FACE RECOGNITION METHOD WITH TWO-DIMENSIONAL HMM

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Abstract. This paper presents an automatic face recognition system, which bases on two-dimensional hidden Markov models. The traditional HMM uses one-dimensional data vectors, which is a drawback in the case of 2D image processing, as part of the information is lost during the conversion. The article presents the full ergodic 2D-HMM and used it to identify faces. The experimental results demonstrate that the system basing on two dimensional hidden Markov models, is able to achieving an average recognition rate of 94%.

Keywords: 2D hidden Markov model, face recognition, image processing

1 Introduction

Automatic identification of a person based on a face image for a long time is of great interest because it is the most natural and the most commonly used by people form of identity verification. Human recognition technology based on the facial image is non-invasive, non-contact, and the most natural of all methods of human identification. The increase in interest in this technology due to the increased safety requirements, as well as the possibility of using it in practice.
The most popular method of face identification is Principal Component Analysis (PCA) [1], which base on proposed by Turk and Pentland [2] Eigenfaces employed Karhunen-Loeve Transform (KLT) [3]. PCA is an unsupervised learning method, which treats samples of the different classes in the same way. Fisherfaces proposed by Belhumeour and Hespanha [4] 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 [5], 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 the same 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.

2 Propose method

2.1 Pre-processing procedure

Pre-processing steps aim to reduce the effects of noise, address intensity inhomogeneities, and perform global intensity level correction and are applied prior to segmentation. These are based on existing techniques and are only presented here for completeness, but are not discussed in detail. 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 [14] 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) location and crop the face region using a rectangle according to face shape; 2) select face area; 3) scales image in that way, that distance between the inner corners of the eyes is equal 120 pixels; 4) histogram equalization. The points coordinates of the inner corners of the eyes are 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 features 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) [5]. 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.

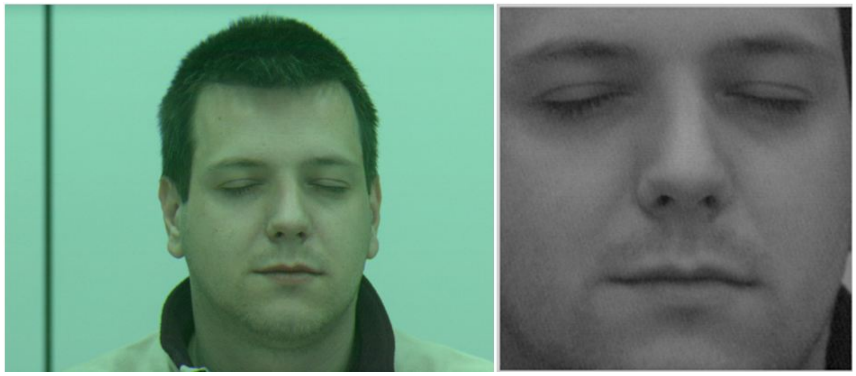

Fig. 1. The effect of pre-processing procedure (image from [14]).

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 [6]. 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 $db10$ from among accessible function.

2.3 Face recognition with 2D HMM

Two-dimensional hidden Markov models (2D HMM) are an development of one-dimensional HMM and provide reasonable method of two-dimensional data modelling, eg. images. In [11] shows the definition and the correctness proof of 2DHMM concept. The presented solutions to these problems were carried out for the input data which is transformed to the one-dimensional vectors. This causes a loss of part of the information contained in the input signal, which may be useful in the recognition systems. For patterns that are images, their structure that is the relative position of pixels is important for the information communicated. Therefore, presented solutions are not fully satisfactory. As a result of the analysis of this problem, it was decided to develop a solution for the use of two-dimensional input data in two-dimensional Markov models.

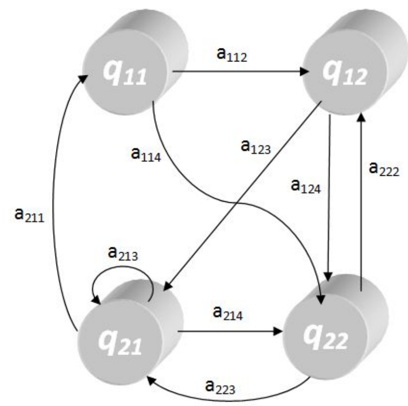

Fig. 2. Two-dimensional ergodic HMM.

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 $k_2 = K$

In the proposed structure of the 2D HMM, $K = N^2$ processes operate parallel. They share the matrix B probabilities of observation generate and are dependent on each other. This feature distinguishes this solution from pseudo 2DHMM proposing solutions.

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 $P(O|\lambda)$

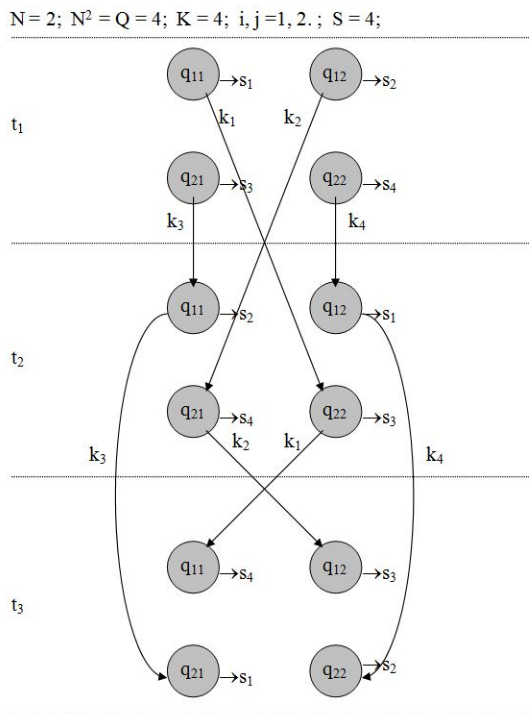

Fig. 3. The idea of 2DHMM.

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:

- $\pi_i\bar{j}k$ = 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 experiment uses the image database *UMB-DB*. The University of Milano Bicocca 3D face database is a collection of multimodal (3D + 2D colour images) facial acquisitions. There are recorded 1473 images of 143 subjects (98 male, 45 female). The images show the faces in variable condition, lighting, rotation and size [14]. The database is available to universities and research centers interested in face recognition. We chose the 30 persons in order to verify the method, and for each individual chose three images for learning and three for testing. The size of each image is 640 x 480 pixels, with 24 bits color. During pre-processing process image is converted to 256 grey levels per pixel and resized to 220 x 220 pixels after normalization selected area of face. As features extraction technique was chosen 2D wavelet transform of second level, and as wavelet function *db10*. The size of features vector was 48400 elements. The 2D HMM implemented with parameters $N = 4; N^2 = 16; K = 16; M = 25$. The parameters were chosen experimentally and for those values were obtained the best results (see Table1). Table 2 reports the results of experiment with another database FERET. The experiment on this database was conducted to compare our method to others popular methods.

Table 1. The results of the experimental parameters selection of HMM.

Number of states N^2	Number of symbols O	Recognition rate [%]
9	10	50
9	20	80
16	10	66
16	20	90
16	25	94
16	50	74
25	25	90
25	50	72

Table 2. Comparison of recognition rate [15].

Method	Databases	Number of images	Recognition rate [%]
PCA	AR-Faces	100	70
LDA	AR-Faces	100	88
ICA	FERET	200	89
NN	FERET	200	99
PCA	UMB-DB	90	94
1D HMM	UMB-DB	90	90
2D HMM	UMB-DB	90	93
2D HMM	FERET	200	96

4 Conclusion

The novel face recognition method is proposed in this paper. The new conception of two-dimensional hidden Markov models working with two-dimensional data 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 one-dimensional data, and thus we do not lose the information contained in the image. The obtained results are satisfactory in comparison to other method and proposed method may be the alternative solution to the others. Average recognition rate of the method is 94%, which is better than classic one-dimensional HMM. Experiments confirmed the validity of the concept of two-dimensional hidden Markov models. In addition, 2D-HMM is a fast method because it only need about 0.7 s to compare two faces.

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