2DHMM-BASED FACE RECOGNITION METHOD

Janusz Bobulski[1]

Czestochowa University of Technology
Institute of Computer and Information Science
Dabrowskiego Street 73, 42-200 Czestochowa, Poland
januszb@icis.pcz.pl

Summary. So far many methods of recognizing the face arose, each has the merits and demerits. Among these methods are methods based on Hidden Markov models, and their advantage is the high efficiency. However, the traditional HMM uses one-dimensional data, which is not a good solution for image processing, because the images are two-dimensional. Transforming the image in a one-dimensional feature vector, we remove some of the information that can be used for identification. The article presents the full ergodic 2D-HMM and applied for face identification.

1 Introduction

Face recognition has great potentials in many applications dealing with uncooperative subjects, in which the full power of face recognition being a passive biometric technique can be implemented and utilised. Face recognition has been an active area of research in image processing and computer vision due to its extensive range of prospective applications relating to biometrics, information security, video surveillance, law enforcement, identity authentication, smart cards, and access control systems. The benefits of facial recognition are that it is not intrusive, can be done from a distance even without the user being aware they are being scanned. A number of approaches have been developed for extracting features from still images. Turk and Pentland [1] proposed Eigenfaces employed Karhunen-Loeve Transform (KLT) [2]. Others popular methods for face features extraction are wavelet transform [3]. The most popular method of face identification is Principal Component Analysis (PCA) [4]. PCA is an unsupervised learning method, which treats samples of the different classes in the same way. Fisherfaces proposed by Belhumeour and Hespanha [5] is a supervised learning method using the category information associated with each sample to extract the most discriminatory features. Other popular methods use Wavelet Transform [6], Hidden Markov Models [7] or characteristic points [8]. Previous methods which based on HMM processed one-dimensional data. This is not a problem in application such as speech recognition, because feature vectors are only one dimension. 1D HMM is unpractical in image processing, because the images are two-dimensional. When we convert an image from 2D to 1D, we lose some information. So, if we process two-dimensional data, we should apply two-dimensional HMM, and this 2D HMM should works with 2D data. One of solutions is pseudo 2D HMM [9, 10], which is extension of classic 1D HMM. There are super-states hiding linear one-dimensional hidden Markov models. So, we have 1D model with 1D data in practise. Article [11] presents analytic solution and proof of correctness two-dimensional HMM, which is similar to MRF [12, 13], and works with one-dimensional data. Additional it can be apply only for left-right type of HMM. This article presents real solution for 2D problem in HMM. There is shown true 2D HMM which processes 2D data. Similar to 1D HMM, the most important thing for 2D HMMs is also to solve two basic problems, namely probability evolution and parameters estimation. Moreover the presented algorithms are regarding ergodic models, rather than of type "left-right" [11]. In this paper we focus on the face recognition method from single digital images with two dimensional hidden Markov models (2D-HMM) base on the feature extraction with wavelets. The paper is organized as follows: first we preprocessing procedure to get the pure face image; next we describe feature extraction; then we present present the problem two dimensional data in HMM; afterwards, experiments are performed on the facial database with different experimental conditions. Finally, conclusions are given in last section.

2 Propose method

2.1 Pre-processing procedure

Pre-processing procedure is the most important step for face recognition. The ideal output of processing is to obtain face images, which have normalized intensity, equal size and containing whole face in vertical pose. Moreover this procedure should also eliminate the effect of illumination and lighting. The database [15] used in the experiment provides the majority of these conditions. The pre-processing procedure of our system performs the following steps in converting image to a normalized face image for feature extraction: 1) locating and cropping the face region using a rectangle according to face shape; 2) selecting face area; 3) scales image in that way, that distance between the inner corners of the eyes is equal 120 pixels. A detailed description of the face normalization procedure can be found in [14]. The points coordinates of the inner corners of the eyes is obtained from database. The effect of pre-processing procedure is shown in Fig.1.

2.2 Features extraction

One of the parts persons identification systems is features extraction, and this process is very important because effectiveness of system depend of it. The fea-

Fig. 1. The effect of pre-processing procedure (image from [15]).

tures extraction has to get out information from a signal (image), which will be base for person identification. The separation of useful information from face is very important, because this data will be use to identification and should describing clearly the face. One of the popular technique for features extraction is Wavelet Transform (WT) [6]. One major advantage afforded by wavelets is the ability to perform local analysis – that is, to analyse a localized area of a larger signal. In wavelet analysis, we often speak about approximations and details. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components. Using 2D WT, the face image is decomposed into four subimages via the high-pass and low-pass filtering. The image is decomposed along column direction into subimages to high-pass frequency band H and low-pass frequency band L. Assuming that the input image is a matrix of m x n pixels, the resulting subimages become m/2 x n matrices. At second step the images H and L are decomposed along row vector direction and respectively produce the high and low frequency band HH and HL for H, and LH and LL for L. The four output images become the matrices of m/2 x n/2 pixels. Low frequency subimage LL possesses high energy, and is a smallest copy of original images. The remaining subimages LH, HL, and HH respectively extract the changing components in horizontal, vertical, and diagonal direction. The very important aspect of features extraction with WT is suitable choice of wavelet function [16]. The choice should adapt shape of wavelet to individual case and take into consideration the properties of the signal or image. The bad choice of wavelet will cause problems of analysis and identification processed signal. In order to point the best wavelet function was made the experiment. The best result achieved with function *db*10 from among accessible function.

2.3 2D HMM

HMM is a double stochastic process with underlying stochastic process that is not observable (hidden), but can be observed through another set of stochastic processes that produce a sequence of observation. HMM is the good tools and solution for process one-dimensional data. Unfortunately, this is unpractical in image processing, because the images are two-dimensional. When we convert an image from 2D to 1D, we lose some information. So, if we process two-dimensional data, we should apply two-dimensional HMM, and this 2D HMM should works with 2D data [17].

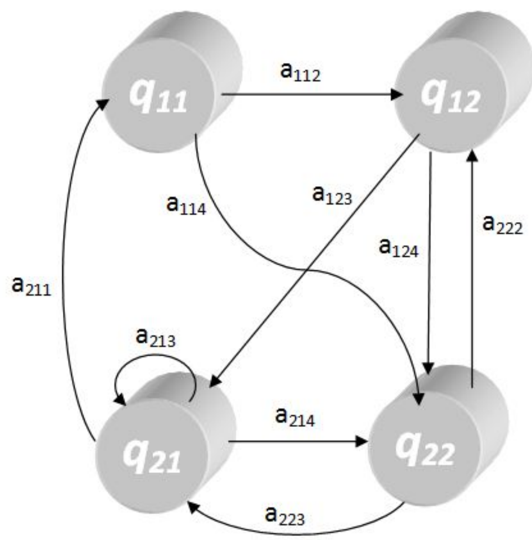

Fig. 2. Two-dimensional ergodic HMM.

The statistical parameters of the 2D model (Fig. 2, 3):

- The number of states of the model N^2
- The number of data streams k_1 x $k_2 = K$
- The number of symbols M
- The transition probabilities of the underlying Markov chain, $A = \{a_{ijl}\}, 1 \leq i, j \leq N, 1 \leq l \leq N^2$, where a_{ij} is the probability of transition from state ij to state l
- The observation probabilities, $B = \{b_{ijm})\}, 1 \leq i, j \leq N, 1 \leq m \leq M$ which represents the probability of gnerate the m_{th} symbol in the ij_{th} state.
- The initial probability, $\Pi = \{\pi_{ijk}\}, 1 \leq i, j \leq N, 1 \leq k \leq K$.

- Observation sequence $O = \{o_t\}, 1 \leq t \leq T, o_t$ is square matrix simply observation with size k_1 x $k_2 = K$

There are two fundamental problems of interest that must be solved for HMM to be useful in face recognition applications. These problems are the following:

1. Given observation $O = (o_1, o_2, ..., o_T)$ and model $\lambda = (A, B, \Pi)$, efficiently compute $P(O|\lambda)$
2. Given observation $O = (o_1, o_2, ..., o_T)$, estimate model parameters $\lambda = (A, B, \Pi)$ that maximize $P(O|\lambda)$

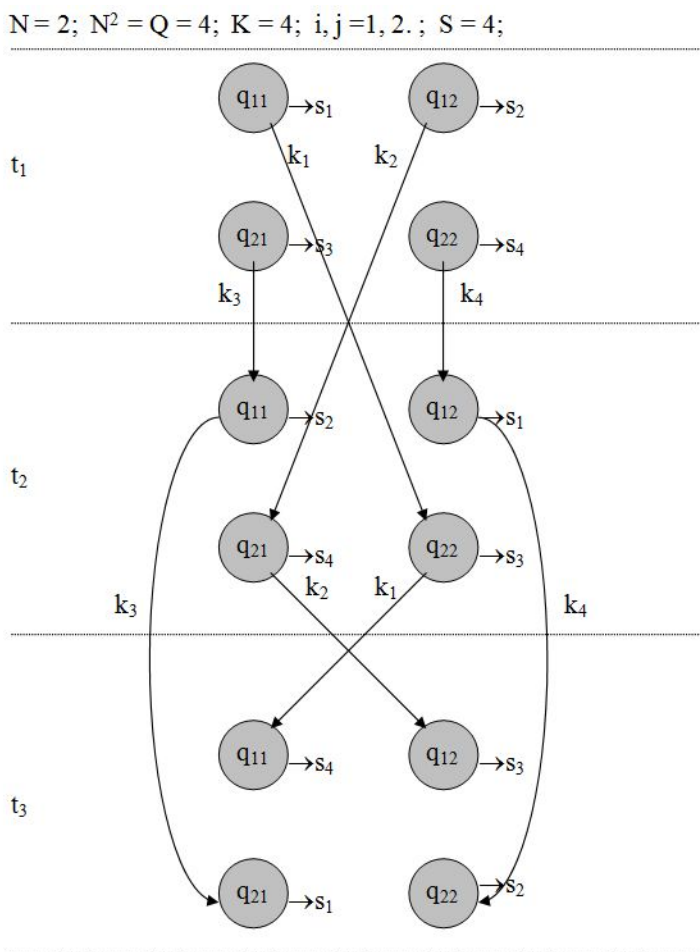

Fig. 3. The idea of 2DHMM.

Solution to problem 1

The modified forward algorithm

- Define forward variable $\alpha_t(i,j,k)$ as:

$$\alpha_t(i,j,k) = P(o_1, o_2, , o_t, q_t = ij|\lambda) \tag{1}$$

- $\alpha_t(i,j,k)$ is the probability of observing the partial sequence $(o_1, o_2, , o_t)$ such that the the state q_t is i,j for each k_{th} stream of data
- Induction
  1. Initialization:

$$\alpha_1(i,j,k) = \pi_{ijk} b_{ij}(o_1) \tag{2}$$

  2. Induction:

$$\alpha_{t+1}(i,j,k) = \left[\sum_{l=1}^{N} \alpha_t(i,j,k) a_{ijl}\right] b_{ij}(o_{t+1}) \tag{3}$$

  3. Termination:

$$P(O|\lambda) = \sum_{t=1}^{T} \sum_{k=1}^{K} \alpha_T(i,j,k) \tag{4}$$

Solution to problem 2

The modified parameters re-estimation algorithm

- Define $\xi(i,j,l)$ as the probability of being in state ij at time t and in state l at time $t+1$ for each k_{th} stream of data

$$\xi_t(i,j,l) = \frac{\alpha_t(i,j,k) a_{ijl} b_{ij}(o_{t+1}) \beta_{t+1}(i,j,k)}{P(O|\lambda)} = \tag{5}$$

$$= \frac{\alpha_t(i,j,k) a_{ij} b_{ij}(o_{t+1}) \beta_{t+1}(i,j,k)}{\sum_{k=1}^{K} \sum_{l=1}^{N^2} \alpha_t(i,j,k) a_{ijl} b_{ij}(o_{t+1}) \beta_{t+1}(i,j,k)}$$

- Define $\gamma(i,j)$ as the probability of being in state i,j at time t, given observation sequence.

$$\gamma_t(i,j) = \sum_{l=1}^{N^2} \xi_t(i,j,l) \tag{6}$$

- $\sum_{t=1}^{T} \gamma_t(i,j)$ is the expected number of times state i,j is visited
- $\sum_{t=1}^{T-1} \xi_t(i,j,l)$ is the expected number of transition from state ij to l

  Update rules:

- $\bar{\pi_i j} k =$ expected frequency in state i,j at time $(t = 1) = \gamma_1(i,j)$

- $\bar{a}_{ij}$ = (expected number of transition from state i, j to state l)/(expected number of transitions from state i, j:

$$\bar{a}_{ijl} = \frac{\sum_t \xi_t(i,j,l)}{\sum_t \gamma_t(i,j)} \tag{7}$$

- $\bar{b_{ij}}(k)$ = (expected number of times in state j and oserving symbol k)/(expected number of times in state j:

$$\bar{b}_{ij}(k) = \frac{\sum_{t,o_t=k} \gamma_t(i,j)}{\sum_t \gamma_t(i,j)} \tag{8}$$

3 Experiment

The image database *UMB-DB* was used for experiments. The University of Milano Bicocca 3D face database is a collection of multimodal (3D + 2D colour images) facial acquisitions. The database is available to universities and research centers interested in face detection or face recognition. They recorded 1473 images of 143 subjects (98 male, 45 female). The images show the faces in variable condition, lighting, rotation and size [15].
We chose three sets of 60 persons each, in order to verify the method, and for each individual chose three images for learning and three for testing. The 2D HMM implemented with parameters $N = 4; N^2 = 16; K = 16; M = 25$. Wavelet transform was chosen as features extraction technigue, and db10 as wavelet function. Table 1 presents the average results of experiments.

Table 1. Comparison of recognition rate

Method	Number of faces	Correctly	incorrectly	Recognition rate [%]
PCA	60	56	4	94
1D HMM	60	54	6	90
2D HMM	60	55	5	92

4 Conclusion

The obtained results are satisfactory in comparison to other method and proposed method may be the alternative solution to the others. Recognition rate of the method is 92%, which is better than 1D HMM. In comparison to PCA the result is worse but our method is faster. In this paper, the new conception of face recognition with two-dimensional hidden Markov models is presented. We show solutions of principle problems for ergodic 2D HMM, which may be applied for 2D data. Presented method allows for faster face processing and recognition because they do not have to change the two-dimensional input data in the image form into a onedimensional data. Therefore, we do not lose the information contained in the image.

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