A New Face Beauty Prediction Model based on Blocked LBP

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Abstract: In recent years, many scholars use machine learning methods to analyze facial beauty and achieve some good results, but there are still some problems needed to be considered, for instance, the face beauty degrees are not widely distributed, and previous works emphasized more on face geometry features, rather than texture features. This paper proposes a novel face beauty prediction model based on Blocked Local Binary Patterns (BLBP). First, we obtain the face area by ASMs model, then, the BLBP algorithm is proposed in accordance with texture features. Finally, we use Pearson correlation coefficient between the output of the facial beauty by our algorithm and subjective judgments by the raters for evaluation. Experimental results show that the method can predict the beauty of face images automatically and effectively.

1 INTRODUCTION

Pursuing beauty is the nature of human beings, especially in terms of facial beauty. In ancient China, "three court five eyes" was considered as an evaluation criterion about facial beauty. The Western society also has a "golden ratio" evaluation criterion. Currently, more and more people pursue beauty, but they are confused on what kind of photos can attract more people's attention when they post photos on the social network. How to define the beautiful faces and how to beautify their face images? Is there a method which can give a reliable beauty index about their photograph? How to evaluate the plastic surgery results? In the beauty pageant, participants evaluate face beauty according to their own tastes, which is often not convincing to the public. Can we use computer technology for the pageant?

In recent years, with the development of computer technology, some scholars began to use computer-related technology to analyze facial beauty (Eisenthal et al., 2006; Kagian et al., 2008). They try to find the common properties of facial beauty and provide a quantitative evaluation. Aarabi (Aarabi et al., 2001) established an automatic scoring system for face beauty. They defined the face beauty in three levels, and chose 40 face images for training and other 40 face images for testing. They got the final classification accuracy of 91% by using *k* nearest-neighbors (KNN). Irem (Irem et al., 2007) proposed a two-levels (beauty or not) model based on a training dataset with 150 female faces, in which the principal component analysis (PCA) and support vector machine (SVM) methods were used for feature extraction and classification, respectively. Finally, the highest accuracy of 89% was achieved by using 170 female face images as the testing data. Gunes (Gunes and Piccardi, 2006) proposed a method based on supervised learning, in which 11 features were involved to describe the face beauty degree. The 17 "golden ratios" rules for face beauty was given by Schmid (Schmid et al., 2008), but it only used some geometric features to describe the face beauty. Douglas (Douglas et al., 2010) contributed a method of quantifying and predicting female facial attractiveness using an automatically learned appearance model which did not require landmark features. Zhang (Zhang et al., 2011) mapped faces on to a human face shape space, and then quantitatively analyzed the effect of facial geometric features on human facial beauty. The experiments showed that human face shapes lay in a very compact region of the geometric feature space and that female and male average face shapes were very similar. Mao (Mao et al., 2011) proposed a computational method for estimating facial activeness based on Gabor features and SVM, experimental results showed that the FeaturePoint Gabor features performed best and obtained the

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correlation of 0.93 with average human ratings, but there were only 100 Chinese female faces in their database, the database was not big enough. Gan (Gan et al., 2014) utilized deep self-taught learning to learn the concept of facial beauty and produce human-like predictors, but its processing was relatively complex.

In summary, previous works have used image processing and machine learning techniques to classify face beauty, and they have achieved initial success on some different data sets. However, there are still some problems: 1) the number of face images for experiment is inadequate. 2) Face beauty degrees are not widely distributed. 3) Previous works emphasized more on face geometry features, rather than texture features.

This paper aims to predict the beauty for female faces by using the texture features. First, the active shape models (ASMs) is used for facial landmark extraction, and 77 landmarks are extracted to represent the face shape. Then, a new method, named Blocked-LBP (BLBP), is proposed based on the rotation invariance of Local Binary Patterns, and Histogram Matching method is employed to analyze face beauty. The BLBP has some advantages: 1) it can generate more samples based on our current samples. 2) In aesthetic research of human face, we mainly use geometric features or global texture features to analyze the beauty of human face. But by experiments, we find that it is more reliable to predict the face beauty by using the local features of face skin. 3) It defines a new scoring model which is different from the usual scoring model. Experiments show that BLBP is effective for face beauty analysis, which gets a Pearson correlation of 0.874 in our database and 0.852 in the database of (Zhang et al., 2011).

The paper is organized as follows: Section 2 describes the preprocessing procedure of obtaining the face area. In Section 3, face texture feature extraction method based on the BLBP algorithm is introduced. Experimental results are shown in Section 4, and the conclusion is given in Section 5.

2 FACE AREA EXTRACTION

Landmark extraction is important in face area extraction. Landmarks refer to the locations of key points of nose, mouth, eyebrows, eyes, and face contours in a face image. In this paper, the active shape models (ASMs) algorithm (Cootes et al., 1995, Sukno et al., 2007) is used for landmark extraction. ASMs are statistical models of the shape of objects which deform iteratively to fit to an example of the object in a new image (Cui et al., 2012). Using this model, 77 landmarks are extracted to represent the face shape. Figure 1(a) is an input image, and Figure 1(b) shows the extracted landmarks.

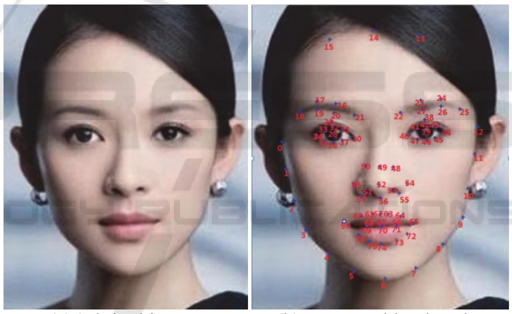
There is usually some background information which would impact the texture feature in a face image. We find a way to segment the face region out so as to eliminate this impact. The main steps are as follows:

(1) Use the ASMs method to get the landmarks, as shown in Figure 1(b).

(2) Find the location of face contour points, including the points from No. 0 to No. 15 in Figure 1(b).

(3) Use the face contour points to get a mask image, whose size should be the same with the face image.

(4) Segment the face image based on the mask image, so the hair and the background can be removed. Figure 2 shows the result.



(a)Original image (b) Extracted landmarks

Figure 1: Landmark extraction by using ASMs.

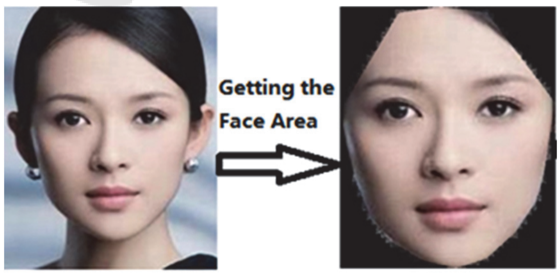


Figure 2: The process to locate the face region.

3 BLOCKED-LBP

3.1 Texture Features of LBP

The basic idea of LBP (Local Binary Patterns) which can learn by Guo (Guo Z et al., 2010) is to summarize the local structure in an image by comparing each pixel with its neighborhoods. For each pixel (x_i, y_i), the LBP value is calculated as follows:

(1) Compare the intensity of 3*3 neighbor pixels of (x_i, y_i) with the intensity of (x_i, y_i). If the intensity of any neighbor pixel is smaller than the intensity of (x_i, y_i), then, denote this neighbor pixel as 0, otherwise 1. This procedure is shown as Figure 3. We can end up with a binary number for each pixel, like 11001111.

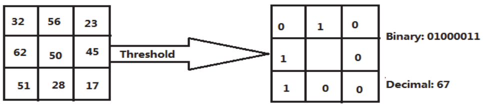


Figure 3: The process for calculating a LBP.

(2) Calculate the LBP value of (x_i, y_i) with the following equation :

$$LBP(x_i, y_i) = \sum_{p=0}^{p-1} 2^p s(i_p - i_c) \tag{1}$$

Where i_c is the grey value of (x_i, y_i), i_p is the gray value of the P^{th} neighbor of (x_i, y_i).In the original LBP algorithm, P is set as 8. The function of $s(x)$ is a symbolic function:

$$S(x) = \begin{cases} 1 & if\ x \geq 0 \\ 0 & else \end{cases} \tag{2}$$

Many researchers have proposed some extensions about the original LBP, such as the rotation invariance LBP which is based on a circular domain. Figure 4 is a circular LBP operator.

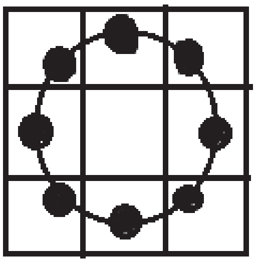


Figure 4: A model for circular LBP operator.

For a point (x_i, y_i), and its neighboring point (x_n, y_n) can be calculated by:

$$\begin{cases} x_n = x_i + Rcos(\frac{2\pi n}{P}) \\ y_n = y_i - Rsin(\frac{2\pi n}{P}) \end{cases} \tag{3}$$

where R is the radius of the circular. If (x_n, y_n) is not on the image coordinates, its interpolation point can be calculated:

$$f(X,Y) \approx \begin{bmatrix} 1-X & X \end{bmatrix} \begin{bmatrix} f(0,0) & f(0,1) \\ f(1,0) & f(1,1) \end{bmatrix} \begin{bmatrix} 1-Y \\ Y \end{bmatrix} \tag{4}$$

3.2 BLBP

In this paper, a Blocked-LBP (BLBP) is proposed based on the rotation invariance LBP (LBPROT) to extract the texture features. It is different from the block LBP for face recognition which is shown in Figure 5, and the detail explaining is given in (Jia et al., 2014).

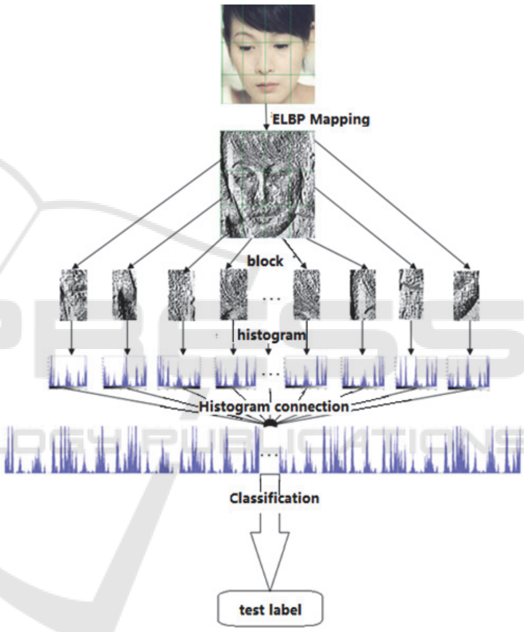


Figure 5: The flowchart of the block LBP for face recognition.

A face image will get low beauty score if there are some bad features on the face, such as scars. Accordingly, we use local features instead of global features and propose the BLBP descriptor, which shown in Figure 6. The detailed description about the BLBP method is as following.

(1) Divide each LBP image which comes from the training set into smaller blocks. (Here the face image is divided into 12 blocks)

(2) During the testing procedure, the first step is to obtain the face region of the test images by the method introduced in Section 3.1. Then, the rotation invariance LBP of the image is calculated. Finally, the images are divided into

blocks. For each block, find the most similar block by Histogram Matching. The beauty score of the training sub-block is set to the human rated score of the corresponding face image. When testing the i^{th} sub-block's score, we find the most similar block according to each training sample's i^{th} sub-block and set its score to the testing sub-block.

(3) The sum of each sub-block's score is treated as the testing image's final score.

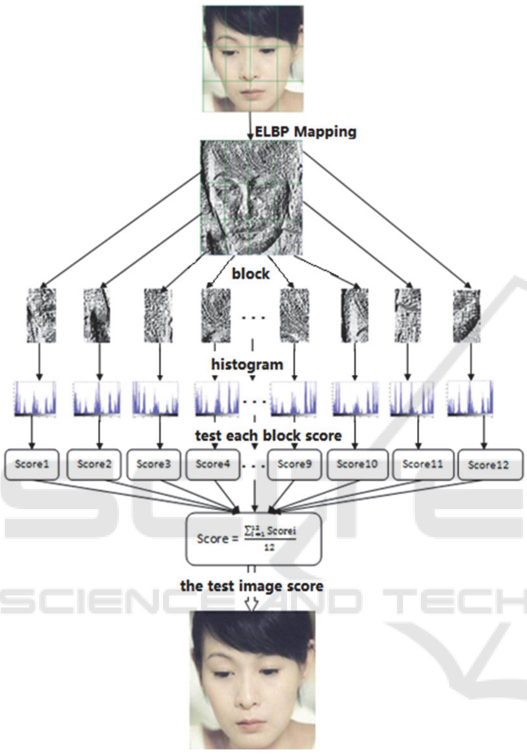


Figure 6: The flowchart of BLBP extraction.

Let I_i denote the i^{th} training image where $i=1,2,3\ldots M$. M is the number of training images, $P_{i,j} \in R^{256}$ denotes a vector which is a LBP image histogram for the j^{th} block of I_i, where $j = 1,2,3,\ldots N$, and N is the number of block. Let $A_j \in R^{M*256}$ denote a histogram matrix and

$$A_j = [P_{1,j}, P_{2,j}, P_{3,j}, \ldots P_{M,j}]' \tag{5}$$

Let T_k denote the k^{th} testing image, $B_{k,j} \in R^{256}$ denotes a histogram vector of the k^{th} block of T_k, and $S(i)$ denotes the i^{th} mean human rater of training image, the testing score of $B_{k,j}$ can be calculated by the following steps:

1) Calculating the distances between $B_{k,j}$ and each row of A_j:

$$distance(i) = \sqrt{1 - \sum_{f=0}^{255} \frac{\sqrt{B_{k,j}(f) * A_j(i,f)}}{\sum_{r=0}^{255} B_{k,j}(r) * \sum_{r=0}^{255} A_j(i,r)}} \tag{6}$$

2) Finding the min distance of $distance(i)$:

$$flag = i \;\; where \; Min(distance(i)) \tag{7}$$

3) The testing score for the k^{th} block of T_k is:

$$TS(j) = S(flag) \tag{8}$$

4) The total score of T_k is:

$$Score(T_k) = \sum_{j=0}^{N} TS(j) \tag{9}$$

Finally, $Score(T_k)$ is used for evaluation.

Comparing the block LBP for face recognition model with BLBP model, there were some differences: BLBP model can generate more samples than block LBP, as shown in Figure 5. For facial beauty prediction, the score of the test sample can be determined by the number of training samples in BLBP model, but the score of the test sample is determined by one sample in block LBP for face recognition model.

4 EXPERIMENTS

A beauty face data base has been established for experiments, which contains 400 high-quality female face images, including some well-known beautiful faces collected from some webs (e.g. Miss World, movie stars, and super models), several existing databases (the Shanghai database of (Zhang et al., 2011)) and some profile pictures. The size of the face images is $480 * 600$. The face images are confined to be frontal and have neutral or gentle smile expressions.

To obtain the human-rated beauty scores, an annotation interface was developed, which displayed the face images in random order and asked the raters to give a score for each face image. The scores are integer from 1 to 10, where "10" means the most beautiful face, and "1" means the ugliest face. Nine volunteers attended the annotation task for all the images. Therefore, we obtained 9 annotations for each image. The average beauty ratings are considered as the human-rated beauty scores. Then, the 10 folds cross-validation technique was chosen as the training and testing method. Some face images are shown in Figure 7. Finally, the Pearson correlation is used for model evaluation (Pearson, 1920; Rodgers and Nicewander, 1988).

Figure 7: Some examples in the image gallery.

Firstly, the optimal block number of BLBP should be determined. We change this parameter from 1*1, 2*2… to 10*10, and the corresponding results are shown in Figure 8. It shows that the best block number is 8*8, and the highest Pearson correlation is 0.874 under this parameter. The face regions need not to normalize to the same size, for example, let $m * n$ be the size of the face region, where m, n may be different for different images. When the block number is $N * N$, then each block size should be $\lfloor m/N \rfloor * \lfloor n/N \rfloor$.

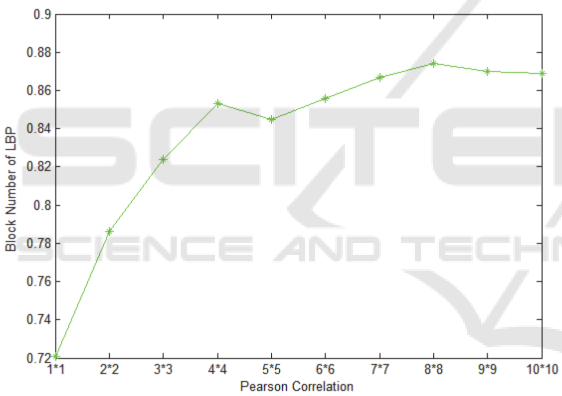


Figure 8: Comparing with different block numbers in BLBP.

Table 1: The results by using the texture feature to analysis face beauty in different database.

Database / Feature	Our database	(Zhang, 2011) database
LBP	0.656	0.588
(Jia et al., 2014)	0.744	0.727
Gabor	0.693	0.678
BGabor	0.739	0.704
(Mao et al., 2011)	0.853	0.837
BLBP	**0.874**	**0.852**

Comparing with LBP, Gabor, Blocked-Gabor (BGabor), and LBP (Jia et al., 2014) which was the block LBP for face recognition model, the proposed BLBP method has better performance in face beauty analysis. The results are listed in Table 1. BLBP can get a correlation coefficient of 0.874 in our database. Testing these methods on the database used in (Zhang et al., 2011), the proposed BLBP also gets the highest correlation coefficient of 0.852.

5 CONCLUSIONS

This paper proposes a novel Face Beauty Prediction Model Based on BLBP. First, we extract the face area by ASMs model and obtain 77 landmark points to segment the face area. Then, a novel Blocked Local Binary Patterns (BLBP) algorithm is proposed in accordance with texture features. Finally, we use Pearson correlation coefficient between the output of the facial beauty by our algorithm and subjective judgments by the rater for evaluation. Experimental results show that the method can predict the face images automatically and effectively, and obtain a correlation coefficient of 0.874 in our database.

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