Face Recognition with 3D Face Asymmetry

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Abstract. Using of 3D images for the identification was in a field of the interest of many researchers which developed a few methods offering good results. However, there are few techniques exploiting the 3D asymmetry amongst these methods. We propose fast algorithm for rough extraction face asymmetry that is used to 3D face recognition with hidden Markov models. This paper presents conception of fast method for determine 3D face asymmetry. The research results indicate that face recognition with 3D face asymmetry may be used in biometrics systems.

Keywords: Face asymmetry · Hidden Markov models · Face recognition · Identity verification

1 Introduction

Biometrics systems use individual and unique biological features of person for user identification. The most popular features are: fingerprint, iris, voice, palm print, face image et al. Most of them are not accepted by users, because they feel under surveillance or as criminals. Others, in turn, are characterized by problems with the acquisition of biometric pattern and require closeness to the reader. Among the biometric methods popular technique is to identify people on the basis of the face image, the advantage is the ease of obtaining a biometric pattern. Low prices of cameras have caused their commonness and they are everywhere. Moreover, the quality of the images captured from modern cameras are so good that they may be used to retrieve biometric patterns, and then for identification. The advantage of the identification with the face image is the ease acquiring pattern and a high acceptance level of this method by users. There are many works on 2D face recognition [20], and made great progress in this field. Among these works there are also techniques that use the asymmetry of the face, and the efficiency of this technique is confirmed in articles [9,10,13,19].

With the development of 3D technology appeared methods of 3D face recognition. In last years, some of the new face recognition strategies tend to overcome face recognition problem from a 3D perspective. The 3D data points proper to the surface of the face give us other kind of information for recognition, and solve the problem of pose and lighting variations in case of 2D data. However,

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3D images have their own problems, e.g. normalization, devices for acquiring faces, time and cost of faces getting [12]. In the literature, we may find a lot of useful reviews of 3D face recognition problem such as [1].

Many works are dedicated to the 3D face recognition problem. There is the method presented by Riccio et al. [16] among them, that uses predefined key-points. These points are used to indicate the several geometric invariants on the basis of which is made identification. Other method, Rama et al. present in article [15]. They propose Partial Principle Component Analysis (P^2CA) for feature extraction and dimensionality reduction by projection 3D data into cylindrical coordinate. In [2], researchers use the iterative closest point (ICP) to adjust the 3D surface points of a face and then realize the recognition based on the minimum distance between the two faces. These methods have high recognition rate, but their main problem is speed and computational complexity.

Using of 3D images for the identification was in a field of the interest of many researchers which developed a few methods offering good results [4]. However, there are few techniques exploiting the 3D asymmetry amongst these methods. The reason for this is, among others, the problem of obtaining 3D images. The cost 3D camera is still higher than traditional camera and therefore their popularity and prevalence is lower. The second major problem in the processing of 3D images is their quality. Imperfection devices for image acquisition cause errors in the measurements and data discontinuity, that is a significant problem in the further processing of the data. At the present moment, however, we need to use the data in the quality of such is, and try to eliminate the disadvantages of these data and develop more effective methods of asymmetry measurement and face recognition based on asymmetry.

Few papers in the literature are dedicated to the 3D asymmetry face recognition task so far. Huang et al. [7] propose method based on Local Binary Pattern (LBP). Their approach splits the face recognition task into two steps: (1) a matching step respectively processed in 2D/2D; (2) 3D/2D a fusion step combining two matching scores. Canonical Correlation Analysis (CCA) is applied in method propose by Yang et al. [18]. They apply CCA to learn the mapping between the 2D face image and 3D face data, and only 3d data is used for enrolment and recognition.

This article presents face recognition method based on 3D face asymmetry. We propose fast algorithm for rough extraction face asymmetry that is used to 3D face recognition with hidden Markov models (HMM) [3].

2 Proposed Method

2.1 Preprocessing

The pre-processing procedure of the system consists of the following steps:

- selection of face area.
- scaling image;
- rotation;

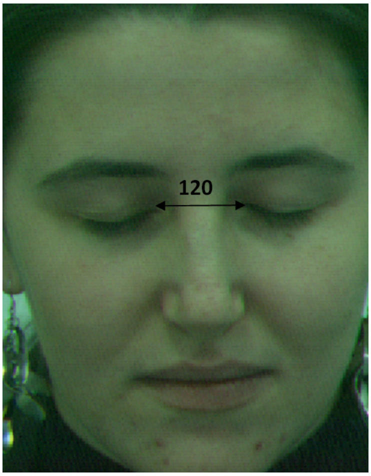

Fig. 1. Result of pre-processing procedure - scaling

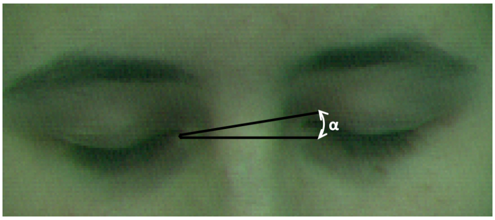

Fig. 2. Please write your figure caption here

$$\alpha = atan(y_2 - y_1, x_2 - x_1) \tag{1}$$

The main area of the face selected and rejected areas that contain little useful information on the outskirts of face. The selection of face area made based on keypoints [6], and the coordinates of these points are obtained from database. Based on inner corners of the eyes, the face image is scaled so that the distance between them was equal to 120 pixels (Fig. 1). Next, the angle of rotation is calculated from the mentioned coordinates (Eq. 1), and face image is rotated by an angle α (Fig. 2). This operation is aimed at establishing the identical position for all faces.

2.2 Measurement of the Asymmetry

There are many methods to found vertical line of face asymmetry. Ostwald et al. [14] propose a definition of the line asymmetry so that the differences between the face and its mirror reflection are as low as possible. Other method is proposed by Kurach et al. [11]. They propose to appoint line asymmetry in such a way

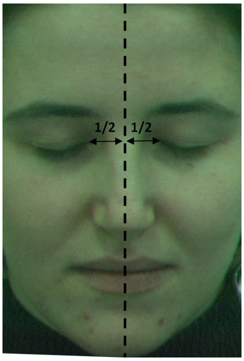

Fig. 3. Line of asymmetry

that the differences between the left and right part of the face are as small as possible. We propose simple and fast method of designate the line of asymmetry. The coordinates of keypoints points obtained from database exploit to find the centre of line connecting the inner corners of the eyes. Thus obtained value is used to determine the x-coordinate defining the lines of facial asymmetry (Fig. 3).

In this way we are dividing the face into the right and left part. Through the mirror vertically they are rising from these parts right face (RF) and left face (LF). From z-coordinate of these two elements and the normal face (NF) the measurement of the asymmetry is being made. In this way, the three metrics are formed that are differences between the RF, LF and NF (Eqs. 2–4) (Fig. 4).

$$LN = |LF - NF| \tag{2}$$

$$RN = |RF - NF| \tag{3}$$

$$LR = |LF - RF| \tag{4}$$

2.3 Recognition System

We have two basic tasks in face recognition application: learning and testing. In case of HMM [17], first task is made with Baum-Welch algorithm, that is based on the forward-backward algorithm. Second task may be made in some ways, but we chose forward algorithm.
Forward Algorithm [8]:

Define forward variable $\alpha_t(i)$ as:

$$\alpha_t(i) = P(o_1, o_2, , o_t, q_t = i|\lambda) \tag{5}$$

$\alpha_t(i)$ is the probability of observing the partial sequence $(o_1, o_2, , o_t)$ such that the the state q_t is i

$$\alpha_{t+1}(i) = \left[\sum_{i=1}^{N} \alpha_t(i) a_{ij}\right] b_j(o_{t+1}) \tag{6}$$

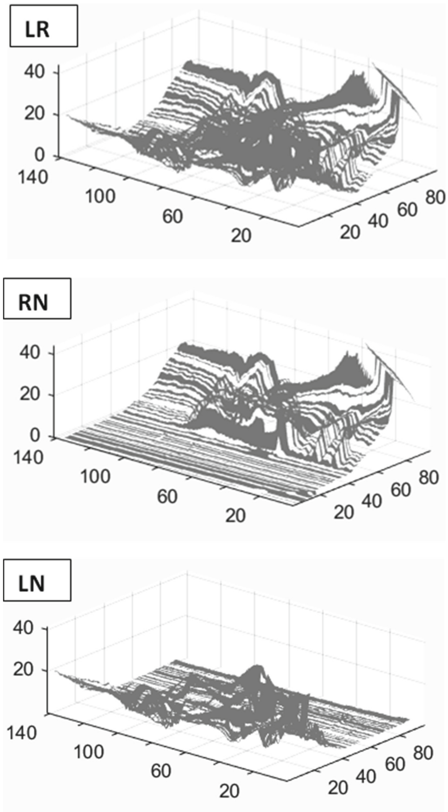

Fig. 4. Results of the measurement of the face asymmetry

Backward Algorithm [8]:

Define backward variable $\beta_t(i)$ as:

$$\beta_t(i) = P(o_{t+1}, o_{t+2}, , o_T, q_t = i|\lambda) \tag{7}$$

$\beta_t(i)$ is the probability of observing the partial sequence $(o_1, o_2, , o_t)$ such that the the state q_t is i

$$\beta_t(i) = \sum_{i=1}^{N} a_{ij} b_j(o_{t+1}\beta_{t+1}(j), \tag{8}$$

$1 \leq i \leq N, t = T-1, ..., 1.$

Baum-Welch Algorithm [8]:

Define $\xi(i,j)$ as the probability of being in state i at time t and in state j at time $t+1$

$$\xi(i,j) = \frac{\alpha_t(i)a_{ij}b_j(o_{t+1})\beta_{t+1}(j)}{P(O|\lambda)} = \frac{\alpha_t(i)a_{ij}b_j(o_{t+1})\beta_{t+1}(j)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_t(i)a_{ij}b_j(o_{t+1})\beta_{t+1}(j)} \tag{9}$$

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

$$\gamma_t(i) = \sum_{j=1}^{N} \xi_t(i,j) \tag{10}$$

Update rules:

- $\bar{\pi}_i$ = expected frequency in state i at time $(t = 1) = \gamma_1(i)$
- $\bar{a}_{ij}$ = (expected number of transition from state i to state j)/(expected number of transitions from state i:

$$\bar{a}_{ij} = \frac{\sum_t \xi_t(i,j)}{\sum_t \gamma_t(i)} \tag{11}$$

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

$$\bar{b}_j(k) = \frac{\sum_{t,o_t=k} \gamma_t(j)}{\sum_t \gamma_t(j)} \tag{12}$$

3 Experiments

In experiments we used the image database UMB-DB. 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 centres interested in face detection or face recognition. They recorded 1473 images of 143

Table 1. Results of experiments

Type of asymetry	No. of test set	Recognition rate
LN	1	58 %
LN	2	62 %
LN	3	60 %
Average		60 %
RN	1	58 %
RN	2	60 %
RN	3	62 %
Average		60 %
LR	1	68 %
LR	2	70 %
LR	3	72 %
Average		70 %

Table 2. Comparison to other methods

Method	Recognition rate
LBP	82 %
CCA	68 %
Our	70 %

subjects (98 male, 45 female). The images show the faces in variable condition, lighting, rotation and size [5]. We chose three datasets, each consist of 50 persons in order to verify the method, and for each individual chose two images for learning and two for testing. The HMM implemented with parameters N = 10, O = 20. Table 1 presents the results of experiments.

4 Conclusion

This paper presented conception of fast and rough method for determines 3D face asymmetry. Presented method allows for faster 3D face processing and recognition because they do not use complex calculation for features extraction. The obtained results are satisfactory in comparison to other method and proposed method may be the alternative solution to the others (Table 2). Experiments confirmed the validity of the concept of 3D face asymmetry, and it is a faster method in comparison to another. The research results indicate that face recognition with 3D face asymmetry may be used in biometrics systems.

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