DWT and LBP Map Based Feature Descriptors for Face Recognition in Harsh Light Variations

Shekhar Karanwal
Graphic Era University (Deemed),
India
shekhar.karanwal@gmail.com

Abstract: *In [11] Karanwal et al. provided enhancements to three descriptors for Face Recognition under illumination variations. The three descriptors for which enhancements are done are Local Binary Pattern (LBP), Horizontal Elliptical LBP (HELBP) and Median Binary Pattern (MBP). By deploying Two Dimensional DWT (2D-DWT) (utilizing haar at level 1) before features extraction of LBP, HELBP and MBP, the enhancements are made. These improved ones outperforms the original descriptors comprehensively. After careful analyzing the work proposed in [11] it has been observed that even after image pre-processing, histograms of LBP, HELBP and MBP unable to capture the efficient information to declare as the robust descriptors in light variations. In the proposed work it has been observed and implemented that map feature of LBP, HELBP and MBP (after image pre-processing by 2D-DWT) yields much better accuracy than the histogram based descriptors. The three proposed descriptors are 2D-DWT+LBP_{map}, 2D-DWT+$HELBP_{map}$, 2D-DWT+MBP_{map}. These map features full and completely outperform its respective histogram features & these are LBP_{hist}, 2D-DWT+LBP_{hist}, $HELBP_{hist}$, 2D-DWT+$HELBP_{hist}$, MBP_{hist} and 2D-DWT+MBP_{hist}. Among all it is 2D-DWT+$HELBP_{map}$ feature which yields best results. The feature compression is fulfilled by the usage of Fishers Linear Discriminant Analysis (FLDA) and classification was done from Support Vector Machines (SVMs). For experiments Yale B (YB) and Extended Yale B (EYB) datasets are used.*

Keywords: *LBP, HELBP, MBP, (2D-DWT), histogram feature, map feature.*

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1. Introduction

Computer Vision and Pattern Recognition are two such fields in which the local descriptors have shown promising results. With the development of new methodologies the research has been progressed very rapidly. Some different applications in which these local descriptors are tested are Face Recognition (FR), Texture Analysis (TA), Object Investigation (OI), Palm print Analysis (PA) and Ear Recognition (ER). Numerous feature extraction algorithms are developed pertaining to these applications. Some produces excellent results but still there are some places where there is the need for more improvement. Local descriptors develops their feature size by extracting & integrating features from different image locations such as eyes, mouth, eyebrows etc. That's why local descriptors are much powerful than the global descriptors. When global descriptors are used as the feature compaction then it is very useful. The challenges which always confronted in way of discriminability are noise, light, blur, emotion, occlusions, pose and corruptions.

There are various local descriptors are invented in literature and some of the examples can be explored from [10, 24, 26, 28]. The most prolific and essential local descriptor invented in the literature is the Local Binary Pattern (LBP). LBP captures local information from 3x3 neighborhood by thresholding the neighborhoods to 1 or 0 based on comparison of neighbors to center pixel. The advantages of LBP are gray scale invariance monotonic property and less complex algorithm. Some disadvantages observed in LBP are large feature size, Macrostructure feature extraction is missing, sensitive to image noise and perform Unwell in harsh light variations. Therefore after LBP development various LBP variants are invented in literature. Most of these LBP variants are histogram based feature extraction techniques. But histogram feature unable to capture the discriminant information in harsh light variations. The performance of histogram based feature is not satisfactory.

In Karanwal *et al*. [11] provided enhancements to three descriptors for FR under illumination variations. The three descriptors for which enhancements are done are LBP, Horizontal Elliptical LBP (HELBP) and Median Binary Pattern (MBP). By deploying 2D-DWT (utilizing haar at level 1) before features extraction of LBP, HELBP and MBP, the improvements are made. These enhanced ones outperforms the original descriptors comprehensively. After careful analyzing the work proposed in [11] it has been observed that even after image pre-processing, histograms of LBP, HELBP and MBP unable to capture the efficient information to declare as the robust descriptors in light variations. In the proposed work it has been observed and implemented that map feature of LBP, HELBP and MBP (after image pre-processing by 2D-DWT) yields much better accuracy than the histogram based descriptors. The three proposed descriptors are called as 2D-DWT+LBP_{map}, 2D-DWT+$HELBP_{map}$, 2D-DWT+MBP_{map}. These map features full and completely outperform its respective histogram features & these are LBP_{hist}, 2D-DWT+LBP_{hist}, $HELBP_{hist}$, 2D-DWT+$HELBP_{hist}$, MBP_{hist} and 2D-DWT+MBP_{hist}. Among all it is 2D-DWT+$HELBP_{map}$ feature which yields best results. The feature compression is fulfilled by the usage of Fishers Linear Discriminant Analysis (FLDA) [22] and classification was done from Support Vector Machines (SVMs) [8]. For experiments Yale B (YB) [6] and Extended Yale B (EYB) [6] datasets are used.

Rest paper is shaped as: Related works are given in section 2, illustration of other descriptors are delivered in section 3, the proposed descriptor with entire frameworks are placed in section 4, experiments are performed in section 5 and conclusion with future scope are posted in section 6.

2. Related Works

Boudra *et al*. [2] developed the MULTI-SCALE STATISTICAL MACRO BINARY PATTERNS (MS-SMBP) for TA. The MS-SMBP is introduced for encoding and distinguishing the macro pattern of distinct bark species. Precisely the sampling technique is defined at higher scales and then intensity distribution is summarized by utilizing the statistical measures. For encoding the distinguishing macro pattern the in-depth gradient is utilized which define the connections among scale levels and their adaptive prototype (statistical). Furthermore a learning framework is also conducted by using ResNet34. Experiments on large scale datasets proves efficacy of invented methods. Saigaa *et al*. [23] discovered the Adjustable LBP (ALBP) for TA. ALBP utilizes the neighbor blocks and a linear connection among the block features to generate binary codewords which can be utilized for image representation. For extracting block features DCT is used. Experiment confirms the ability of the proposed method. Zhang and Wang [29] developed the Multi Feature Partitioned LBP (MFPLBP) for analysis of finger vein. By utilizing the partition processing, the global & local aspect of image is improved and effect of noise is minimized. Furthermore the concept of multi-feature fusion is utilized to cope up for the uniqueness of the traditional methods. Experiments conforms the capability of the developed method. Karanwal and Diwakar [12] proposed OD-LBP for FR. In OD-LBP, there is formation of three gray differences for every orthogonal locations of both the groups in the 3x3 patch. Then a novel thresholding method is deployed for generating the OD-LBP code. Experiments on different datasets proves the efficacy of the OD-LBP.

Karanwal and Diwakar [13] Presented the Multiscale Block ZigZag LBP (MB-ZZLBP) for FR. In MB-ZZLBP, there is usage of mean filter for developing the mean patch. The mean patch reduces the image noise. After obtaining mean patch then zigzag pixels are compared in 8 neighbor locations. 1 is threshold if first neighbor is bigger or equal to the second neighbor otherwise 0 is threshold. In each switching the position of the first and second neighbors are changed. Ultimately MB-ZZLBP code is generated by giving weights and summing values. MB-ZZLBP outperforms various benchmark methods. Zheng *et al*. [31] proposed Circumferential LTP (CLTP) for identification of Anti-Counterfeiting pattern. CLTP generates the efficient local features by utilizing the inkjet painting random features. This allows the method to persist not only in light and noise variations but also to reorganize and encode the finer structures of linear shape. Experiments confirms the potent of the invented method. Chaabane *et al*. [3] invented the FR method by using the statistical features and SVM classifier. For extracting the statistical features the statistical analysis is conducted and then SVM method is utilized for integrating and classifying the features. Experiments conducted on Olivetti Research Laboratory (ORL) datasets demonstrates the effectiveness of the developed method. Pan *et al*. [21] discovered the Adaptive Center Pixel Strategy (ACPS) for TA. In ACPS, initially interpolation concept is deployed to cope up for the lost pixels. By using interpolation concept there is evolution of additional center pixel positions with extra texture details. Then gradient based descriptor is utilized for obtaining gradient (edge) image. The motive of producing edge image is to find patterns of non-uniform nature at edge places. After obtaining center pixel positions and edge image the ACPS method is introduced into the LBP framework. By choosing adaptively best center pixel, one pattern of non-uniform nature can recuperate possibly to uniform pattern and retrieve its robustness. Experiments on various datasets demonstrates the ability of ACPS method. Chandrakala and Devi [4] presented the FR by using the LBP and Histogram of Oriented Gradients (HOG) features. LBP acquire the local features from 3x3 patch by comparing the neighbors to the center and HOG captures the gradient features by using 1D-mask. Finally the HOG and LBP features are fused to develop the whole feature size. Experiments on ORL datasets confirms the potent of the developed method.

3. Illustration of Other Descriptors

3.1. Local Binary Pattern (LBP)

LBP [18] was introduced for TA after that it was utilized in other applications also. In 3x3 patch, the neighbors are transfigured to 1 for higher or equal value to center pixel. For less than condition 0 is allocated. This yields eight bit pattern from the neighbors. By granting weights (binomial) and values addition forms LBP code for one place. Computing LBP code in all positions generates LBP image. Ultimately LBP image generates the histogram size of 256. Equation 1 displays the LBP concept. In Equation 1 S, D, $H_{D,S}$ and H_C signify the total neighbor size, radius scale, individuals intensity of neighbors and center gray intensity.

$$LBP_{S,D}(x_c) = \sum_{s=0}^{S-1} p\left(H_{D,S} - H_c\right)2^s, \quad p(x) = \begin{pmatrix} 1 & x \geq 0 \\ 0 & x < 0 \end{pmatrix} \tag{1}$$

3.2. Horizontal Elliptical (HELBP)

HELBP [19] was introduced for FR after that it was utilized in other applications also. In 3x5 patch, the eight horizontal neighbors are transfigured to 1 for higher or equal value to center pixel. For less than condition 0 is allocated. This yields eight bit pattern from the neighbors. By granting weights (binomial) and values summation forms HELBP code for one place. Computing HELBP code in all positions generates HELBP image. Ultimately from HELBP image, the histogram derived the size of 256. Equation 2 displays HELBP concept. In Equation 2, S, D_1, D_2, $H_{D1,Dz},s$ and H_C signify the total neighbor size, radius D_1 (scale), radius D_2 (scale), individuals intensity of neighbors and center gray intensity.

$$\mathrm{HELBP}_{S,\,D_1,\,D_2}(x_c) = \sum_{s=0}^{S-1} p\left(H_{D_1,\,D_2,s} - H_c\right)2^s,\quad p(x) = \begin{pmatrix} 1 & x \geq 0 \\ 0 & x < 0 \end{pmatrix} \tag{2}$$

3.3. Median Binary Pattern (MBP)

MBP [7] was developed for TA after that it was used in the other applications also. In 3x3 patch, all places are transfigured to 1 for higher or equal value to median value of whole patch. For less than condition 0 is allocated. In MBP there is option to include or discard the center position. For this work center position is discarded. This yields eight bit pattern from the neighbors. By granting binomial weights and adding values forms MBP code for one place. Computing MBP code in all positions generates MBP image. Ultimately from MBP image, the histogram derived the size of 256. Equation 3 displays the MBP concept. In Equation 3, S, D, $H_{D,S}$ and H_{median} signify total neighbor size, radius scale, individuals intensity of neighbors and median of whole patch.

$$\mathrm{MBP}_{S,D}(x_c) = \sum_{s=0}^{S-1} p\left(H_{D,s} - H_{median}\right)2^s,\quad p(x) = \begin{pmatrix} 1 & x \geq 0 \\ 0 & x < 0 \end{pmatrix} \tag{3}$$

3.4. 2D-Discrete Wavelet Transform (2D-DWT)

In various image applications the 2D-DWT [1] is used as pre-processing technique. In 2D-DWT, input image is decomposed into four sub-bands by using specific class of wavelet. First sub-band is the approximation coefficient and other 3 are detail ones which are diagonal, vertical and horizontal coefficients. The different class of wavelets are haar, sym, bio, db2 etc. Depending on the requirement 2D-DWT is performed at different levels. 2D-DWT is effective illumination normalization technique.

3.5. 2D-DWT+LBP$_{hist}$

In Karanwal [11], provide improvement to the LBP descriptor by utilizing 2D-DWT before LBP feature extraction. By deploying 2D-DWT (utilizing haar at level 1) the image (input) is partitioned into 4 sub-bands. Then from each sub-band LBP features are extracted and fused. Each sub-band develops the 256 feature size therefore 2D-DWT+LBP$_{hist}$ size is 1024.

3.6. 2D-DWT+HELBP$_{hist}$

In Karanwal [11], provide improvements to HELBP Descriptor by utilizing 2D-DWT before HELBP feature extraction. By deploying 2D-DWT (utilizing haar at level 1) the image (input) is partitioned into 4 sub-bands. Then from each sub-band HELBP features are extracted and fused. Each sub-band develops the 256 feature size therefore 2D-DWT+HELBP$_{hist}$ size is 1024.

3.7. 2D-DWT+MBP$_{hist}$

In Karanwal [11], provide improvement to the MBP descriptor by utilizing 2D-DWT before MBP feature extraction. By deploying 2D-DWT (utilizing haar at level) 1 the image (input) is partitioned into 4 sub-bands. Then from each sub-band MBP features are extracted and fused. Each sub-band develops the 256 feature size therefore 2D-DWT+MBP$_{hist}$ size is 1024.

4. The Proposed Descriptors with Full Frameworks

In Karanwal [11], provide improvements to three state of art descriptors (in light variations) by performing 2D-DWT (utilizing haar at level 1) before LBP, HELBP and MBP feature extraction. The improved are 2D-DWT+LBP$_{his}$, 2D-DWT+HELBP$_{his}$ and 2D-DWT+MBP$_{his}$. These improved ones provides much better accuracy than the original descriptors in front of light variations.

After careful evaluation of the work proposed in by Karanwal [11], it has been noticed that still there is scope of improvement to these descriptors to declare them as the effective and efficient descriptor. During experiments it has been analyzed that even image pre-processing (by 2D-DWT) increases the discriminatively of the LBP, HELBP and MBP based descriptors but due to capturing histogram features from the pre-processed images the accuracy is restricted to huge extent. In contrast to histogram based features if map features is utilized then there is much enhancement in accuracy as compared to the histogram based features. With this not three descriptors are presented in the proposed work and these three are improvements to LBP, HELBP, MBP, 2D-DWT+LBP$_{hist}$, 2D-DWT+HELBP$_{hist}$ and 2D-DWT+MBP$_{hist}$ based descriptors. The description of these three proposed ones are defined as.

4.1. 2D-DWT+LBP$_{map}$

By using 2D-DWT there is generation of four sub-bands as explained earlier. Now the concept of LBP is deployed on all four sub-bands. Which further results in the four LBP maps (one from each sub-band). Now instead of using global histogram of the entire image (as it performance is unwell in light variations) the transformed image feature is used for further processing. The transformed image is converted into one dimensional feature vector. For resized 112x92 image size the four sub-bands develops size of 56x46 and after deploying LBP on each sub-band four transformed image sizes are 54x44, which are all converted into one dimensional feature vectors and added. Therefore 2D-DWT+LBP$_{map}$ develops the size of 9504. The steps of feature compaction and classification are conducted afterwards.

4.2. 2D-DWT+HELBP$_{map}$

By using 2D-DWT there is generation of the four sub-bands as explained earlier. Now the concept of HELBP is deployed on all four sub-bands. Which further results in the four HELBP maps (one from the each sub-band). Now instead of using global histogram of the entire image (as it performance is unwell in light variations) the transformed image feature is used for further processing. The transformed image is converted into one dimensional feature vector. For resized 112x92 image size the four sub-bands develops size of 56x46 and after deploying HELBP on each sub-band four transformed image sizes are 54x44, which are all converted into one dimensional feature vectors and added. Therefore 2D-DWT+HELBP$_{map}$ develops the size of 9504. The steps of feature compaction and classification are conducted afterwards.

4.3. 2D-DWT+MBP$_{map}$

By using 2D-DWT there is generation of four sub-bands as explained earlier. Now the concept of MBP is deployed on all four sub-bands. Which further results in the four MBP maps (one from the each sub-band). Now instead of using global histogram of the entire image (as it performance is unwell in light variations) the transformed image feature is used for further processing.

The transformed image is converted into one dimensional feature vector. For resized 112x92 image size the four sub-bands develops size of 56x46 and after deploying MBP on each sub-band four transformed image sizes are 54x44, which are all converted into one dimensional feature vectors and added. Therefore 2D-DWT+MBP$_{map}$ develops the size of 9504. The steps of feature compaction and classification are conducted afterwards.

4.4. The Proposed Framework

As three novel descriptors are created therefore each one yields one framework. But in this section one framework is formed for all three proposed descriptors. Although they are separately implemented. After extracting map feature of 2D-DWT+LBP, 2D-DWT+HELBP and 2D-DWT+MBP, the next step is to reduce the feature size, because feature size is on the higher size. The task of feature compaction is conducted by FLDA and then classification was performed by RBF, the SVMs approach. Figure 1. Shows the complete flow diagram of proposed work

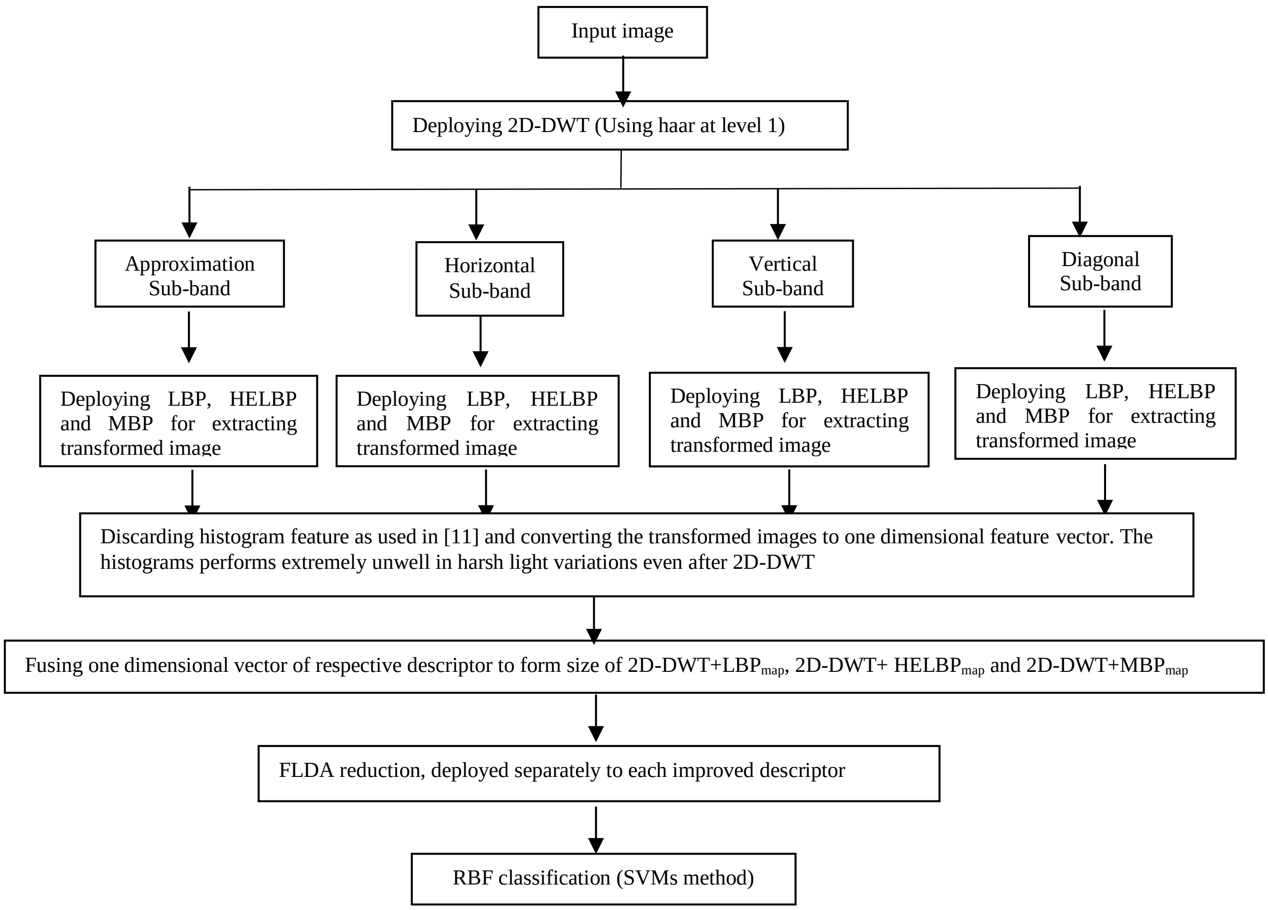


Figure 1. The proposed framework diagram of 2D-DWT+LBP$_{map}$, 2D-DWT+HELBP$_{map}$ and 2D-DWT+MBP$_{map}$.

5. Experiments

5.1. Datasets Description

The detailed description of the two datasets utilized for the evaluation are given as.

First dataset is of YB, which contribute 5760 gray scale images of 10 subjects under 9 poses in 64 light varying conditions. By including 1 ambient image of each subject the dataset pertains to 5850 images. For this work the frontal posed samples are taken for evaluation. In totality these samples are 650. These 650 have the image resolution of 192x168. Figure 2-a) delivers some samples of the YB dataset.

Second dataset is of EYB, which contribute 2432 gray scale frontal posed images of 38 subjects acquired in 64 light varying conditions. During forming the dataset 18 samples become corrupts, which sets the total to 2414. The resolution of these samples is 192x168. During FLDA compression, PCA is deployed on 2414 samples and for LDA compression the samples are regained to 2432 by zero bit padding. Figure 2-b) delivers some samples of EYB dataset.

a) YB. b) EYB.

Figure 2. Some samples of YB and EYB.

5.2. Feature Size Characteristics

Both YB and EYB provide the crop version of the image but still the images have large size. To make more compact image size all the samples are resized to 112x92. From this compact size nine methods are evaluated for feature extraction and these are LBP_{hist}, 2D-DWT+LBP_{hist}, 2D-DWT+LBP_{map}, $HELBP_{hist}$, 2D-DWT+$HELBP_{hist}$, 2D-DWT+$HELBP_{map}$, MBP_{hist}, 2D-DWT+MBP_{hist} and 2D-DWT+MBP_{map}. The feature size generated from these are 256, 1024, 9504, 256, 1024, 9504, 256, 1024 and 9504. To build short and discriminant feature FLDA is deployed to all of them. After FLDA the size evolves are [9, 83] and (124, 24) on YB and EYB datasets. The former is PCA size and latter is LDA size. The LDA size is conceived by the RBF classifier for evaluation. The working environment is MATLAB R2021.

5.3. Accuracy Computation

The accuracy is formulated by the formula/protocol defined in Equation. 4 Equation 4 portrays 3 ingredients and these are ACC, TT_{se} and W_{mts}. ACC signifies the computed accuracy in %. TT_{se} Specifies the test size and W_{mts} states the wrong matches. Wrong matches are those which are matched incorrectly. Another ingredient TG_{se} define the training size.

$$\mathrm{ACC} = \frac{\text{Correctly Recognized Samples } (\mathrm{TT_{se}} - \mathrm{W_{mts}})}{\text{Total samples in Test size } (\mathrm{TT_{se}})} * 100 \tag{4}$$

On YB, TG_{se} = (5, 10, 15, 20) and TT_{se} (60, 55, 50, 45). Ratio wise these subsets are formed and these are 5/60, 10/55, 15/50 and 20/45. The total samples in each subset are 50/600, 100/550, 150/500 and 200/450. The finest ACC on every subset is recorded after running the classifier 24 times. Table 1 shows the observed ACC. It has been noticed from Table 1. That respective map feature outperforms the hist based features. 2D-DWT+LBP_{map} outperforms the ACC of LBP_{hist} and 2D-DWT+LBP_{hist} by attaining ACC of [99.16% 99.63% 99.80% 100%]. 2D-DWT+$HELBP_{map}$ outperforms the ACC of $HELBP_{hist}$ and 2D-DWT+$HELBP_{hist}$ by attaining ACC of [99.33% 99.63% 99.80% 100%]. 2D-DWT+MBP_{map} outperforms the ACC of MBP_{hist} and 2D-DWT+MBP_{hist} by attaining ACC of [99.83% 98.72% 99.40% 99.70%]. This proves the efficacy of proposed descriptors. ACC analysis through graph is shown in Figure 3-a).

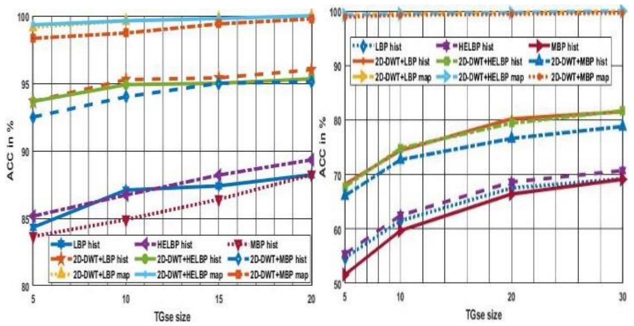
On EYB, TG_{se}=(5, 10, 20, 30) and TT_{se}=(59, 54, 44, 34). Ratio wise these subsets are formed and these are 5/59, 10/54, 20/44 and 30/34. The total samples in each subset are 190/2242, 380/2052, 760/1672 and 1140/1292. The finest ACC on every subset is recorded after running the classifier 34 times. Table 2 shows the observed ACC. It has been noticed from Table 2. That respective map feature outperforms the hist based features. 2D-DWT+LBP_{map} outperforms the ACC of LBP_{hist} and 2D-DWT+LBP_{hist} by attaining ACC of the [99.19% 99.51% 99.70% 99.92%]. 2D-DWT+$HELBP_{map}$ outperforms the ACC of $HELBP_{hist}$ and 2D-DWT+$HELBP_{hist}$ by attaining ACC of [99.28% 99.46% 99.70% 100%]. 2D-DWT+MBP_{map} outperforms the ACC of MBP_{hist} and 2D-DWT+MBP_{hist} by attaining ACC of [98.92% 99.22% 99.40% 99.61%]. This proves efficacy of proposed descriptors. ACC analysis through graph is shown in Figure 3-b).

Table 1. ACC analysis on YB.

	TG_{se} details			
	TG_{se}=5	**TG_{se}=10**	**TG_{se}=15**	**TG_{se}=20**
Descriptors	**ACC in %**			
LBP_{hist}	84.33	87.09	87.40	88.22
2D-DWT+LBP_{hist}	93.66	95.27	95.40	96.00
2D-DWT+LBP_{map}	99.16	99.63	99.80	100
$HELBP_{hist}$	85.16	86.72	88.20	89.33
2D-DWT+$HELBP_{hist}$	93.66	94.90	95.00	95.33
2D-DWT+$HELBP_{map}$	99.33	99.63	99.80	100
MBP_{hist}	83.66	84.90	86.40	88.22
2D-DWT+MBP_{hist}	92.50	94.00	95.00	95.11
2D-DWT+MBP_{map}	98.33	98.72	99.40	99.77

Table 2. ACC analysis on EYB.

	TG_{se} details			
	TG_{se}=5	**TG_{se}=10**	**TG_{se}=20**	**TG_{se}=30**
Descriptors	**ACC in %**			
LBP_{hist}	54.7	61.5	67.5	69.2
2D-DWT+LBP_{hist}	68.2	74.4	80.2	81.5
2D-DWT+LBP_{map}	99.19	99.51	99.70	99.92
$HELBP_{hist}$	55.4	62.5	68.6	70.7
2D-DWT+$HELBP_{hist}$	67.7	74.8	79.4	81.7
2D-DWT+$HELBP_{map}$	99.28	99.46	99.70	100
MBP_{hist}	51.6	59.7	66.4	69.1
2D-DWT+MBP_{hist}	66.1	72.7	76.6	78.8
2D-DWT+MBP_{map}	98.92	99.22	99.40	99.61



a) YB. b) EYB.

Figure 3. ACC investigation through graph on YB and EYB.

5.4. Accuracy Comparison With Literature Methods

On both datasets it is 2D-DWT+HELBP$_{map}$ which secures better ACC than other map features. Therefore 2D-DWT+HELBP$_{map}$ is used for the comparison with the other state of art methods.

5.4.1. YB Dataset

On YB, the totality of 11 methods are compared with the proposed method. The ACC description of all are defined: CLBP [14], tLBP [14] and LC-LBP [14] attains the ACC of [93.83% 94.72% 95.40% 96.88%], [88.66% 89.63% 90.40% 90.88%] and [85.16% 85.45% 87.20% 88.66%] on TG_{se}=5, 10, 15 and 20. 2DLDA [18], W-2DLDA [18] and Xu=2DLDA [18] attain ACC of [79.00% 80.00%], [79.50% 80.40%] and [79.25% 80.10%] on TG_{se}=15 and 20. AWULBP_MHOG [25] and VGG_PCA [25] secures the ACC of 97.20% and 79.06% when TG_{se}=32. DLSL [17], TTRLSR [17] and RRNN [17] procure the ACC of 92.33%, 87.33% and 86.30% when TG_{se}=100. The invented method outstrip ACC of all methods on compared TG_{se}. Table 3 shows all ACC.

5.4.2. EYB Dataset

On EYB totality of 14 methods are compared with the proposed method. The ACC description of all are defined as: 6x6 MB-LBP [14] and VELBP [14] achieves the ACC of [79.00% 80.80%] and [71.65% 74.69%] on TG_{se} = 20 and 30. NCDB-LBPac [15] and NCDB-LBPc [15] procure the ACC of [98.53% 98.98% 99.14%] and [98.53% 98.86% 99.07%] when TG_{se} = 10, 20 and 30. HO-GCMNR [5] and GRF [5] get the ACC of 90.60% and 78.00% when TG_{se}=20. RSLP [9] and LGC [9] pulls of the ACC of 93.63% and 88.68% on TG_{se}=10. I-LSPFC [30] and D-LSPFC [30] procure the ACC of [62.48% 74.21 82.55%] and [63.86% 77.06% 86.41%] when TG_{se}=5, 10 and 20. MSDA [27], OG-OTLPP [27], COC-LBP [16] and OC-LBP [16] secure the ACC of 80.29%, 81.39%, 97.01% and 95.31% when TG_{se}=5. The invented method outstrip the ACC of all the methods on the compared TG_{se}. Table 4 shows all the ACC. The best ACC is marked with black (bold).

Table 3. ACC comparison on YB.

	TG_{se} details				
	TG_{se} =5	**TG_{se} =10**	**TG_{se} =15**	**TG_{se} =20**	**Other TG_{se}**
Methods	**ACC in %**				
CLBP [14]	93.83	94.72	95.40	96.88	NA
tLBP [14]	88.66	89.63	90.40	90.88	NA
LC-LBP [14]	85.16	85.45	87.20	88.66	NA
2DLDA [18]	NA	NA	79.00	80.00	NA
W-2DLDA [18]	NA	NA	79.50	80.40	NA
Xu-2DLDA [18]	NA	NA	79.25	80.10	NA
AWULBP_MHOG [25] TG_{se}=32	NA	NA	NA	NA	97.20
VGG_PCA [25] TG_{se}=32	NA	NA	NA	NA	79.06
DLSL [17] TG_{se}=100	NA	NA	NA	NA	92.33
TTRLSR [17] TG_{se}=100	NA	NA	NA	NA	87.33
RRNN [17] TG_{se}=100	NA	NA	NA	NA	86.30
2D-DWT+HELBP$_{map}$	99.33	99.63	99.80	100	NA
NA-Not Available					

Table 4. ACC comparison on EYB.

	TG_{se} details			
	TG_{se} =5	**TG_{se} =10**	**TG_{se} =20**	**TG_{se} =30**
Methods	**ACC in %**			
6x6 MB-LBP [14]	NA	NA	79.00	80.80
VELBP [14]	NA	NA	71.65	74.69
NCDB-LBPac [15]	NA	98.53	98.98	99.14
NCDB-LBPc [15]	NA	98.53	98.86	99.07
HO-GCNMR [15]	NA	NA	90.60	NA
GRF [5]	NA	NA	78.00	NA
RSLP [9]	NA	93.63	NA	NA
LGC [9]	NA	88.68	NA	NA
I-LSPFC [30]	62.48	74.21	82.55	NA
D-LSPFC [30]	63.86	77.06	86.41	NA
MSDA [27]	80.29	NA	NA	NA
OG-OTLPP [27]	81.39	NA	NA	NA
COC-LBP [16]	97.01	NA	NA	NA
OC-LBP [16]	95.31	NA	NA	NA
2D-DWT+HELBP$_{map}$	99.28	99.46	99.70	100
NA-Not Available				

6. Conclusions with Future Scope

In Karanwal [11] provide enhancements to 3 descriptors for FR under illumination variations. The three descriptors for which enhancements are done are LBP, HELBP and MBP. By deploying 2D-DWT (utilizing haar at level 1) before LBP, HELBP and MBP features extraction, the improvements are made. These improved ones outperforms the original descriptors comprehensively. After careful analyzing the work proposed in [11] it has been observed that even after the Image pre-processing, histograms of LBP, HELBP and MBP unable to capture the efficient information to declare as the robust descriptors in light variations. In the proposed work it has been observed and implemented that map feature of LBP, HELBP and MBP (after image pre-processing by 2D-DWT) yields much better accuracy than histogram based descriptors. The 3 proposed descriptors are 2D-DWT+LBP$_{map}$, 2D-DWT+HELBP$_{map}$, and 2D-DWT+MBP$_{map}$. These map features full and completely outperform its respective histogram features and these are LBP$_{hist}$, 2D-DWT+LBP$_{hist}$, HELBP$_{hist}$, 2D-DWT+HELBP$_{hist}$, MBP$_{hist}$ and 2D-DWT+MBP$_{hist}$. Among all it is 2D-DWT+HELBP$_{map}$ feature which yields best results. The feature compression is fulfilled by the usage of FLDA and classification was done from SVMs. For experiments YB and EYB datasets are used.

In future the proposed descriptors will be analyzed on more tough challenges and these are noise variations, blur variations, pose variations, emotion changes, image occlusion and image corruptions. Additionally the novel descriptor will also be introduced in future.

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Shekhar Karanwal attained his B.Tech. Degree in CS and IT from IET MJP Rohilkhand University, Bareilly. He obtained his M.E. in CSE from PEC University of Technology, Chandigarh. Currently he is pursuing Ph.D. (Full Time) in CSE Dept. from Graphic Era Deemed to be University, Dehradun, Uttarakhand. His research interests includes Image processing, Pattern recognition, Computer vision and Biometrics.