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Radon Transform + HMM Based Face Recognition

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Abstract: Face recognition is the process of identifying or verifying a person from a digital image or video frame from video source. It is used in security purposes like in mobile phones, doors and banking systems. The work presented in this paper describes a Hidden Markov Model (HMM)-based framework for face recognition. Here Radon transform is used to extract features and achieve high recognition rate. When used together, Radon and wavelet transform provide high accuracy compared to DCT based approach.

Keywords: Radon Transform, Wavelet Transform, Hidden Markov Models, Forward Backward Algorithm.

I. Introduction

Face recognition plays an important part in human activities. In a world where security has become a very high priority, computers and especially software have developed to such an extent, that they are able to distinguish one human from another. In recent years biometric based techniques such as fingerprints, iris retina and hand geometry have been emerged as the most promising option for recognizing individuals. Biometric measures requires physical contact whereas the facial images can easily be acquired from a distance and facial images can be collected without any prior knowledge. So in this paper we are going to propose a novel method to recognize individuals from their facial images.

II. Early Works

The previous work on face recognition is carried out from the statistical analysis stand point. Inherent advantages of DCT (Discrete Cosine transform) and HMM (Hidden Markov Model) are exploited to get better performance. The first efforts to use HMMs as a face recognition tool were made by Samaria & Young (1994). They introduced the HMM as quite a robust mechanism to deal with face recognition. In HMM, face recognition based on wavelet transform and FFT are also performed. Previous work attempts to develop a face recognition system has high recognition rate include the correlation method, the Eigen face method and the linear discriminant method.

III. Feature Extraction

In this paper, the face is recognized by a combination of feature obtained from Radon transform & wavelet transform.

A. *Radon Transform:*

The Radon transform of an image represented by the function f(x,y) can be defined as a series of line integrals through f(x,y) at different offsets from the origin. This is shown in Figure 1 and defined mathematically as:

$$R(p,\tau) = \int_{-\infty}^{\infty} f(x, px + \tau)dx$$

Where p and τ are the slope and intercepts of the line. A more directly applicable form of the transform can be defined by using a delta function:

$$R(r,\theta)=\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)\delta(x\cos\theta + y\sin\theta - r)dxdy$$

Where theta is the angle of the line, and r is the perpendicular offset of the line.

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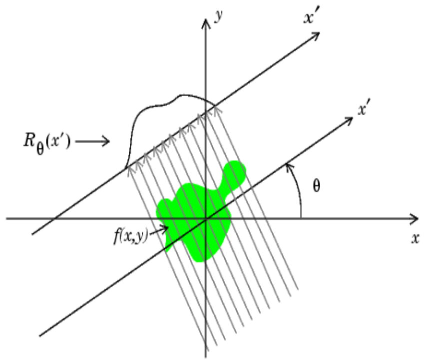

Fig. 1. Radon Transform

The acquisition of data in medical imaging techniques such as MRI, CT and PET scanners involves a similar method of projecting a beam through an object, and the data is in a similar form to that described in the second equation above. The plot of the Radon transform, or scanner data, is referred to as a sinogram due to its characteristic sinusoid shape. Figure2 shows a simple non-homogeneous shape and the sinogram created by taking the Radon transform at intervals of one degree from 0 to 180 degrees.

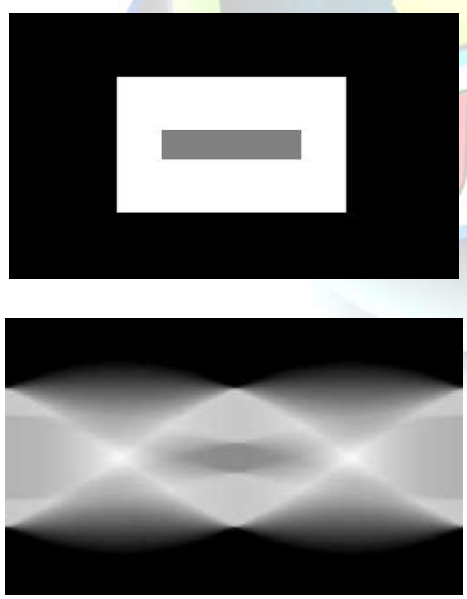

Fig. 2.A simple image (top) and the sinogram (bottom) produced by applying the Radon Transform.

B.Wavelet Transform

By applying DWT on an image, we gain benefits which are very useful in data analysis. Those benefits are:

- Dimensionality Reduction, which will lead to less computational complexity.
- Insensitive Feature extraction

IV. Hidden Markov Models

Hidden Markov Models (HMM) are a set of statistical models used to characterize the statistical properties of a signal. HMM consist of an underlying, unobservable Markov chain with a finite number of states, a state transition probability matrix and an initial state probability distribution and a set of probability density functions associated with each state.
The elements of a HMM are:

- *N* , the number of states in the model. If *S* is the set of states, then S = {SI, *S2*, ..., S,}. The state of the model at time *t* is given by q_t ε S, $1 \leq t \leq T$, where *T* is the length of the observation sequence (number of frames).
- *Π,* the initial state distribution, i.e
  $\Pi = \{\pi_{ij}\}$ where $\pi_i = P[q_1 = S_i]$, $1 \leq i \leq N$
- A, the state transition probability matrix, i.e. A= *{aij}* where
  $a_{ij} = P[q_t = S_j | q_{t-1} = S_i]$ $1 \leq i,j \leq N$,
  with a constraint $0 \leq a_{i,j} \leq 1$ and $\sum_{j=1}^{N} a_{ij} = 1$, $1 \leq i \leq N$.
- B, the state probability matrix, i.e. B = $\{b_j(O,)\}$.In a continuous density HMM, the states are characterized by continuous observation density functions. The most general representation of the model probability density function (pdf) is a finite mixture of the form:
  $B_i(O_t) = \sum_{k=1}^{M} C_{ik} N(O_t, \mu_{ik}, U_{ik})$ $1 \leq i \leq N$

Where c_{ik} is the mixture coefficient for the k th mixture in state i. Without loss of generality $N(O_t, \mu_{ik}, U_{ik})$ is assumed to be a Gaussian pdf with mean vector μ_{ik} and covariance matrix U_{ik}.

Using a shorthand notation, a HMM is defined as the triplet $\lambda = (A, B, \pi)$.

A separate HMM is trained for each subject to be recognized. i.e. to recognize M subjects we have M distinct HMMs at our disposal.

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V. PROPOSED METHOD

The steps included in the face recognition are discussed below.

Step1:

Read the images from database and convert it into greyscale images in the size of 112x112.

Step2:

Scan the face like shown in the figure 3. (in clockwise direction) with size of 112x16 window.Exclude the middle (36-72)of the window because of maximum overlapping.So scanned window is 72x16.

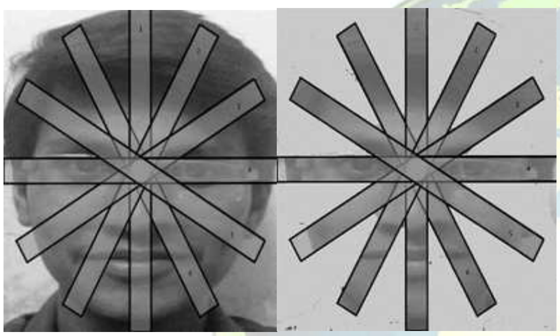

Fig. 3.Scanning a Face

Step 3:

Apply radon tranform for the sub windows which extracted from the face.Also apply the transform for one of the most overlapped regions in the scans.

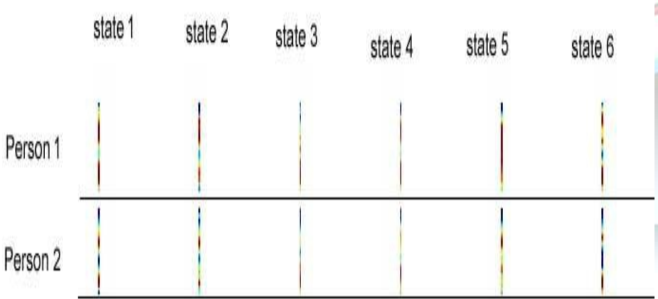

Fig. 4.Radon output for states

*Step 4***:**

Apply wavelet transform for the values.

Step 5:

Do the steps upto 4 for one individual and store it.Take mean of the values.

A.HMM Training:

Following steps give a procedure of HMM training.

Step 1:

Cluster all training sequences, generated from R number of face images of one particular subject, each cluster will represent a state of the training vector. Let them be numbered from 1 to N.

Step 2:

Train the HMM model using the Baum-Welch algorithm. It is a specific instance of the expectation-maximization algorithm. The algorithm is explained below.

The inputs for HMM are n states, m observations. A transition matrix having n rows & n columns, O transition matrix with n rows & m columns, are derived from m observations with appropriate uniform probability values. This is iterated for k observations in a vector Y with elements Y_j for each time step 1 to k.

i) Expectation Step:

1. Do forward-backward algorithm to get forward probabilities $F_{i,j}$ and backward probabilities $B_{i,j}$, where the subscripts mean state i, time step j, where F and B are both 2D arrays with n rows and k+1 columns.

2. Finish forward-backward algorithm to get the final 2D array of probabilities P with n rows and k+1 columns, where elements $P_{i,j}$ is the probability of being at state i at time j.

ii) Maximization step:

1. The probabilities of being at state α at time j, and β at time j+1, is find out using the following calculation.

$$\theta_{\alpha,\beta,j} = \frac{F_{\alpha,j}A_{\alpha,13}B_{\beta,j+1}O_{\beta,Y_{j+i}}}{\sum_{C=1}^{n}\sum_{d=1}^{n}F_{C,j}A_{C,\alpha}B_{d,j+1}O_{d,Y_{j+1}}}.$$

The probability of being at state α at time j, times the transition probability from α to β , the probability of being at state β at time j+1, and the probability of the observation is now at state β. This is store in a 3D array.

2. The new transition matrix A by calculating each element

$$A_{\alpha,\beta} \equiv \frac{\sum_{t=0}^{k-1}\theta_{\alpha,\beta,t}}{\sum_{t=0}^{k-1}P_{\alpha,t}}$$

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This can be summarized as the sum of probabilities of going from state α to β at each time stamp over the sum of probabilities of just being in state i (and going anywhere for the next state).

3. The new transition matrix B by calculating each element.

$$O_{\alpha,\beta} = \frac{\sum_{t\equiv 0}^{k-1} \theta_{\alpha,\beta,t}}{\sum_{t\equiv 0}^{k-1} P_{\alpha,t}}$$

This is calculating the probabilities of being in a state at the times that the observation x happened divided by the probabilities that we are in that state at any time.

Step 3:

The log likelihood of the model is find out by returns log P(x | model) using the forward part of the forward-backward algorithm. Then the trained model is saved.

B. Recognition Phase:

Once, all the HMMs are trained, proceed to recognition step. For the face image to be recognized, the data generation step is followed as described in previous section. The trained HMMs are used to compute the likelihood function as follows: Let 0 be the DCT based observation sequence generated from the face image to be recognized,

1. Using the Viterbi algorithm, we first compute Q_f = argmax P[O, Q/λ_i]

2. The recognized face corresponds to that i for which the likelihood function P[O, Q_i/λ_i] is maximum.

VI. Experimental Results

ORL, face database is used in the experiments. There are 400 images of 40 subjects - 10 poses per subject. All the face images have are of size 92 x 112 with 256 grey levels. The face data has are male or female subjects, with or without glasses, with or without beard, with or without some facial expression. Here 15 different subjects were used.5 images for training and 5 images for testing.

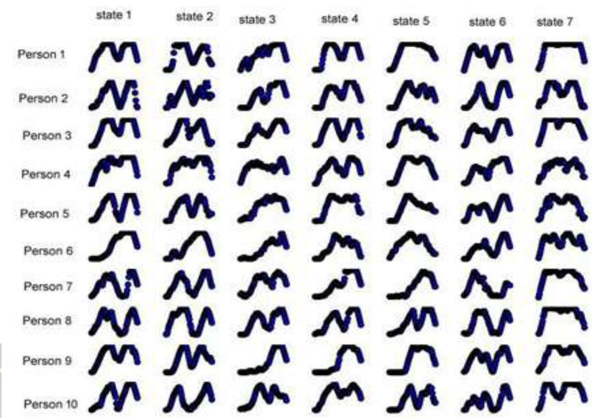

Fig. 5. Radon Transform results

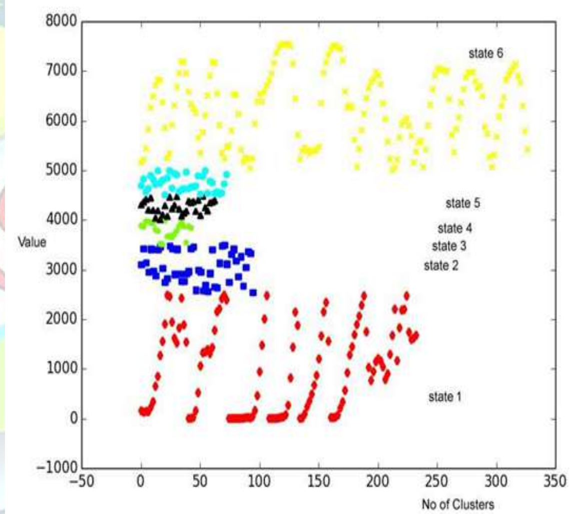

Fig. 6. Clustered sequences

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S.No	Approach	Database	Trained Images	Tested images	No of Subjects	Classifier	Recognition %
1	DCT	ORL	5	5	15	HMM	86.6
2	Radon+ Wavelet	ORL	5	5	15	HMM	93.33
3	Radon+ Wavelet	Yale	5	5	10	HMM	90.0

Table 1 Comparison of results

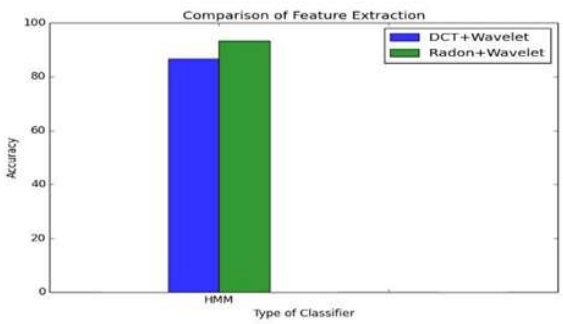

Fig 7 .Comparison graph

VII. CONCLUSION

In DCT based approach the scanning of the image with overlapping, may go wrong for different poses. The clockwise scan window appropriately scans the face. And Radon transform gives unique features of individuals. Thus the accuracy is improved in the proposed method. The prediction rate is 6.67% more than the DCT based method.

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