Recognition of 3D Frontal Face Images Using Local Ternary Patterns and MLDA Algorithm

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Abstract: ***As one of the most successful applications of image analysis and understanding, face recognition has received significant attention during the past several years. Among various types of face images, a 2D intensity image has been the most popular and common image data used for face recognition, since it is easy to acquire and utilize. However, 2D image has the intrinsic problem that it is vulnerable to the variations in illumination and poses. To overcome the limitation of 2D intensity images, 3D images are being used. In this paper, 3D range images of human faces are considered and a novel approach for 3D frontal face recognition is proposed using local ternary patterns with multi-linear discriminant analysis algorithm.***

Keywords: Local Ternary Patterns, DOG filtering, LDA, Multi-Linear Discriminant analysis, LBP

1. Introduction

Automated person identification is a problem of considerable practical significance. It has numerous applications including automated screening, surveillance, authentication and human computer interaction. Face recognition and verification have been at the top of the research agenda of the computer vision community in recent times. Due to its applications envisaged in physical and logical access control, security, man-machine interfaces and low bit rate communication. A facial recognition system is a computer application for automatically identifying or verifying a person from a digital image or a video frame from a video source. One of the ways to do this is by comparing selected facial features from the image and a facial database. In this paper, a method for three dimensional faces recognition based on local ternary patterns with MLDA algorithm.

2. Related Works

Biometric systems for human recognition are an ongoing demand. Among all biometric technologies which are employed so far, face recognition is one of the most widely outspread biometrics. Its daily use by nearly everyone as the primary mean for recognizing other humans and its naturalness have turned face recognition into a well-accepted method. Furthermore, face image procurement is not considered as intrusive as the other alternatives e.g., finger prints, iris, etc.,[Zhao et al.,2003] [Chang et al.,2005][Bowyer Kevin et al.,2006]. Nonetheless, in spite of the various facial recognition systems which already exist, many of them have been unsuccessful in matching up to expectations. 2D facial recognition systems are constrained by limitations such as physical appearance changes, aging factor, pose and changes in lighting intensity.

Recently, to overcome these challenges, 3D facial recognition systems have emerged as the new biometric technique, showing a high level of accuracy and reliability, being more robust to face variation due to the different factors[Abate et al. , 2007] [Kachare & Inamdar , 2010]. In 2D images, landmarks such as eye, eyebrow, mouths etc, can be reliably detected. In contrast, nose is the most important landmark in 3D face recognition [Chellappa et al.,1995]. The 3D information (depth and texture maps) corresponding to the surface of the face may be acquired using different alternatives: A multi camera system (stereoscopy), range cameras or 3D laser and scanner devices.

Different approaches have been presented from the 3D perspective. The first approach would correspond to all 3D approaches that require the same data format in the training and in the testing stage. The second philosophy would enclose all approaches that take advantage of the 3D data during the training stage but then use 2D data in the recognition stage.

Approaches of the first category report better results than of the second group; however, the main drawback of this category is that the acquisition conditions and elements of the test scenario should be well synchronized and controlled in order to acquire accurate 3D data [Chang et al.,2003] [Zou et al.,2007]. Thus, they are not suitable for surveillance applications or control access points where only one normal 2D texture image (from any view) acquired from a single camera is available.

The second category encloses model based approaches. Nevertheless, model-based face recognition approaches present the main drawback of a high computational burden required to t the images to the 3D models [Ortiz et al. , 2004] [Barrett et , 1997]. Linear discriminant analysis (LDA) is a standard pattern recognition tool. LDA is a single-exemplar method in the sense that each class during classification is represented by a single exemplar, i.e. the sample mean of the class.

The single-exemplar property offers a simple classification mechanism, which is often very efficient in terms of classification results. The underlying assumption of LDA is that each class possesses a normal density with a different mean vector but a common covariance matrix. Under the above assumption, LDA coincides with the optimal Bayes classifier. Even though LDA has been successfully applied to face recognition [2, 9, 15], its recognition effectiveness is limited to controlled scenarios, as documented in [6, 11]. For example, when the faces are in a frontal view, under a frontal illumination, and with a neutral expression, the recognition performance is quite accurate. However, when the image conditions of the training, gallery, and probe sets are different, the recognition performance drops quickly.

3. Background

3.1 Generation of LTP

Local binary pattern (LBP) is a simple yet effective local texture description technique. LBP was used for grayscale and rotation-invariant texture analysis. Formally, the LBP operator can be represented as:

$$\mathrm{LBP}_{P,R}(x_c, y_c) = \sum_{p=0}^{P-1} s(i_p - i_c)\, 2^p,$$

$$s(x) = \begin{cases} 1, & x \geq 0, \\ 0, & x < 0. \end{cases} \quad (1)$$

The local ternary pattern (LTP), which extends the binary LBP code to a 3-valued ternary code in order to provide more consistency in uniform and near-uniform regions. The LTP codes are more resistant to noise, and are not strictly invariant to gray-level transformations. In the LTP encoding process, gray values in a zone of width about the center pixel are quantized to 0, and those above +t and below –t are quantized to +1 and −1, respectively. Hence, the indicator s(x) in (1) is substituted by a 3-valued function:

$$s'(i_p, i_c) = \begin{cases} 1, & i_p \geq i_c + t, \\ 0, & |i_p - i_c| < t, \\ -1, & i_p \leq i_c - t. \end{cases} \quad (2)$$

The LTP encoding procedure is illustrated in Figure 1. Here the threshold is set to 5.

89	54	51
55	55	38
60	20	10

$\Rightarrow$

1	0	0
1	c	-1
1	-1	-1

[55-t, 55+t], Threshold, t=5and the tolerance level is [50-60]
Ternary code: 100(-1) (-1) (-1)11

Figure 1: illustration of the basic LTP

3.2 DOG Filtering

As a feature enhancement algorithm, the difference of Gaussians (DOG) can be utilized to increase the visibility of edges and other detail present in a digital image. A wide variety of alternative edge sharpening filters operate by enhancing high frequency detail, but because random noise also has a high spatial frequency, many of these sharpening filters tend to enhance noise, which can be an undesirable artifact. The difference of Gaussians algorithm removes high frequency detail that often includes random noise, rendering this approach one of the most suitable for processing images with a high degree of noise.

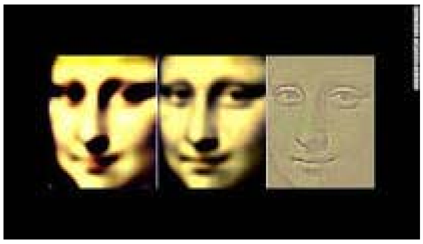

Figure 2: Effect of DOG filtering

3.3 Image Fusion

The objective in image fusion is to reduce uncertainty and minimize redundancy in the output while maximizing relevant information particular to an application or task. Fusion is done using Image Averaging. This technique is a basic and straight forward technique and fusion could be achieved by simply averaging the corresponding pixels in the two images that are to be fused. The method is demonstrated by Anjali Malviya and Bhirud (2009).

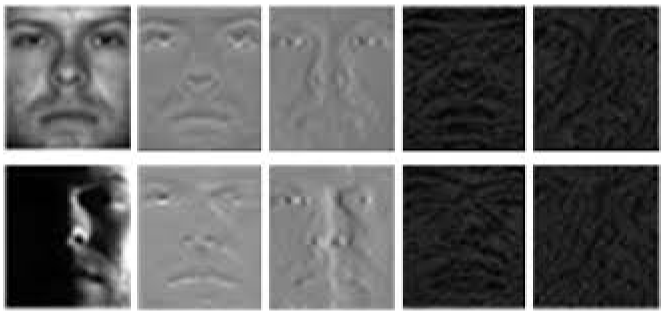

Figure 3: Fusion of LTP and DOG filtering images

4. Proposed Methodology

Here, 3D range images of human faces are considered and a novel approach for 3D frontal face recognition is proposed using local ternary patterns with multi-linear discriminant analysis algorithm. The flow chart of the proposed face recognition system is shown in Figure 4. Input images with varying lighting conditions are considered. Hence, the image passes through a preprocessing stage prior to the recognition stage. The algorithm developed using the fusion of LTP and DOG filter performs well under difficult lighting conditions. The fused image is obtained using DOG filtered image and the LTP and face recognition is then performed using MLDA algorithm. Since the recognition is performed by taking the fusion of DOG and LTP rather than by taking any one alone, the performance of the proposed technique is better. The image after preprocessing is fed to the face recognition stage.

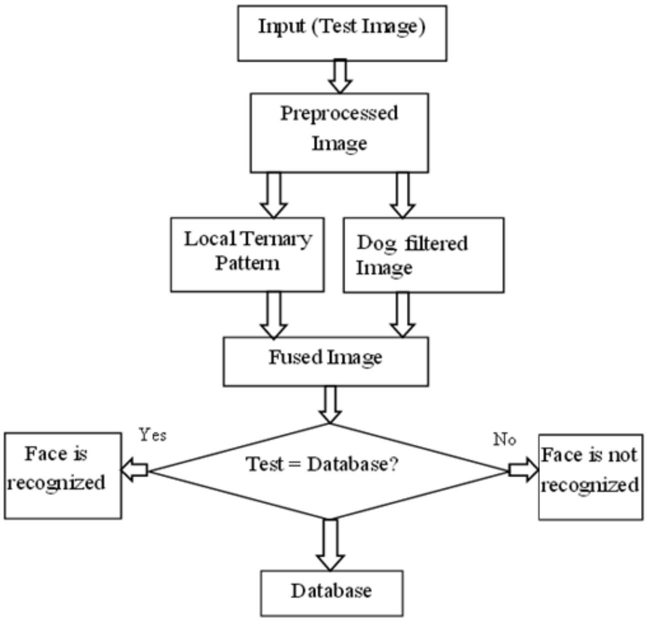

Figure 4: Flow chart of the proposed face recognition system

4.1 Multi-Linear Discriminant Analysis

LDA first estimates the within-class and between-class scatter matrices of size d × d, denoted by ∑W and ∑B, respectively, given by

$$\Sigma_W = \sum_{i=1}^{C} \mathrm{p}^i \Sigma_W^i = \frac{1}{N} \sum_{i=1}^{C} \sum_{j=1}^{N_i} (\mathrm{x}_j^i - \mu^i)(\mathrm{x}_j^i - \mu^i)^{\mathrm{T}},$$

$$\Sigma_B = \sum_{i=1}^{C} \mathrm{p}^i \Sigma_B^i = \frac{1}{N} \sum_{i=1}^{C} N_i \sum_{j=1}^{N_i} (\mu^i - \mu)(\mu^i - \mu)^{\mathrm{T}},$$

where

$$\mu^i = \frac{1}{N_i} \sum_{j=1}^{N_i} \mathrm{x}_j^i; \quad \mu = \frac{1}{N} \sum_{i=1}^{C} \sum_{j=1}^{N_i} \mathrm{x}_j^i = \sum_{i=1}^{C} \mathrm{p}^i \mu^i.$$

And $\sum^i$W is the covariance matrix estimate for class i given by

$$\Sigma_W^i = \frac{1}{N_i} \sum_{j=1}^{N_i} (\mathrm{x}_j^i - \mu^i)(\mathrm{x}_j^i - \mu^i)^{\mathrm{T}},$$

and $\sum^i$B is the scatter matrix between the class i and the 'grand class' given by

$$\Sigma_B^i = (\mu^i - \mu)(\mu^i - \mu)^{\mathrm{T}}.$$

Then, LDA finds a projection matrix W, say of size r×d, that maximizes the criterion function. The basic principle of LDA is to minimize the within class distance while maximizing the between-class distance, with each class represented by a single exemplar. Since MLDA uses all the available exemplars per class, the within-class distance in LDA becomes the within-class exemplar distance (i.e. the distances between exemplars belonging to the same class). Mathematically, we re-define the matrices ∑W and ∑B as follows:

$$\Sigma_W = \sum_{i=1}^{C} \frac{1}{N_i^2} \sum_{j=1}^{N_i} \sum_{k=1}^{N_i} (\mathrm{x}_j^i - \mathrm{x}_k^i)(\mathrm{x}_j^i - \mathrm{x}_k^i)^{\mathrm{T}}; \tag{3}$$

Then, LDA finds a projection matrix W, say of size r×d, that maximizes the criterion function defined as

$$J_{\mathrm{W}} = \frac{det\{\mathrm{W}^{\mathrm{T}} \Sigma_B \mathrm{W}\}}{det\{\mathrm{W}^{\mathrm{T}} \Sigma_W \mathrm{W}\}},$$

where det{.} denotes matrix determinant,

The basic element in (3) is a pair wise difference between any two exemplars belonging to the same class. Alternatively, we can view these basic elements as samples of a new space. This construction of such a space is validated by the property *C3* to capture the common 'shape' of the face appearance manifold. Similarly, the between-class distance in LDA becomes the between-class exemplar distance (i.e. the distances between exemplars belonging to different classes),

$$\Sigma_B = \sum_{i=1}^{C} \sum_{j=1; j \neq i}^{C} \frac{1}{N_i N_j} \sum_{k=1}^{N_i} \sum_{l=1}^{N_j} (\mathrm{x}_k^i - \mathrm{x}_l^j)(\mathrm{x}_k^i - \mathrm{x}_l^j)^{\mathrm{T}},$$

and a so-called extra-personal space (EPS) can be constructed. The proposed MLDA approach is find the projection matrix $W_{d \times r}$ such as the same cost function JW is maximized.

But, here the number of projection directions r can exceed C − 1. Given a test pattern y, its class label Cy is determined as

$$C\mathrm{y} = \arg \min_{i=1,2,\ldots,C} \{ \min_{j=1,2,\ldots,N_i} \{|\mathrm{W}^{\mathrm{T}}(\mathrm{y} - \mathrm{x}_j^i)|^2 + \mathrm{D}_i\}\}.$$

Without much difficulty, our MLDA analysis can be extended to handle the cases where not all samples are used in classification and only several exemplars are extracted from the sample set to represent the class.

5. Experimental Results

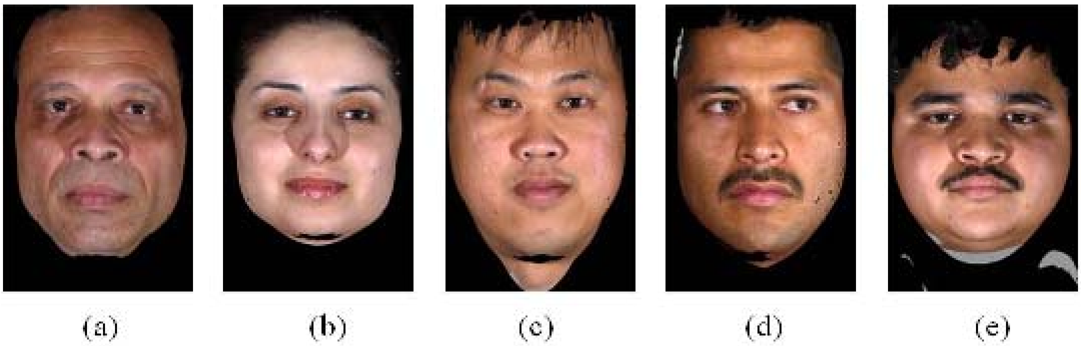

Figure 5: Some sample facial texture images.

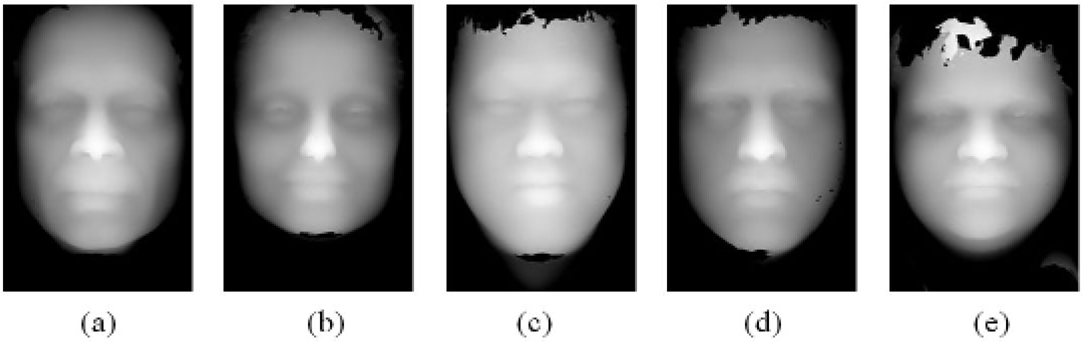

Figure 6: Sample 3D face image after image fusion of LTP and DOG filtering of the training set.

For comparison, we implement the following three discriminant methods besides [15] (PCA followed by LDA), and the Bayesian face recognition ('BayesFR') approach [12]. In addition, we also implement the 'IPS' approach in which the projection vectors are eigenvectors of the IPS. For each of the tested approaches, We tune the parameters (e.g. the number of components) to maximize the recognition performance. Table 1 lists the recognition rates obtained by all tested approaches, using the top one match. It is not surprising that the LDA approach records the worst performance since the underlying assumptions of LDA are severely violated. The 'sub LDA' approach over performs the LDA approach which highlights the virtue of Eigen-smoothing as a preprocessing method. The 'BayesFR' approach is also better than the LDA approach; however the improvement is not very significant possibly because the fitted density is unspecified. The 'IPS' approach is very competitive, which confirms the face characteristics *C3*, i.e., the IPS characterizes the 'shape' of the face manifold. The proposed MLDA approach yields the best performance since it performs a discriminant analysis of the IPS and EPS, with multi linear discriminants.

Table 1: A summary of recognition rates obtained by different approaches.

Method	*Expression*	*Illumination*
MLDA	66%	72%
IPS	64%	69%
BayesFR	50%	50%
SubLDA	55%	59%
LDA	44%	43%

6. Conclusion

In this paper, we illustrated the characteristics of face recognition other than those of regular pattern recognition. These characteristics inspire the proposed multi-linear discriminant analysis in lieu of regular linear discriminant analysis. The preliminary results are very promising and we still need to investigate the recognition performance on a large-scale database. Finally, even though we use face recognition as an application, our analysis is quite general and is applicable to other recognition tasks, especially those involving very high dimensional patterns.

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