REAL-TIME FACE ATTENDANCE SYSTEM USING DEEP LEARNING

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Abstract: Face is the representation of one’s identity. Hence, we have proposed an automated student attendance system based on face recognition. Face recognition systems are useful in life applications, especially security control systems. The airport protection system uses face recognition to identify suspects and the FBI (Federal Bureau of Investigation) uses face recognition for criminal investigations. In our proposed approach, firstly, video framing is performed by activating the camera through a user-friendly interface. The face ROI is detected and segmented from the video frame using the Viola-Jones algorithm. In the pre-processing stage, scaling of the size of images is performed if necessary to prevent loss of information. The median filtering is applied to remove noise followed by conversion of colour images to grayscale images. After that, contrast-limited adaptive histogram equalization (CLAHE) is implemented on images to enhance the contrast of images. In the face recognition stage, enhanced local binary pattern (LBP) and principal component analysis (PCA) are applied correspondingly to extract the features from facial images.

I. PROJECT INTRODUCTION

The main objective of this project is to develop a face recognition-based automated student attendance system. To achieve better performance, this proposed approach's test images and training images are limited to frontal and upright facial images that consist of a single face only. The test images and training images have to be captured by using the same device to ensure no quality difference. In addition, the students have to register in the database to be recognized. The enrolment can be done on the spot through the user-friendly interface.

II. PROBLEM STATEMENT

Traditional student attendance marking techniques is often facing a lot of trouble. The face recognition student attendance system emphasizes its simplicity by eliminating classical student attendance marking techniques such as calling student names or checking respective identification cards. There are not only disturbing the teaching process but also causes distraction for students during exam sessions. Apart from calling names, attendance sheet is passed around the classroom during the lecture sessions. The lecture class especially the class with a large number of students might find it difficult to have the attendance sheet being passed around the class. Thus, face recognition student attendance system is proposed in order to replace the manual signing of the presence of students which are burdensome and causes students get distracted in order to sign for their attendance. Furthermore, the face recognition based automated student attendance system able to overcome the problem of fraudulent approach and lecturers does not have to count the number of students several times to ensure the presence of the students. The paper proposed by Zhao, W et al. (2003) has listed the difficulties of facial identification. One of the difficulties of facial identification is the identification between known and unknown images. In addition, paper proposed by Pooja G.R et al. (2010) found out that the training process for the face recognition student attendance system is slow and time-
consuming. In addition, the paper proposed by Priyanka Wagh et al. (2015) mentioned that different lighting and head poses are often the problems that could degrade the performance of face recognition-based student attendance system.

III. AIMS AND OBJECTIVES
The objective of this project is to develop face recognition based automated student attendance system. Expected achievements in order to fulfill the objectives are:

- To detect the face segment from the video frame.
- To extract the useful features from the face detected.
- To classify the features in order to recognize the face detected.
- To record the attendance of the identified student.

IV. METHODOLOGY FLOW
The approach performs face recognition based student attendance system. The methodology flow begins with the capture of image by using simple and handy interface, followed by pre-processing of the captured facial images, then feature extraction from the facial images, subjective selection and lastly classification of the facial images to be recognized. Both LBP and PCA feature extraction methods are studied in detail and computed in this proposed approach in order to make comparisons. LBP is enhanced in this approach to reduce the illumination effect. An algorithm to combine enhanced LBP and PCA is also designed for subjective selection in order to increase the accuracy. The details of each stage will be discussed in the following sections.

The flow chart for the proposed system is categorized into two parts, first training of images followed by testing images (recognize the unknown input image) shown in Figure 3.1 and Figure 3.2 respectively.

3.2 Input Images
Although our own database should be used to design real time face recognition student attendance system, the databases that are provided by the previous researchers are also used to design the system more effectively, efficiently and for evaluation purposes.

Yale face database is used as both training set and testing set to evaluate the performance. Yale face database contains one hundred and sixty-five grayscale images of fifteen individuals. There are eleven images per individual; each image of the individual is in different condition. The conditions included centre-light, with glasses, happy, left-light, without glasses, normal, right-light, sad, sleepy, surprised and wink. These different variations provided by the database is able to ensure the system to be operated consistently in variety of situations and conditions.

VII. FACE DETECTION
Viola-Jones object detection framework will be used to detect the face from the video camera recording frame. The working principle of Viola-Jones algorithm is mentioned in Chapter 2. The limitation of the Viola-Jones framework is that the facial image has to be a frontal upright image, the face of the individual must point towards the camera in a video frame.

Pre-Processing
Testing set and training set images are captured using a camera. There are unwanted noise and uneven lighting exists in the images. Therefore, several preprocessing steps are necessary before proceeding to feature extraction.

Pre-processing steps that would be carried out include scaling of image, median filtering, conversion of colour images to grayscale images and adaptive histogram equalization. The details of these steps would be discussed in the later sections.

Scaling of Image
Scaling of images is one of the frequent tasks in image processing. The size of the images has to be carefully manipulated to prevent loss of spatial information. (Gonzalez, R. C., & Woods, 2008). In order to perform face recognition, the size of the image has to be equalized. This has become crucial, especially in the feature extraction process, the test images and training images have to be in the same size and dimension to ensure the precise outcome. Thus, in this proposed approach test images and train images are standardized at size 250 × 250 pixels.
Median Filtering
Median filtering is a robust noise reduction method. It is widely used in various applications due to its capability to remove unwanted noise as well as retaining useful detail in images. Since the colour images captured by using a camera are RGB images, median filtering is done on three different channels of the image. Figure 3.3 shows the image before and after noise removal by median filtering in three channels. If the input image is a grayscale image, then the median filtering can be performed directly without separating the channels.

Conversion to Grayscale Image
Camera captures color images, however the proposed contrast improvement method CLAHE can only be performed on grayscale images. After improving the contrast, the illumination effect of the images able to be reduced. LBP extracts the grayscale features from the contrast improved images as 8 bit texture descriptor (Ojala, T. et al., 2002). Therefore, color images have to be converted to grayscale images before proceeding to the later steps. By converting color images to grayscale images, the complexity of the computation can be reduced resulting in higher speed of computation (Kanan and Cottrell, 2012). Figure 3.4 shows the conversion of images to grayscale image.

Contrast Limited Adaptive Histogram Equalization
Histogram equalization or histogram stretching is a technique of image contrast enhancement. (Pratiksha M. Patel, 2016). The contrast improvement is usually performed on the grayscale images. Image contrast is improved by stretching the range of its pixel intensity values to span over the desired range of values, between 0 and 255 in grayscale. The reason that Contrast Limited Adaptive Histogram Equalization (CLAHE) is used instead of histogram equalization is because histogram equalization depends on the global statistics. Hence, it causes over enhancement of some parts of image while other parts are not enhanced properly. This distorts the features of the image. It is a serious issue because the features of the image have to be extracted for the face recognition. Thus, CLAHE which is depend on local statistic is used. The result of CLAHE will be discussed in Chapter 4.

Feature Extraction
Different facial images mean there are changes in textural or geometric information. In order to perform face recognition, these features have to be extracted from the facial images and classified appropriately. In this project, enhanced LBP and PCA are used for face recognition. The idea comes from nature of human visual perception which performs face recognition depending on the local statistic and global statistic features. Enhanced LBP extracts the local grayscale features by performing feature extraction on a small region throughout the entire image. On the other hand, PCA extracts the global grayscale features which means feature extraction is performed on the whole image.

Working Principle of Original LBP
LBP is basically a texture based descriptor which it encoded local primitive into binary string. (Timo Ojala et al., 2002). The original LBP operator works on a 3 × 3 mask size. 3 × 3 mask size contains 9 pixels. The center pixel will be used as a threshold to convert the neighboring pixels (the other 8 pixels) into binary digit. If the neighboring pixel value is larger than the center pixel value, then it is assigned to 1, otherwise it is assigned to 0. After that, the neighborhoods pixel bits are concatenated to a binary code to form a byte value representing the center pixel.
where \( P_c \) indicates centre pixel and \( P_n (n = 0,\ldots, 7) \) are 8 of its neighbouring pixels respectively. The starting point of the encoding process can be any of neighbouring pixels as long as the formation of binary string is following the order either in clockwise or anticlockwise rotation. The thresholding function \( f(y) \) can be written as follows.

3.4.2 Working Principle of Proposed LBP

The original LBP operator is composed of \( 3 \times 3 \) filter size with 9 pixels. Instead of the circular pattern, it looks more rectangular in shape. The 9 pixels adjacent to each other means every detail will be taken as sampling points even the non-essential details. It is more affected by uneven lighting condition because the small filter size emphasizes small scale detail (Lee and Li, 2007), even the shadow created by non-uniform lighting condition. In our proposed approach, a larger radius size, \( R \) is implemented in LBP operator. In the paper of Md. Abdur Rahim et al. (2013), the equation of modifying the radius size has been introduced. However, the paper did not mention the effect of changing the radius size. In the proposed approach, analysis is done on different radius sizes in order to enhance the system and reduce the illumination effect. By increasing the radius size, the filter size will be increased. \( R \) indicates radius from the centre pixel, \( \theta \) indicates the angle of the sampling point with respect to the center pixel and \( P \) indicates number of sampling points on the edge of the circle taken to compare with the centre pixel. Given the neighbouring’s notation \( (P, R, \theta) \) is implemented, the coordinates of the centre pixel \((X_c, Y_c)\) and the coordinates of the \( P \) neighbours \((X_p, Y_p)\) on the edge of the circle with radius \( R \) can be computed with the sines and cosines shown in the equation (Md. Abdur Rahim et al., 2013):

\[
X_p = X_c + R \cos(\theta/P) \\
Y_p = Y_c + R \sin(\theta/P)
\]

Although the radius has been increased, total 8 sampling points are taken which is similar to the original LBP operator. In the approach, CLAHE is performed on the grayscale input facial images to improve the contrast. The contrast improved images remain as grayscale images. The proposed LBP operator extracts the grayscale features from the contrast improved grayscale images which requires only 8 bit computation. After that, the pixels at the sampling points will be encoded as 8 bit binary string in the same way as original LBP operator encoding process. Enhanced LBP with radius size two, perform better compared to original LBP and has more consistent recognition rate compared to other radius size. Hence, enhanced LBP with radius size two will be used as proposed approach. The proposed LBP operator will be further explained in Chapter 4 (result and discussion).

Basically, the increasing in the size of the radius means extending the circular pattern of LBP externally. The green spots within the blocks indicate the sampling pixels to be encoded into binary string. For the sampling pixel located in between the blocks, it indicates the average pixel value is computed from the adjacent pixels (diagonal).

The feature vector of the image is constructed after the Local Binary Pattern of every pixel is calculated. The histogram of the feature vector image is computed in order to be classified by distance classifier. However, it loss spatial information because histogram representation does not include spatial information but only discrete information. (Gonzalez, R. C., & Woods, 2008). In order to overcome this problem, the feature vector image is then divided into blocks. A histogram is constructed in each region respectively. Every bin in a histogram represents a pattern and contains the frequency of its appearance in the region. The feature vector of entire image is then constructed by concatenating the regional histograms in the sequence to one histogram. (Md. Abdur Rahim et al., 2013). This histogram remains its regional spatial information and represents the identity of single image which is then classified to perform the recognition.
Working Principle of PCA
In this proposed approach, PCA face recognition is studied, as it is one of the popular face recognition methods that was suggested and used by the previous researchers. The accuracy of PCA is computed in order to compare with the enhanced LBP.
PCA includes a few steps which will briefly be described in the following paragraphs. For PCA, the image scale, length (M) and height (M) is not so important. This is because PCA is mostly dealing with number of total images, N instead of M. However, same size of test image and training image is a must for PCA computation. Same length and height of the image is assumed in the following equation for illustration. Given a training set of N images with size \( M \times M \), the first step of PCA is to convert two dimensional vectors to one dimensional vector. The one dimensional vector can be either column vector or row vector. In this approach, the column vector conversion is done. For each facial image with matrix notation \( M \times M \) will be converted to column vector \( \Gamma_i \), with dimension \( M \times 1 \). There are N facial images, each face is represented by column vector \( \Gamma_1, \Gamma_2, \Gamma_3, \ldots, \Gamma_N \). Feature vector of each face is stored in this column vector. The dimension reduced face matrix is constructed by concatenating every single column vector.

Step 2: Obtain the mean/average face vector
Next, the average face vector which is also known as mean face is calculated. The mean is computed row by row between the column vectors.

Step 3: Subtract the mean/average face vector
In order to ensure the image data is centred at the origin, the mean face is subtracted from each column vector.

Step 4: Calculate the covariance matrix
\( A = [\Phi_1 \Phi_2 \cdots \Phi_N] \), \( (M \times N) \)
where \( A \) is the matrix constructed from the concatenation of the column vectors after remove the mean face.

The purpose of covariance matrix to be constructed is to compute the eigenvectors and eigenvalues. However, \( AA^T \) have dimension \( M \times M \) which is extremely large to be calculated. \( AA^T \), and \( A^TA \) have the same eigenvalues, \( \lambda \) and their eigenvectors can be related as \( u_i = A v_i \). Hence \( A^TA \) which have dimension \( N \times N \) is calculated instead of \( AA^T \) because \( N \ll M \), less computational time is required.

Step 5: Calculate the eigenvectors and eigenvalues from the covariance matrix.
\( u_i = A v_i \quad i = 1, 2, \ldots, N-1 \)
\( u_i \) is the eigenvector of \( AA^T \) whereas \( v_i \) is eigenvector of \( A^TA \). Eigenvalues of \( A^TA \), are calculated and sorted. Eigenvalues less than 1 are eliminated so the number of non-zero eigenvectors may be less than \( N-1 \). (Kalyan Sourav Dash, 2014). The eigenvectors of \( AA^T \), \( U = [u_1 \cdots u_N] \) is also known as Eigen face.

The facial image is projected on the Eigen face by using the equation to obtain the projected image \( \Omega. \) \( \Gamma_i - \varphi \) is the centered vector, which the mean face is removed.

Steps 1 to 6 are used to train the training image set. For test image only step 1, 2, 3 and 6 is required. Step 4 and 5 are not required for test image as the Eigen face is needed only to compute once while training. The Euclidean distance is then used as distance classifier to calculate the shortest distance between the projected image and projected test image for recognition.

3.4.4 Feature Classification

Chi-square statistic is used as a dissimilarity measure for LBP to determine the shortest distance between training image and the testing image. On the other hand, Euclidean distance is used to compute the shortest distance between trained and test image after PCA feature extraction. Both classifiers, Chi-square statistic and Euclidean distance determine the closest or nearest possible training image to the testing image for face recognition. However, the nearest result might not be always true. Therefore, an algorithm to combine enhanced LBP and PCA is applied in order to increase the accuracy of the system.

3.4.5 Subjective Selection Algorithm and Face Recognition

The feature classification that has been performed in previous part gives the closest result but not absolute. In order to increase the accuracy and suppress the false recognition rate, an algorithm to combine enhanced LBP and PCA is designed in this proposed approach.

In this proposed approach, best five results are obtained from enhanced LBP and PCA. This means that five individuals which have closest distance with respect to input image will be identified. LBP and PCA are two different algorithms which have a different working principle. Hence, LBP and PCA will not have exactly the same five individuals identified. In order to ensure the system capability to suppress the false recognition, one is only classified as recognized if and only if he or she is the first common individual that is identified by both LBP and PCA. From chapter 2, LBP shows higher accuracy compared to PCA. Thus, LBP is designed to have higher priority compared to PCA. This is shown in the Figure 3.14, Student_1 is recognized instead of Student_3 because LBP is prioritized. As a result, the first common individual is selected from PCA with respect to LBP and classified as recognized. If there is no common term between LBP and PCA then the system will not recognize any subject. This subjective selection algorithm is designed to be automated in the system.

VIII. RESULT

In this proposed approach, face recognition student attendance system with user-friendly interface is designed by using MATLAB GUI (Graphic User Interface). A few buttons are designed in the interface, each provides specific function, for example, start button is to initialize the camera and to perform face recognition automatically according to the face detected, register button allows enrolment or registrations of students and update button is to train the latest images that have been registered in the database. Lastly, browse button and recognize button is to browse facial images from selected database and recognized the selected image to test the functionality of the system respectively.

IX. REFERENCES


