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An Image Region Selection with Local Binary Pattern based for Face Recognition

Dr. V. S. MANJULA
Associate Professor & Head Information System & Network Engineering
St. Joseph University College of Engineering & Technology
Dar-Es-Salaam, Tanzania, East Africa

ABSTRACT: *In this paper, we present a novel framework for face recognition, namely Selective Ensemble of Image Regions (SEIR) is proposed and which considers both shape and texture information to represent face images. In this framework, all possible regions in the face image are regarded as a certain kind of features. This technique can be adapted to accurately detect facial features. However, the area of the image being analyzed for a facial feature needs to be regionalized to the location with the highest probability of containing the feature. By regionalizing the detection area, false positives are eliminated and the speed of detection is increased due to the reduction of the area examined. The face area is first divided into small regions from which Local Binary Pattern (LBP) histograms are extracted and concatenated into a single, spatially enhanced feature histogram efficiently representing the face image. The recognition is performed using a nearest neighbor classifier in the computed feature space. The FERET data tests which include testing the robustness of the method against different facial expressions, lighting and aging of the subjects. In addition to its efficiency, the simplicity of the proposed method allows for very fast feature extraction a method to accurately and rapidly detect faces within an image.*

Keywords*: Face Recognition, Region Selection, Multiple Eigenspaces, Ensemble learning, Selective Ensemble, PCA, Histogram Equation*

I. INTRODUCTON

In this paper we introduce a new approach for face recognition which considers both shape and texture information to represent the face images. Human faces are complex, changeful and high dimensional patterns. Although it is to recognize familiar faces, face recognition is a formidable task for machines. Even so, the vast potential applications, face recognition have become an active research area of computer vision and pattern recognition for decades. As opposed to the EBGM approach, a straightforward extraction of the face feature vector (histogram) is adopted in our algorithm. The face image is first divided into small regions from which the Local Binary Pattern (LBP) features [8,9] are ex-tracted and concatenated into a single feature histogram efficiently representing the face image. The textures of the facial regions are locally encoded by the LBP patterns while the whole shape of the face is recovered by the construction of the face feature histogram. The idea behind using the LBP features is that the face images can be seen as composition of micro-patterns which are invariant with respect to monotonic grey scale transformations. Combining these micro-patterns, a global description of the face image is obtained.

Despite these achievements, face recognition continues to be an active topic in computer vision research. This is due to the fact that current systems perform well under relatively controlled environments but tend to sober when variations in different factors (such as pose, illumination and etc.) are present. Therefore, the goal of the ongoing research is to increase the robustness of the systems against different factors. Ideally, to develop a face recognition system this mimics the remarkable capabilities of human visual perception. Before attempting to reach such a goal, one needs to continuously learn the strengths and weaknesses of the proposed techniques in order to determine new directions for future improvements. To facilitate this task, the FERET database and evaluation methodology have been created.

The main goal of FERET is to compare different face recognition algorithms on a common and large database and evaluate their performance against different factors such as facial expression, illumination changes, aging and etc. Among the major approaches developed for face recognition are Principal Component Analysis (PCA), Linear Discriminate Analysis (LDA) and Eigenface is based on the global feature of face images, it uses the whole face image as training data. When there are gross variations in the input images that greatly. However, in this situation, local features such as eyes, mouth and nose are often less dejected. So these local features can help recognize faces. They used four masks respectively to get the regions of eyes, nose, mouth and the whole face.

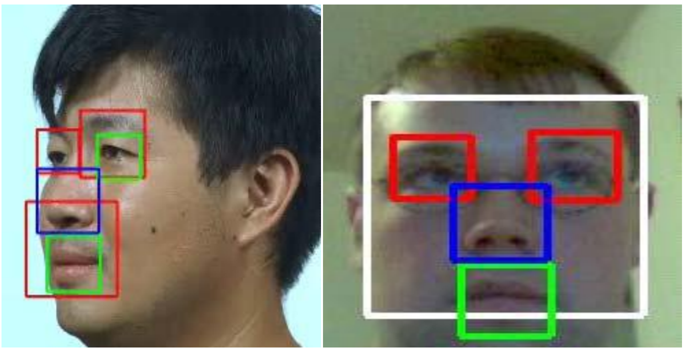

Figure1(a) Figure1(b)

Figure 1.Manually extracted facial feature regions

The face features detected of eyes, nose and mouth are shown in Figure 1(a). They claimed that local features could achieve better performance than global features. Figure 1(b), where the white rectangles show the regions of four local features, i.e. left eye, right eye, nose and mouth. They indicated that the Eigen features alone were sufficient in achieving a high recognition rate equal to that of the eigenface, and the combination of eigenface and Eigen features could achieve even better performance.

II. IMAGE REGION SELECTION:

In face recognition using multiple features can be re-explained from another point of view. In fact, each feature can be used to classify faces, i.e. each feature can be used to train a weak classifier. Then the multi-feature methods can be regarded as special ensemble learning methods. If the definition of features is extended to all possible rectangular regions in the face image, then using several features for face 2 recognition can be regarded as selective ensemble learning [7].

Figure 2. Original images and synthetic images

Several approached works on feature selection for face recognition, such as Local Feature Analysis (LFA) , and the Ada Boosted Gabor Features. However, until now there is no work on region selection for face recognition.

2.1 Image Region Selection Algorithm:

Given *K* example face images (each person has two images, one is gallery face and the other is probe face), *m* regions are to be selected from the exhausted set of *N* regions in the face images *R*1, *R*2, ….,*RN*.

1. For $i = 1 \ldots.N$:
   (i). Train a classier based on the region Ri using the gallery faces as training set.
   (ii). Recognize all the probe faces using the classier, getting the recognition rate of Ri, denoted by ri .
2. Sort Ri according to descending order of ri. Get a sequence of regions: $Ri1, Ri2, \ldots RiN$.
3 $S = \{Ri1\}$, $A = \{Ri2, \ldots.,Rin\}$, where $m << n<< N$.
4 For $t = 1\ldots (m - 1)$:
   - For each region Ri in A, calculate ci, the number of the probe faces that Ri correctly recognizes but at least one of the regions in S doesn't.
   - Find the region with the largest ci, denoted by Rl.
   - Remove Rl from A and add it to S.

5 There are m selected regions in S.

III. FACE DESCRIPTION WITH LOCAL BINARY PATTERNS

The original LBP operator is a powerful means of texture description. The operator labels the pixels of an image by thresholding the 3x3-neighbourhood of each pixel with the center value and considering the result as a binary number. Then the histogram of the labels can be used as a texture descriptor. In Figure 2 for an illustration of the basic LBP operator. Later the operator was extended to use neighborhoods of divergent sizes [8]. Using circular neighborhoods and bilinear interpolating the pixel values allow any radius and number of pixels in the neighborhood. For neighborhoods we will use the notation (P, R) which means P sampling points on a circle of radius of R.

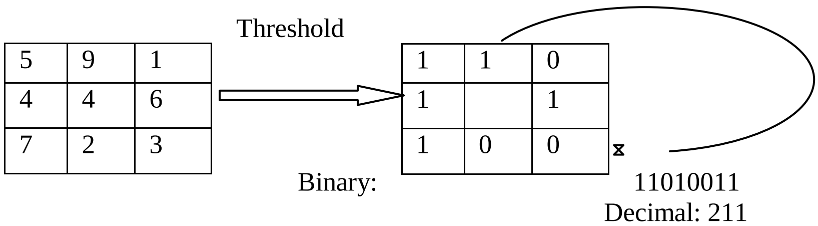

Figure 3. The basic LBP Operator

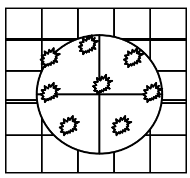

Figure 4 for an example of the circular (8,2) neighborhood.

The pixel values are bilinear interpolated whenever the sampling point is not in the center of a pixel transitions from 0 to 1 or vice versa when the binary string is considered circular.

For example, 00000000, 00011110 and 10000011 are uniform patterns. In this experiments with texture images, uniform patterns account for a bit less than 90 % of all patterns when using the (8,1) neighborhood and for around 70% in the (16,2) neighborhood.

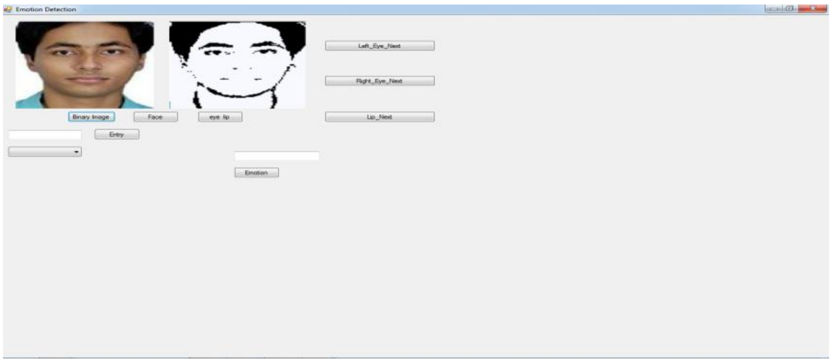

Figure 5. Original images and synthetic images

When viewing all possible rectangular regions in the face images as a kind of features, region selection becomes a nature idea to improve the performance of face recognition systems, just like other feature selection procedures. Nevertheless, neither eigenface nor eigenfeature seems to perform any selection procedure. In fact, the selection is unconsciously performed by the operators. It is up to the operators to determine which regions and how many of them should be used. Based on the common sense that facial features, such as eyes, nose and mouth, are crucial in face recognition, most algorithm designers choose to use the image regions around those salient facial features. But this is a very rough selection principal, which has at least two defects. First, although these facial features are salient in human faces, they are not guaranteed to be the most discriminative features. Second, even these features are the most discriminative ones, no one knows how to take full advantage of them. For example, it is uncertain whether the two eyes should be put into the same rectangle like Figure 1 (a), or Figure 1 (b). Consequently, automatic image region selection algorithm should be designed for face recognition.

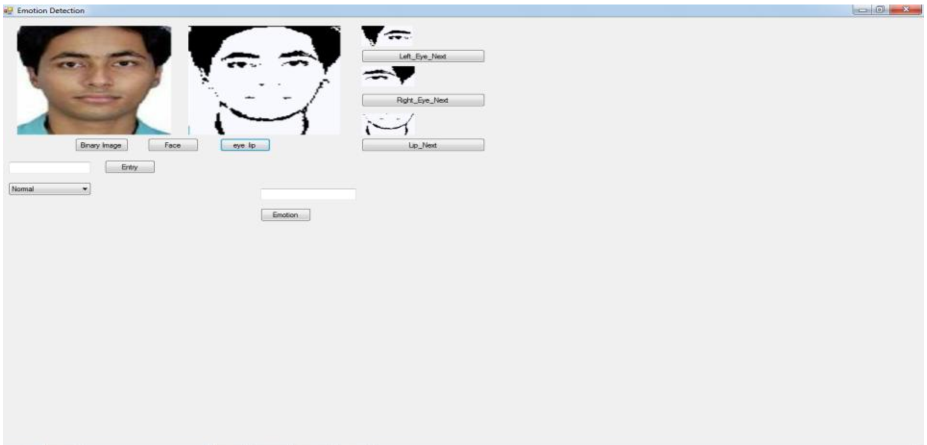

Figure 6. Face Detection and Tracking

The human face poses even more problems than other objects since the human face is a dynamic object that comes in many forms and colors. However, facial detection and tracking provides many benefits. Facial recognition is not possible if the face is not isolated from the background. Human Computer Interaction (HCI) could greatly be improved by using emotion, pose, and gesture recognition, all of which require face and facial feature detection and tracking [2]. Although many different algorithms exist to perform face detection, each has its own weaknesses and strengths. Some use flesh tones, some use contours, and other are even more complex involving templates, neural networks, or filters. These algorithms suffer from the same problem; they are computationally expensive [2]. An image is only a collection of color and light intensity values. Analyzing these pixels for face detection is time consuming and difficult to accomplish because of the wide variations of shape and pigmentation within a human face.

IV. LEARNING COMPONENTS:

However, it is not clear what exactly the size and shape of these components should be and whether there are other components which are equally important for recognition. Furthermore, this can be accomplished by an algorithm for learning components which was developed in the context of face detection. The algorithm starts with a small rectangular component located around a preselected point in the face. The component is extracted from each face image build a training set. A component classifier is trained according to the one-vs-all strategy. The components of one person are trained against the components of all other people in the database. We estimate the prediction error of each component classifier by cross-validation. To do so, we extract the components from all images in the cross validation set based on the known locations of the reference points. Analogous to the training data, the positive cross validation set includes the components of one person and the negative set includes the components of all other people.

V. EXPERIMENTS & RESULTS:

5.1 Training Classifiers for Facial Features:

Detecting human facial features, such as the mouth, eyes, and nose require that Haar classifier cascades first be trained. In order to train the classifiers, this gentle AdaBoost algorithm and Haar feature algorithms must be implemented. The OpenCV library is designed to be used in conjunction with applications that pertain to the field of Human Computer Interaction, robotics, biometrics, image processing, and other areas where visualization is important and includes an implementation of Haar classifier detection and training [8]. To train the classifiers, two set of images are needed. One set contains an image or scene that does not contain the object, in this case a facial feature, which is going to be detected.

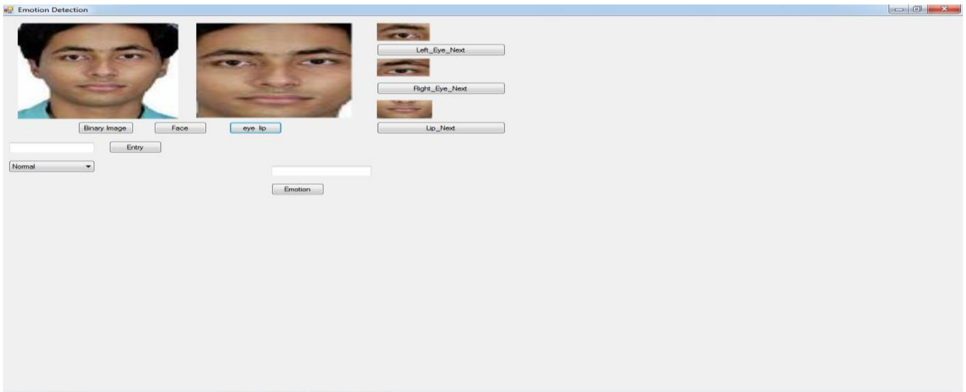

Figure 7. Robust facial feature detection

This set of images is referred to as the negative images. The other set of images, the positive images, contain one or more instances of the object. The location of the objects within the positive images is specified by: image name, the upper left pixel and the height, and width of the object. For training facial features 5,000 negative images with at least a mega-pixel resolution were used for training. These images consisted of everyday objects, like paperclips, and of natural scenery, like photographs of forests and mountains. In order to produce the most robust facial feature detection possible, the original positive set of images needs to be representative of the variance between different people, including, race, gender, and age. A good source for these images is National Institute of Standards and Technology's (NIST) Facial Recognition Technology (FERET) database. This database contains over 10,000 images of over 1,000 people under different lighting conditions, poses, and angles [10]. In training each facial feature, 1,500 images were used. These images were taken at angles ranging from zero to forty five degrees from a frontal view. This provides the needed variance required to allow detection if the head is turned slightly [1]. Three separate classifiers were trained, one for the eyes, one for the nose, and one for the mouth. Once the classifiers were trained, they were used to detect the facial features within another set of images from the FERET database and the accuracy of the classifier was then computed. With the exception of the mouth classifier, the classifiers have a high rate of detection. However, as implied by figure 7, the false positive rate is also quite high.

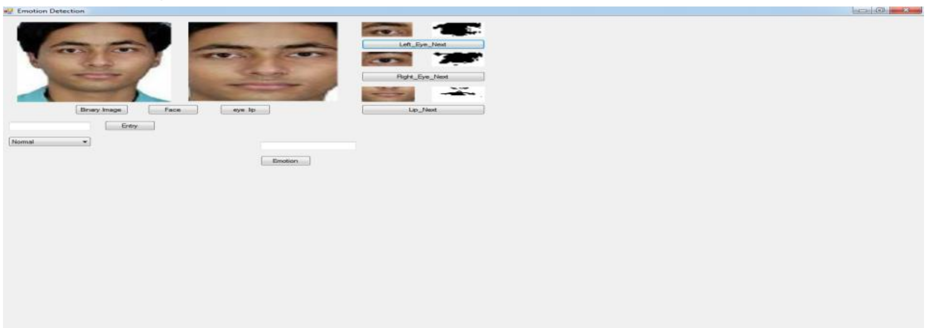

Figure 8. Classification of facial feature detection

Facial Feature	Positive Hit Rate	Negative Hit Rate
Eyes	93%	23%
Nose	100%	29%
Mouth	67%	28%

Table 1 Accuracy of Classifiers

VI. CONCLUSION

The first step in facial feature detection is detecting the face. This requires analyzing the entire image. The second step is using the isolated faces to detect each feature. Since each the portion of the image used to detect a feature is much smaller than that of the whole image, detection of all three facial features takes less time on average than detecting the face itself. Since a frame rate of detected feature using a much faster processor, regionalization provides efficiency in facial feature detection. Regionalization also greatly increased the accuracy of the detection. All false positives were eliminated, giving a detection rate of around 95% for the eyes and nose. The mouth detection has a lower rate due to the minimum size required for detection. By changing the height and width parameter to more accurately represent the dimensions of the mouth and retraining the classifier the accuracy should increase the accuracy to that of the other features. With the successful detection of facial features, the next goal is to research the ability for more precise details, like individual points, of the facial features to be gathered. These points will be use to differentiate general human emotions, like happiness and sadness.

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Author Profile

Dr.V.S. Manjula has Completed MCA, M.Phil., B.Ed., Ph.D and She received Ph.D degree in Computer Science from Bharathiar University in 2013. She worked in Head in MCA Department, Gurushree Shantivijai Jain College, Chennai. At present she is working in Associate Professor and Head of the Department of Information System and Network Engineering in St. Joseph University College of Engineering & Technology, Dar-Es-Salaam in Tanzania, East Africa. She is a Research Supervisor in Information & Communication Technology (ICT) in St. Eugene University in Zambia and she is a member of Research Journal of International Association of Computer Science & Information Technology (IACSIT). She has published more than 11 International Journals and National & International Conferences.