Face Recognition using 2D-Discrete Wavelet Transform & Vertical Segmentation Method

Two Dimensional Discrete Wavelet Transform, Overlapping Local Binary Pattern & Vertical Segmentation Method

Divya T. M.
Assistant Professor,
UVCE, Bangalore, India

Parimala Gandhi
Associate Professor,
Dept. of ECE, RRIT, Bangalore, India

ABSTRACT

Biometrics recognizes a human being based on a physiological or behavioral characteristic. A physiological characteristic is a stable physical characteristic such as a fingerprint pattern, face recognition, hand geometry pattern or iris pattern. These characteristics are unchangeable and unalterable. A Behavioral Characteristic includes signature,how person types at a keyboard and how a person speaks. The degree of variation in a physiological characteristic is smaller than a behavioral characteristic. Face Recognition is capable of identifying a face from a digital image or video. Face Recognition is the powerful biometric. Face recognition system compares selected features of the inputimage with faces in the database.

Keywords: Face Recognition, 2d-DWT,OLBP,VSM

INTRODUCTION:

Feature extraction is one of the most important part for face recognition. The facial feature description method is broadly classified into two schemes: Holistic scheme and Local scheme. In the holistic scheme, features are obtained entirely from the facial image. In the local scheme, features are obtained from parts of face and recognized as a combined feature. Faces can be taken by the user or they can be captured by surveillance cameras. There is a great need for safety and security based applications like forensic science.
In this paper, 2-d dimensional Discrete wavelet transform, overlapping local binary pattern and vertical segmentation method have been proposed for face recognition. Section II states a related work of the algorithm. Section III explains DWT, OLBP & VSM.Section IV gives the proposed algorithm. Section V gives result analysis for different database. Finally, sectionVI conclusion of this paper.

Related Work:

A 3D face acquisition involves a mobile sensor based on fringe projection. The aim of this work is to implement a mobile depth and color acquisition system on a smart phone, offers good accuracy and short capture time for acquiring face data was proposed by Marco Piccalilli et.al [1]. Dominik Jelsovka et al. [2] presented Canonical Analysis approach based on detected facial curves from 3d mesh surface. He implemented modified 2d-3d face recognition approach using facial curves from 3d mesh surface. This algorithm decreases computation complexity compared to the conventional 3d face recognition. Cheng Zhong et al.[3] proposed the quad tree clustering algorithm to for facial codes. He proposed a 3-d textons to represent and recognize different textures.
In this proposed recognition model, features are extracted from the trained and test images of Yale database with 15 different poses for each image. In the pre-processing step, color image is converted to gray image and resized.The proposed face recognition system includes two phases namely the training phase and testing phase. In the training phase, feature extraction is performed using OLBP. The recognition of features is done using Euclidean distance.

Discrete Wavelet Transform:

The wavelet transform represents signal in the form of mother wavelets using dilation and translation. The wavelet functions have finite duration both in time and frequency. These represents both in spatial and frequency domain. The features extracted by this transform yields better results in recognizing as well as bifurcates low and high frequency components as approximation band and detailed band respectively. The commonly used wavelets are Haar, Symelt and DBI. Discrete wavelet transformreduces the size without losing much of the resolution, reduces redundancy and reduces computational time.

Haar Transform:

Haar functions were introduced by the Hungarian Mathematician Alfred Haar in 1910. Haar wavelet is discontinuous in nature and resembles a step function. For an input represented by numbers, the Haar wavelet transform simply pair up values in the list of numbers, stores the difference and passes the sum. The process is repeated,pairs up the sums to provide the next scale, results in differences and one final sum. The Haar wavelet transform is a form of compression which involves averaging and differencing, stores the detailed coefficients and reconstructing the matrix such that the resulting matrix is similar to the initial matrix. The Haar transform decomposes a discrete signal into sub bands of half of its length. One sub-band has running average; the other sub-band has running difference.

Single level decomposition of DWT:

The implementation of dimensional DWT through sub-band coding can be easily extended to two dimensional signals for digital images. In this sub-band analysis, the approximate form in horizontal and vertical directions are extracted. Details in horizontal direction gives detection of horizontal edges, details in vertical direction gives detection of vertical edges and details in both horizontal and vertical direction gives detection of diagonal edges. The analysis of 2-d signals requires two-dimensional filter functions through multiplication of separable scaling and wavelet functions in horizontal(n1) and vertical(n2) directions which is given below:
The approximated signal is given by

$$\Phi(\mathrm{n1},\mathrm{n2}) = \Phi(\mathrm{n1})\,\Phi(\mathrm{n2}) \quad \text{------- (1)}$$

The signal with horizontal details is given by

$$\psi^H(n1,n2) = \psi(n1)\Phi(\mathrm{n2}) \quad \text{------- (2)}$$

The signal with vertical details is given by

$$\psi^V(n1,n2) = \psi(n2)\Phi(\mathrm{n1}) \quad \text{------- (3)}$$

The signal with diagonal details is given by

$$\psi^D(n1,n2) = \psi(n1)\psi(\mathrm{n2}) \quad \text{------- (4)}$$

The filtering in each direction sub-samples by a factor of 2, so that each of the sub-bands corresponding to the filter output contains one-fourth of the number of samples, as compared to the original 2-d signal. The bands $\Phi(\mathrm{n1},\mathrm{n2})$,$\psi^H(n1,n2)$, $\psi^V(n1,n2)$ and $\psi^D(n1,n2)$ are referred as LL, LH, HL and HH respectively. The first letter indicatesit is low-pass or high pass filtered along the columns and the second letter indicates it is low pass or high pass filtered along the row. LL sub-band has most significant information compared to other sub-bands. An original image of size 128 X 128 is taken, each sub-band has dimension of 64 X 64. In this proposed model, only LL sub-band is considered for feature extraction as shown in figure 3.1.

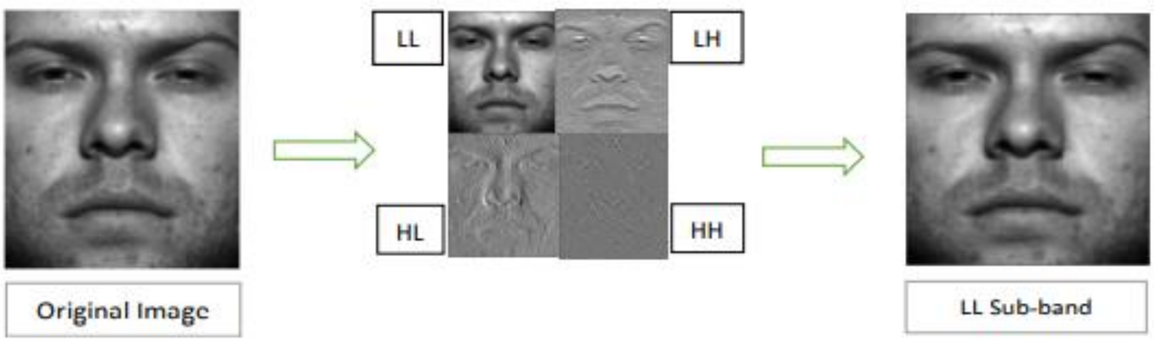

Fig 3.1: Formation of LL sub-band by 2d-Discrete Wavelet Transform method

The LL sub-band face image is divided into symmetrical vertical segments. The below steps summarizes the procedure for resizing of LL sub-band face image.

i. First note the rows(r) and columns(c) of the matrix representation of the image.
ii. Let the number of vertical segments is represented by 2N (same number of segments in both left and right side of the image)
iii. The following generalized formula is used to get the new number of columns represented by C'
   $C' = c - (c \,\%\, 2N)$ ------ (5)
   $c \,\%\, 2N$ is the remainder when c is divided by 2N

The resized image will have matrix representation with r rows and C' columns.
If the size of an image is 112 X 92, r = 112 and c = 92,then

1. Assume 2N=4, C'=92-(92%4) = 92-(0) = 92, the resized image will be 112 X 92
2. Assume 2N=6, C'=92-(92%6)= 92-(2) = 90 , the resized image will be 112 X 90.

Fig 3.2: Resizing of LL Sub-band image

Vertical Segmentation Method (VSM):

In VSM, the given resized face image A_{mxn} is divided into vertical segments along the direction parallel to the symmetric axis of the face. Let N represents the number of segments, so totally 2N segments are there. Each region in the left half face is denoted as $A_{LK}(K = 1,2,..N)$ where K represents the position of each region in half face image and it increases from the face centre to its border. Similarly, the regions in the right half face is denoted as $A_{RK}(K = 1,2,..N)$. after these regions are obtained, OLBP is performed on them to extract local facial features.

Fig 3.3: Vertical Segmentation of resized image

The resized image shown in figure 3.3 is vertically segmented into N=2, so 2N =4 parts. Two left parts and two right parts. The corresponding left and right segments are symmetrical in nature.

Overlapping Local Binary Pattern(OLBP)& Vertical flip of OLBP segmented region:

Local Binary Pattern (LBP) is a texture operator. LBP labels each pixels of an image which thresholds the neighborhood of each pixel and the result is considered as a binary number.The 2-dimensional surface textures can be described by local spatial patterns and gray scale contrast. The original LBP operator(Ojala et al. 1996) labels the image pixels by thresholding the 3 x 3 neighborhood of each pixel with the center value and consider the result as a binary number. The histogram of these $\mathbf{2^8}$= 256 different labels are used as a texture descriptor. This operator used with a simple local contrast measure provides very good performance (Pietikainen et al. 1999). The first step of the LBP is to create an intermediate image that describes the better original image, which highlights the facial characteristics. The algorithm uses a sliding window, based on the parameter's radius R and pixel neighbors P. The following steps summarizes the computation of LBP

i. A gray scale image of the face is taken.
ii. A part of the image is taken as a window of pixel size 3 x 3 which is a 3 x 3 matrix which contains the

intensity of each pixel (0 to 255).

iii. The centre value of the matrix is the threshold value.
iv. This value is used to define the new values from the 8 neighbors.
v. A new binary value will be set for each neighbor of the centre value. A value ‘1’ is set for the neighbor whose value is higher than the threshold and value ‘0’ is set for neighbors whose values are lower than the threshold.
vi. The matrix contains only binary values. Each binary values are concatenated from the matrix, line by line into a new binary value (eg. 10001101).
vii. Convert this binary value into decimal value and set as the the central value of the matrix.

In case of overlapping LBP, the next adjacent pixel to the centre pixel of first LBP operator is considered as the threshold for the next LBP operator i.e., if we consider (x_c, y_c) as the centre pixel (threshold) for first LBP operator, then the next adjacent pixel i.e.,(x_{c+1}, y_{c+1}) is considered as a threshold for the next adjacent LBP operator. An example of OLBP is shown in figure 3.4. A 3x5 matrix is taken, in this matrix three overlapping 3x3 matrices are marked with three different colors. In case ofOLBP, by considering center value 55 as threshold LBP of first overlapping 3x3 block is done. Similarly, by considering center value 68 and 96 as threshold for second and third overlapping 3x3 block LBP is done.

65	21	3	26	26
36	55	68	96	26
25	65	84	77	74

Three overlapping 3x3 blocks

65	21	3
36	55	68
25	65	84

First overlapping 3x3 block

21	3	26
55	68	96
65	84	77

Second overlapping 3x3 block

3	26	26
68	96	26
84	77	74

Third overlapping 3x3 block

Fig 3.4: Overlapping LBP

OLBP is performed on each of the 4 vertical segments obtained by VSM. The process is shown in figure

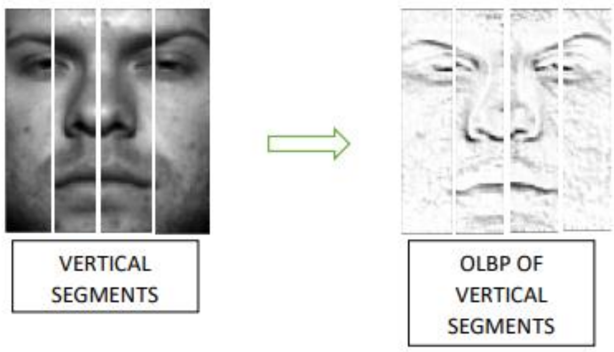

Fig 3.5: OLBP of four vertical segments

Vertical flipping of OLBP segmented region:

A matrix $\boldsymbol{A} = (\boldsymbol{a_{ij}})_{\boldsymbol{mxn}}$, *If matrix B =* $\begin{bmatrix} a_{1n} & \cdots & a_{11} \\ \vdots & \ddots & \vdots \\ a_{mn} & \cdots & a_{m1} \end{bmatrix}$ *is called the vertical flip matrix of A, represented as* $\boldsymbol{B} = \boldsymbol{A^P}$

According to one of the property of vertical flip matrix, if $\boldsymbol{I_n}$ *represents the n-order unit matrix and its vertical flip matrix is* $\boldsymbol{J_n}$ *, then the vertical flip matrix of A can be rewritten as*

$\boldsymbol{A^P} = A\,\boldsymbol{J_n}$ ----- (5)

In the next step, the vertical flip matrices of all the OLBP representations above are calculated by multiplying the sub-unit matrix $\boldsymbol{J_n}$

$[\boldsymbol{OLBP}(\boldsymbol{A_{Lk}})^{\boldsymbol{P}}] = \boldsymbol{OLBP}(\boldsymbol{A_{Lk}})\ X\ \boldsymbol{J_n}$ k = 1,2… M ------ (6)

$[\boldsymbol{OLBP}(\boldsymbol{A_{Rk}})^{\boldsymbol{P}}] = \boldsymbol{OLBP}(\boldsymbol{A_{Rk}})\ X\ \boldsymbol{J_n}$ k = 1,2… M ------ (7)

The four OLBP segmented region obtained in previous section is vertically flipped. This is shown in figure 3.6. The four regions are shown in (i), (ii), (iii) and (iv) respectively.

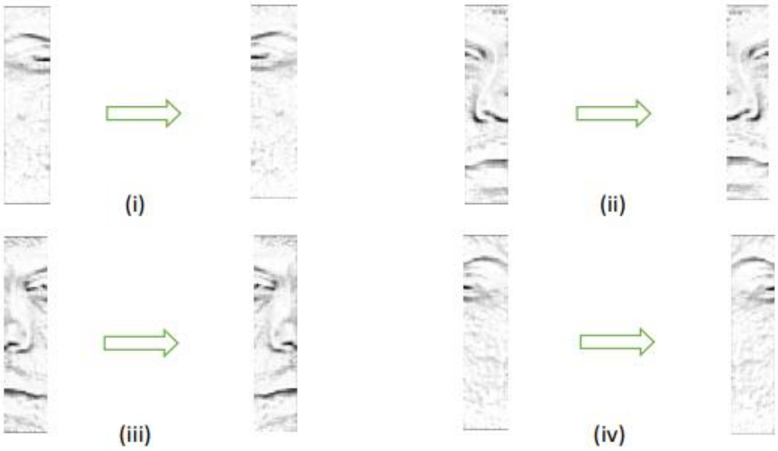

Fig 3.6: Vertical flip of OLBP segmented region

Proposed Model Algorithm:

The following steps illustrates the proposed algorithm

STEP 1. Images are loaded from database.
STEP 2. RGB image is converted to Gray scale image.
STEP 3. Two dimensional Haar wavelet transform is applied on face images shown in fig 3.1
STEP 4. LL sub-band is considered and resized shown in fig 3.2
STEP 5. The Resized image is divided into four vertical segments
STEP 6. OLBP is applied to all four vertical segments as shown in fig 3.5
STEP 7. The four OLBP segments are vertically flipped as shown in fig 3.6
STEP 8. Average the segments obtained in step-6 & step-7.

The local facial feature are obtained by averaging the OLBP segments of each region with the vertical flip matrix. The final representation of the original face image is obtained by the following formula:

Avg $(\boldsymbol{A_{Lk}}) = \frac{[\boldsymbol{OLBP}(A_{Lk})] + [\boldsymbol{OLBP}(A_{Rk})]^{\boldsymbol{P}}}{2}$, k = 1,2,… M ……. (8)

Avg $(\boldsymbol{A_{Rk}}) = \frac{[\boldsymbol{OLBP}(A_{Rk})] + [\boldsymbol{OLBP}(A_{Lk})]^{\boldsymbol{P}}}{2}$, k = 1,2,… M ……. (9)

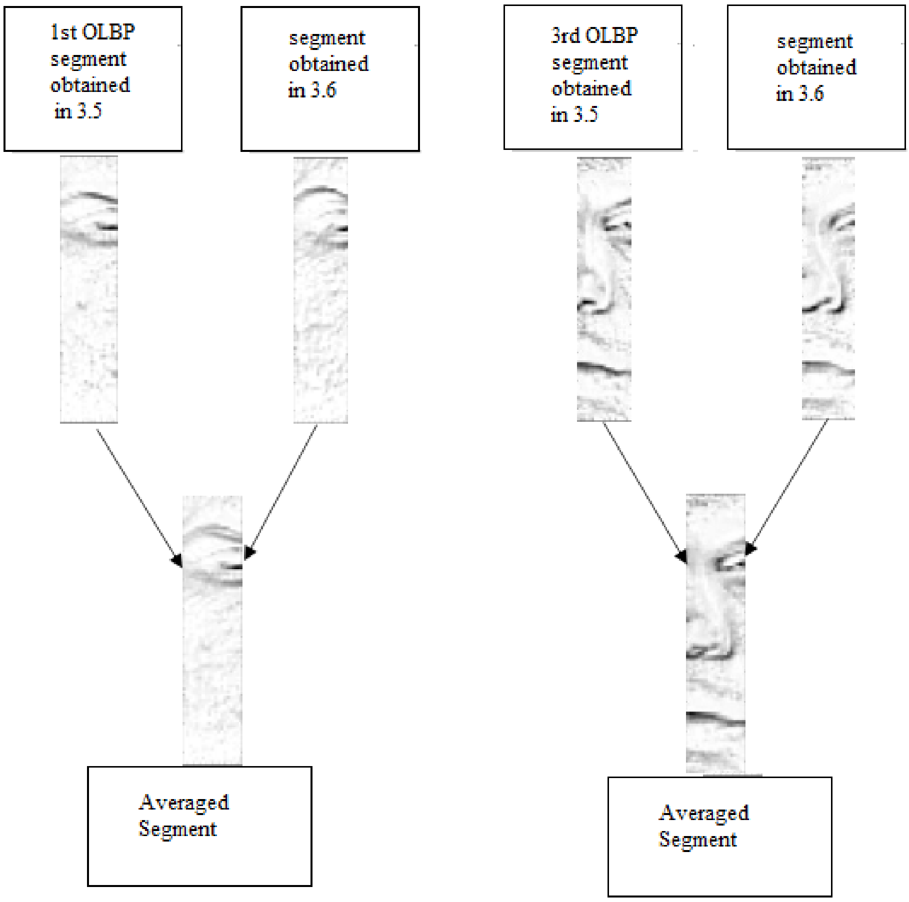

Fig 4.1: Average of Segments

STEP 9. Concatenate segments obtained in step 8.

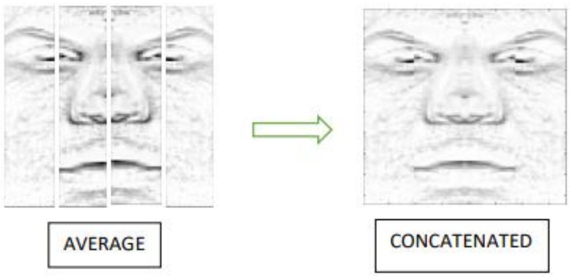

Fig 4.2: Concatenation of Averaged Segments

STEP 10. Repeat steps 1 to 9 for test images.

The test images are considered and single level DWT is performed to get the LL sub-band. The LL sub-band is resized and then divided into vertical segments. OLBP is performed on the vertical segments and then vertically flipped. The two type of segments are then averaged to get the local facial features and then the face image is reconstructed by concatenating the segments.

STEP 11. Matching of the features from database and test image using Euclidean distance.

The features of test image are compared with the feature of database images using Euclidean distance (ED) formula as given below

$$D(p,q) = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(p_i - q_i)^2} \qquad \text{------ (10)}$$

where M is the dimension of feature vector.
p_i is the database feature vector

$q_i$is the test feature vector.

The overall procedure of a face image for 2M = 4 segments is shown in below figure

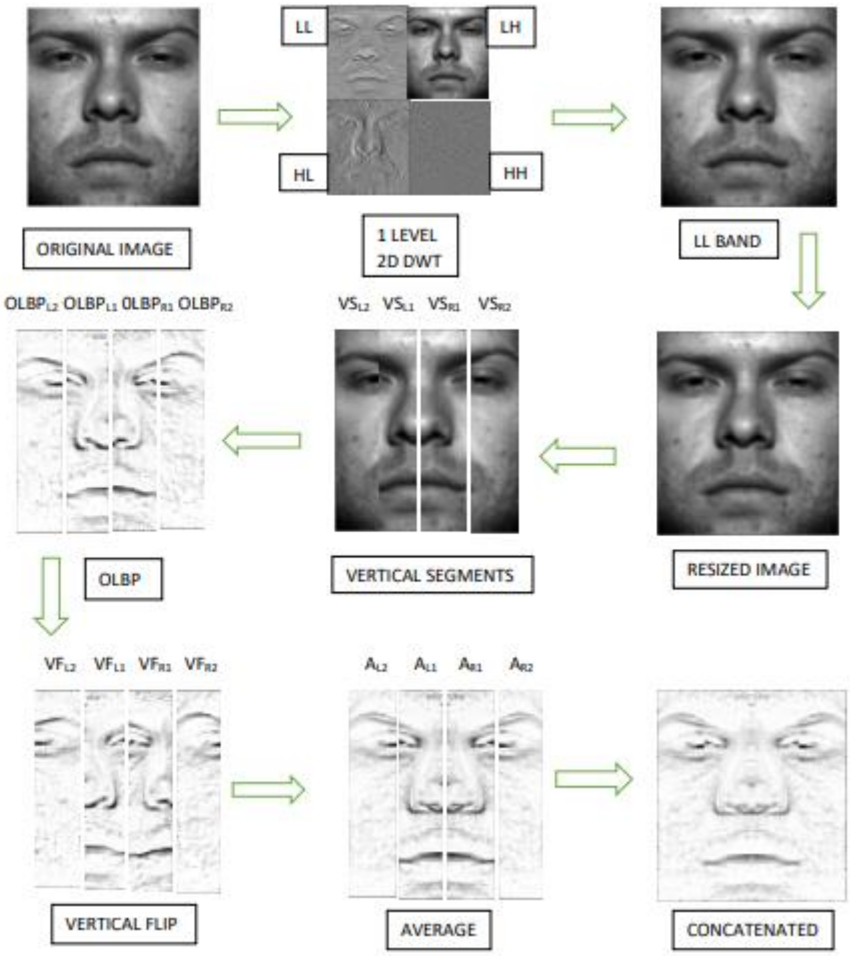

Fig 4.3 : Flow chart of the proposed method for M=2 (2M=4 segments)

As shown in the figure, after taking the resized LL sub-band of the original face image, it is divided into 2M=4 symmetrical vertical segments two on left and two on right from the middle of the face images. The left vertical segments are mentioned as VS_{LK} (where K =1,2) and right vertical segments are mentioned as VS_{RK}(where K = 1,2). OLBP is performed on all the vertical segments and the corresponding segments are named as $OLBP_{Lk}$ (where K=1,2) and $OLBP_{Rk}$(where K=1,2). Each of the OLBP performed vertical segments are then vertically flipped with the formulae (6) and (7). The corresponding vertically flipped segments of the $OLBP_{Lk}$ and $OLBP_{Rk}$ are named in the figure as VF_{LK} and VF_{RK}. Now to get the facial feature the OLBP segments and VF segments are averaged as mentioned in formulae (8) and (9). The averaged segments are named in the figure as A_{LK} and A_{RK}. Finally, the face image is reconstructed by concatenating all the averaged segments as in the figure.

RESULTS and DISCUSSIONS:

The two databases were used:ORL face database and Yale face database shown in figure 5.1 & 5.2
Database:
Ten face images of 30 individuals from ORL database are highlighted for each and every subject. The images are taken under various lighting conditions and different poses, and also facial expressions. The resolution of each image is 112x92, with 256 grey levels per pixel. The files are in PGM format.

Fig 5.1: Image samples of ORL database

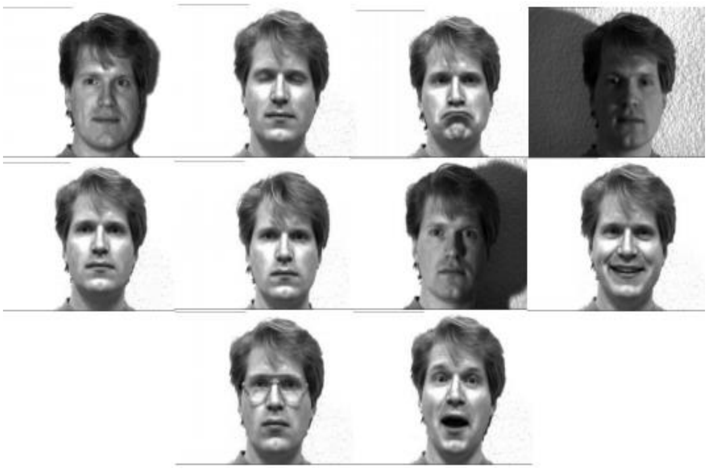

Fig 5.2: Image samples of Yale database

Result Analysis:

The definition of performance parameters, and the performance analysis using ORL and Yale database are given. The values of FRR, FFR, OTSR and MTSR are computed.

Definitions:

- False Accept Rate (FAR): It is the probability that the system matches incorrectly with images stored in the database.
- FAR is given as

$$FAR = \frac{\textbf{\textit{NO.of persons accepted out of database}}}{\textbf{\textit{Total No.of persons in database}}}$$

- False Rejection Rate (FRR): It is the ratio of number of correct persons rejected in the database to the total number of persons in database.
- FRR is given as

$$FRR = \frac{\textbf{\textit{NO. of correct persons rejected}}}{\textbf{\textit{Total No.of persons in database}}}$$

- Equal Error Rate (EER): The value where both the FRR and FAR rates are equal.
- True Success Rate (TSR): It is the ratio of total number of persons correctly matched to the total number of persons in the database and is calculated by below equation

$$TSR = \frac{\textbf{\textit{NO. of persons correctly matched in the database}}}{\textbf{\textit{Total No.of persons in database}}}$$

- The value of TSR at point of EER is known as optimum True Success Rate (OTSR) and the maximum value of TSR is known as Maximum True Success Rate (MTSR).

Table 1.1: variation of parameters of ORL & Yale Database

DATABASE	% EER	% OTSR	% MTSR
ORL	28.5	75	100
Yale	32	68	100

Comparison of Recognition rate of proposed algorithm with existing methods:

TheRecognition rate using ORL& Yaleface database of proposed method is compared with existing methods presented by Dr. Eyad I. Abbas et al.[7] and Shui-Guang Tong et al. [15] which is given in the table below. It is observed that recognition rate is more in the proposed method compared to existing methods.

Table 1.2: variation of performance parameters

SL No	DATABASE	AUTHORS	%MTSR
1	ORL	Dr. Eyad I. Abbas et al.[7]	98
		Proposed Method	100
2	Yale	Shui- Guang Tong et al. [27]	93.8
		Proposed Method	100

CONCLUSION:

The face recognition is used for several applications in day to day activities. In this paper, Vertical Segmentation Method (VSM) based feature extraction is used for face identification using DWT and OLBP. The standard databases are used for the proposed method for different performance parameters. The 2D-DWT is applied on faces and only the compressed LL sub band is considered. The LL sub-band is resized by a generalized formula. VSM is applied on resized LL sub-band to obtain the vertical segments of the face image. Then by performing vertical flip and overlapping LBP of the face, we average the two and obtain the reconstructed face. The final matching is done by using Euclidean distance and the recognition rate is noted down. It is observed that the performance of the proposed method is better than the existing method.

REFERENCES:

Chen Zhong, Zhenan Sun and Tieniu Tan, “Learning Efficient Codes for 3D Face Recogniton”, ICIP, Pp. 1928-1931,2008

Chin-Seng Chua, Feng Han and Yeong-Khing Ho “3D Human Face Recognition Using Point Signature”, IEEE International Conference On Automatic Face and Gesture Recognition”, Pp.1-6, 2012

Dominik Jelsovka, Robert Hudec, Martin Breznan and Patrik Kamenkay, “2D-3D Face Recognition Using Shapes of Facial Curves Based On Modified CCA Method”, 22ndInternational Conference Radio Elektronika, Pp.1-4, 2012

Dr.Eyad I. Abbas, Mohammed E.Saf And Dr. Khalida S.Rijab, “Face Recogntio Rate Using Different Classifier Methos Based On PCA”, International Conference On Current Research In Computer Science And Information Technology(ICCIT), Pp.37-40,2017

Hongyan Zou and Feipeng Da, “3D Face Recognition Methods Based On Medium Frequency Information of Geometry Image”, International Conferenec On Mechatronic Sciences, Electric Engineering and Computer(MEC), Pp. 1075-1078, 2013

Jan Andrzej Napieralski, Michal Miroslaw Pastuszka And Wojciech Sankowski, “3D Face Geometry Analysis For Biometric Identification” 21st Intenational Conference “Mixed Design Of Integrated Circuits And Systems”, Pp.519-522,2014

Javier Galbally, Sebastian MarcelAnd Julian Fierrez, “Image Quality Assessement For Fake Biometric Detection: Application To Iris, Fingerprint, And Face Recognition”, IEEE Transactions On Image Processing, VOL.23, No.2,Pp.10-714,2014

Marco Piccirilli, Gianfranco Doretto, Arun Ross, And Donald Adjeroh, A Mobile Structured Light System For 3D Face Acquisition” , IEEE Sensors Journal,Vol.16,No.7, Pp.1855, 2016

Mingli Song, Dacheng Tao, Shengpeng Sun, Chun Chen, And Stephen J. Maybank, “Robust 3D Face Landmark

Localization Based On Local Coordinate Coding", IEEE Transcations On Image Processing, VOL.23, No.12,Pp.5108-5122,2014

Ms. G.Geetha, Ms.M.Safa, Ms.C.Fancy,Ms.K.Chittal, "3D Face Recognition Using Hadoop", International Conference On Energy, Communication , Data Analytics And Soft Computing,Pp.1882-1885,2017.

Narayan T.Deshpande And Dr.S.Ravishankar, " Face Detection And Recognition Using Viola-Jones Algorithm And Fusion Of PCA And ANN", Advances In Computational Sciences And Technology Volume 10,Number 5,Pp.1173-1189,2017

Naveen S, Rugmini K P, Dr R.S Moni, "3D Face Recognition By Pose Correction, Patch Cloning And Texture Wrapping", International Conference On Communication Systems And Networks(Comnet),Pp.112-116,2016

Riddhi A. Vyas, Dr.S.M.Shah, "Comparison Of PCA And LDA Techniques For Face Recognition Feature Based Extraction With Accuracy Enhancement", International Research Journal Of Engineering And Technology(IRJET) Volume : 04 Issue:06,Pp-3332-3336,2017

Shui-Guang Tong, Yuan Huang And Zhe-Ming Tong " A Robust Face Recognition Method Combining LBP With Multi Mirror Symmetry For Images With Various Face Interferences", International Journal Of Automation And Computing, Pp.1-12,2018

Zhen-Hua Feng, Guosheng Hu, Josef Kittler, William Christmas, And Xiao-Jun Wu, " Cascaded Collaborative Regression For Robust Facial Landmark Detection Trained Using A Mixture Of Synthetic And Real Images With Dynamic Weighting" , IEEE Tarnscations On Image Prcessing, Pp.1-16,2015
