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2D-DCT HMM Based Approach for Face Recognition

Prashant Joshi
Assistant Professor, G.H. Raisoni Institute of Engineering & Technology, Pune, India
S. S. Deshmukh
Assistant Professor, Pimpri Chinchwad College of Engineering, Pune, India

Abstract:
The work presented in this paper focuses on the use of Hidden Markov Models for face recognition. A new method based on the extraction of 2D-DCT feature vectors is described, and the recognition results are compared with other face recognition approaches. The method introduced in this paper reduces significantly the computational complexity of previous HMM-based face recognition system, while preserving the same recognition rate.

1. Introduction

Hidden Markov Model (HMM) based approaches are one of techniques which can deal with the geometric variations. An excellent survey on face recognition is given in [1]**.**Previous attempts to develop a face recognition system that has a high recognition rate, that include the correlation method [2], the eigenfaces method [3] and the linear discriminant method [4]**.** However, the recognition rate in each of these methods decreases rapidly when the face orientation or the face image size change. In order to avoid these problems, for each of these methods a view based approach was developed [5]**.** In the first stage of these methods, the orientation, or facial expression is determined, and then the recognition is performed using the database corresponding to images that have the given orientation or facial expression. Given the success of HMMs in speech recognition and character recognition, and the work of Samaria [6]**.**

High frequency signal bearing noise information was discarded. Previously, there was no evidence of showing discriminability of using these features. The extracted features directly served as observation data for maximum likelihood (ML) estimation of HMM parameters. ML HMM parameters were assured to optimally match the observed features in terms of likelihood measure. However, model discriminability was not guaranteed. In this paper, we concern on two issues in establishing HMMs for high dimensional observation data. The first issue involves the hybrid process of feature extraction and model estimation. We aim to merge two operations under the common objective function. Secondly, we exploit a new discriminative training criterion derived from hypothesis test theory. The maximum confidence objective function is carried out for discriminative HMM estimation, which is different from other discriminative training algorithms

2. Review

2.1. D HMM Face Recognition

HMM, as described in the previous section, is applied to I-D observation sequence, hence called I-D HMM. Samaria [8] has applied 1-D HMM to the problem of face recognition. Clearly, the problem had to be reformulated in order to fit the 2-D image in a 1-D observation sequence such that the 1-D HMM can handle it. The 1-D sequence of observations consists of the luminance of vertically successive strips that scan the image from top to bottom or blocks that scan from left to right and top to bottom. The overlap between consecutive strips is permitted up to one pixel less than the strip width. 85% accuracy has been reported using 5-state top-to-bottom 1-D HMM with strip width of 10 pixels.

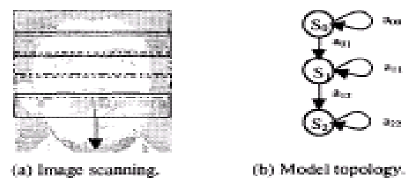

Fig.1. 1-D HMM

Figure 1

The HMM feature vector consists of the DCT coefficients that correspond to DC and lower frequency bands, exploiting the fact that the lower frequency bands are the most significant bands for normal images. Only the lower 3x13 coefficients out of the 10x92 DCT coefficients are considered for each strip to form 39-dimensional HMM feature vector. The main contribution in [7] is the complexity reduction due to the partial spectral processing. A similar accuracy of 85% has been achieved but with lower complexity.

2.2. D PHMM Face Recognition

The 2-D PHMM is a recent variation of the original HMM designed to deal with the 2-D signal. It has been introduced to many applications including the optical character recognition [9], color image retrieval [10], and face recognition [8]. The 2-D PHMM is composed of an I-D HMM whose states are called super states. Each of these super states contains a 1-D HMM arranged in the transverse dimension, left-to-right in this case. This way, the 2-D PHMM deals with one dimension at a time. The image is divided into blocks instead of strips. The blocks are arranged in one 1-D sequence before being fed to the 2-D PHMM that is equivalent to an I-D HMM. The equivalent 1-D HMM is either unrestricted or restricted. In the restricted equivalent 1-D HMM, an extra state, called end-of-line state, is inserted between each two consecutive sub-chains to ensure that no row is shared between two super states.

3. Face Image HMM

Hidden Markov Models have been successfully used for speech recognition where data is essentially one dimensional. Extension to a fully connected two dimensional HMM has been shown to be computationally very complex [SI. In [11], Kuo and Agazzi have used a pseudo two dimensional HMM for Character recognition that was shown to perform reasonably fast for binary images. In this paper we investigate the recognition performance of a one dimensional HMM for gray scale face images.

For frontal face images, the significant facial regions (hair, forehead, eyes, nose, and mouth) come in a natural order from top to bottom, even if the images are taken under small rotations in the image plane and/or rotations in the plane perpendicular to the image plane. Each of these facial regions is assigned to a state in a left to right 1D continuous HMM. The state structure of the face model and the non-zero transition probabilities *aij* are shown in Figure 3.

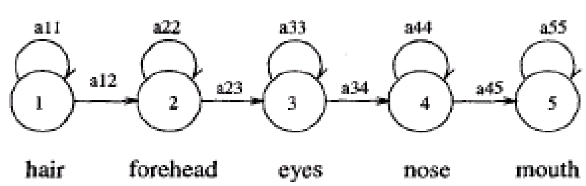

Fig.3. Left to Right HMM for Face Recognition

Figure 3

4. Feature Extraction

Each face image of width *W* and height *H* is divided into overlapping blocks of height *L* and width *W*. The number of blocks extracted from each face image equals the number of observation vectors T and is given by:

$$T = \frac{H - L}{L - P} + 1, \quad \text{-------- (1).}$$

The choice of parameters *P* and *L* can significantly affect the system recognition rate. A high amount of overlap *P* significantly increases the recognition rate because it allows the features to be captured in a manner that is independent of the vertical position. The choice of parameter *L* is more delicate. Using a small *L* can bring insufficient discriminant information to the observation vector, while large *L* increases the probability of cutting across the features. The use of the pixel values as observation vectors has two important disadvantages: First, pixel values do not represent robust features, being very sensitive to image noise as well as image rotation, shift or changes in illumination and second, the large dimension of the observation vector leads to high computational complexity of the training and recognition systems, and therefore increases the processing time required for recognition. This can be a major problem for face recognition over large databases or when the recognition system is used for real time applications. In this paper, the observation vectors consist of a set of 2D-DCT coefficients that are extracted from each block. The DCT compression properties for natural images make the use of this transform a suitable feature extraction technique for the face recognition system.

5. Recognition and Results

In the recognition phase, a set of 200 test images, not used in the training, are considered to determine the recognition performances of the system. After extracting the observation vectors as in the training phase, the probability of the observation vector given each HMM face model is computed. The face recognition system has been tested on the Olivetti Research Ltd. database (400 images of **40** individuals, **10** face images per individual at the resolution of **92 x 112** pixels). The database contains face images showing different facial expressions, hair styles, eye wear (glasses/no glasses), and head orientations. The system achieved a recognition rate of **84%** with $L = 10$ and $P = 9$. On the same database the recognition rate of the eigenfaces method is **73%** and the recognition rate of the HMM based approach presented in [6] is **84%** over a fraction of the same database.

Figure 4: Images from training set

6. Conclusion

Due to the compression properties of the DCT, the size of the observation vector in the current approach is reduced from $L x W$ ($L = 10$ and $W = 92$) to 39, while preserving the same recognition rate (The recognition performance in [12] was based on a fraction of the database, while the experiments presented here were conducted over all images of the same database). The use of a lower dimensional feature vector (over 23 times smaller than the size of the observation vector in the previous method) leads to a significant reduction of the computational complexity of the method and consequently to a significant decrease of the face recognition time. The HMM modeling of human faces appears to be an encouraging method for face recognition under a wider range of image orientations and facial expressions. Future work will be directed on the study of pseudo 2D HMM for face image recognition, the inclusion of state duration in face modeling, as well as other feature extraction techniques.

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