Learning Approach for Offline Signature Verification Using Vector Quantization Technique

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Abstract. Signature is a behavioral trait of an individual and forms a special class of handwriting in which legible letters or words may not be exhibited. Signature Verification System (SVS) can be classified as either offline or online. [1] In this paper, we used vector quantization technique for signature verification. The data is captured at a later time by using an optical scanner to convert the image into a bit pattern. The features thus extracted are said to be static. Our system is designed using cluster based features which are modeled using vector quantization as its density matching property provides improved results compared to statistical techniques. The classification ratio achieved using Vector Quantization is 67%.

Keywords: Off-line Signature Verification, Feature Extraction, Vector Quantization.

1 Introduction

Signature has been a distinguishing feature for person identification through ages. Approaches to signature verification fall into two categories according to the acquisition of the data: On-line and Off-line. 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, 2]. Online systems use this information captured during acquisition. Off-line data is a 2-D image of the signature. Processing Off-line is complex due to the absence of stable dynamic characteristics. Difficulty also lies in the fact that it is hard to segment signature strokes due to highly stylish and unconventional writing styles. The non-repetitive nature of variation of the signatures, because of age, illness, geographic location and perhaps to some extent the emotional state of the person, accentuates the problem. All these coupled together cause large intra-personal variation. A robust system has to be designed which should not only be able to consider these factors but also detect various types of forgeries [3]. It should have an acceptable trade-off between a low False Acceptance Rate (FAR) and a low False Rejection Rate (FRR). Numerous approaches have been proposed for

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Handwritten Signature Identification, Recognition and Authentication systems. Many research works on signature verification have been reported. In March, 2007, Debnath Bhattacharyya, Samir Kumar Bandyopadhyay and Poulami Das [4] have proposed a new recognition technique; an Artificial Neural Network is trained to identify patterns among different supplied handwriting samples [4, 5]. Another important method for offline signature verification is the application of Hidden Markov's rule. Justino, Bortolozzi and Sabourin proposed an off-line signature verification system using Hidden Markov Model [5]. Hidden Markov Model (HMM) is one of the most widely used models for sequence analysis in signature verification. A well chosen set of feature vectors for HMM could lead to the design of an efficient signature verification system. Application of Support Vector machine (SVM) at the time of signature verification is also a new dimension in this field. Emre Ozgunduz, Tulin _enturk and M. Elif Karslıgil has proposed an algorithmic approach according to which off-line signature verification and recognition can be done by Support Vector Machine [7, 9]. In this paper we deal with Offline signature Verification System.

Vector Quantization is a clustering technique mainly used for speech recognition and lossy image compression [23]. Here we use vector quantization in training our system. The main advantage of VQ in pattern recognition is its low computational burden when compared with other techniques such as dynamic time warping (DTW) and hidden markov model (HMM). It works by dividing a large set of points (vectors) into groups having approximately the same number of points closest to them. This feature set is based on Vector Quantization.

2 Methodology

This section describes the methodology behind signature verification system development. It starts with data acquisition through scanner followed by pre-processing, feature extraction, training and at last classification (Fig. 1).

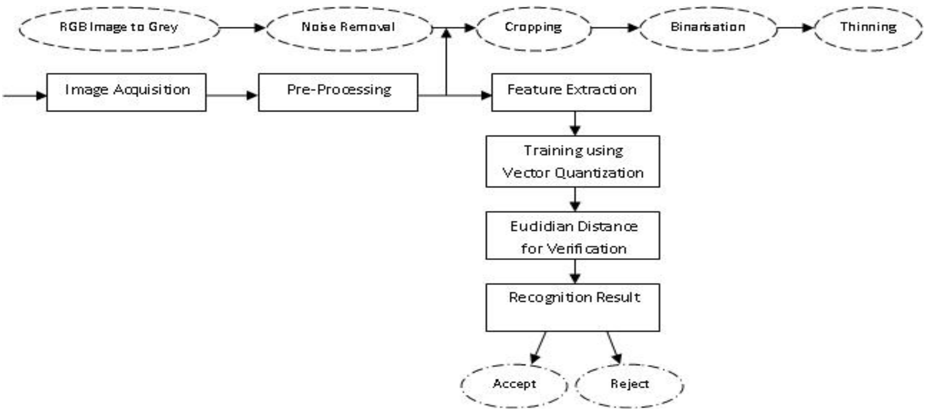

Fig. 1. Block Diagram of Proposed Signature Verification System

2.1 Image Acquisition

Handwritten signature images are collected from different individuals. The system has been tested for its accuracy and effectiveness on data from 25 users with 10 specimens of each making up a total of 250 signatures. The proposed verification algorithm is tested on both genuine and forged signature sample counterparts. So we developed a signature database which consists of signatures from all the age groups. Our database is also language independent and also it consists of signatures done with different pens with different colors. 10 users were asked to provide genuine signatures, 5 were asked to do skilled forgeries, 5 provide casual forgeries and 5 did random forgeries. A scanner is set to 300-dpi resolution in 256 grey levels and then signatures are digitized. For further working we cut and pasted scanned images to rectangular area of 3 x 4 cm or 200 x 200 pixels and were each saved separately in files.

2.2 Pre-processing

The pre-processing step is normally applied to make signatures ready for further working. It is also applied to improve the efficiency and performance of the SVS. Signatures are scanned in color. We have assumed that background is white and signature is done with any colored pen. Following are the preprocessing steps that are implemented:-

(a) RGB to grayscale image conversion: - For signature verification, color of signature has no importance. Only the form of the two signatures must be compared. Hence, all the scanned images are converted to grayscale images. This conversion makes future coding easier.

(b) Noise Removal: - This step involves removing noise from images. Noises are the disturbances (like spurious pixels) that can be attached to the image during scanning time. These noises are not a part of signature and should be removed. In this paper, we have assumed that background is white and signature is made from black points. The points which are far from black points are considered noises. The noise removal module returns a noise free image of the same size as the input image. For noise removal, a median filter is used followed by the mean filter.

(c) Image Cropping: - In this step, the Region of Interest (ROI) is determined using auto cropping approach. ROI is the signature object itself from which unwanted region apart from signature is removed. Using auto cropping, we segment the signature smoothly.

(d) Grayscale image to binary image: - Binarizing is a process of converting the image into black and white image, so that further processing could be easy.

(e) Thinning: - Thinning is a process that deletes the dark points and transforms the pattern into a "thin" line drawing called skeleton. Image thinning reduces a connected region in the image to a smaller size and minimum cross-sectional width character [24]. The minimum cross-sectional width could be one character in which case it would be a stick figure representation. The thinned pattern must preserve the basic structure of the original pattern and the connectedness. Thinning [10] plays an important role in digital image processing and pattern recognition, since the outcome of thinning can largely determine the effectiveness and efficiency of extracting the distinctive features from the patterns.

2.3 Feature Extraction

Decision of authenticated signatures is usually based on local or global features extracted from signature under processing. A feature is called global if it is extracted from the whole signature and is called local if it is extracted from each sample point [12]. The global features can be extracted easily and are robust to noise. But they only deliver limited information for signature verification. On the other hand, local features provide rich descriptions of writing shapes and are powerful for discriminating writers, but the extraction of reliable local features is still a hard problem.

This is the most vital and difficult stage of any off-line signature verification system. The accuracy of the system depends mainly on the effectiveness of the signature features use in the system. Here we extracted Skewness, Kurtosis, Signature area (Signature Occupancy Ratio, height, width, horizontal projection, vertical projection, and width to height Ratio (Aspect Ratio), centre of gravity, density of thinned image, density of smoothed image and normalized area of black pixels. These features are robust and work well with vector quantization technique used in training phase.

2.4 Training Phase and Verification

In order to analyze the discriminatory power of each individual feature, we have used vector quantization technique.

Vector quantization is a statistical clustering technique which allows the modeling of probability density functions by the distribution of prototype vectors. Vector quantization is presented as a process of redundancy removal that makes effective use of four interrelated properties of vector parameters: linear dependency (correlation), nonlinear dependency, shape of the probability density function (pdf), and vector dimensionality itself. It is based on competitive learning technique and hence is related to self-organizing feature map. It follows the principle of dividing a large set of input points or vectors into groups having approximately the same number of points closest to them and those groups are called as "code book" vectors [15]. In Vector quantization, input is given to input layer and this is used for training our network. In training phase, the output units are used for decision and assigning class to which the input vector belongs. After our network is trained, Vector quantization can classify the input vector by assigning it to appropriate class. Hence, it is a form of supervised learning because each output unit has a known class. If the given input matches our target output, it is considered as accepted otherwise rejected.

In vector quantization, the vector X is mapped onto another real-valued, discrete-amplitude, N dimensional vector Y. We say that X is quantized as Y, and Y is the quantized value of X. We write Y = Q(X) where Q is the quantization operator [28].

First, the signature image to be verified is partitioned into a set of blocks represented by feature vectors X. Y={$y_{i;}$i=1,2,…,N} is the set of reproduction vectors which is called a codebook. Each K-dimensional input feature vector X=(x_1,$x_{2,}$…,x_k) is then compared with all the codewords in the codebook, and quantized to the closest codeword or best match. A reference vector Y is considered to best match a feature vector X=(x_1,$x_{2,}$…,x_k) in the sense that appropriately defined distortion measure such as the squared error $\|X - Y\|^2$ is minimal. This distortion measure is actually Euclidean distance. Each time an input X is presented, we first make an ordering of the elements of a set of distortions E_x = {||X - Y]],i =l;.. ;N} and then determine the adjustment of reference vector Y. For the given training set and initial codebook, the block performs an iterative process.

Verification is a process that decides whether a signature is genuine or forged [21]. The reference feature vector containing the values of 13 global features are given as input to the system and the comparison is based on the assumption that the values of the feature sets extracted from genuine signatures are more stable than the signatures that are forged. That is, the intra-personal variations are smaller than inter-personal variations. The neural network techniques that are used for verification is VQ.

The verification process consists of two parts: - comparison and decision making. The varying values of vigilance parameters are given to the system to gain maximum efficiency so that more and more forgeries can be detected.

3 Results

The efficiency and execution time of VQ is computed on above defined database. The main advantage of using Vector Quantization is that the efficiency does not vary with the varying value of learning rate ρ. For our system ρ=0.9. Following setup is done in Matlab to implement vector quantization.

Table 1. Results of Simulation using Matlab

Simulation Parameters	Results
No. of layers	2
No. of input units	13
No. of output units	2
Learning rate	(0.1-0.9)
Training algorithm	VQ
Initial weights	Randomized
Initial biases	Randomized
No. of signatures used for training	50
No. of tested signatures	200
No. of recognized signatures	154
No. of iterations performed	34

Having worked on Vector quantization, the efficiency achieved is 67% and execution time required is 11 seconds. The results of our simulation for forged and genuine signatures are as shown in the Table 1. The system is robust; it rejected all the random forgeries but 5 false signatures are accepted in case of casual forgeries leading to a FAR of 1%. Out of the 100 genuine signatures that were fed in, 5 were rejected as forgeries. This yielded a FRR of 5%. Also out of 50 skilled forgeries fed into the system, 5 signatures were accepted. This gave us a FAR of 2.5%

Table 2. The value of FAR & FRR at Different Samples

Nature of Signature	Samples	FAR	FRR
Genuine	100	………..	5%
Random	50	0%	………
Casual	50	1%	………
Skilled	50	2.5%	……....

4 Conclusion

Vector Quantization has been used for signature verification. They have adaptive nature of supervised learning by example in solving problems. This feature makes them computational models very appealing for a wide variety of application domains including pattern recognition. The distortion measure between trained signature set and test signature is done using Euclidean distance. The system has been tested for its accuracy and effectiveness on data from 25 users with 10 specimens of each making up a total of 250 signatures. The classification ratio achieved by the system using Vector quantization is 67%. The FAR and FRR computed are 2.5% and 5% respectively. The system can be further designed using local features classification.

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