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A Facial Recognition System using KNN based on DWT Segmentation Combined with ULBPH

Munikrishna D[1], Kiran Kumar R[2], Preetham Y[3], K B Raja[4], Venugopal K R[5]
[1, 2, 3, 4] Dept. of Electronics and Communication Engineering, University Visvesvaraya College of Engineering, Bangalore University, Bangalore, India
[5]Vice-Chancellor, Bangalore University, Bangalore, India

Abstract: Human face recognition based on face images is an important field for researchers. The face images of human beings are complicated due to the variations in intensities, pose variation, background variations etc., are some challenging to develop algorithms for real time applications. In this paper, we present a facial recognition system using KNN based on DWT segmentation combined with ULBPH. The face images are resized to the required dimension and Discrete Wavelet Transform (DWT) is used to partition and denoise the images to improve recognition rate. The LL band of DWT is considered and segmented into 25 parts with each part is 9x11 dimensions. The Uniform Local Binary Pattern (ULBP) is applied to each 5x5 segments to generate only 58 decimal equivalent values in place of 256 gray scale values. The histogram is used to map ULBP decimal equivalent index between 0 and 57 bins and all non ULBP decimal equivalent values are mapped to the 58th bin of histogram leads to a total of 59 bins. The total number of features is reduced due to DWT and ULBP is an advantageous. The KNN classifier algorithm with seven distance equations is used to validate the performance of the system. The system is tested with benchmark face datasets such as ORL, YALE and JAFEE and achieved a better recognition rate compared to existing methods.

Keywords: Biometrics, DWT, Face Recognition, KNN, LBPH

I. INTRODUCTION

Human identification is an exciting mission in the world for several applications by the earlier approaches such as password, PIN and ID cards, which were having many drawbacks viz., hard to remember password and pin ID cards may be lost or stolen by thieves. An alternative technique to earlier methods of human identification is Biometrics which are corresponding to human body parts and human behavior. The biometric parameters can't be lost and stolen hence this method of human authentication is reliable, secure and safe [1,2]. The biometrics are classified into two classes viz., physiological and behavioral biometrics. The physiological parameters relate to human body parts, hence it is almost constant, whereas behavioral parameters relate to mood and circumstances around human beings, hence it is variable [3,4]. The biometric traits must satisfy certain characteristics such as universality, distinctiveness, performance, collectability, acceptability and circumvention. The biometric systems are categorized into two groups viz., unimodal biometric systems and multimodal biometric systems. The output result of unimodal systems depends on only one biometric trait, whereas multimodal biometric system performance output depends on two or more biometric traits. Advantages of the unimodal biometric system are simple and easy to build real time system with less architectural complexity and cost, however unimodal biometric system has several disadvantages such as universality issues, spoofing attacks, less reliable and less security. The advantages of multimodal biometric systems are absent of universality, higher reliability, higher accuracy, less spoofing attacks and more robust compared to unimodal systems. The disadvantages of multimodal biometric systems are more circuit complexity since the system is a fusion of a minimum of two unimodal biometric systems, the number of final features is large which leads to decrease in speed of performance computation.

The advantages of biometrics are hard to remember password are replaced, ID frauds are eliminated, entry into house/office/ vehicles using keys are replaced and also the major advantage of biometrics is that a malicious hacker has to be in our physical vicinity in order to gather the information required to login etc. The disadvantages of biometrics are the authentication of a person through Iris biometric trait is difficult for a person affected with diabetes, the fingerprint recognition for people working in chemical industries is challenging, the face recognition over a period of time is problematic as the face of a person varies with age [5]. The biometric recognition algorithms are segmented into two groups such as verification and identification systems. An identification system is the device of relating the biometric sample of an individual to be tested by many people already stored in the database and it is known as one to many matches.

A verification system is a method of validating an identity of a person by comparison with the earlier extracted and stored biometric data in the system and is known as one to one match [6]. The applications of biometric systems are computer login, e-commerce, internet access, Automated Teller Machine (ATM), Nationality Identity Card, driving license, welfare disbursement, passport, criminal investigation, parenthood determination, Cloud Computing, bio data analytics etc.

1) *Contribution:* The research is to enhance recognition rate of face recognition using DWT combined with ULBPH for least number of features. The KNN with seven distance equations are used to classify face images effectively. The LL band of DWT reduce the number of features by considering only low frequency components and also reduces the noise of the original face image. Further ULBPH on LL band segments reduce features, which are classified by the KNN algorithm to achieve a higher recognition rate.
2) *Organization:* The research paper is arranged as, section 2, we explain the existing techniques of face recognition presented by several authors. The background of LBP and DWT are deliberated in section 3. In section 4, the projected technique is explained in detail. The proposed algorithm is presented in section 5. In section 6, the investigational results are given. The conclusion and future work are present in section 7.

II. LITERATURE SURVEY

The existing methods of preprocessing, feature extraction and classifiers developed by the researchers are explained in this section. Nicholl et al., [7] proposed face recognition using Discrete Wavelet Transform (DWT). Initially features are mined using multiscale vector creation (MVC) from DWT. Coefficients extracted using MVC are then optimized using Multiscale Vector Optimization (MVO) by selecting most discriminating coefficients. The MVC + MVO based face recognition have better results. Mohie El-Din et al., [8] studied the effect of wavelet decomposition on face recognition approaches using DWT, PCA, 2D-PCA, FLDA, SVM. The decomposition levels of DWT are used along with combination of different feature extraction methods. In one method 3 level DWT is applied on face image. After using DWT, PCA is used for feature abstraction and lastly SVM is used for classification. In other method same 3 level DWT is applied on face image but FLDA is used for feature extraction and finally SVM is used for classification. In last method 2D-PCA and FLDA is used for feature extraction. After applying 3 levels DWT on face image, initial features are extracted using 2D-PCA and SVM is used for classification. Ridha Ilyas Bendjillali et al., [9] proposed face recognition based on DWT feature for CNN. In the pre-processing, human face is detected from input image using Viola-Jones algorithm. The contrast of the face detected images is enhanced using histogram equalization. Facial features are extracted by applying DWT. The convolution neuron network (CNN) is used to classify the face image and to test the face recognition. Morooj K. Luaibi and Faisel G. Mohammed [10] proposed a Face recognition using DWT, HOG, PCA and MLP. In the preprocessing stage, human face is detected from input image using Viola-Jones algorithm and resized to original image size. Later contrast stretching, histogram equalization and image normalization are performed. The image transformation is done using DWT. Initial features are extracted using HOG feature extraction method. Final features are obtained using PCA function with reduced number of features. Multi-Layer Perceptron (MLP) classifier is used to test the face recognition. Fahima Tabassum et al., [11] proposed human face authentication with the mixture of DWT and machine learning. The coherence of DWT is joint with error vector of principal component analysis (PCA), Eigen vector of PCA, Eigen vector of linear discriminant analysis (LDA) and convolution neural network (CNN). Then all outcomes are combined using entropy of detection probability and Fuzzy system. Yi-Kang Shen, and Ching-Te Chiu [12] proposed a descriptor called local binary pattern orientation by combining LBP texture and SIFT orientation. The histogram equalization is done in preprocessing to enhance contrast on input images. The initial features are obtained by SIFT feature detection and final features are obtained by LBP orientation descriptor. The descriptor is collected of two parts, the histogram of gradient and the LBP orientation. Magnitude and angle information is obtained from the histogram of gradient and finally 8 bins orientation histogram is obtained. The matching method used is XOR distance to obtain matching pairs and then coordinate distance is for filter out incorrect matching pairs.

Mohannad A Abuzneid and Ausif Mahmood [13] proposed boosted human face recognition using LBPH descriptor, multi-kNN, and back-propagation neural network. In preprocessing, face detection is performed using Haar cascade detection and converted to grayscale image. The histogram equalization is performed to reduce noise. Uniform LBP descriptor is used to extract local features and combined to form global description using histogram method. Distance between training image and other training images are obtain using five distance methods and combined to form robust -dataset using the square-root of the sum of the squares (RSS). Finally, BPNN algorithm is used to test the recognition. Soo-Chang Pie et al., [14] proposed compact LBP and WLBP descriptor with magnitude and direction difference for face recognition. A robust image descriptor has been proposed to extract features of the image.

The descriptor consists of two parts sign part and magnitude, difference part. The sign part is represented by LBP, a uniform LBP or a WLBP and the magnitude and difference part is represented as second spatial histogram. Finally, both parts are concatenated to obtain the descriptor. Zhihua Xie et al., [15] presented combination of LBP and HOG using Multiple Kernel Learning for Infrared Face Recognition. The local binary patterns are applied to mine the texture features of an infrared face and then edge features are mined by using HOG operator. Lastly, Multiple Kernel Learning (MKL) is useful to fuse the texture features and edge features. Ze Lu et al., [16] proposed a LBP-based color feature called Ternary-Color LBP (TCLBP). During pre-processing translated, rotated, cropped and resized color face image is transformed from the RGB color space to the RQCr color space. To reduce the dimension of color face PCA is used and then features are extracted using inter channel LBP and intra channel LBP process. Then both process is concatenated to form Ternary-Color LBP (TCLBP). The Mahalanobis distance is used in matching section for face recognition. Jou Lin, and Ching-Te Chiu [17] proposed LBP edge-mapped descriptor using Maxima of Gradient Magnitude (MGM) interest points for face recognition. The pre-processing is done to decrease the noise to boost contrast. The interest points are extracted using MGM detection. Then LBP edge-mapped descriptor is used to extract edge pixels of MGM image and to extract LBPs from pre-processed image with MGM points. Finally matching method which calculates the similarity using XNOR gate and distance judgement is used for face recognition. Zheng Xiang et al., [18] presented the excellent properties of a dense grid-based HOG feature on face recognition compared to Gabor and LBP. The pre-processing is used to divide numerous grids from the face image. Then features are extracted from each block. Finally, Euclidean distance is used to compare features for face detection. Nhat and Hoang [19] proposed face recognition algorithm using feature combination by LBP, HOG, GIST descriptors and Canonical Correlation Analysis. The LBP, GIST and HOG features are mined from the given image separately. Then Canonical Correlation Analysis is used for concatenating any two feature vectors out of three feature vectors i.e., LBP-HOG, HOG-GIST, LBP-GIST descriptors. Finally, nearest neighbor classifier is used for face recognition.

III. BACKGROUND

The spatial and transform domain procedures such as LBP and DWT are discussed in detail.

A. Local Binary Pattern (LBP)

In recent years, the LBP algorithm proposed by Ojala et al. [20] has great advantage in image processing applications because of lesser computational complexity and robustness to the rotational invariance. The LBP operator is the comparative relationship of grey values in images and transforms into grey-scale translation within a certain range. The initial basic LBP technique is used on 3x3 matrix of an image and convert into binary coding according to the pixel intensity value difference between center pixel and neighborhood eight pixels in the sampling zone [21, 22]. The neighborhood pixel values are related with the center pixel value, in the sampling zone is illustrated in Fig 1. The neighborhood pixel value is assigned 1 if its value is more than the center pixel value else it is assigned 0. The binary code is obtained using Equation 1. The gray scale values of basic LBP vary from 0 to 255 ie., it has 256 gray levels.

$$Bn = \begin{cases} 1, & Pn \geq P \\ 0, & Pn < P \end{cases} \quad \text{--} (1)$$

Where Bn= Binary value

Pn= neighborhood pixel values

P=Centre pixel value

n=1 to 8

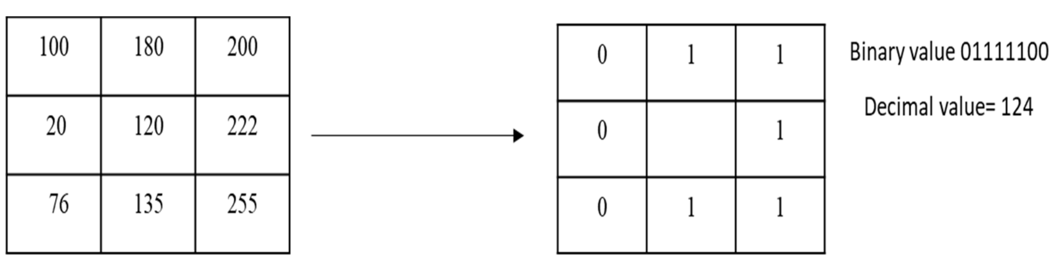

Fig 1. Illustration of basic LBP

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The drawback of this basic LBP operator is that it is applied to only small 3x3 matrix and unable to capture principal features with large scale structures and sensitive to illumination changes. The limitation of basic LBP is addressed by the generalized neighborhoods method with different radius sizes viz., R=2,3 for large scale structures [23]. Another limitation of basic LBP is higher gray level values (256) and are reduced to 58 levels in Uniform LBP (ULBP) which has uniform patterns ie., used to decrease the size of the gray scale levels. In ULBP, the binary pattern comprises at most two bitwise changeovers from 0 to 1 or vice versa while the bit pattern measured is circular [24]. For instance, the patterns 00000000 (0 transitions), 01110000 (2 transitions) and 11001111 (2 transitions) are uniform, however the patterns 11001001 (4 transitions) and 01010011 (6 transitions) are non-uniform. The ULBP reduces the number of gray levels to only 58, when compared 256 gray levels of basic LBP. The 58 uniforms binary patterns of ULBP are corresponding to the integer values of 0, 1, 2, 3, 4, 6, 7, 8, 12, 14, 15, 16, 24, 28, 30, 31, 32, 48, 56, 60, 62, 63, 64, 96, 112, 120, 124, 126, 127, 128, 129, 131, 135, 143, 159, 191, 192, 193, 195, 199, 207, 223, 224, 225, 227, 231, 239, 240, 241, 243, 247, 248, 249, 251, 252, 253, 254 and 255. These integer values are mapped onto histogram bins from 0 to 57 for histogram plot.

The ULBP is demonstrated in the Fig 2, by considering a 5x5 matrix with radius R=2 and the number of samples 8. The center pixel value is 175 in the 5x5 matrix which is surrounded by 8 pixel positions at 1,2,3,4,5,6,7 and 8 are marked by dots in (figure 2 b, c). The four sample points 1,3,5 and 7 falls in the exact appropriate positions of pixels with corresponding values 250, 25,225, and 190, hence the binary values 1, 0, 1, and 1 assigned on comparison with the central pixel value 175. The remaining other four points viz., 2, 4, 6 and 8 does not fall in the exact positions of pixels, hence the values of sample points 2,4,6 and 8 are calculated using bilinear interpolation.

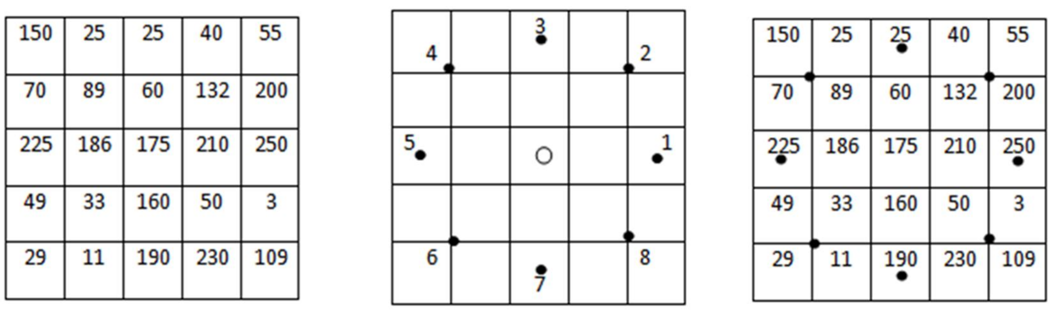

Fig 2. ULBP Illustration with R=2 and 8 samples

The Sample point 2 falls on four pixel values 40, 55,132, and 200, therefore, using interpolation method, its value is calculated with radius 2 and center pixel is surrounded by 8 neighbor samples.

1) Interpolation Method Computation for Sampling Point 2

The sample point coordinate values for i=1 to 8 are calculated with respect to the center pixel coordinate position (x, y) = (3,3) is as follows and are tabulated in Table 1.

Sample points SP(i,1) = -radius*sin((i-1) *a);

Sample points SP(i,2) = radius*cos((i-1) *a);

Where i= 1 to 8 no. of neighbors

$$a \text{ is angle step } = \frac{2*\pi}{\text{no of neighbors}} = 0.7854$$

For i=1,

SP (1,1) = - 2 sin ((1-1)0.7854) = 0

SP (1,2) = 2 cos ((1-1)0.7854) = 2

For i=2,

SP (2,1) = - 2 sin ((2-1)0.7854) = -1.4142

SP (2,2) = 2 cos ((2-1)0.7854) = 1.4142

For i=3,

SP (3,1) = - 2 sin ((3-1)0.7854) = -2

SP (3,2) = 2 cos ((3-1)0.7854) = 0

For i=4,
SP (4,1) = - 2 sin ((4-1)0.7854) = -1.4142
SP (4,2) = 2 cos ((4-1)0.7854) = -1.4142
For i=5,
SP (5,1) = - 2 sin ((5-1)0.7854) = 0
SP (5,2) = 2 cos ((5-1)0.7854) = -2
For i=6,
SP (6,1) = - 2 sin ((6-1)0.7854) = 1.4142
SP (6,2) = 2 cos ((6-1)0.7854) = -1.4142
For i=7,
SP (7,1) = - 2 sin ((7-1)0.7854) =-2
SP (7,2) = 2 cos ((7-1)0.7854) = 0
For i=8,
SP (8,1) = - 2 sin ((8-1)0.7854) = -1.4142
SP (8,2) = 2 cos ((8-1)0.7854) = 1.4142
The new center pixel coordinate positions for sample point 2, ie., for i=2
x = Sample Points (i, 2) + initial x coordinate value of center pixel = Sample Points (2, 2) +3
x = Sample Points (2, 2) +3 = 1.4142+3 = 4.4142
y = Sample Points (i, 1) + initial y coordinate value of center pixel= Sample Points (2, 1) +3
y = Sample Points (2, 1) + 3 = -1.4142+3= 1.5858
fx=Floor (x) =Floor (4.4142) = 4
fy = Floor (y) =Floor (1.5858) = 1
tx = x-fx =4.4142– 4= 0.4142
ty =y-fy =1.5858-1= 0.5858
weight w1 = (1-tx) (1-ty) = 0.5858 x 0.4142=0.2426
weight w2 = tx (1-ty) = 0.4142 x 0.4142=0.1716
weight w3 = (1-tx) ty = 0.5858 x 0.5858 = 0.34316
weight w4 = (tx) (ty) =0.4142 x 0.5858 = 0.2426
The interpolated pixel value at sample point 2 = (w1x40) +(w2x55) +(w3x132) +(w4x200)
= (0.2426x40) + (0.1716x55) +(0.3431x132) + (0.2426x200)
=112.96

TABLE 1
Sampling Point Coordinate Values

Sampling Points (i)	SP(i, 1)	SP(i, 2)
1	0	2
2	-1.4.42	1.4142
3	-2	0
4	-1.4142	-1.4142
5	0	-2
6	1.4142	-1.4142
7	-2	0
8	-1.4142	1.4142

The computed resultant value of sample point 2 is 112.96 and since it is less than the central pixel value (175), hence its assigned with bit value is 0. Similarly, for sample points 4, 6 and 8, the computed interpolated values are 79.32, 30.85 and 92.39 respectively, hence its binary corresponding bit values are 0, 0 and 0 on comparison with the center pixel value (175) and is shown in Fig 3.

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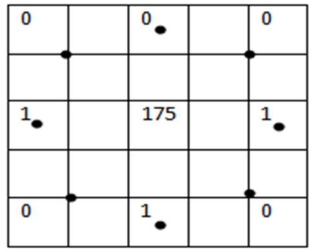

Fig 3. ULBP stream representation for R=2 with 8 samples

Therefore, sample points 1,2,3,4,5,6,7 and 8 binary values are 1,0,0,0,1,0,1 and 0. Considering anticlockwise direction, starting from sample point 1 as LSB, the final binary pattern is 01010001(LSB) whose decimal value is 81. Therefore, the new value of the center pixel is 81 replacing 175. Since the binary pattern is nonuniform, while performing mapping all non-uniform values are replaced with single value 58 and is marked on the 58th bin of the histogram.

B. Discrete Wavelet Transform (DWT)

The wavelet is a small wave and is a mathematical function used to split time signal into dissimilar scale modules. The wavelet transform is the depiction of a function of wavelets. The DWT is used to analyse waveforms in both time and frequency simultaneously. Some of the most popular mother wavelets are Haar, Shannon or Sinc, Daubechies, Gaussian or Spline, Biorthogonal, Morlet's Mexican Hat and Coiflet. The few applications of DWT are audio compression, speech recognition, image and video compression, denoising signals, motion recognition and tracing, etc. The filters of different cut-off frequencies are used to analyse the Discrete Signal (DT) at different scales in DWT. The DT signal is passed through a series of Low Pass Filters (LPF) and High Pass Filters (HPF) to analyse the low and high frequencies [25].

1) Illustration of DWT computation [26]

Consider 2x2 matrix $x = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$

The DWT is applied in matrix *x* to obtain four bands viz., LL, LH, HL, and HH as follows

LL band = (a+b+c+d)/2

LH band = (a+b-c-d)/2

HL band = (a-b+c-d)/2

HH band = (a-b-c+d)/2

DWT is applied on 4x4 matrix y, to compute 4 bands

$$y=\begin{bmatrix} 100 & 130 & 200 & 120 \\ 255 & 70 & 30 & 210 \\ 75 & 205 & 190 & 165 \\ 155 & 75 & 70 & 45 \end{bmatrix}$$

$$LL\ (y) = \begin{bmatrix} 277.5 & 280 \\ 305 & 235 \end{bmatrix}, \qquad LH\ (y) \begin{bmatrix} -47.5 & 40 \\ -25 & 120 \end{bmatrix}$$

$$HL\ (y) = \begin{bmatrix} 77.5 & -50 \\ -75 & 25 \end{bmatrix}, \qquad \text{HH (y)} = \begin{bmatrix} -107.5 & 130 \\ -55 & 0 \end{bmatrix}$$

It is noticed that the coefficient values of the LL band are high compared to other three bands, hence the LL band is considered as significant band and remaining three bands are considered as insignificant bands.

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IV. PROPOSED MODEL

The face recognition system proposed in this section is based on salient compressed features of ULBPH on a partitioned LL band of DWT. The algorithm KNN is used for classification of query face image features with stored features of face datasets.

A. Face Databases

The standard face databases such as YALE, ORL and JAFFE are considered to test and validate the proposed model.

1) *YALE Dataset*: The eleven face images of each person with dissimilar expressions thru glasses, without glasses, center-light, left-light, right-light is captured for every person, having moments of happy, sad, normal, sleepy, surprised, wink was captured. The face images of a single person are given in Fig. 4. The face database covers 15 people with 11 face image samples for each individual. The dimensions of each face image are 320x243 with the GIF format.

Fig 4. Face Image samples of Yale database [27]

2) *ORL Dataset:* An Olivetti Research Laboratory (ORL) bench marked face image database consists face images obtained between 1992 and 1994. Ten dissimilar facial expressions like open/closed eyes, smiling/not smiling, with/without glasses, changing lightening conditions of single person are captured. Similarly, face images of forty persons were taken under dissimilar conditions. A shady background with upright frontal and slight tilt of the head positions are considered while capturing images. The total number of 400 images of 40 persons is in PGM format and each image dimension is 92x112. Ten image samples of each person are revealed in Fig. 5.

Fig. 5. ORL face image samples of single person [28]

3) *Japanese Female Face Expression (JAFFE):* It comprises ten particular people and 20 distinctive pictures for every individual and seven facial emotions totaling to two hundred and thirteen samples of images. The measure of each picture is gray-scale with 256 x 256 dimensions. The dataset pictures were taken in an upright, frontal positions. The seven distinctive, enthusiastic facial expressions with tiff format images of one person is shown in Fig. 6.

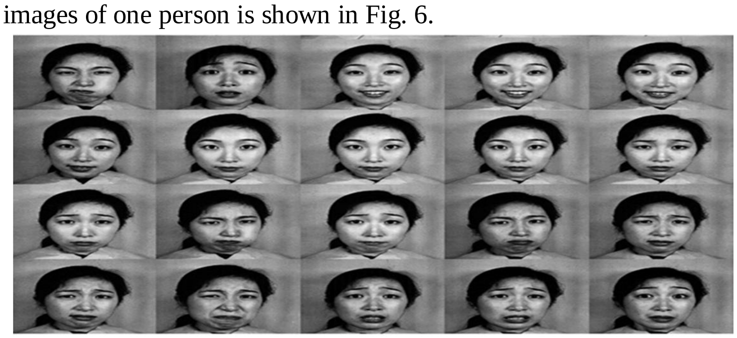

Fig. 6. Face Image samples of JAFFE dataset [29]

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B. Preprocessing

The face images of various datasets with different dimensions are converted into uniform dimensions of 90x110 and also RGB images are converted into gray scale images.

C. Discrete Wavelet Transform (DWT)

The two dimensional DWT is applied to resized preprocessed images, which is used for de-noising and reduce the dimensionality of an image leads to image compression. The DWT algorithm decomposes the image into four sub-bands by passing an image through low and high pass filters repeatedly. The sub-band LL is obtained after an original image passed through two low pass filters**.** The LL band is corresponding to low frequency components and has significant information about the original image. The sub-bands LH, HL, and HH are obtained after an original image passed through low and high filters. These bands are corresponding to high frequency components and has detailed insignificant information of original image related to edge information's. DWT output extracts the detailed output of input image. Each sub band has size of 45x55 which is exactly half the size of the original face image is as shown in the Fig.7.

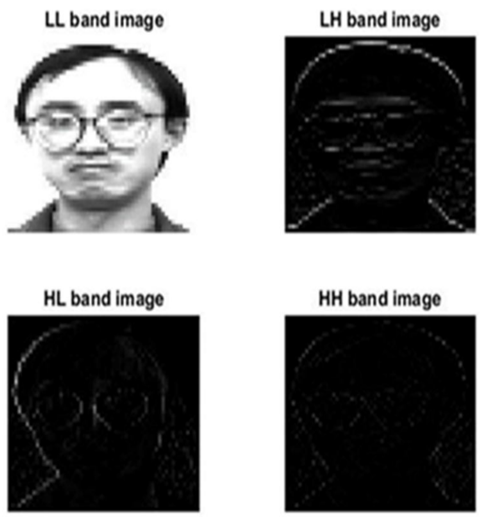

Fig 7. DWT Decomposition of face image

D. Uniform Local Binary Pattern Histogram (ULBPH)

The LL band of DWT of size 45x55 which has significant information of an original face image is considered and divided into 25 (5x5) local regions as shown in the Fig. 8 with each segment of dimension of 9x11. The ULBP texture with R=2 and the number of neighbor's P = 8 descriptors technique is applied to each segment independently to compute ULBP coefficients. The total number of ULBP texture decimal values is only 58 gray scale levels in place of 256 gray levels for gray scale images. The remaining grey level decimal numbers of 198 out of 256 levels belong to non ULBP texture decimal values.

9x11	9x11	9x11	9x11	9x11
9x11	9x11	9x11	9x11	9x11
9x11	9x11	9x11	9x11	9x11
9x11	9x11	9x11	9x11	9x11
9x11	9x11	9x11	9x11	9x11

Fig 8. Segmentation of LL band into 25 segments

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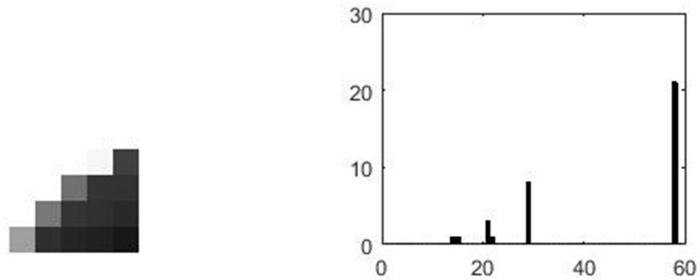
The histogram is applied to each segment and the number of ULBP texture coefficients are mapped on to 0 to 57 bins i.e., 58 bins of histogram plot. The non ULBP texture coefficients are mapped onto 58th bin of histogram plot. The total number of bins in the histogram plot is 59 to accommodate both ULBP and non ULBP texture features as shown in the Fig. 9.



(a) Image of First sub-band image (b) Histogram of ULBP and non ULBP

Fig 9. Histogram of one sub-band image

Similarly, the histograms for all the sub-band images are computed and concatenated to form a global description of the face image to obtain final features. The total number of final features is 59x25 = 1475 and the corresponding histogram is as shown in the Fig. 10.

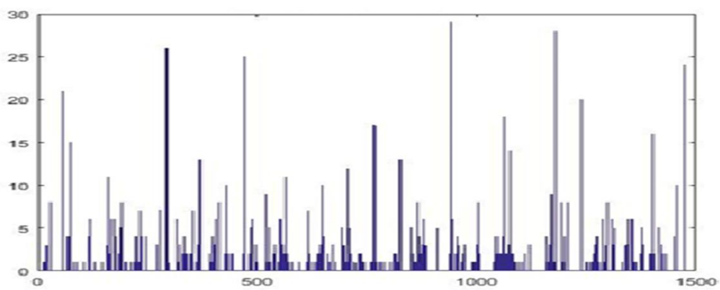


Fig 10. Histogram of final features

E. K-NN Algorithm

The k-nearest neighbors (KNN) algorithm is a simple, easy-to-implement type of supervised machine learning (ML) algorithm that is used to resolve both classification and regression glitches [30, 31]. KNN, is loaded with the training datasets i.e., the final features of face image datasets. The value of K which is of any integer is chosen i.e., the value of nearest data points of stored face dataset features from the query face image feature dataset. Initialize the value of K is 1 in our algorithm and Calculate the distance between query data features and each stored training data feature sets with the help of the distance methods, namely Euclidean, Manhattan, Correlation, Minkowski (order = 0.5), Sum of squared distance (SSD), Cosine, and Spearman as given equations 2-8. Now, based on the distance value, sort them in ascending order and choose the top *K* value from the sorted array and assign query set with that stored dataset.

1) Euclidean (a,b) = $\sqrt{\sum_{i=1}^{n}(ai-bi)^2}$ --- (2)
2) Manhattan (a,b) = $\sum_{i=1}^{n}|ai-bi|$ --- (3)
3) Minkowski (a,b) = $(\sum_{i=1}^{n}|ai-bi|^p)^{\frac{1}{p}}$ -- (4)
   where p is order
4) Correlation (a, b) = $\frac{Cov(a,b)}{\sigma a \ \sigma b}$ ---(5)
   where Cov is Covariance matrix and σ is standard deviation
5) Sum of squared difference(SSD) (a,b) = $\sum_{i=1}^{n}(ai-bi)^2$ -------------------------(6)
6) Cosine distance (a,b) = $1-\frac{\sum_{i=1}^{n}ai\times bi}{\sqrt{\sum_{i=1}^{n}ai^2}\times\sqrt{\sum_{i=1}^{n}bi^2}}$ -------------------------------------(7)
7) Speareman distance (a,b) = $1-\frac{6\sum_{i=1}^{n}(rank(ai)-rank(bi))^2}{n(n^2-)}$ ----------------------- (8)

V. PROJECTED ALGORITHM

1) *Problem definition:* The human beings are identified effectively using physiological biometric facial images with the help of DWT combined with LBPH features and given in table 2.
2) *Objectives:* The face recognition algorithm is developed using salient features with the objective of increasing recognition rate using KNN classifier for different training and testing combinations using various distance methods.

TABLE 2
Projected Algorithm

Input: Face image datasets
Output: Face recognition
1. Various datasets are considered.
2. The pre-processing technique is used to convert RGB face images to grey scale images and different image size are converted into a uniform size of 90x110.
3. The DWT is used on resized face images to de-noise and compress by considering the approximate (L, L) band of size 45x55.
4. The LL band of size 45x55 is segmented into 25 local regions of each dimension of 9x11.
5. The ULBPH texture technique with r=8 and p=8 is applied on local regions to obtain only 58 grey scale levels in place of 256 grey scale levels. The remaining grey scale levels belong to non ULBP.
6. The ULBP texture features are mapped onto 58 bins varies from 0 to 57 and non ULBP features are mapped onto 58th bin of histogram plot.
7. Each local region generates 59 features. The total number of global features for face image are equal to 59x25=1475.
8. The KNN algorithm is used to compare stored features and query images to identify human beings.

VI. RESULT ANALYSIS

The percentage Recognition Rate (RR) performance measure metric is the ratio of total number persons matched correctly to the total number of persons in the training dataset used to verify the result of the proposed method for standard face databases such as YALE, ORL and JAFFE. The percentage recognition rate is computed using the KNN algorithm using seven distance equations Euclidean, Manhattan, Correlation, Minkowski (order = 0.5), Sum of Squared Distance (SSD), Cosine, and Spearman.

A. *Investigation Based on the YALE face Dataset*

The quantitative percentage of RR value is noted by increasing training ratios from 50% to 90% using YALE face dataset. The percentage RR values for training and testing ratios of 50:50, 70:30 and 90:10 using a KNN algorithm through seven different distance equations are shown in Table 3. The % RR values increase as the percentage ratio of training increases. The 100% RR is recorded for training ratio of 90% with all seven different distance equations. The low value of %RR is recorded for training ratio of 50%. The computation of percentage RR using a KNN algorithm with Minkowski distance equation yields maximum average % RR value compared to other six distance equations. The low value of % average RR is recorded with Euclidean and SSD distance equations.

TABLE 3
RR Values with Different Blends Of Training And Testing Ratios Using Yale Face Dataset

Distance methods	% Recognition Rate			
	Training=50%, Testing=50%	Training=70%, Testing=30%	Training=90%, Testing=10%	% Average Value
Euclidean	89.33	91.11	100	93.48
Manhattan	94.66	95.55	100	96.74
Correlation	92	91.11	100	94.37
Minkowski (order = 0.5)	97.33	97.77	100	98.37
SSD	89.33	91.11	100	93.48
Cosine	92	91.11	100	94.37
Spearman	93.33	95.55	100	96.29

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B. *Investigation Based on the ORL face Dataset*

The quantitative percentage of RR value is documented by increasing training ratios from 50% to 90% using ORL face dataset. The percentage RR values for training and testing ratios of 50:50, 70:30 and 90:10 using a KNN algorithm through seven different distance equations are shown in Table 4. The % RR values increase as the percentage ratio of training increases. The 100% RR is documented for a training ratio of 90% with all seven different distance equations. The low value of %RR is recorded for training ratio of 50%. The computation of percentage RR using a KNN algorithm with Spearman distance equation yields maximum average % RR value compared to other six distance equations. The low value of % average RR is recorded with Correlation and Cosine distance equations

TABLE 4
RR Values With Different Blends of Training And Testing Ratios Using Orl Face Dataset

Distance methods	% Recognition Rate			
	Training=50%, Testing=50%	Training=70%, Testing=30%	Training=90%, Testing=10%	% Average Value
Euclidean	92.5	95.83	100	96.11
Manhattan	97.5	96.66	100	98.05
Correlation	93.5	93.3	100	95.60
Minkowski (order = 0.5)	97	96.66	100	97.89
SSD	92.5	95.83	100	96.11
Cosine	93.5	93.3	100	95.60
Spearman	98.5	97.5	100	98.67

C. *Investigation Based on JAFFE face Dataset*

The quantitative percentage of RR value is documented by increasing training ratios from 50% to 90% using JAFFE face dataset. The percentage RR values for training and testing ratios of 50:50, 70:30 and 90:10 using a KNN algorithm through seven different distance equations are shown in Table 5. The % RR values increase as the percentage ratio of training increases. The 100% RR is documented for a training ratio of 90% and 70% with all seven different distance equations. The low value of %RR is recorded for training ratio of 50%. The computation of percentage RR using a KNN algorithm with all distance equation yields maximum average % RR value. The little low value of % average RR is recorded with Correlation, Minkowski and Cosine distance equations. The variations in face images of JAFFE dataset are very much less, hence the % RR is very high for all training sets and distance equations.

TABLE 5
RR Values With Different Blends Of Training And Testing Ratios Using Jaffe Face Dataset

Distance methods	Recognition Rate in %			
	Training=50%, Testing=50%	Training=70%, Testing=30%	Training=90%, Testing=10%	% Average Value
Euclidean	100	100	100	100
Manhattan	100	100	100	100
Correlation	99	100	100	99.67
Minkowski (order = 0.5)	99	100	100	99.67
SSD	100	100	100	100
Cosine	99	100	100	99.67
Spearman	100	100	100	100

D. Experimental Result Comparison of Proposed method with Existing Methods on ORL face Dataset

The quantitative percentage RR comparison of the proposed method is with existing methods presented in research papers by several authors Abuzneid and Mahmood [32], Pingping Tao et al., [33], John hanaseely et al., [34], Purnomo et al., [35], Ayyavoo and Jayasudha [36], Fan et al., [37] and Lone et al., [38] are shown in Table 6. The developed method of face recognition has better percentage RR in comparison with existing methods and also an advantage in the least number of salient features because of DWT.

TABLE 6
Comparison Of The Proposed Method With Existing Techniques Using Orl Face Dataset

Sl No.	Authors	Year	Techniques	%RR
1	Abuzneid and Mahmood [32]	2018	LBPH, Multi KNN, and BPNN	98.00
2	Pingping Tao et al., [33]	2018	2D-PCA combined with WT and frame theory	94.80
3	John dhanaseely et al., [34]	2016	Gray-level Co-occurrence Matrix (GLCM) features + feed forward neural network	89.00
4	Purnomo et al., [35]	2015	Hybrid method from Gabor Wavelet and Non-negative Matrix Factorization (NMF)	95.00
5	Ayyavoo and Jayasudha [36]	2013	DWT + K Means clustering algorithm + Fuzzy K Nearest Neighbour classifier	87.00
6	Fan et al., [37]	2012	DWT + PCA	95.00
7	Lone et al., [38]	2011	PCA, DCT, Correlation, Partitioned Iterative Function System	86.80
8	Proposed Method	2020	DWT, ULBPH and KNN	98.5

E. Experimental Result Comparison of Proposed Method with Existing Methods on YALE and JAFEE face Datasets

The quantitative percentage RR comparison of the proposed method is with existing methods presented in research papers by several authors Abuzneid and Mahmood [32], and John dhanaseely et al., [34], are shown in Table 7. The developed method of face recognition has better percentage RR in comparison with existing methods and also an advantage in the least number of salient features because of DWT.

TABLE 7
Comparison Of The Proposed Method With Existing Techniques Using Yale And Jafee Face Datasets

Sl No	Authors	Year	Techniques	% RR	
				YALE	JAFEE
1	Abuzneid and Mahmood [32]	2018	LBPH, Multi KNN, and BPNN	97.7	------
2	John dhanaseely et al., [34]	2016	Gray-level Co-occurrence Matrix (GLCM) features + feed forward neural network	96.00	96.70
3	Proposed Method	2020	DWT, ULBPH and KNN	98.37	99.85

VII. CONCLUSION

The face recognition is a superior biometric system to identify human beings as the face images can be captured without the knowledge and contact of a person. We proposed higher face recognition rate based on DWT and ULBPH along with KNN classifier. The face images are resized to 90x110 to maintain uniform dimension for all datasets. The DWT is applied and considered only LL band of 45x55 corresponding to low frequency components for de-noising and compress face images. The LL band is segmented to 25 blocks with each size of 9x11. The ULBPH technique is used on each local block to obtain features of size 59. The final features are obtained by concatenating features of 25 local blocks, which yield 1475 features. The KNN algorithm with 7 distance methods are used to compute performance of the proposed method. It is noticed that the proposed work is advantageous with the least number of salient features and better recognition rate compared to existing techniques. In future, the technique can be implemented in hardware to test the speed of computation for real-time applications.

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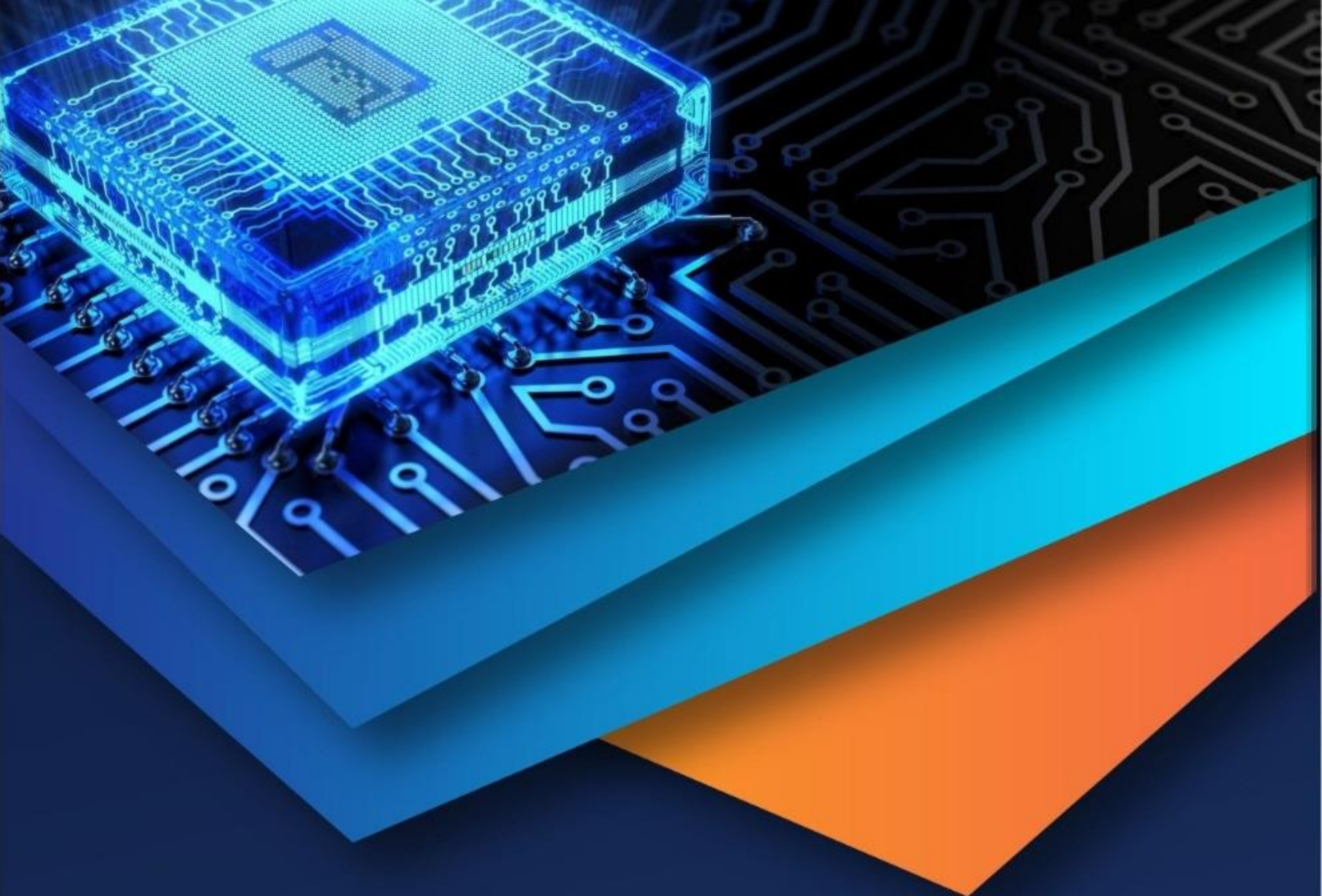

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