Offline Signature Recognition using Hidden Markov Model (HMM)

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ABSTRACT
HMM has been used successfully to model speech and online signature in the past two decades. The success has been attributed to the fact that these biometric traits have time reference. Only few HMM based offline signature recognition systems have be developed because offline signature lack time reference. This paper presents a recognition system for offline signatures using Discrete Cosine Transform (DCT) and Hidden Markov Model (HMM). The signature to be trained or recognized is vertically divided into segments at the centre of gravity using the space reference positions of the pixels. The number of segmented signature blocks is equal to the number of states in the HMM for each user notwithstanding the length of the signatures. Experimental result shows that successful signatures recognition rates of 99.2% is possible. The result is better in comparison with previous related systems based on HMM and statistical classifiers.

General Terms
Pattern Recognition, Security.

Keywords
Offline Signature, DCT Features, Hidden Markov Model.

1. INTRODUCTION
Biometric recognition has been described as automatic identification of an individual based on physiological and behavioral characteristics. Biometrics traits (signature, voice, iris, fingerprint etc) are preferred to traditional methods (namely passwords, PIN numbers, smartcards etc) because biometric characteristics of individual are not easily transferable; they are unique and cannot be stolen. Within biometric methods, automatics signature recognition is an important research area because of the social, legal and wider acceptance of handwritten signature as means of identification. Signature recognition systems can generally divided into two classes called online and offline. In an offline technique, signature is signed on a piece of paper and scanned to a computer system. In an on-line technique, signature is signed on a digitizer and dynamic information like speed, pressure is captured in addition to image of the signature. Recognition decision is usually based on local or global features extracted from signature under processing. Excellent recognition results can be achieved by comparing the robust model of the query signature with all the user models using appropriate classifier. Signature recognition system can be described as a two-class classification system, the classes are genuine and forgery. The aim of any signature recognition/verification system is to detect one or more category of signature forgeries namely random, simple, and skilled. Random or zero-effect forgery is any scribbled written signature of genuine signature of another person. Simple or casual signature forgery is forged by a forger who is familiar with the name of the genuine user but has no access to his/her signature samples. Skilled signature forgery is forged by a forger who has unrestricted access to one or more signature samples of the genuine user. The performance of a signature verification or recognition system is generally evaluated according to the error representation of a two-class pattern recognition problem, the error representations are False Rejected Ratio (FRR) and False Acceptance Ratio (FAR). [1][2][3][4].
An effective signature recognition system must have high recognition rate. Recognition accuracy depends on the ability of the system to reduce intra variation within the signatures of the same person while increase the inter variation between signatures of different people. And this depends on techniques adopted in training and classification of signatures. It also depends on the extracted features.
Many researchers have used combination of different features and classifiers to developed signature recognition systems. Among various stochastic approaches, HMMs have proven very effective in modeling both dynamic and static signals [5][6][7][8]. Previous HMM based signature recognition systems used unsuitable HMM topology, different number of states for users and weak features for training and classification of signature images [5][8][9][10][11]. These shortcomings need to be corrected to enhance the effectiveness of the systems.
In this paper, combination of DCT signature features and HMM are incorporated to develop a robust model framework and signature classification algorithm. This work is different from previous work based on HMM because space sequence is considered in segmenting the signature image into four states irrespective of the length of each of the signatures and 4L-R HMM is used to model each of the user signatures.
Section 2 provides the description of the system, the preprocessing, and feature extraction technique. Section 3 presents signature modeling. Recognition and result are given in section 4. Finally conclusions are presented in section 5.

2. PROPOSED SYSTEM

Off-line signature recognition system proposed in this study is basically divided into five stages namely, data acquisition, preprocessing, feature extraction, training and recognition stages as shown in Fig. 1.

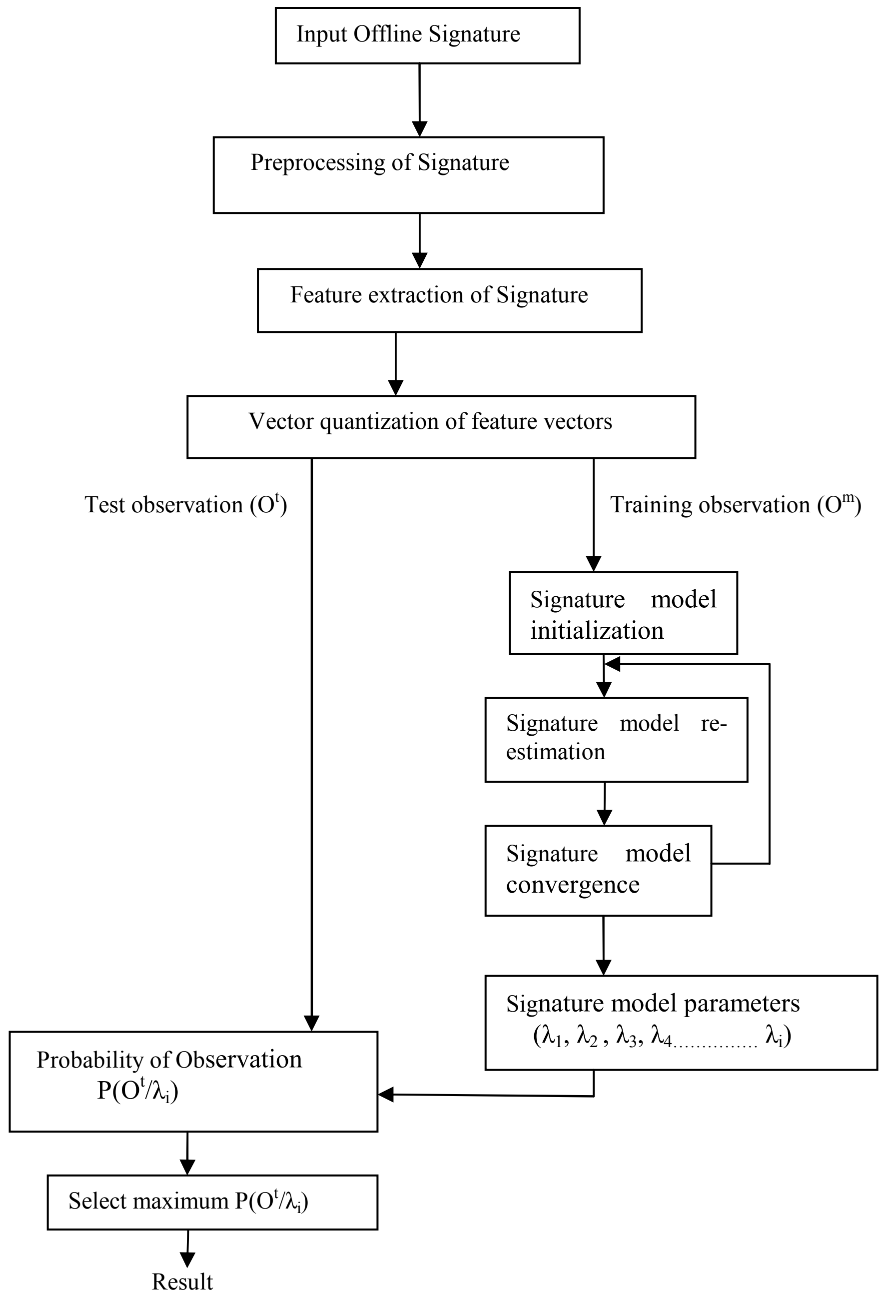


Figure 1. **Signal flow diagram of** the **proposed system**

2.1 Input Signature Data

The input data to the proposed system are genuine signatures of the registered users. Genuine signatures are collected from 250 students at Covenant University Ota, Nigeria; each of the students contributed 7 genuine signature samples. The genuine signatures are collected over a period of three months to account for variations in the signatures with time. Fig. 2 shows example of genuine signatures used in the proposed system.

2.2 Preprocessing

The offline signatures are preprocessed to prepare the signature for feature extraction process. The grayscale signatures are smoothened in order to remove noise introduced during image scanning. Smoothened signature is converted to binary image using morphological operations.

2.3 DCT Feature Extraction

In offline signature verification or recognition technique only features related to the signature shape are available for extraction. Discrete Radon Transform (DRT) feature and Discrete Cosine Transform (DCT) feature are extracted from segmented image in [5][6][7]. Axial slant angle, pixel distribution, pixel density, stroke curvature are extracted from signature image using grid segmentation [8][9][10][11]. Vertical and horizontal centre points, pixel centre angle, cell size are extracted from signature image by vertical and horizontal splitting technique [12][13][14]. In the proposed system robust feature is extracted using DCT at sub- image level. DCT transforms spatial information in each of the signature cells into frequency information in form of DCT coefficients.

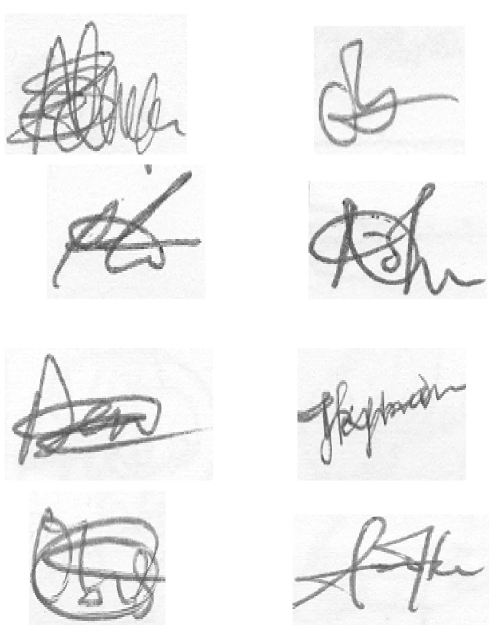


Figure 2. Example of genuine offline signature images

Before DCT coefficient is computed, the signature is vertically segmented into four blocks and each of the block images is further segmented into 16 smaller cells at the centre of gravity using vertical and horizontal splitting technique [13][14].

The feature extraction algorithm is stated as follows:

(1) Locate signature image bounding box.

(i) Scan the signature image from top to bottom to obtain the signature image height.

(ii) Scan the signature image from left to right to obtain the signature image width.

(2) Centralization of the signature image.

(i) Calculate centre of gravity of the signature image using (1).

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x(i),$$

$$\bar{y} = \frac{1}{N}\sum_{j=1}^{N} y(j). \tag{1}$$

(ii)Then move the signature image centre to coincide with centre of the predefined image space.

(3) The image is partitioned into two sub- image parts

(i) Locate the centre of the signature image using (1).

(ii) Through point $\bar{x}$ and $\bar{y}$ make a vertical splitting across the signature image.

(4) Partition each of the two sub-images into four rectangular blocks B1, B2, B3, and B4 as shown in Fig 3a.

(i) Locate the centre of each sub-image parts using (1).

(ii) Through point $\bar{x}$ and $\bar{y}$ make a vertical splitting across each of the sub- images.

(5) Partition each of the block images in Fig 3a into 4 signature cells

(i) Locate the centre of each of the block image parts using (1).

(ii) Through point $\bar{x}$ make a horizontal splitting across the block of the image.

(iii) Through point $\bar{y}$ make a vertical splitting across the block of the image.

(6) Partition each of the signature cells into 4 smaller cells so that we have 16smaller cells in each block as shown in Fig 3b.

(i) Locate the centre of each of the cell parts using (1).

(ii) Through point $\bar{x}$ make a horizontal splitting across the signature cell.

(iii) Through point $\bar{y}$ make a vertical splitting across the signature cell.

(7) The DCT coefficient of each of the cells in the block image is computed.

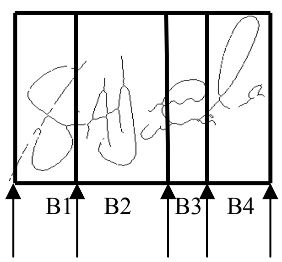
(i) The DCT coefficient of image cell (f (x, y)) is obtained using (2) and (3).

$$G(u,v) = \alpha(u)\alpha(v)\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y) \cos\left(\frac{(2x+1)u\pi}{2M}\right)\cos\left(\frac{(2y+1)v\pi}{2N}\right) \quad (2)$$

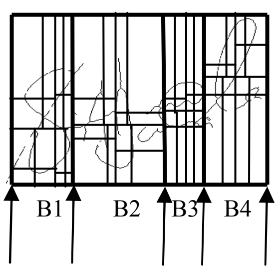
$$\alpha(u) = \begin{cases} 1/\sqrt{M}, & u=0 \\ \sqrt{2/M}, & 1 \le u \le M-1 \end{cases}$$

$$\alpha(v) = \begin{cases} 1/\sqrt{N}, & v=0 \\ \sqrt{2/N}, & 1 \le v \le N-1 \end{cases} \quad (3)$$

These DCT coefficients are then used to form the observation vector.



(a)



(b)

Figure 3. Features extraction diagrams

3. SIGNATURE MODELING

Hidden Markov Model (HMM) is a probabilistic pattern matching technique that has ability to absorb both the variability and the similarity between signature samples. As shown in Fig 4. Hidden Markov Models (HMM) represent a signature as a sequence of states. In each state an observation vector can be generated, according to the associated probability distribution. Transitions among the states are governed by a set of probabilities called transition probabilities. The probabilities, or parameters, of an HMM are trained using observation vector extracted from a representative sample of signature data. Recognition of an unknown signature is based on the probability that a signature was generated by the HMM [15][16].

In order to define an HMM completely, the following elements are needed.

1. A set of N state, (S_1………S_N) where q_t is the state at time (t).
2. A set of K observation symbol, (V_1……..V_K) where O_t is the observation at time (t).
3. A state transition probability matrix ($A = A_{ij}$) where the probability of transition from state S_i at time (t) to state S_j at (t + 1) is $a_{ij} = P(q_{t+1} = S_j / q_t = S_i)$.
4. A set of output probability distributions B, where for each state j, $b_j(k) = P(O_t = V_k / q_t = S_i)$.
5. An initial state distribution: $\pi = (\pi_i)$, where π_i,$= P(q_i = S_1)$.

3.1 2D-Signatures Model

Conventional HMMs model one dimensional data. HMM can be used to model a two dimensional data by converting the 2D data to 1D data, without any lost of information. In this paper, a two dimensional signature image is converted to one dimensional feature vector. Each of the segmented blocks of the signature represent a state in the HMM. 16 DCT coefficients are extracted from each of the segmented signature blocks. These feature vector form 1D observation vector for signature training and testing. The sequence of the segmented blocks over the image is fashion from left to right as shown in Fig. 5.

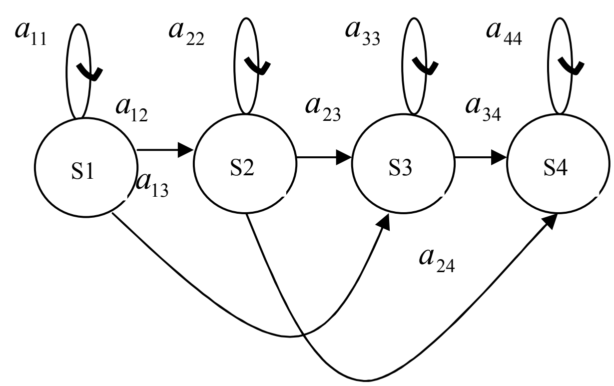


Figure 4. HMM topology for a signature image

3.2 Training Steps

Each of the user signatures is modeled by estimating the parameters for HMM for a given set of observations. A set of five signature images from each of the users are used to train each HMM. A set of 16 feature value extracted from each block are used to form the observation vector. Parameters are chosen based on a maximum likelihood criterion that maximize the likelihood of the observation data (O). This maximization is performed using the Baum-Welch algorithm [15][16]. The follow steps are involved.

Firstly, the HMM λ = (A, B, π) is initialized. Each of the training signatures is segmented into 4 states (S_1, S_2, S_3 and S_4) and observation vectors from the segments of the five training signatures are clustered into m dimensional vector using k-mean algorithm [15]. The values obtained are used to obtain the initial estimate of the observation probability matrix B. The initial values for A and π are set from the left to right fashion of the HMM topology.

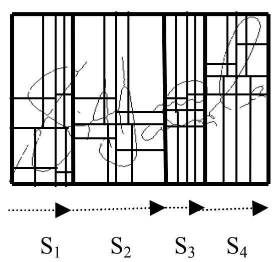


Figure 5. Signature image segments in four states.

The next step is to re-estimate model parameters using Baum-Welch equation in order to maximize $P(O/\lambda)$. The iterative procedure stops when the difference between the likelihood scores of the current iteration (k+1) and those of the previous one (k) is smaller than a preset threshold (H) as given in (4).

$$\left|P\left(O/\lambda^{(k+1)}\right)-P(O/\lambda^{(k)})\right| \prec H \quad (4)$$

4. RECOGNITION AND RESULTS

In the recognition stage, a set of 500 genuine signature images are used to determine the recognition ability of the proposed system. As it was done in the training stage, the extracted feature vectors from each of the states of the test signature are used to form the observation vectors. The trained HMMs are used to compute the likelihood function as follows:

(1). Given $O^{(t)}$ as the DCT based observation sequence generated from the signature image to be recognized.
(2). The probability of the observed vector given each signature model $P(O^{(t)}/\lambda_i)$ is computed using Viterbi algorithm[15][16].
(3). The observed vector is labeled with class model which maximize the probability $P(O^{(t)}/\lambda_i)$.
(4). A test signature image (t) is recognized as signature image (k) in the database if:

$$P(O^{(t)}/\lambda_{(k)}) = \max_n P(O^{(t)}/\lambda_i) \quad (3)$$

The recognition performance of the system is 99.2%, out of 500 signature images tested only four signatures are not recognized. The result is better in comparison with result obtained in [5][6][11][12].

5. CONCLUSIONS

In the proposed system, we have presented an offline signature recognition method. The technique is based on Discrete Cosine transform and Hidden Markov Model. In the feature extraction phase signature images are segmented into equal number of HMM states notwithstanding the length of the signatures. The application of DCT features coupled with well defined HMM topology framework contributed greatly to the generation of robust signature models. The performance of the proposed system is encouraging in comparison with previous systems.

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