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Deep Learning for Face Recognition under Complex Illumination Conditions Based on Log-Gabor and LBP

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Abstract: The complex light conditions, and this is one of the most important and difficult problems in practical face recognition, in this paper, we propose a new deep learning-based method to solve the problem of the effect of the light of the changes in the facial recognition process. First, the primary treatment of the lighting can be used to improve the negative effects of intensive changes in the lighting of a photo of a face, and for a second, the Log-Gabor filters in order to get the images used in the Log-Gabor features at different scales and in different directions, and then, the LBP (Local Binary Pattern) features on the image subblock is obtained. Finally, the histogram of the texture of the features of the formation and the visual layer of the deep belief network (DBN) to drop, and then the classification and the recognition is done with a deep-learning-DBN. The experimental results show that superior performance can be obtained in the application of the strategy in comparison to some of the modern technology.
Keywords: complex illumination, Log-Gabor filter, LBP features, deep learning.

I. INRODUCTION

Face recognition (FR) can be defined as distinguishing known or unknown faces, after comparing it to known people stored in a database. Facial Expression Recognition (FER) is a computer program that automatically detects or confirms people's emotions displayed on their face from a digital photo or video frame from a video source by comparing it to a database. Facial recognition uses different facial features such as different subcutaneous items such as: Nose, Eye, Bones, Chin, Lips, Forehead, Eye distance, nose length, and jaw angle raises the type of expression. Like anger, disgust, fear, happiness, neutrality, sadness, surprise.

II. IMPLEMENTATION

A. Gabor Wavelets (GWS)

Facial features can be used to identify and identify individual features. In this project, a recognition process is proposed based on the Gabor Wavelet (GW) where GW is used to remove a human face. The face recognition system consists of four (4) main stages namely pre-processing of the image, feature extraction, matching process and partitioning process. In the feature release phase, the input images are converted to a Gray image before using 2D GWs. Paid feature vectors are used to test points such as facial feature carriers in the database. Square-chi is used to measure the distance in the simulation phase where it compares between the feature vectors found in the input image and that in the database. If the range value is below the pre-set threshold, the face image is classified as a valid user and will be given access to the system. We are also investigating the effect of a change in light on the proposed identification algorithm. The results produced in this study indicate that the effectiveness of this process is greatly affected by the light change. This suggests that the use of GW only to remove the feature will not provide a robust facial recognition system in changing the brightness. It is suggested that GW in conjunction with another feature removal process could address this issue. The best way to extract a feature is a binary location pattern (LBP) as it is able to output a local image feature and GW renders a global feature. It is expected that the GW-LBP hybrid will improve the performance of the face recognition algorithm.

B. LBP

Automatic face recognition has been an important area of biometric authentication and verification system for a variety of systems including crime detection, access control, video surveillance, tracking service and other related sites. Methods / Mathematical Analysis: In this study, we introduced the Gray Level Co-occurrence Matrix (GLCM) over Local Binary Patterns (LBP) called GOL for surface layout. These tests were performed on the AT&T Cambridge Laboratory face images also known as (ORL face) and Georgia Tech (GT-face) data details respectively. Findings: We performed a comparative analysis of the GLCM and LBP method separately and the results showed that the proposed GOL method passes in terms of average sensitivity, median specificity, and recovery time. These findings reflect the effectiveness of our proposed system.

III. METHODOLOGY

A. GWT

1) Photo and face detection At the beginning of the process, the image of the input face needs to be detected. From the input, the surface interest (ROI) of the face will be extracted.
2) Feature removal To start this process, the input image image must be converted to a gray image using rgb2gray (RGB). At this stage, the facial feature release will use 2D GWs to work to be displayed as power values at different levels and shapes. The final result vector of the features will use the following procedure.
3) Photo and Face Detection This last step to verify someone else's identity in the database is the same as at the moment. To achieve this result, a Chi-square metric method is required to calculate the distance between feature vectors found in the input image image and database. If the scorer complies with the lower limit, it means that the person has the same identity as the database.

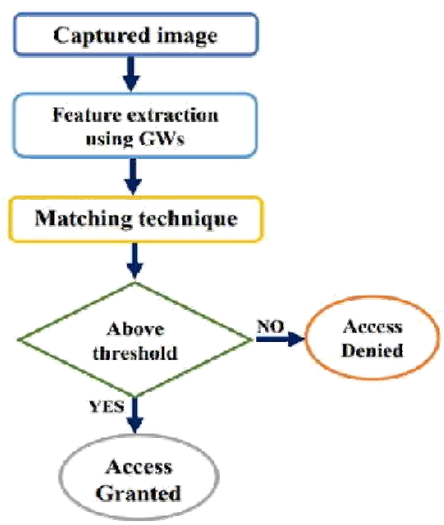

Fig: The process of the face recognition using GWs

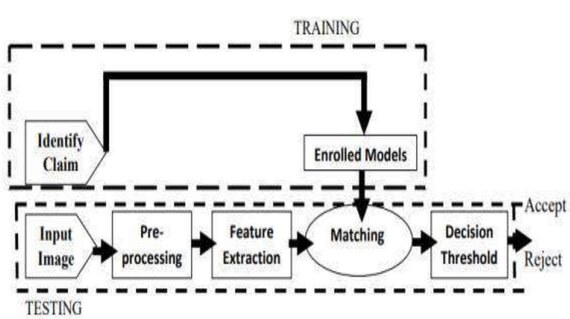

Fig 3.2: Block diagram process of the face recognition using GWs

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B. LBP

Two algorithms are: GLCM and LBP are designed separately for face detection. And they are put together to find the way GOL is installed. The main steps of the face recognition algorithm are:

1) *Step 1:* First, a photo of the face of the application is included in the program.
2) *Step 2:* Subsequently pre-processing techniques include image standardization and color space conversion.
3) *Step 3:* The textural elements are extracted using the LBP and GLCM method and also the GOL integrated method. Step 4: Finally, the results obtained from each method are compared with the other.

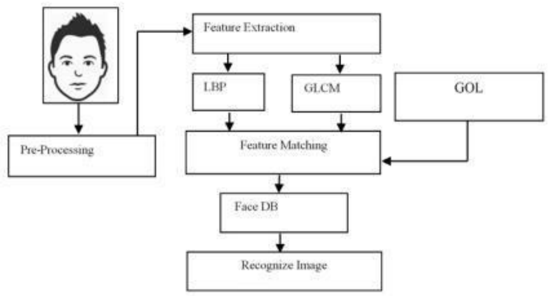

Fig. Algorithm for face recognition.

a) *Face Feature Extraction:* Automatic facial recognition uses Digital Image Processing techniques and machine learning techniques. They are also divided into four types: Full Support or Appearance, Template, Part Based, and Feature. This paper presents a method based on facial recognition using GLCM and LBP texting methods.
b) *Local Binary Patterns (LBP) Method*

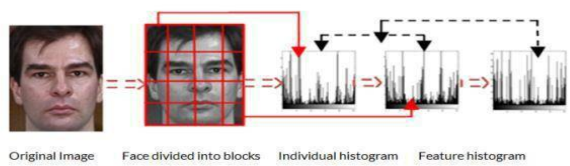

Fig. BP for Face Description

LBP is a method of texture planning, first proposed by Ojala et al., And used successfully in facial recognition in real time. Also, this algorithm is not computer-assisted because it describes the difference in Gray on the scale and provides a two-dimensional local pattern pattern and image analysis as shown in Figure3. - skipping equal blocks. A 3 x 3 matrix is used on top of each block. The LBP histogram is then performed with each block separately to describe the local texture characteristics. Finally, the features are grouped together with the histogram feature of the face image.

c) *Gray Level Co-Occurrence Matrix (GLCM) method:* GLCM is a mathematical method for texture analysis, first proposed by Haralick et al. Highlights the texture of the image by calculating the coefficient pixels from those with a different value in relation to the specified local relationships. And this relationship is found in different offsets and angles. the color image is converted to a gray scale and is divided into 16 equal-size blocks. Mathematical moments such as entropy, power, diversity and equality of people are drawn to each block, which ultimately gives a place view of the texture elements. After that each element is grouped together to give a vector of the GLCM image element.

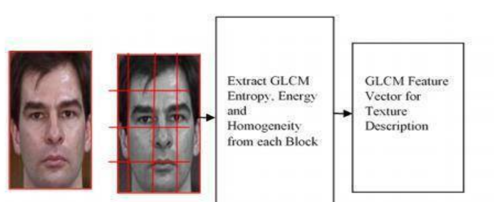

Fig. GLCM for face description.

In this section, the proposed method is defined for the use of GLCM over LBP. face image of the LBP feature extracted and managed by GLCM. As a result, they represent a structural and numerical feature of facial separation. Similarly, the obtained image of LBP was divided into 16 equal-size blocks. Then GLCM statistical times are taken from each block. This enters into entropy, power, diversity, and homosexuality. Finally, the features obtained from each block are grouped together, resulting in a picture of the texture of the earth.

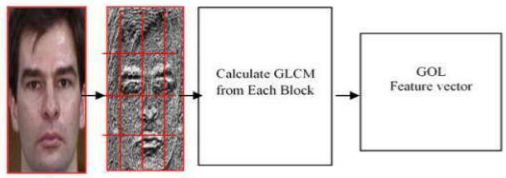

Fig. GOL feature image descriptor.

C. RRC

1) Iteratively Reweighted Regularized Robust Coding (Ir3c) Algorithm

RRC reduction is a repetitive process, and weights V and V are regenerated alternately to obtain the desired vector α. While we can only have a suitable local solution for the RRC model, fortunately at FR we are able to implement the right one to achieve optimal performance. In this section we suggest that the advanced measurement algorithm (IR3C) is an algorithm to reduce the weight of the RRC. When the image of the face of question y arrives, in order to start with W, we must start with the rest of the coding on y. We make e as e = y - Dcy $^{(1)}$, where α $^{(1)}$ is the first coding vector. Because we do not know in what category the image of the face of the question is, the sensible α $^{(1)}$ can be set as

$$\alpha^{(1)} = \left[\frac{1}{m};\frac{1}{m};\ldots;\frac{1}{m}\right]$$

That is, Dα $^{(1)}$ is the mean image of all training samples. With the initialized coding vector α When IR3C converges, we use the same classification strategy as in SRC to classify the face image y:

$$\text{identity}(y) = \arg\min_c \{\ell_c\}$$

where $\ell_c = \left\| W_{final}^{1/2}(y - D_c\hat{\alpha}_c)\right\|_2$, Dc is the lower dictionary associated with class c, ˆc α is the last coding vector associated with class c, and Wfinal is the final weight class.

IR3C merger

$$\hat{\alpha} = \arg\min_{\alpha}\left\{\left\|W^{1/2}(y - D\alpha)\right\|_2^2 + \lambda\|\alpha\|_1\right\}$$

The above eqn is a local approximation of the RRC

$$\hat{\alpha} = \arg\max_{\alpha}\{\ln P(y\,|\,\alpha) + \ln P(\alpha)\}$$

In the above eqn and in each iteration the objective function of the iqn decreases with the IR3C algorithm, i.e., in steps 3 and 4, the α
(t) to be solved will do As the cost of the eqn function above is bound (≥0), the process of reducing iterative in the IR3C will come together. Specifically, we stop repeating if the following catches up:

$$\left\|W^{(t+1)} - W^{(t)}\right\|_2 \Big/ \left\|W^{(t)}\right\|_2 < \delta_W$$

Where δW is a small positive scalar.

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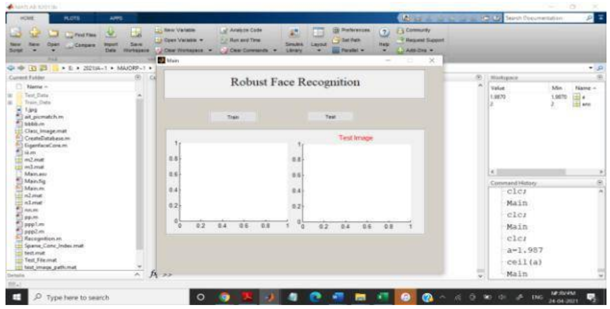
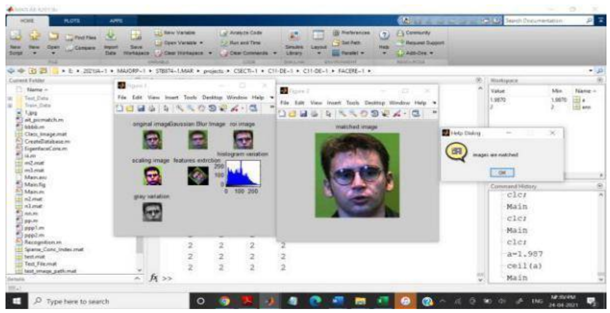
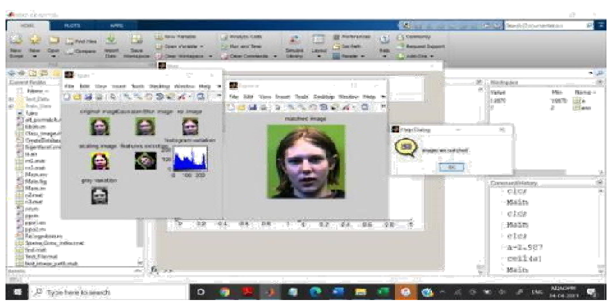
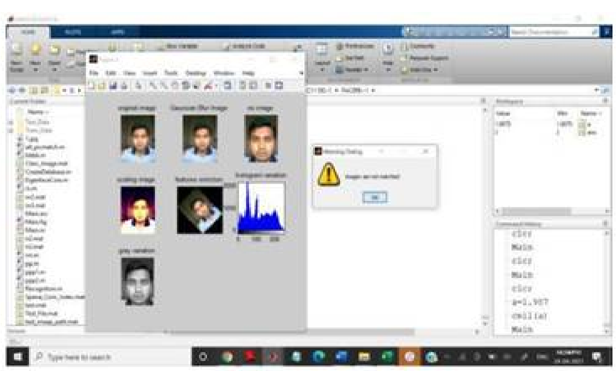
IV. RESULT

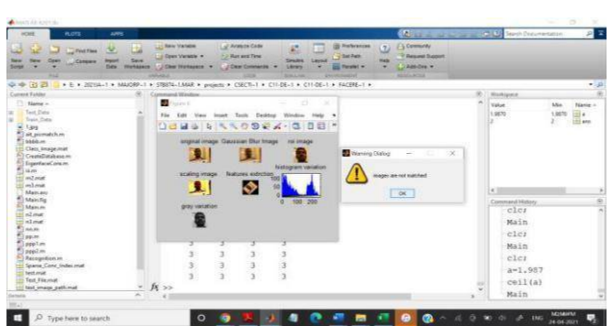
MATLAB Experimental Results:











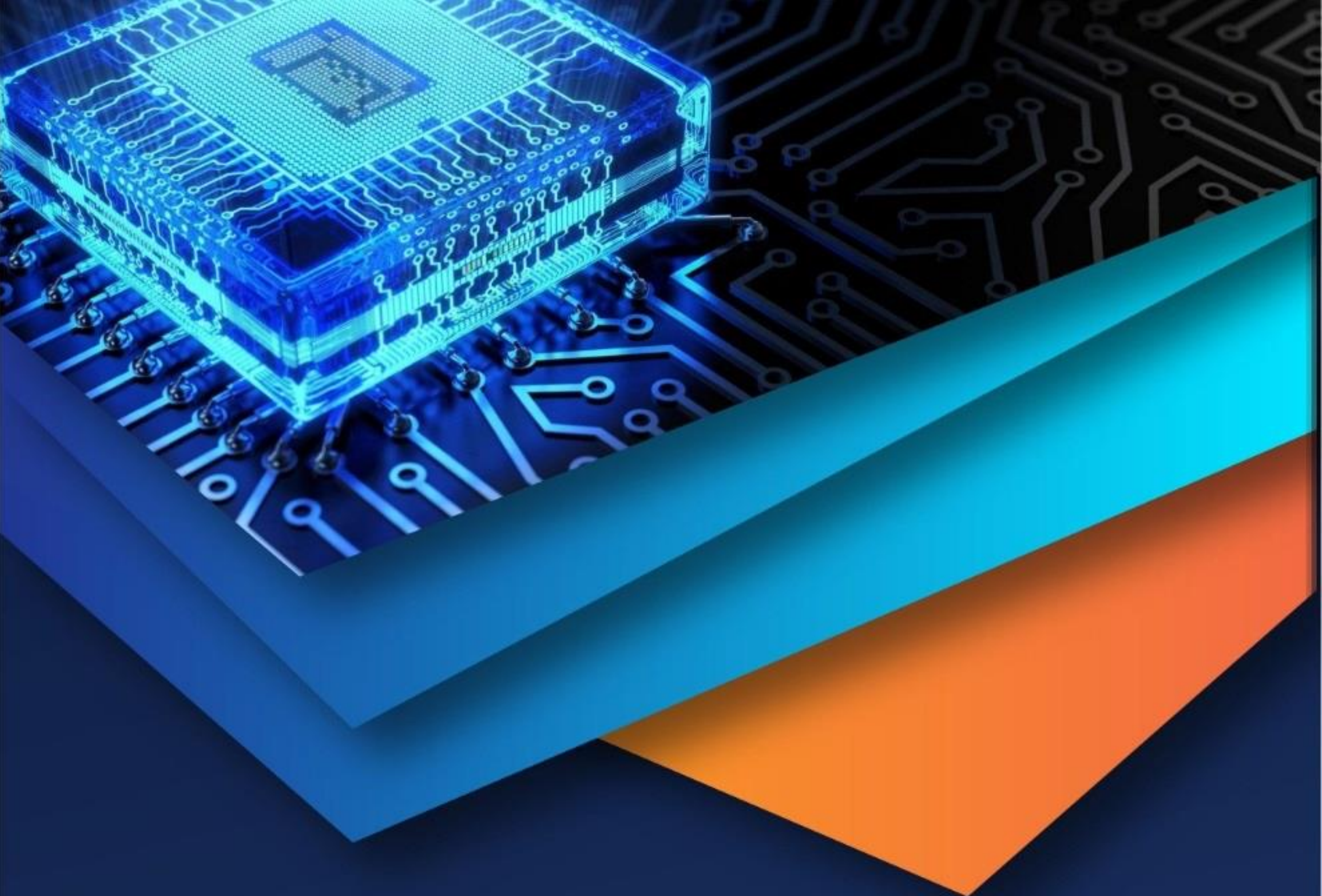
We performed tests on face-to-face measurement information to demonstrate the effectiveness of the RRC. In the section we provide the parameter setting of the RRC; In the section we examine the FR RRC without closure, showing the RRC's firmness to the FR with random pixel corruption, random blocking and actual concealment; in the Section tests are conducted to reject invalid test images. In the section, the operating time is introduced. Finally, further parameters of the parameter selection are given in the section All facial images are determined and aligned using eye areas. We are familiar with the query image (or feature) and the training image (or feature) to have the unit strength l2-norm. With AR and Extended B data, eye areas are provided with details. In the Multi-PIE database, we get an eye for doing tests in section 4.2, and then automatically detect the face region with the test face detector

V. CONCLUSION

In view of the limited representation, we have proposed a comprehensive framework / approach to address the age-old problem of face recognition in computer viewing. The proposed coding model (RRC) and the high-level measurement algorithm (IR3C) for powerful facial recognition (FR) are powerful for various types by seeking a limited measure of the background solution to the writing problem. By flexibly and repeatedly assigning metals to pixels according to their writing scripts, the IR3C algorithm can firmly identify exporters and reduce its effects on the writing process. The proposed RRC methods were extensively evaluated in FR in a variety of contexts, including diversity of lighting, speech, closure, corruption, and facial verification. Test results clearly show that the RRC is far superior to previous technologies.

REFERENCES

[1] W. Zhao, R. Chellppa, P.J. Phillips, and A. Rosenfeld, “Face recognition: A literature survey,” ACM Computing Survey, vol. 35, no.4, pp. 399–458, 2003.
[2] M. Turk and A. Pentland, “Eigenfaces for recognition,” J. Cognitive Neuroscience, vol. 3, no. 1, pp. 71–86, 1991.
[3] P.N. Belhumeur, J.P. Hespanha, and D.J. Kriengman, “Eigenfaces vs. Fisherfaces: recognition using class specific linear projection,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp. 711–720, 1997.
[4] B. Heisele, P. Ho, and T. Poggio, “Face recognition with support vector machine: Global versus component-based approach,” Proc. IEEE Int’l Conf. Computer Vision, 2001.
[5] A. Lanitis, C.J. Taylor, and T.F. Cootes, “Automatic Interpretation and Coding of Face Images Using Flexible Models,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp. 743-756, 1997.
[6] T. Ahonen, A. Hadid, and M. Pietikainen, “Face description with local binary patterns: Application to face recognition,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 28, no. 12, pp.2037–2041, 2006.
[7] A. Leonardis and H. Bischof, “Robust recognition using eigenimages,” Computer Vision and Image Understanding, vol. 78, no. 1, pp. 99-118, 2000.
[8] S. Chen, T. Shan, and B.C. Lovell, “Robust face recognition in rotated eigenspaces,” Proc. Int’l Conf. Image and Vision Computing New Zealand, 2007.
[9] A.M. Martinez, “Recognizing Imprecisely localized, partially occluded, and expression variant faces from a single sample per class,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 24, no. 6, pp. 748-763, 2002.
[10] S.Z. Li and J. Lu, “Face recognition using nearest feature line method,” IEEE Trans. Neural Network, vol. 10, no. 2,



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