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Gender recognition from face images using texture descriptors for human computer interaction

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ABSTRACT

The gender recognition from face images has possible applications in visual surveillance, content-based indexing and searching, biometrics, human-computer interaction systems (HCI), demographic studies and targeted advertising. Although significant work has been done on automatic gender recognition, the current systems are still not close to the human perceptual system due to appearance variations viz. lighting, expression, illumination, face pose, scale and aging. The innovative approach for gender recognition based on the information obtained from facial images is proposed to overcome the problem of illumination and expression. The system can spontaneously locate the face from input images and the located facial area is used for further processing. Hence the objective of this proposed system is to classify the gender of a person. Identifying a face as a male or female is an easy task for human but it is very difficult for a machine. In order to achieve improved recognition rate, the face image can be categorized by using the texture descriptors. The descriptors used to recognize the gender are the local binary pattern (LBP) and Weber's law descriptor (WLD) and their spatial enhanced versions (SLBP and SWLD). Spatially enhanced descriptors performance is better and it has very less algorithmic complexity compared to other approaches. The linear SVM is used as a classifier. By using texture descriptors, the face image is recognized as male or female. In order to appraise the performance of the proposed system, the FERET database was used. This proposed method gives better classification accuracy.

KEY WORDS: Human computer interaction, Weber's law descriptor, local binary pattern, gender recognition.

1. INTRODUCTION

Human–computer interaction involves the study, planning, design and implementing the uses of interaction between people and computers. In HCI based face image analysis, face image consists of large information and the analysis of face image can provide many cues for various purposes. The scope of face image analysis includes not only face recognition, facial expression recognition, but also gender determination, age estimation etc., The face image analysis consists of four modules such as face localization, feature extraction, feature selection by dimensionality reduction techniques and decision making based on feature-dependent analysis. The decision can be made toward gender determination and age estimation.

Human–Computer Interaction based on face image analysis is useful in many applications. In a museum, investigation of the viewer in terms of gender, age group and emotions is an important one for automatic tourist guide system. For this kind of application, HCI based on face image analysis can be used.

This paper proposes new system for improving the classification rate using the texture descriptors which was obtained from the faces. In this system a local descriptor, called Weber Local Descriptor (WLD) is used. It is based on the human perception of a pattern and it depends not only on the change of incentive but also on the original intensity. WLD consists of two main parameters one is differential excitation and other is orientation. The WLD overtakes the other descriptors such as HOG, Gabor, LBP, RIFT and SIFT.

The LBP is a descriptor which is invariant to grayscale of the given image. The LBP feature can be used with various conventional models of texture descriptors. The most important property of the LBP feature is its tolerance against illumination changes and computational simplicity, which is the most important factor to examine the images in difficult environment. The LBP method widely used in various applications including human computer interaction, visual inspection, biometric identification, image retrieval, computer vision, environment modeling, remote sensing, facial image processing, biomedical analysis, and indoor/outdoor scene analysis.

Related work: Gender recognition by humans is an easy process. However, for a computer, it is quite difficult. Similar to face recognition, gender classification from facial images faces many problems due to the variant illumination, rotations, and poses. Another problem occurs because of the large number of features extracted by feature descriptors. For the gender classification, many researchers have introduced complex systems based on either geometrical or appearance features. For the analysis using geometrical features, principal component analysis (PCA) and artificial neural networks (ANNs) was first used for gender classification.

Moghaddam and Yang (2000) proposed gender classification from facial images with size of 21×12 pixels using SVM. Nakano (2004) proposed the gender classification in which edge details are used as features and used a neural network classifier. Lu and Shi (2009) introduced the concept of using pixel information of the face area for effective discrimination about the gender with support vector machine classifier.

For analyzing the texture features, a local binary pattern [1] approach was used for the entire image. Jabid (2010), inspired by LBP, proposed a feature extraction technique named local directional pattern (LDP) technique with an SVM classifier from the FERET database. Ning (2006), used Local Binary Pattern features for gender classification with Chi-Square test and Ada Boost algorithms to classify the gender from the FERET dataset.

2. PROPOSED SYSTEM

The block diagram of the proposed system is exposed in Figure.1. The three major modules of the system are face detection, feature extraction and classification. For feature extraction, spatial WLD descriptor is used. Final decision is provided by support vector machine classifier.

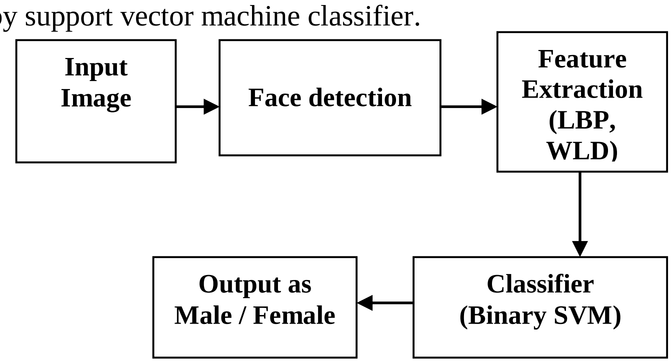

Figure.1. Block diagram of the system

Face detection: The first step in the proposed systems is face detection. It can be solved easily by humans. But there is a difficult task to make a computer to solve the work. In order to solve the task, Viola–Jones limits to find the full view frontal upright faces. To detect, the entire face must point towards the camera and it should not be tilted. It should be compromise the criteria for being unconstrained, the detection algorithm must often will be succeeded by a recognition algorithm. The consideration for detecting these demands seems to be different and quite reasonable.

Local Binary Pattern (LBP): Local Binary Pattern features have been implemented very well in numerous applications, such as computer animation, face image analysis and surveillance. LBP is very important descriptor because of its illumination resistivity, stumpy computational complication and easy to code the fine details. LBP labels the image by considering the surrounding pixels. Computation of LBP features and histogram of the LBP (HLBP) is explained in the fig. 2.

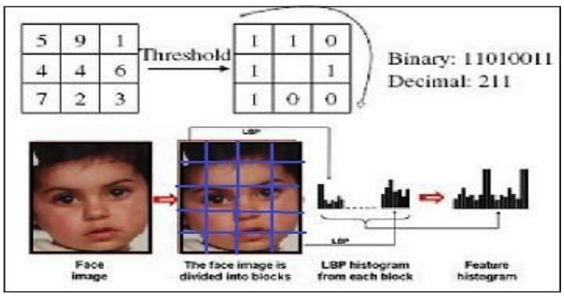

Figure.2.HLBP

For a given pixel at (x_c, y_c), the LBP result can be determined as follows:

$$LBP(x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c)2^n \qquad (1)$$

Where n is the number of surrounding pixels around the center pixel, i_c and i_n are the gray values of the center and surrounding pixels. S(x) is 1 if $x \geq 0$, otherwise it is 0.

Weber's Law Descriptor (WLD): This descriptor represents a face image as a two dimensional histogram using the parameters orientations and differential excitations, and it has more interesting properties such as robust to noise and illumination changes.

WLD descriptor is formed based on Weber's law. The law states that the size of the noticeable changes is a constant proportion of the original stimulus value. Motivated by this law, Chen (2010), proposed the descriptor called WLD for analyzing the texture. The computation of WLD descriptor consists of 3 steps, they are differential excitations calculation, gradient orientations calculation and building the histogram from them.

Differential Excitation: For determining the differential excitation $\mathcal{E}(x_c)$ of a pixel x_c ,the difference between intensity of x_c to its neighboring values of x_i, i = 1, 2, …, p are calculated. The fraction of sum of intensity difference of x_c with its neighbor's value x_i to the intensity of x_c is calculated.

The differential excitation $\mathcal{E}(x_c)$ is calculated as follows:

$$\varepsilon(x_c) = \arctan\left[\sum_{i=0}^{p-1} \frac{I_i - I_c}{I_c}\right] \quad (2)$$

The differential excitation gives the relation between the current pixels with the surrounding pixels.

Gradient Orientation: The gradient orientation for a current pixel x_c is calculated by using the following equation:

$$\theta(x_c) = \arctan\left[\frac{I_7 - I_3}{I_5 - I_1}\right] \quad (3)$$

Where gradient orientation, $\theta \in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right]$.

I_0	I_1	I_2
I_7	x_c	I_3
I_6	I_5	I_4

Figure.3. 3×3 sub image

The gradient orientations are divided into N dominant orientations as follows:

$$\phi_n = \frac{2n}{N}\pi$$

Where $n = \operatorname{mod}\left(\left\lfloor \frac{\theta'}{2\pi/N} + \frac{1}{2} \right\rfloor, N\right) \quad (4)$

Where $\theta' \in [0, 2\pi]$ is calculated by means of Eq. (3).

Holistic WLD Descriptor: After manipulating the differential excitation and dominant orientation, WLD descriptor is built to each orientation ϕ_n : n = 0, 1, 2,……N-1. The differential excitations are formulated as a histogram H_i. Then each histogram H_i where i = 0, 1, 2, …, N-1 is uniformly subdivided into S sub histograms $H_{s,i}$: s = 0, 1, 2, …, S-1, each one consist of K bins. These two dimensional histograms are used to build a matrix. In a matrix, each column represents the dominant direction and each row represents the segment of differential excitation. Each row of this matrix in the bin is combined together to form a histogram $H_s = \{ H_{s,i}$: i = 0, 1, 2, …, N-1}. Subsequently, histograms H_s where s = 0, 1, 2… S-1 are concatenated into a new histogram H = {H_s: s = 0, 1, 2, …., S-1}. Now the histogram is named as WLD descriptor. The WLD descriptor includes following parameters such as N, the quantity of dominant orientations and S, the quantity of segments and K, the quantity of bins in the segment.

Spatial WLD Descriptor: To increase the differentiating ability of WLD descriptor, spatial WLD descriptor establishes spatial information into the descriptor. To construct the SWLD, the image is separated as a number of blocks, and computes WLD histogram for each block, then concatenate them to form a SWLD descriptor (SWLD).

Support Vector Machines: A SVM is a supervised learning algorithm for pattern categorization and regression of facial images. The logic behind SVMs is to determine the best possible linear hyper plane by which the error rate of classification for the test samples is reduced and the performance of generalization is improved to higher level. Based on the structural risk minimization inductive law, a task that classifies the training data correctly and it identifies a set of functions with the lowest dimension will to generalize best regardless of the dimensionality.

3. EXPERIMENTAL RESULTS

In our proposed system, FERET face database was used for experimentations, which is the familiar face database for evaluating the task of face recognition; it consists of more number of facial images and has an excellent diversity in terms of age, pose and gender. The lighting condition, orientation of the face, and capturing moment may differ for different sets. Resizing of face image is done prior to conducting tests. The System was tested with the neighborhood values for both LBP and WLD descriptor. For spatially enhanced LBP and WLD descriptor, various block sizes are used for comparison strategy. For Spatially enhanced WLD descriptor computation, WLD parameters (N, S and K), i.e., N = 8; S = 6; K = 8 is used.

For training phase, 96 images (48 male, 48 female) were used. For testing 284 images (142 male, 142 female) were used. The performance evaluation of the recognition of given image gender is exposed in table 1 and table 2. From the table, it is observed that the spatial enhanced WLD accuracy is high when compared to spatial enhanced LBP. From the performance evaluation of SEWLD and SELBP it is inferred that the block size 16 is optimum for producing higher accuracy of image size 128*128. Similarly SVM classifier performs better accuracy than K-NN classifier.

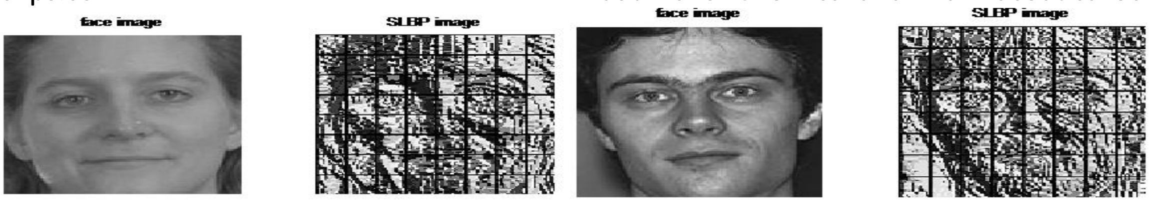

Figure.4. Results of Spatial LBP

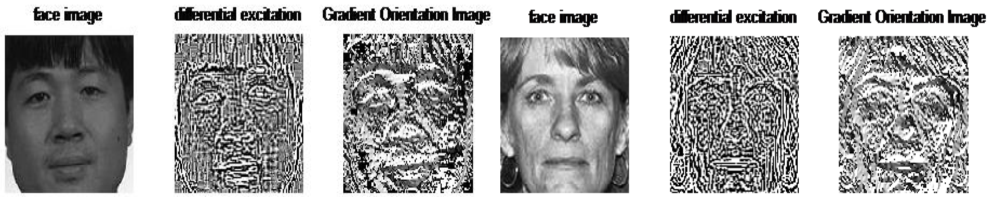

Figure.5. Results of SEWLD

Table.1. Performance Evaluation of SEWLD and SELBP

SEWLD			SELBP		
Block Size	**Accuracy**		**Block Size**	**Accuracy**	
	SVM	**K-NN**		**SVM**	**K-NN**
16	91.37	80.98	16	90.14	86.27
32	90.67	76.76	32	84.67	78.52
64	85.63	72.54	64	82	75

4. CONCLUSION

The proposed system provides better gender classification rate using spatially enhanced WLD-based facial representation with support vector machines than spatially enhanced LBP with support vector machines. The computation of regional and global descriptions of face images using LBP is incredibly simple and fast. But gender recognition accuracy was less. The computation of regional and global descriptions of face images using WLD is very complex and slow. But gender recognition accuracy was high compared to LBP on the FERET face Database and comparatively SVM classifier produces higher accuracy results than K-NN classifier.

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