Face recognition system for uncontrolled environment

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***Abstract*: Biometrics is a technique for identifying and authenticating a person based on a set of recognized and verifiable data that is unique and distinctive to that person. As a result, it recognizes the individual based on both global and local characteristics. Because many identity methods, such as password/PIN systems and token systems, have problems with counterfeiting, theft, and lapses in human memory, biometric identification systems have been developed as a response. The identifying mechanism in these biometric identification systems is based on physiological features. For recognition, the Principle Component Analysis (PCA) and Linear Discriminant Analysis (LDA) algorithms use global features and Elastic Bunch Graph Matching (EBGM) recognizes images based on a similarity function between the given images and the graph that has been generated. In the Local Binary Pattern (LBP) approach, the image of the face is first split into smaller components, from which LBP retrieved features are fused into a feature space histogram that effectively describes the facial image. Face recognition will face issues such as facial variation, illumination from a range of light sources, image aging, occlusion, and so on. In order to solve most of the issues, a new method using the LBP Contrast Adjustment, Bilateral Filter, and Histogram Equalization were proposed as part of the algorithm. Experiments are carried out on both standard and real data sets to show that the suggested technique outperforms previously proposed algorithms.**

***Index Terms*: Pattern Recognition, Local Binary Pattern, Feature Extraction, Histogram, Face Recognition, Local Ternary Pattern.**

I. INTRODUCTION

Biometric systems initially collect the sample of the feature for face identification. Then it is translated into a biometric template using a mathematical formula. The biometric template will represent the feature in a normalized, efficient, and highly discriminating manner to authenticate identity by comparing it to other templates. The biometrics systems have two operational modes: enrollment and identification. The better performance of the biometric is described by the use of a feature that is highly distinctive, stable, and easy to record thereby avoid the misrepresentation. One of the hardest issues for a face recognition system is comparing two faces with varying illumination. A little adjustment in lighting conditions, has always been known to have an impact on the outcomes. If the same individual is captured with the same sensor and has a virtually identical facial expression and attitude, the images can fluctuate dramatically depending on the illumination. The identification procedure in biometric identification systems is based on physiological features.

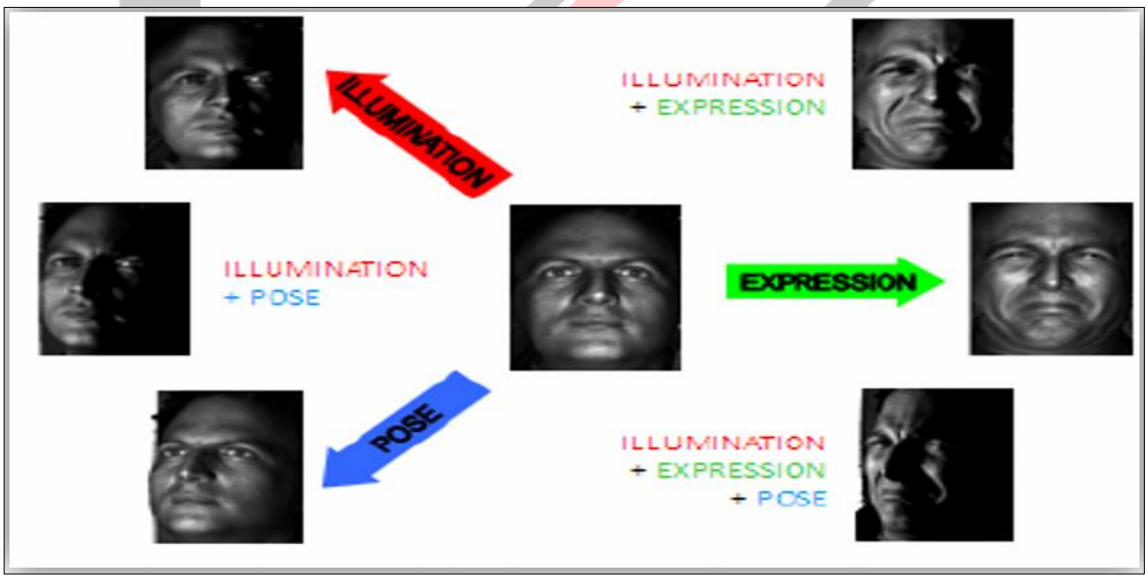

Fig. 1.1 Example for Challenges in Face recognition system

The LBP method's performance is dependent on the feature extraction, also dependent on the quality of images used in the face training and testing phase. The bulk of facial recognition systems have been used in situations when participants make cooperative presentations to a camera, such as part of a benefit or ID credential application or during access control. Face masks or other occlusions would not be present in such photos, with a few exceptions. With the SARS-CoV-2 pandemic, however, one should expect a demand for people wearing masks to be authenticated. For instance, in immigration scenarios where the subjects are not required

to remove their masks. Then the recognition process is complicated because mask-obscured mouth and nose areas, contain information relevant for both recognition and, perhaps, the detection stage that precedes it. Previous work on occluded face recognition has focused on scenarios such as crime scenes where participants were intentionally uncooperative, i.e. acting to avoid face detection and recognition. Image features (poor resolution, video compression, uncontrolled head orientation) are common in these applications, which are known to decrease the accuracy. The DCT (Discrete Cosine Transform) algorithm, in particular, appears to be particularly efficient, allowing for the concentration of information, reducing the problem's dimensionality, and granting faster and better results than alternative classic methods, such as eigen faces, especially when combined with an RBF neural network classifier [1].

Finding effective descriptors that can overcome substantial fluctuations in illumination, position, facial expression, ageing, partial occlusions, and other alterations is one of the most difficult process in face identification. Face recognition in varying lighting conditions is a difficult problem to solve. The goal of this method is to create and develop a reliable Face recognition system that can recognize a person's face in a variety of lighting conditions and environments. There was a need to build a new strategy for face identification after examining various ways. This new approach can deliver better results by exploiting texture information, which improves image quality. The LBP method is utilized to partially tackle the problem in this project. Because LBP alone is insufficient to detect an image with issues such as illumination and expression variation, ILBP is implemented, which enhances LBP with a series of image preprocessing and equalization algorithms. The proposed framework's performance is assessed by comparing the performance of an existing face recognition system to that of the new system. The following are some of the challenges associated during facial recognition (Fig 1.1):

Pose Variations: Face recognition systems are sensitive to changes in posture. Changes in face appearance caused by head motions or different camera POVs inevitably produce intraclass variances, lowering automated face recognition rates dramatically. When the rotation angle is increased, identifying the true face becomes more difficult.
Expressions: Facial expressions are usually altered by a variety of moods, emotions and expressions. Happiness, sadness, rage, disgust, fear, and surprise, are examples of human expressions.
Illumination: Light fluctuations are referred to as illumination. Variation in the lighting conditions poses a substantial difficulty for recognition. The appearance of the face is radically altered by illumination.

II. Literature Review

An overview of the primary human face recognition method is presented in the literature survey section, which is mostly applied to frontal faces. The benefits and drawbacks of each strategy are also briefly discussed here. Linear LBP, Linear blending technology, Geometrical feature matching, and Template matching are the methodologies studied [2]. The techniques are evaluated based on the facial representations they employ. The face image is a multi-dimensional structure that includes emotion, feeling, and facial characteristics. Although many advances have been achieved in the development of facial recognition methods, some fundamental difficulties connected with these methods must be greatly minimized or solved in order to achieve human-level facial recognition accuracy. In order to create a dependable and accurate automatic attendance management system based on facial recognition, which can be particularly valuable in the area of substantiation. Lighting conditions, scale, occlusion, position, background, emotion, and other factors all play a role in successful face detection and recognition systems. To overcome these issues, a variety of techniques and strategies have been presented.

The following are some of the methodologies on face recognition that have been investigated:

Face recognition methods authorize a person by identification or verification process using the facial images stored in a database. Generally, the two dimensional (2D) face recognition algorithms are categorized into holistic methods, feature-based, template-based, part-based and hybrid methods. Holistic methods use the entire face region as raw input with its statistical moments. Some of the holistic methods are PCA – Eigen faces [3], Independent Component Analysis (ICA) [4], Laplacian faces and nonlinear dimension reduction [5], Linear Discriminative Analysis (LDA) – Fisher faces [6] and sparse representation [7]. Feature-based methods use the local features like eyes, nose and mouth. Their location and related statistics geometry are used as classifiers. Few feature based methods are gabor wavelet features with elastic graph matching [8] and binary features using Local Binary Pattern (LBP) histograms [19][10]. Template based methods are template-matching methods. For every person a template is created and during identification/verification the similarity score is computed between the test and stored images. The highest similarity score is used to find the matching person. Few templates based algorithms are developed using Active Shape Model (ASM) [11] and Active Appearance Model (AAM) [12]. Part based methods are in contrast with the feature based methods, extract the facial features individually and combine them for face recognition process. Component-based face recognition [13] and scale-invariant feature transform (SIFT) [14] are part based methods.

The multi-label feature extraction approach has traditionally been used to extract local features of blur images under poor lighting conditions. The extraction efficiency is low and the computational complexity is exceedingly high. As a result, under complex illumination conditions, a local feature intelligent extraction approach is proposed. These images are clustered and segmented using segmentation technique based on local fuzzy C-means clustering. The wavelet transforms and LBP log domain feature extraction algorithms can also be used to recognize images [15]. The features extracted by LDP (Local Directional Pattern) and the features retrieved by CBP (Centralized Binary Pattern) are fused after feature extraction to improve feature discrimination. Furthermore, the k-nearest neighbor pre-classification is used in the classification and recognition, also the regional energy calculated by HOSVD (Higher-Order Singular Value Decomposition) is used to compare two images to see how similar they are [16]. Most of the LBP

algorithms neglect the spatial contextual information between them. So, the 2D-LBP approach for obtaining spatial contextual information that uses a sliding window to calculate rotation invariant uniform LBP pattern pairings. Finally, by integrating the predictions on each 2D-LBP with single resolution, a two-stage classifier that works as an ensemble learning step is used to produce an accurate classification [17]. A face identification method based on histograms of oriented gradients (HOG) is utilized to effectively describe facial features in complex situations. The HOG characteristics are extracted when the facial image is partitioned into several dense grids. The feature expression of the entire face is then realized by composing all of the grid HOG feature vectors, and the closest neighbor classifier is employed for recognition [18]. Along with Local binary pattern, Zernike moments features are also used for recognizing the faces, which gives better accuracy [19]. Robust illumination normalization, local texture-based face representations, distance transform based matching, kernel-based feature extraction, and multiple feature fusion are all used to solve the problem of uncontrolled illumination. A simple and efficient pre-processing chain is used to remove the majority of the impacts of changing illumination while maintaining the basic appearance features required for recognition. Also introduces the impact of local ternary patterns (LTP), a generalization of the local binary pattern (LBP) [20].

III. METHODOLOGY

The LBP texture operator calculates pixel value in the image by thresholding each pixel's. The LBP method separates the face picture into spatial arrays initially. Following that, a 3X3 pixel matrix is mapped over each array square. To generate the binary code, the central is used as a threshold and pixel if it is less than the threshold, it is given a zero; otherwise, it is given a one. Finally, a histogram of these codes is constructed for each array square, and the histograms are concatenated to generate the feature vector.

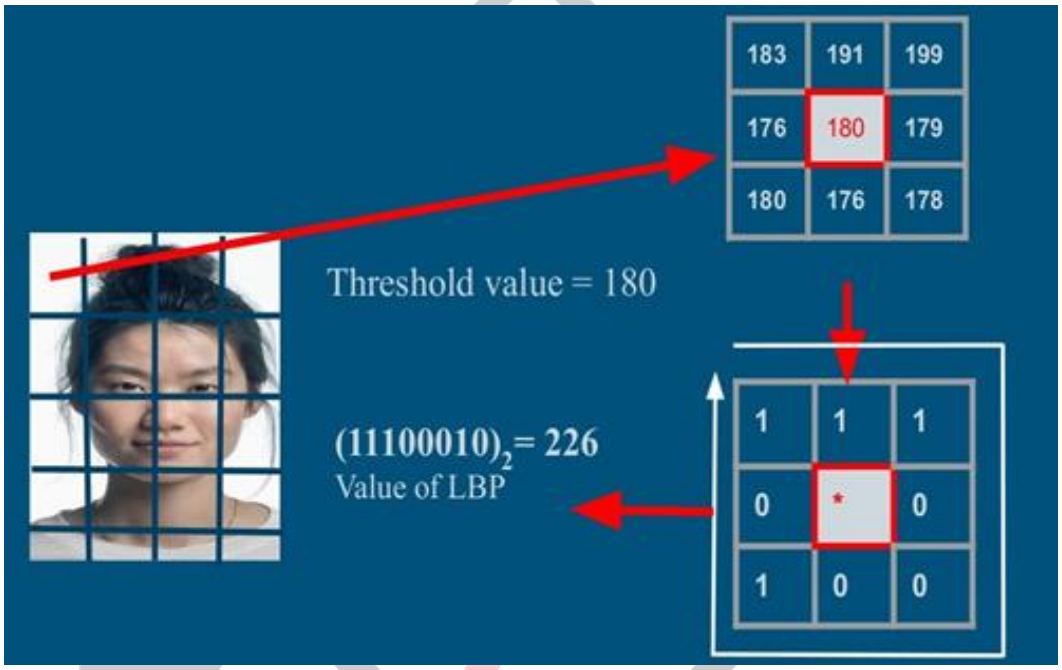

Fig. 3.1 LBP operator

Proposed System

Images of the highest quality that expose more details, allowing for the best feature extraction and thus superior outcomes. Proposed method of Improved LBP (ILBP) uses contrast adjustment, bilateral filter, histogram equalization steps and then LBP method is used to get the better result [21]. The Contrast Adjustment method, as specified in equation (1), is our initial step to improving our input face images. Then, using several values of a and b, test this method to find the best results (1.5 and 0.0).

$$g(i, j) = a * f(i,j) + b \quad (1)$$

$$FL(i,j) = (\Sigma_i \Sigma_j (P(i,j)W(i,j))/ (\Sigma_i \Sigma_j W(i,j)) \quad (2)$$

(Where i and j varies from –N to N)

$$NC(i,j) = g(i,j) * FL(i,j) \quad (3)$$

$$HEQ = NCD(NC(i, j)) \quad (4)$$

$$LBP_{p,r} (x_c, y_c) = \Sigma_n(2^n SN(i_n, i_c) \quad (5)$$

(Where n varies from 0 to p-1)

$$SN(z) = t \qquad (6)$$

(Where t is **0** if z<0 else it is **1**)

where f(i, j) - input image,
g(i,j) - contrasted image,
W(i,j) - filter weighting function,
P(i,j) - neighborhood pixel of the input image,
FL(i,j) - outcome of a bilateral filter,
NC(i,j) - function to minimize noise
NCD - normalized cumulative distribution
HEQ - Histogram Equalization,
LBP - Local Binary Pattern,
SN - Sign Function

Then use bilateral filter as given in the equation-2. To minimize noise and control contrast effects in the input images use the equation-3. The above resultant images are equalized using the image histogram equalization approach specified in equation-4. As illustrated in Fig. 3.1, the LBP method uses a 3 X 3 neighborhood window for processing. The equation-5 is used to extract LBP features. The sign function in equation-6 is used to threshold the 3 X 3 neighborhood. The optimal LBP result can be obtained by altering the image quality using equations 1 to 5. Noise, lighting, sharpness, and resolution concerns were much reduced when each window of the 3X3 neighboring pixels of the output images from equations 4 and 5 was examined. Using equation 5, with the proposed method, it is possible to obtain improved high quality images, which will enhance overall face recognition accuracy.

IV. EXPERIMENTAL RESULTS

Testing is performed using the ORL and Real Datasets. The proposed approach ILBP method is compared to the LBP method for efficiency. The ORL face dataset is a collection of 400 images made up of 10 samples of 40 different people shot at different times with different lighting, facial expressions like open or closed eyes, and facial characteristics like spectacles or no glasses. Real data set consists of 300 images made up of 10 samples of 30 different individuals.

Fig. 4.1 Example for ORL Dataset

Table 4.1: Results of two feature extraction technique (LBP and ILBP)

Method	Database	Testing			
		1	*2*	*3*	*4*
LBP	***ORL***	89.00	90.50	91.50	91.00
	Real	85.00	90.00	89.50	90.00
ILBP	***ORL***	90.50	92.00	93.50	93.50
	Real	87.50	89.50	92.00	91.50

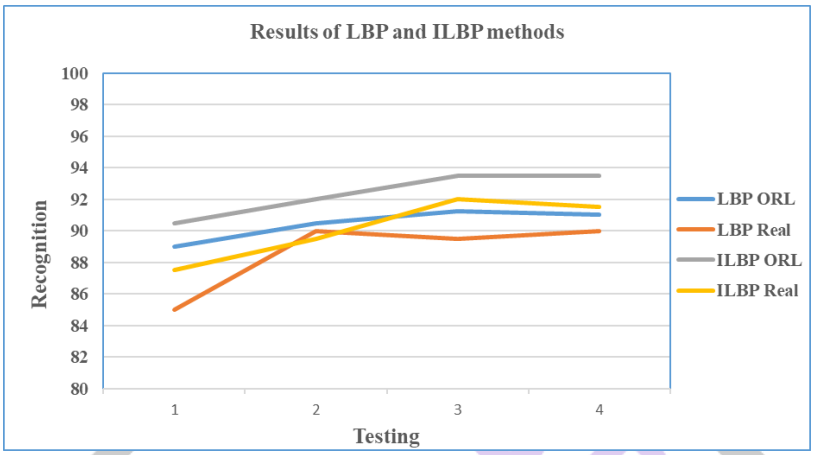

Fig. 4.2 Comparison of LBP and ILBP methods

Experimental setup on ORL Dataset

For the individual in the dataset, the first to fourth samples are considered for the training, and fifth to tenth samples are for testing in the 1st setup. Similarly, three other random combinations of the training and testing setups are made. Table 4.1 shows the ORL dataset's recognition rate using LBP and ILBP. From figure 4.2 it is clear that ILBP outperforms the LBP method on ORL dataset.

Experimental setup on Real Dataset

Ten images of each of the 30 person are taken in .jpg format. For the individual in the dataset, first to fourth samples are considered for the training, and fifth to tenth samples are for testing in the 1st setup. Similarly, three other random combinations of the training and testing setups are made out of real dataset. Table 4.1 also shows the Real dataset's aggregated recognition rate using LBP and ILBP. Figure 4.2 also shows the ILBP results are better than LBP on Real dataset.

V. Conclusion

Face recognition can be used for airport security, passport verification, criminals list verification at police departments, Visa processing, voter identification verification, and ATM card security. The proposed method uses MATLAB/Python for feature extraction and matching utilizing Euclidean distance in ILBP-based face recognition. According to the comparison, the recognition rate of LBP for the ORL database is 91.50%, whereas the recognition rate of ILBP for the ORL dataset is 93.50% also for Real dataset 90.00% and 92.00% on LBP and ILBP respectively. Many hardware-based, software-based, neural network-based, and other designs have been used to achieve optimum results. Some have been shown to be superior to some existing systems, but none has been deemed the greatest to date. The efforts in the research community will continue until a thorough answer to the problem at hand is found. Face recognition software must be able to recognize a person's face in a variety of imaging scenarios. It will find faces quickly and efficiently without having to search the entire image. Face recognition systems are expected to be widely used in smart environments. When using face masks or other obscured environments, the application is unable to distinguish faces. In this scenario, there is also no dataset of “with mask” images. Another issue that arises during recognition is that the system fails to recognize the test face when the image orientation is too far to the left or right. Recognition of the face a system with mask is a future technology.

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