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Radius Based Block LBP for Facial Expression Recognition

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Abstract

This paper presents a 'significant facial region' in which the block size is extracted based on the radius length on the face area to improve the recognition performance and reduce size of feature vector. We introduces region selection using various critical point and report our result using benchmark database. The original LBP techniques focus in dividing the whole image into regions and for the proposed scheme, we focus on critical region, which gives more impact to the recognition performance. This technique is known as Radius Based Block Local Binary Pattern (RBB-LBP). We defined four critical point represent left eye, right eye, nose and mouth, from this four main point we derived the next nine point. We assessed on the face recognition problem using the Colorado State University Face Identification Evaluation System with images from the Japanese Female Facial Expression (JAFFE) database. Our experimental results clearly show that our approach outperforms the other methods. With RBB-LBP, the best facial expression recognition rate was achieved at 94.37% on hardest testing method – Leave One Out (LOO), which is an increase of 0.97% compared to linear programming algorithm and non-uniform LBP with usage of feature vector 1298 compared to 19456.

Key Words: Radius Based Block Local Binary Pattern (RBB-LBP), Local Binary Pattern (LBP), Face Recognition, JAFFE, Significant Facial Region

1. Introduction

Facial expression and recognition is an increasingly important field of study that has several applications in areas such as human-computer interaction, human emotion analysis, biometric authentication and fatigue detection. Facial expression provides the most powerful, natural and immediate means for human beings to communicate their emotions and intensions. Therefore deriving an effective facial representation from the original face images is a vital step for successful facial expression recognition. A face recognition system can be used in two modes: authentication (or verification) and identification. An authentication system involves confirming or denying the identity claimed by an individual. On the other hand, an identification system attempts to establish the identity of a given person out of a pool of different people. Identification generally operates on a closed-set scenario (the individual to identify is present in the database), while authentication operates on an open-set scenario, where people's face not present in the database could try to fool the system. Although these tasks are slightly different, both modes usually share the same classification algorithms. The importance of face recognition have been utilize in applications such as face recognition security system during the 2008 Olympic in Beijing using the Local Binary Pattern (LBP).

A variety of systems have been developed to perform facial expression recognition [1,2] and all of these systems possess some common characteristics. First, they classify facial expressions using adult facial expression databases. For instances, the authors in ref [2] used the JAFFE database to recognize seven main facial expressions: happy, neutral, angry, disgust, fear, sad and surprise. While in [3], they used AR database to classify three facial expressions: neutral, smile and angry. Secondly existing facial expression recognition systems are divided into two categories: facial feature extraction and facial expression recognition. Facial feature extraction attempts to find the most appropriate representation of the face image for recognition. There are two common approaches to extract facial features: holistic matching method and local matching method, depending on the way the face image is processed. In the holistic matching method, the whole face image is represented as a high-dimensional vector. Due to the size of dimensionality, such vectors cannot be compared directly. Hence, holistic methods use dimensionality reduction techniques to resolve this problem and thus derive lower-dimensional vectors for subsequent classification. The most popular examples among such approaches are based on Principal Component Analysis (PCA) [4] and on Linear Discriminant Analysis (LDA) [5]. On the other hand, local matching methods are typically using a set of local observations obtained from the face image to derive a model of an individual, which is subsequently used for recognition. One of the most representative systems in this family is the Local Binary Patterns (LBP) [6], where the face is represented by a set of concatenated LBP histograms, each one being computed in a different block of pixels along the image. Recognition is then performed by measuring the similarity between histograms. Many state-of-the-art machine learning methods utilize image texture descriptors [7]. Local binary patterns (LBP), first proposed in [8], is one of the most widely used descriptors because of its resistance to lighting changes, low computational complexity, and ability to code fine details. LBP has been extensively studied in a wide array of fields and has demonstrated superior performance in several comparative studies [1,9]

In this paper, we present a novel feature extraction method, which focuses on critical region or local matching, hence increasing the recognition performance. This technique is also known as Radius Based Block Local Binary Pattern (RBB-LBP). Since JAFFE database is commonly used in measuring the performance of facial expression recognition systems, we applied our system on this database and perform comparisons with other systems as reported by [2].

2. Materials and Methods

The original LBP operator was introduced by Ojala et al. [8]. This operator works with the eight neighbours of a pixel, using the value of the centre pixel as a threshold. All neighbours that have values higher than the value of the central pixel are given value 1 and all those that have values lower or equal to the value of the central pixel are given value 0. The eight binary numbers associated with the eight neighbours are then read sequentially in the clockwise direction to form a binary number. This binary number or its decimal system may be assigned to the central pixel and it may be used to characterize the local texture (Fig. 1).

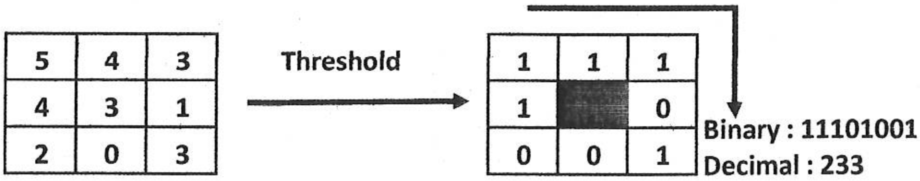

Fig. 1 The Original LBP Operator

As the original LBP techniques focus in dividing the whole image into regions. In this paper, we propose a scheme which focuses on critical region. This scheme focuses on three main area which is the eye (including eyebrow), mouth and nose. We defined four critical points which represent left eye (T_1), right eye (T_2), nose (T_3) and mouth (T_4). From this four main points we derived the next nine points (T_5-T_{13}) as shown in Fig. 2.

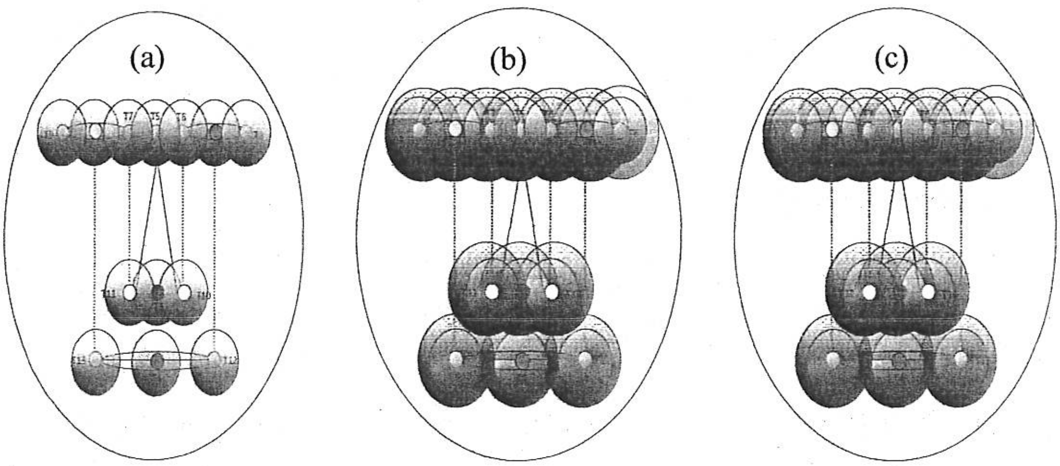

Fig. 2 (a) Region with radius n_1 (b) Region with radius n_2 (c) Combination of radius n_1 and n_2

Based on the points generated, images are divided into T_m windows to provide more efficient representation of the face. The window size is extracted based on the radius size from 3 to 10. By dividing the images into m windows, the length of the feature vector becomes m times larger for every radius chosen. Fig. 2a show region with radius n_1 from the centre point and Fig. 2b shows region with radius n_2 from the centre point. This approach will automatically create the redundancy in various region and for every radius size window a robust histogram with all possible labels constructed. This means that every bin in a histogram represents a pattern and contains the number of its appearance in the windows or region. We also test the combination of various size radius windows as shown in Fig. 2c. The feature vector is then constructed by concatenating the regional histograms to one big histogram. Once the Local Binary Pattern for every pixel is calculated, the feature vector of the image can be constructed. The general histogram model for critical regions extracted as follow:

$$\sum_{i=1}^{n} R_i + \sum_{i=1}^{n} (R_i - R_{i-1}) = \sum_{i=1}^{n} R_i + (R_i - R_{i-1}) = \sum_{i=1}^{n} 2R_i - R_{i-1} \qquad (1)$$

where R_i is the region of i-th window of all sequences m and n respectively.

3. Results and Discussion

In [10,11] the images are registered using eye coordinates and cropped with an elliptical mask to exclude other area from the image. As a result, the size of each preprocessed image is 150×128. They achieved 93.8% average recognition rate. In [12], a multilayer perceptron was used with 90.1% recognition accuracy. In [13], a technique called feature selection via linear programming was used and they achieved an accuracy of 91%. In [14], a recognition result of 92% using linear discriminant analysis (LDA) was reported, but they only included nine people's face images and, hence, only 193 of the 213 images were used. In [11] they achieved 93.4% classification performance using Active Appearance Model and non-uniform LBP for feature extraction with selected 76 blocks and constructing a very huge histogram of 19456 (256x76) bins.

Our experimental results clearly shows that our approach outperforms the other methods. With RBB-LBP, the best facial expression recognition rate was achieved at 94.37% on hardest testing method – leave one out (LOO). Table 1 shows performance of RBB-LBP increase by 0.97% compared to linear programming algorithm and non-uniform LBP with usage of feature vector 1298 compared to 19456 [29], and also an increase of 0.24% and 0.69% when compared to Shih et al.[2] using leave one-out and cross-validation testing method. In addition, it should be noted that only two positions of the eyes are needed in our approach while 34 fiducial points are manually selected in other methods [13-14].

Table 1 Expression Classification Performance for JAFFE Database

Study	Performance (%)	Strategy
Lyon et al [14]	92.00	Cross-validation
Zhang et al [15]	90.10	Cross-validation
Buciu et al [16]	90.34	Leave-one-out
Dubuisson et al [17]	87.60	Cross-validation
Shinohara and Otsu [18]	69.40	Cross-validation
Shih et al [2]	95.71	Cross-validation
Shih et al [2]	94.13	Leave-one-out
Feng et al [11]	93.40	Cross-validation
Our proposed method	**96.40**	**Cross-validation**
	94.37	**Leave-one-out**

4. Conclusion

In this paper, we propose a scheme which focuses on critical region, directly increasing the recognition performance as discussed above. This scheme focuses on three main area which is the eye (including eyebrow), mouth and nose. We defined four critical points which represent left eye, right eye, nose and mouth. From this four main points we derived the next nine critical points. Our experimental results clearly show that our approach outperforms the other methods. With RBB-LBP, the best facial expression recognition rate was achieved at 94.37% on hardest testing method – leave one out (LOO), an increase of 0.97% compared to linear programming algorithm and non-uniform LBP with usage of feature vector 1298 compared to 19456. Our current work only covers fundamental research on region selection. Future work will include further exploration in combining with other method such as Gabor and LDA.

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