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Face Recognition in Various Illuminations

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Abstract
Face Recognition (FR) under various illuminations is very challenging. Normalization technique is useful for removing the dimness and shadow from the facial image which reduces the effect of illumination variations still retaining the necessary information of the face. The robust local feature extractor which is the gray-scale invariant texture called Local Binary Pattern (LBP) is helpful for feature extraction. K-Nearest Neighbor classifier is utilized for the purpose of classification and to match the face images from the database. Experimental results were based on Yale-B database with three different sub categories. The proposed method has been tested to robust face recognition in various illumination conditions. Extensive experiment shows that the proposed system can achieve very encouraging performance in various illumination environments.
Keywords: Face Recognition, Gamma Correction, Illumination, Dog Filtering, Image Preprocessing, Equalization Of Normalization, Clahe (Contrast-Limited Adaptive Histogram Equalization), Log (Laplacian Of Gaussian).

I. INTRODUCTION

Face recognition becomes an important task in computer vision and one of the most successful application areas recently. Face recognition technologies have been motivated from the application area of physical access, face image surveillance, people activity awareness, visual interaction for human computer interaction, and humanized vision. The research on face recognition has been conducted for more than thirty years, but, still more processes and better techniques for facial extraction and face recognition are needed. This research work aims to resolve the classical problem of human face recognition under dim light conditions and develop an intelligent and efficient method for recognizing human faces. The most existing techniques like Eigen faces, Principal Component Analysis, Elastic Graph Bunch Matching etc., has the low dimension of the solution to classification and generalization problems. Also, it is a challenging task in a less-controlled environment like different illumination variations for large databases. In order to overcome the above limitations, an intelligent agent is proposed to integrate three techniques viz., Illumination Normalization, Feature Extraction and Classification for face recognition in various illumination conditions to identify the match. This research work focuses on the frontal view faces subjecting under various illumination conditions. The remaining paper is organized as follows: Section 2 describes some of the related works in face recognition on various illumination conditions; feature extraction techniques and the different identification approaches. The Section 3 focuses on recognizing the human face in various illumination conditions using the proposed new scheme. In

Section 4, the proposed methods experimental and their results are comprised. Section 5 outlines the summary of the author’s conclusion.

II. RELATED WORK

There have been only a few studies reported in the literature on utilizing various lighting variations, which develops a historical and current perspective of activities in the field of Face Recognition.

Xiaoyang Tan et al [1] proposed Illumination Normalization preprocessing chain technique which incorporates a series of stages designed to counter the effects of illumination variations, local shadowing, and highlights while preserving the essential elements of visual appearance. The local texture feature sets called the LBP (Local Binary Pattern)/LTP (Local Ternary Pattern) descriptor used for the feature extraction and improved KPCA classifier.

Padraig Cunnigham et al [5] highlighted that k-NN process is transparent and so it is easy to implement and it can be very effective if an analysis of the neighbors is useful as explanation of the output of the classifier is useful. Zeenathunisa et al [2] implemented an integrated approach towards recognizing the face under dim light conditions using preprocessing chain, Local Binary Pattern and K-Nearest Neighbor Classifier Zeenathunisa et al [3]implemented approach towards recognizing face in various dark illuminations they only consider medium intensity level as a good face recognition. Anila and Devarajan, et al [4] used preprocessing method is simple they concentrate for extended Yale-b dataset. In their proposed preprocessing steps if gamma correction has been applied to very low illumination level image of edges of the face cannot be identified.

III. CONCEPTUAL PREPROCESSING STEPS FOR FACE RECOGNITION

The proposed method combines the features of CLAHE contrast enhancement, LOG filtering and contrast equalization techniques. Over all stages of proposed preprocessing method is shown in Fig 1. The input image given to the image is preprocessed to remove the dimness and local shades by using the illumination normalization technique. Then the features from the normalized image are extracted by the agent using a gray-scale invariant texture measure called Local Binary Pattern. Then the extracted features are trained by the intelligent agent using the classifier k-Nearest Neighbor to get the identified image. Preprocessing stage of face recognition in various illumination is given below fig.1

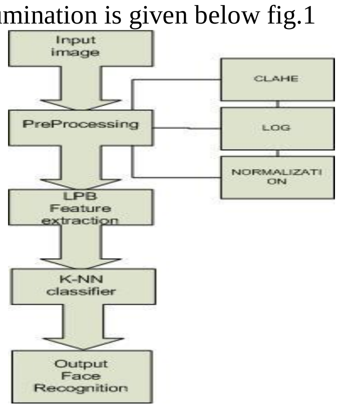


Fig.1 face recognition system steps

The face recognition in various illumination systems some sequential steps to identify a matcher from the existing data set. The procedure is as follows:

ALGORITHM

Step 1: Accept the image as an input.

Step 2: The preprocessing phase follows the following steps from 2.1 to 2.3 and repeat it for every given image to remove the darkness and obtain the brighter image.

Step 2.1: The gray-scale image is projected under CLAHE which removes the darkness from the image block by block window

Step 2.2: face-shaped edge from left lower jaw to right lower jaw can be detected using LOG

Step 2.3: The final step of the preprocessor is to apply equalization of normalization which rescales the image intensity, still preserving the required information of the input face image.

Step 3 : Apply Local Binary Pattern feature descriptor for the preprocessed image for feature extraction which stores the features in the form of feature vector.

Step 4: These feature vectors are trained with the k–NN recognizer to recognize the given image from the training data set.

Step 5: If the recognized image exists in the training set, then the recognizer identifies the image else does not identified.

Step 6: Repeat the steps from 1 to 5 for each and every input face image to find the matcher.

3.1 INPUT IMAGE

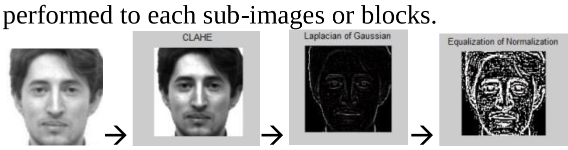
The Input Image for the preprocessor has the dimension 159 x 159 which has been taken from the Yale – B database. The images considered are subjected to different light variations. One input face image is projected to different illumination variations.

3.2 PREPROCESSING

The proposed method combines the features of CLAHE, LOG filtering and contrast equalization techniques. Over all stages of proposed preprocessing method is shown in Fig2

3.2.1 CLAHE (CONTRAST-LIMITED ADAPTIVE HISTOGRAM EQUALIZATION)

Histogram equalization is to get an image with uniformly distributed intensity levels over the whole intensity scale. Histogram equalization might produce the worse quality of result image than that of the original image since the histogram of the result image becomes approximately uniform. Large peaks in the histogram can be caused by uninteresting area. So, histogram equalization might lead to an increased visibility of unwanted image noises. This means that it does not adapt to local contrast requirement; minor contrast differences can be entirely missed when the number of pixels falling in a particular gray range is relatively small An adaptive method to avoid this drawback is block-based processing of histogram equalization. In this method, image is divided into sub-images or blocks, and histogram equalization is performed to each sub-images or blocks.



Gray scale

Fig 2. Image before and after preprocessing sample for proposed method

The CLAHE (Contrast-Limited Adaptive Histogram Equalization) [12] introduced clip limit to overcome the noise problem. The CLAHE limits the amplification by clipping the histogram at a predefined value before computing the CDF. The value at which the histogram is clipped, the so-called clip limit, depends on the normalization of the histogram and thereby on the size of the neighborhood region. The redistribution will push some bins over the clip limit again, resulting in an effective clip limit that is larger than the prescribed limit and the exact value of which depends on the image.

In this experiment, size of neighborhood region is set as fixed value as 8 x 8. This region is actually a window. Some experiment has been made and the window size gives good result and operates in quite short of time. The bigger size of window, the longer operation time consumed. Another parameter that needs to be set up is clip-limit value. An adaptive value of clip-limit has been set up in this experiment. This value is the entropy of grayscale input image. Image entropy becomes relatively low when histogram is distributed on narrow intensity region while image entropy becomes high when histogram is uniformly distributed. Therefore, the entropy of the histogram equalized image becomes higher than that of the original input image. Entropy of image is calculated by using [15]

$$H(x) = -\sum_{i=1}^{N} p(x_i)\ \log_2 p(x_i) \qquad \text{Formula 3.1}$$

As explained above that CLAHE works on a window with certain size that adaptively enhances contrast locally. It is different with gamma correction because the adjustment of contrast and brightness is applied directly to whole one image at one time.

3.2.2 LAPLACIAN OF GAUSSIAN (LOG)

Laplacian filters are derivative filters used to find areas of rapid change (edges) in images. Since derivative filters are very sensitive to noise, it is common to smooth the image (e.g., using a Gaussian filter) before applying the Laplacian. This two-step process is call the Laplacian of Gaussian (LoG) operation. Generally LoG is calculated by using single equation below:

$$LoG = -\frac{1}{\pi\sigma^4}\left[1 - \frac{x^2+y^2}{2\sigma^2}\right] e^{-\frac{x^2+y^2}{2\sigma^2}} \qquad \text{Formula 3.2}$$

In this experiment, we found that by using sigma value = 1, gives better result in recognition.
Laplacian is a second derivative of image or first derivative of Gaussian output. Laplacian is used as high pass filter meanwhile, Gaussian as part of LoG is used to smooth image to remove noise. Meanwhile, DoG works as high pass filter but in different way. Each Gaussian used has different value of Sigma. After applying both Gaussian filters to same image, then the difference is taken between both Gaussian results. The subtracted result becomes the final result of filtering. While using laplacian, we can get and emphasize edges of object in image.

3.2.3 EQUALIZATION OF NORMALIZATION:

The final stage of the preprocessing chain rescales the image intensities. It is important to use a robust estimator because the signal typically contains extreme values produced by highlights, small dark regions such as nostrils, garbage at the image borders, etc. One could use (for example) the median of the absolute value of the signal for this, but here a simpleand rapid approximation is preferred based on a two stage process as follows:

$$\mathrm{I(x,y)} \leftarrow \frac{i(x,y)}{(mean\left(\left(x',y'\right)|^{\alpha}\right))^{1}/_{\alpha}} \qquad \text{Formula 3.3}$$

$$\mathrm{I(x,y)} \leftarrow \frac{i(x,y)}{(mean\ (\min(\tau,|I\left(\left(x',y'\right)|^{\alpha}\right))^{1}/_{\alpha}} \qquad \text{Formula 3.4}$$

Here, α is a strongly compressive exponent that reduces the influence of large values, **t** is a threshold used to truncate large values after the first phase of normalization, and the mean is over the whole (unmasked part of the) image. By default we use α =0:1 t = 10[Tan and Triggs, 2010][6].

3.3 FEATURE EXTRACTOR

The well-known binaries features feature set robust to illumination variations is the Local Binary Patterns (LBP), which have been very effective for face recognition tasks and gives a great performance on standard face detection data sets [1]. Therefore, the intelligent agent uses this elegant technique LBP for feature extraction of its preprocessed images. In the year 2006, Ahonen et al [9] introduced Local Binary Pattern (LBP) features that the face image is divided into several blocks or regions from which the features are extracted and concatenated into an enhanced feature vector. This approach has been successfully utilized in face recognition and face detection. The Local Binary Pattern is a highly discriminative function and widely used in ordinary analysis of facial appearances. The proposed approach towards recognizing face under dim light condition is very robust since the local binary operator is subject to invariant against any monotonic transformation of the gray scale. Another additive advantage of this invariant operator is its computational efficiency towards identifying the features exactly. The LBP operator takes the local neighborhood which is threshold at the gray level value of the center pixel into a binary pattern. It is defined for 3 x 3 neighborhood giving 8–bit integer codes based on the eight pixels around the center pixel.

$$\mathrm{LBP} = (x_x, y_x) = \sum_{n=0}^{7} 2^n\ s(i_n - i_c) \qquad \text{Formula 3.5}$$

In this case, where **n** runs over the 8 neighbors of the central pixel **c,** $\mathbf{i_c}$ and $\mathbf{i_n}$ are respectively the grey-level values of **c** and n, and s(w) is 1 if w > 0 and 0 otherwise. LBP's are resistant to lighting effects in the sense that they are invariant to monotonic gray-level transformations, and they have been shown to have high discriminative power for texture classification [9]. However because they threshold exactly at ic, they tend to be sensitive to noise, es-specially in near-uniform image regions. The LBP encoding process is illustrated in Fig.3

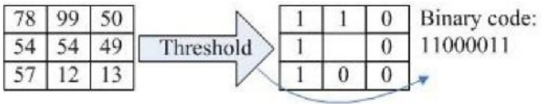


Fig.3 Illustration of the basic LBP operator

In [9], T. Ahonen et al. introduced an LBP based method for face recognition that divides the face into a regular grid of cells and histograms the uniform LBP's within each cell, finally using a nearest neighbor classifier over the x^2 histogram distance for recognition. Excellent results were reported on the FERET dataset [1]. Some recent advances in using LBP for face recognition are summarized in [2].

3.4 CLASSIFIER:

The classifier considered by the agent in this research work is k-Nearest Neighbor (k-NN) classifier which is a very intuitive method that classifies unlabeled features based on their similarity with features in their training sets. The k-NN algorithm measures the distance between the query face image and a set of images in the dataset. This is a method for classifying objects based on closest training examples in the feature space to determine the person's identity or to make the decision. It's a non-parametric lazy learning algorithm which is applied to classification tasks. Classification of nearest neighbor can be done by comparing feature vectors of the different points of the images. Using the weighted k-NN, where the weights by which each of the k nearest points' class is multiplied are proportional to the inverse of the distance between that point and the point for which the class is to be predicted also significantly improves the results. Rabbani et al [13] described that the simplest method for determining which face class provides the best description of an input face image is to find the face class k that minimizes the Euclidean distance. The Euclidean distance is the straight line distance between two pixels. Figure 6 represents the common illustration of the image pixels and its distance transform. the distance between the two pixels can be computed using some distance function *d(x, y)* where x, *y* are image pixels composed of N features, such that x = $\{x_h, x_2,...,x_N\}$ and$y$ = $\{y_h, y_2,...,y_N\}$.The distance function considered here is the Euclidean distance function:

$$d_E(\mathrm{x,y}) = \sum_{t=1}^{n} \sqrt{x_t^2 - y_t^2} \qquad \text{Formula 3.}$$

here the arithmetic mean across the dataset is considered to be 0 and the standard deviation σ(x) to be 1. Their corresponding functions can be described as follows:

$$\overline{x} = \frac{1}{N}\sum_{t=1}^{n} x_t \qquad \text{Formula 3.7}$$

$$\sigma\,(x)=\sqrt{\sum_{t=1}^{n}(x_t - \overline{x})^2} \qquad \text{Formula 3.8}$$

0	0	0
0	1	0
0	0	0

1.41	1.0	1.41
1.0	0.0	1.0
1.41	1.0	1.41

Image **Distance Transform**

Fig. 4 Illustration of Euclidean Distance

Using this distance measures which are used to identify the alikeness of different items in the database, the agent makes the classification. Once a similarity measure is defined, each feature to be classified will be compared to each predefined feature which is extracted using LBP technique. Whenever the classification is to be made for a new input face image, its distance to each feature in the training set must be determined. Only the k closest entries in the training set are considered for matching. Fig 5. Illustrates a process for k–NN classification and the three closest points for a center pixel in the training set are shown.

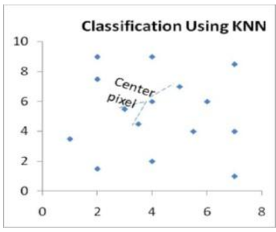


Fig 5. Classification of k-NN

IV. EXPERIMENTAL RESULT:

4.1 CALCULATING GAR AND FER:

In this experiment, we provide 150 images that consist of 45 images of lowest dimness, 45 images of medium dimness and 45 images of highest dimness. From 45 images of each subcategory, we tried to combine number of images for training and testing. The best result is when we use 6 images which consist of 1 image from each subcategories of each class. Class means varies of faces. In this experiment, we use 15 different faces or class.

GAR is calculated by using formula below:

$$\text{GAR (\%)} = \frac{\#Corrected\ \ Images}{\#Images\ \ in\ Training\ \ Dataset} \times 100$$

Formula 3.9

The experiment was started by examining face recognition method described in base paper for organized images testing and training. From 45 images for testing in each subcategory, we observed that recognition GAR for low is 95% with 2 false recognized, high is 57% with 19 false recognized and for medium is 93% with 3 false recognized. Fig 6. Below depicts comparison between GAR and FER of proposed method.

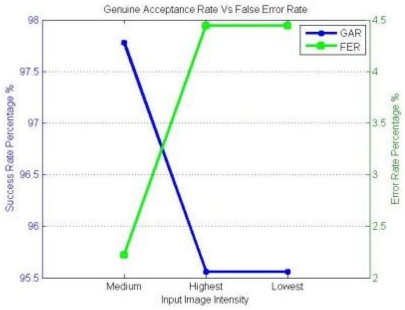


Fig.6 Proposed method Graph

V. Conclusion

A new technique of preprocessing has been proposed for face recognition in various illuminations. We got encouraging results. Also it does not need much computation time. It can be achieved by using a simple, efficient image preprocessing phase that recognition performance will be high when compared to the techniques where face recognition is performed with typical preprocessing. As a future vision, the most elegant LBP technique can be utilized for multi–view faces subjected under various illuminations for face recognition.

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