLASSIFICATION (PCC) OF TEST SETS FOR 50 SIGNATURE RECOGNITION NEURAL NETWORKS WITH PARAMETERS: $\alpha = 0.1$

S	Subset	EP	I	Tr	Ts	NH	Best pcc %	Ave pcc	σ
10	#1	1000	270	120	150	10	98.7%	98.1%	0.34
10	#2	1000	270	120	150	10	94.7%	93.2%	0.72
20	#1 & #2	1500	540	240	300	20	92.7%	91.9%	0.48

I = images (total), Tr = training set, Ts = test set

For the next step, the same experiment is repeated with an increased number of subjects (20), and hence the number of unseen test signature images (300). The rate of correct classification for the best network classifier reduces to 92.7%.

VI. Conclusion

In modern pattern recognition systems all the stages of pattern recognition could be performed by a single scheme such as neural networks and genetic algorithms which has the inherent capabilities of noise filtering, data reduction, feature extraction and classification. The advantage of using neural networks is that they can extract the most discriminative and representative set of features.

We have presented a learning vector quantization neural network architecture based on varying parameters and eliminating redundant hidden layer units or blind neurons that learns the correlation of patterns and recognizes handwritten signatures. The network classifier is trained on the random training samples to perform recognition task on the input signature image. Empirical results yield an accuracy rate of 98% for a random test set of 150 handwritten signature images of 10 persons on the network that is trained with another set of 120 images of same subjects.

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