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Discriminant Fused Local Pattern (DFLP) In Face Recognition under Pose variations

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***Abstract*: In [1] Karanwal et al. imposed novel local descriptor Fused Local Pattern (FLP). FLP builds its size by merging the features of MRELBP-NI, RD-LBP and 6x6 MB-LBP. FLP outperforms various individual and the several benchmark methods. After evaluating carefully the descriptor launched in [1], the one major shortcoming which is observed is that FLP builds its size by integrating only 3 descriptors. If one or more descriptors are added then discriminancy of the descriptor is assured. With this note the proposed work makes use of 4 descriptors and develops novel and discriminant descriptor called as DFLP. First three descriptor remains same as used earlier. The additional descriptor which is appended to these 3 is ELBP. Therefore DFLP feature is formed from MRELBP, RD-LBP, 6x6 MB-LBP and ELBP, by merging the features of all. PCA and SVMs are used for feature reduction and matching. For evaluating descriptors ORL used. Results suggest that accuracy enhancement is achieved by using DFLP, which beats the performance of the individually evaluated descriptors and FLP. DFLP also beats the performance of various literature techniques. The accuracy achieved by DFLP is [88.88% 93.75% 98.21%], which is much higher than the compared ones. The matlab environment used for evaluation is R2021a.**

Keywords: Local, Global, Hybrid, Compression, Matching, Dataset**.**

I. Introduction

In last few years local descriptors has proven as most effective and most demanding descriptors in the fields of computer vision and pattern recognition. The performance of these local descriptors is far beyond the imagination in different applications. Some major applications are Face Recognition (FR), Object Recognition (OR), Texture Analysis (TA) and Ear Recognition (ER). In local descriptors, the size is formed from different portions of the original image or the transformed image. The different portion includes nose, eyes, lips, mouth and forehead. Then all features are merged to develop full feature size. There are several unconstrained conditions persists in front of achieving the discriminativity. These are light, expression, pose, blur and noise. The performance of global descriptors are not as impressive as it is of the local descriptors. Although in reducing the feature size these global descriptors are very useful. In global, the feature extraction is dome from full image (the input image or the transformed image) which are then taken by the classifier for evaluation. The combination of local and global descriptors referred to as the hybrid descriptor. Among several local descriptors invented, the most prolific one is (LBP) [2]. LBP has various advantages: its algorithm is less complex, low computational complexity and easy to implement. Apart from this various demerits are also noticed in LBP: limited spatial ability, large dimension, ineffective in extreme light changes and noisy thresholding function. As a result various LBP variants were introduced. These LBP variants achieves good results in contrast to the LBP and many others. Description of some of the LBP variants are defined as: Shakoor et al. developed the feature selection and mapping of LBP to resolve feature size problem. Precisely by proposing mapping methods the feature reduction is done and then these features are mapped into the histogram. All developed methods are light & rotation invariant. Furthermore the discriminant features are selected by using the method called as constrained method. On various datasets the proposed methods proves its potency [3]. Karanwal et al. [4] proposed the Triangle LBP (TLBP) and Orthogonal LBP (OLBP) for two different challenges i.e. pose and expression variations. TLBP feature extraction is done in the vertical and horizontal directions by utilizing 5x3 and 3x5 image patches by triangle rotation in 180^0 and 0^0 directions. For extracting OLBP features the orthogonal locations are used. To build a discriminant feature size both features are merged and called as TAO-LBP. On five datasets TAO-LBP justify it's potent.

In last few years, the deep learning methods has attracted the significant attention in FR application. The reason behind is their discriminativity and robustness in unconstrained conditions. These deep learning methods outperforms the results of local and global methods on most of the times. Some of the popular deep learning methods are CNN, AlexNet, LetNet and VGG. Deep CNN methods uses final layers (connected completely) of pre-trained CNN models. There is also option of using activation function from other layers for the feature extraction. These functions (activation) are softmax function and classification layers. Besides this various demerits are also noticed in these deep methods: the computational complexity is on the higher side, they require huge amount training data and parameter settings difficulty adaptation. All these factors restricts the usage of deep learning methods. In contrast, some of local methods achieve stupendous outcomes than deep learning methods. Some authors incorporate deep learning methods with the local descriptors and achieves stupendous outcome.

The pose variations are considered as the most major challenge in different applications. To build discriminant descriptor in front of pose variations is the most difficult task. Some work exists in the literature which deals with the challenge pose variations but they are not effective as it should be in such condition. Some used integration of local and global descriptors and achieves good results. Some used deep learning methods and achieve encouraging results. Some used integration of local descriptors and deep learning methods and achieve good results. Some used local, global and deep learning methods to build their feature size. Some used integration of multiple local descriptors and global descriptor to build their feature size. But after careful investigation it has been observed that there is a need of more discriminant descriptor in pose variations for the application FR. Among all reported work, fusion of multiple descriptors with the global descriptor achieves astonishing outcomes. This motivate author to propose the novel local descriptor in pose changes for FR.

In [1] Karanwal et al. imposed novel local descriptor Fused Local Pattern (FLP). FLP builds its size by merging the features of MRELBP-NI [5], RD-LBP [6] & 6x6 MB-LBP [7]. FLP outperforms various individual and the several benchmark methods. After evaluating carefully the descriptor launched in [1], the one major shortcoming which is observed is that FLP builds its size by integrating only 3 descriptors. If one or more descriptors are added then discriminancy of the descriptor is assured. With this note the proposed work makes use of 4 descriptors and develops novel and discriminant descriptor called as DFLP. First three descriptor remains same as used earlier. The additional descriptor which is appended to these 3 is ELBP. Therefore DFLP size is formed from MRELBP, RD-LBP, 6x6 MB-LBP and ELBP [8], by merging the features of all. PCA [9] and SVMs [10] are grasped for reduction and matching. For evaluating descriptors ORL [11] is utilized. Results suggest that accuracy enhancement is achieved by using DFLP, which beats the performance of the individually evaluated descriptors and FLP. DFLP also beats the performance of various literature techniques. The accuracy achieved by DFLP is [88.88% 93.75% 98.21%], which is much higher than the compared ones. The matlab environment used for evaluation is R2021a.

Road map: Sect. II discuss works related to the local descriptors, all methods are discussed in sect. III, results are accomplished in sect. IV, discussions are planted in sect. V with conclusions and prospect of future in sect. VIyou submit your paper print it in two-column format, including figures and tables. In addition, designate one author as the "corresponding author". This is the author to whom proofs of the paper will be sent. Proofs are sent to the corresponding author only.

II. Related Works

Vu et al. proposed the FR which is mask based, by merging LBP and CNN. First, RetinaFace (CNN technique) is used as the efficient and fast encoder that learns extra and self-supervised information from different scales. The LBP features derived from various image portions are joined with features extracted earlier. Results conducted on various datasets confirms capability of merged method, which beats the accuracy of the various techniques [12]. Wajih et al. introduced novel method Center Symmetric LBCNN (CS-LBCNN) for recognition of handwritten bilingual digit. CS-LBCNN addresses the issue of LBCNN. Additionally the improved version of CS-LBPCNN is also proposed to resolves the issue of 0 thresholding function. This improved version is called as TCS-LBPCNN. The developed methods are compared to the various other methods to check its efficacy. The developed methods proves better than the various existing LBCNN models [13]. Shakoor et al. developed the feature selection and mapping of LBP to resolve feature size problem. Precisely by proposing mapping methods the feature reduction is done and then these features are mapped into the histogram. All developed methods are light & rotation invariant. Furthermore the discriminant features are selected by using the method called as constrained method. On various datasets the proposed methods proves its potency [3]. Karanwal et al. [4] proposed the Triangle LBP (TLBP) and Orthogonal LBP (OLBP) for two different challenges i.e. pose and expression variations. TLBP feature extraction is done in the vertical and horizontal directions by utilizing 5x3 and 3x5 image patches by triangle rotation in 180^0 and 0^0 directions. For extracting OLBP features the orthogonal locations are used. To build a discriminant feature size both features are merged and called as TAO-LBP. On five datasets TAO-LBP justify it's potent. Luo et al. [14] developed the novel method Improved LBP (ILBP) to overcome the shortcomings of LBP. In ILBP, the descriptor is developed with 2 operators and these are LBP based on ranking magnitude and segmentation operator of the global threshold. In contrast to other methods the ILBP much finer than others. Karanwal et al. introduced ND-LBP and NM-LBP in FR. In former descriptor neighbor pixels are compared lined up in the direction clockwise, for building its feature size. In latter one, the comparison is done among neighbors and mean to build its feature size. Further both features are merged to build robust descriptor ND-LBP+NM-LBP. Results on ORL and GT shows that the fused descriptor conquer the accuracy of individual descriptors [15].

Khanna et al. presented image classification method by LBP and STFT techniques. LBP is used as the local feature and STFT is used as the domain of the frequency feature. The amalgamated features of LBP and STFT is made compacted by FDR, variance threshold and chi-square. For matching those features the SVMs is used. Results proves capability of merged feature [16]. Mohmmad et al. proposed a novel feature extraction method called as Extended Informative LBP (EILBP). In proposed method, loss of global details are minimized. Precisely, instead of generating the global joint histogram, EILBP compute the VAR region wise and correct them by using LBP bins. In this process, the size of huge datasets (of training) are greatly minimized. For matching SVMs is used, in which improved feature is taken as the input to generate the accurate match results. Results shows the potent of EILBP [17]. Karanwal et al. imposed the three LBP variants in FR called as MLBP, MnLBP and CLP. MLBP form its code by comparing the neighbors with the whole patch mean. MnLBP form its code by comparing the neighbors with whole patch median. Both mean and median achieves better results than the LBP. Further, to make more informative and effective face descriptor LBP, MLBP and MnLBP are merged so-called CLP. CLP beats the results of alone descriptors and it also conquers several literature methods [18]. Karanwal et al. presented MB-ZZLBP in FR. In first step the mean computation is done from different regions (2x2) of 6x6 patch. Then zigzag oriented pixels are collated with each other. Specifically, the differentiation is conducted among the higher and lower order pixels (higher-lower). For difference value higher or similar to 0, the 1 is given as the label else 0 is given. Then by putting weights, the MB-ZZLBP code is formed. Results shows capability of MB-ZZLBP [19].

Nigam et al. [20] used Uniform Rotation Invariant LBP (URI-LBP) for analysis of human activity in multiview domain. There are precisely three modules of proposed work and these are: (i) Detection of humans by subtraction of background, (ii) Extraction of feature by using rotation invariant and uniform LBP, (iii) Matching by using SVMs. The developed framework provides the humans action consistent view from which multiple individuals are looked at different views. The use of uniform pattern provides the better discriminative power than the large histogram feature. Results on various datasets illustrates introduced method ability. Kola et al. invented noise discriminant feature extraction method for ER. Initially, LBP is computed by four and diagonal neighbors. Then for effective description of feature, adaptive patch concept and mean in radial directions are also presented. The matching was conducted by SVMs. On different datasets, the results shows efficacy [21]. Karanwal et al. proposed WLBP for FR in harsh lightning variations. Initially DWT is used as the image pre-processing, from which four sub-bands are generated. First is app. and other are detailed ones. Then LBP is deployed for feature generation. In contrast to histogram feature, map feature is more discriminant all sub-bands map features are merged for full size making. Results on EYB and YB proves the ability of WLBP [22].

Bedi et al. [23] developed MLBP for images of Liver Ultrasound. In MLBP, the neighboring pixels mutual connection is transformed to the pattern (binary) based on their templates of the distance Euclidean based and deviation Standard based. The color feature and GLCM are also utilized. Results proves the ability of MLBP. Over existing methods, the MLBP proves effective and impressive. For testing various datasets are used. Karanwal et al. imposed the ROM-LBP for FR in harsh lightning variations. In harsh light changes, the performance of most of the local descriptors are not adequate (especially of LBP and OC-LBP), therefore the ROM-LBP is introduced. In ROM-LBP, mean of orthogonal radial pixels are used for thresholding in contrast to the center pixel (done by previous descriptors). This concept proves much better accuracy than LBP and other variants [24]. Tabatabaei et al. introduced MACCBP, the noise discriminant method for TA. In MACCBP, a novel mechanism is deployed for correction and detection of noisy center pixel. Furthermore, pixels in neighbors are changed by median of various neighboring pixels located at different radius. This allows to capture both micro and macro structure features. Additionally the concept of CLBP is also deployed which is characterized with the sign and magnitude features, so it increases the discriminativity. On different datasets the MACCBP proves its ability [25]. Borlea et al. presented the direction for improving clusters (resulted) accuracy of resulted clusters post processing in conjunction with the learning algorithm supervised in nature. For generation of the resulted clusters the K-mean concept is used. The main motive is to enhance the resulting clusters quality and not to minimize the time taken during processing. The proposed method attains astounding outcome [26]. Karanwal et al. invented the COC-LBP in FR. OC-LBP has the limitation of only using the sign feature extraction. The magnitude feature is missing in OC-LBP. The COC-LBP moves one step forward and launch a novel descriptor COC-LBP. The COC-LBP contains both sign and magnitude details as the feature therefore COC-LBP is more discriminant and robust than OC-LBP. COC-LBP proves also better than the various literature methods [27]. Arican et al. presented RGB-D descriptor for OR. In RGB-D, the extraction of features is accomplished by using Bag of Words (BoW), which is novel and efficient technique persisting in literature. This technique develops far better accuracy than the original. The RGB-D results are very encouraging [28].

III. Description of descriptors

A. MRELBP-NI

This descriptor [5] is very impressive in unconstrained conditions as macrostructure and microstructure essentials are acquired. The higher and lower scale features, both are used for the making of the MRELBP-NI feature size. By taking 9x9 patch, the median values are generated in the 9 regions. After generating medians, 3x3 patch evolves. Then neighborhood medians are thresholded to 1 for median values higher or similar to mean of those else 0 is granted. The 8 bit size pattern evolves and that is transformed to decimal code by binomial weights allocation. The decimal code generation for every location generates map image and that results in size of 256. In eq. 1, the MRELBP-NI code generation procedure is shown for single location and eq. 2 generates mean value. Variables P, R_2, $(\phi(W_{R_2,P,3,p}))$ and $\mu_{R_2,P,3}$ signifies size of neighbor, radius, median filter & mean. Figure 1 shows MRELBP-NI example.

$$\mathrm{MRELBP-NI}_{P,R_2,3} = \sum_{p=0}^{P-1} h\left(\phi\left(W_{R_2,P,3,p}\right) - \mu_{R_2,P,3}\right) 2^p,$$

$$h(x) = \begin{pmatrix} 1 & x \geq 0 \\ 0 & x < 0 \end{pmatrix} \quad (1)$$

$$\mu_{R_2,P,3} = \frac{1}{P} \sum_{p=0}^{P-1} \phi\left(W_{R_2,P,3,p}\right) \quad (2)$$

B. RD-LBP

In RD-LBP [6], neighborhoods difference (among two radial pixels, by differentiating the lower scale from the higher scale) is thresholded to 1 for value larger or same to 0 else 0 is given. The 8 bit size pattern evolves and that is transformed to decimal code by binomial weights allocation. The decimal code generation for every location generates map image and that results in size of 256. In eq. 3, RD-LBP concept is shown for single location. The variables P, R_1, R_2, $W_{R_2,p}$ and $W_{R_1,p}$ signifies the size of neighbor, radius (R_1 and R_2), pixels placed at scale R_2 and pixels placed at scale R_1. Figure 2 shows RD-LBP example.

$$RD-LBP_{P,R_1,R_2} = \sum_{p=0}^{P-1} h(W_{R_2,p} - W_{R_1,p})2^p,$$

$$h(x) = \begin{pmatrix} 1 & x \geq 0 \\ 0 & x < 0 \end{pmatrix} \quad (3)$$

C. MB-LBP

This descriptor [7] is very impressive in unconstrained conditions as macrostructure and microstructure essentials are acquired. MB-LBP utilizes different scales of filters to form its size. In this work the scale size utilized is 6x6. In 6x6 MB-LBP, there are 9 regions and each region size is 2x2. Initially, mean is generated in all locations of 9x9 patch. This forms the 3x3 mean patch. Then neighbors are thresholded to 1 for mean values larger or same to the center else 0 is granted. The 8 bit size pattern evolves and that is transformed to decimal code by binomial weights allocation. The decimal code generation for every location generates map image and that results in size of 256. In eq. 4, the mean generation procedure is displayed and eq. 5 generates the 6x6 MB-LBP code for single location. The variables $L_{i,j}$ and $W_{i,j}$ in eq. 4 specifies the region size and mean. The variables P, R, $W_{R,p}$ and W_c signifies the size of neighbor, radius, sole places of pixels and center pixel. Figure 3 shows the 6x6 MB-LBP example.

$$W_{i,j} = mean(L_{i,j}) \quad (4)$$

$$6x6\ MB-LBP_{P,R}(x_c) = \sum_{p=0}^{P-1} h(W_{R,p} - W_c)2^p,$$

$$h(x) = \begin{pmatrix} 1 & x \geq 0 \\ 0 & x < 0 \end{pmatrix} \quad (5)$$

D. ELBP

ELBP was proposed for FR [8]. ELBP forms its size by integrating features in horizontal and vertical directions. The horizontal directional feature is known as Horizontal Elliptical LBP (HELBP) and vertical directional feature is known as Vertical Elliptical LBP (VELBP). In HELBP, 8 horizontally and elliptically placed pixels are thresholded to 1 for value higher or similar to center else 0 is granted. The 8 bit size pattern evolves and that is transformed to decimal code by binomial weights allocation. The decimal code generation for every location generates map image and that results in size of 256. In eq. 6, the HELBP code computation concept is given. In eq. 6, P, R_1, R_2, $W_{R_1,R_2,p}$ and W_c signifies size of neighbor, radius (R_1 and R_2), pixels placed at scale (R_1 and R_2) and pixels placed at center. In VELBP, 8 vertically and elliptically placed pixels are thresholded to 1 for value higher or similar to center else 0 is granted. The 8 bit size pattern evolves and that is transformed to decimal code by binomial weights allocation. The decimal code generation for every location generates map image and that results in size of 256. In eq. 7, VELBP code computation concept is given. In eq. 7, P, R_1, R_2, $W_{R_2,R_1,p}$ and W_c signifies the size of neighbor, radius (R_1 and R_2), pixels placed at

4	5	1	4	5	1	5	5	3
6	6	2	6	6	2	1	1	1
4	5	3	5	5	3	1	1	2

scale (R_1 and R_2) and pixels placed at center. To form the ELBP size, the HELBP and VELBP size are merged. Therefore ELBP forms the size of 512. Figure 4 and 5 gives the HELBP and VELBP examples.

$$HELBP_{P,R_1,R_2}(x_c) = \sum_{p=0}^{P-1} h(W_{R_1,R_2,p} - W_c)2^p,$$

$$h(x) = \begin{pmatrix} 1 & x \geq 0 \\ 0 & x < 0 \end{pmatrix} \quad (6)$$

$$VELBP_{P,R_1,R_2}(x_c) = \sum_{p=0}^{P-1} h(W_{R_2,R_1,p} - W_c)2^p,$$

$$h(x) = \begin{pmatrix} 1 & x \geq 0 \\ 0 & x < 0 \end{pmatrix} \quad (7)$$

E. FLP

In [1], Karanwal et al. invented FLP descriptor. FLP size is formed by merging features of 3 discriminant descriptors. Therefore FLP develops size of 768. Figure 6 gives FLP illustration. Figure 7 shows the block diagram of work invented in [1].

F. DFLP

After investing carefully the work proposed in [1], the one major shortcoming is that the FLP size is merged histograms of only 3 descriptors. If one or more features are added then discriminancy of the descriptor is surely improved. With that note, the proposed work launches novel local descriptor DFLP by merging features of 4 robust descriptors and these are MRELBP-NI, RD-LBP, 6x6 MB-LBP and ELBP. ELBP is the new feature added to these features. Former 3 develops size of 256 and last one develops size of 512. Their integration develops size of 1280. Compression and matching was done by PCA and SVMs (RBF technique). RBF is most effective technique therefore used for the evaluation. Figure 8 shows the block diagram of proposed work. Figure 9 shows the DFLP illustration for single position. Figure 10 shows the flow chart of the proposed method.

IV. Results

A. Dataset used

The dataset utilized for the evaluation is the ORL. ORL also known as AT&T dataset is utilized for the evaluation of all descriptors. ORL has been successfully used in different applications therefore ORL is taken for evaluation. ORL occupy 400 samples of 40 humans with each human have 10 distinct images. These images are taken under the challenge pose variations. The other two challenges i.e. light and emotion are on the lower side. The size of these samples are 112x92. The image size is consistent on the ORL dataset i.e. all the samples possesses the same image resolution. Figure 11 shows some samples. In Figure 11 different subject samples are shown.

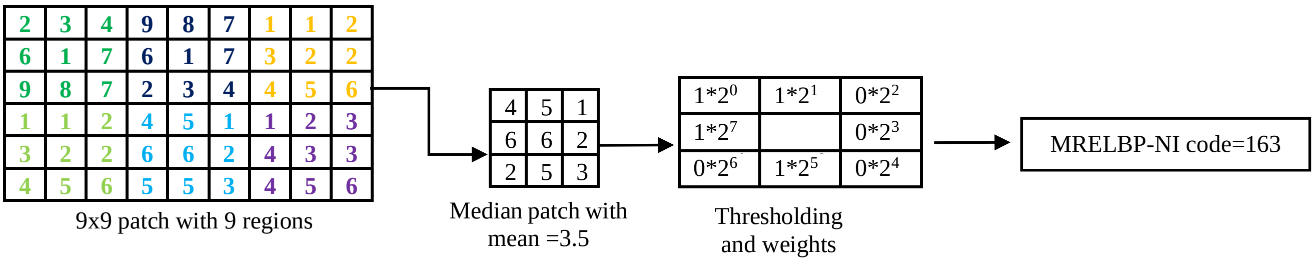


Figure 1. MRELBP-NI example

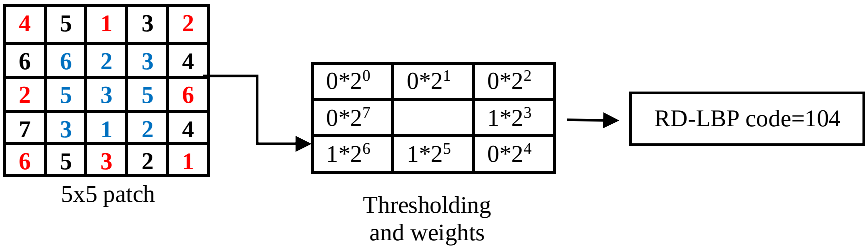


Figure 2. RD-LBP example

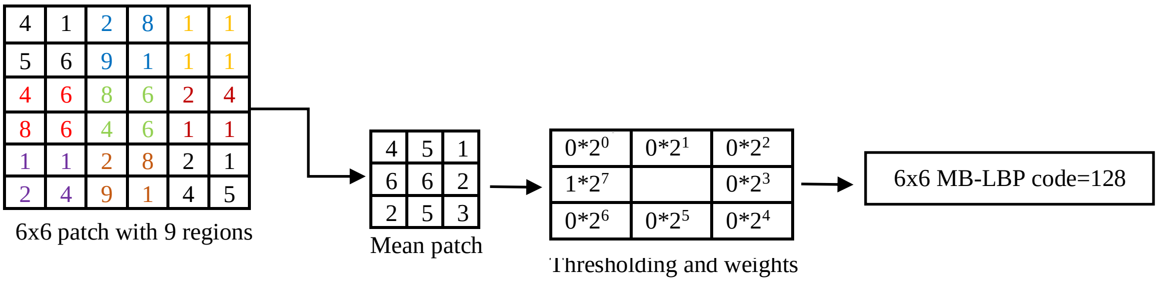


Figure 3. 6x6 MB-LBP example

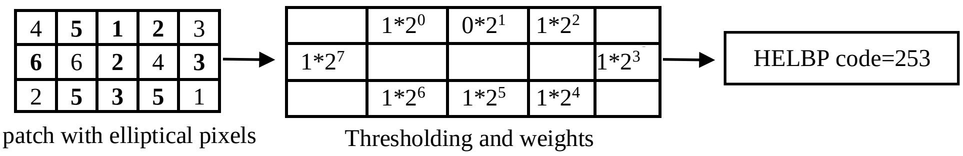


Figure 4. HELBP example

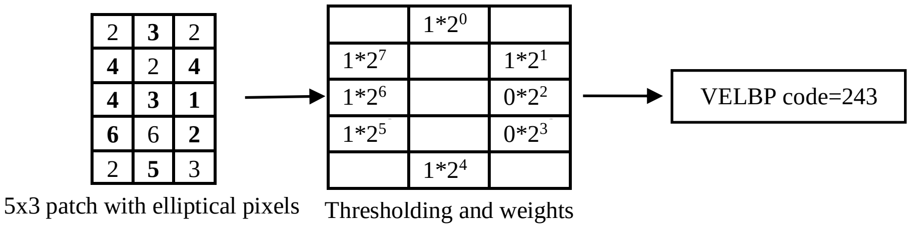
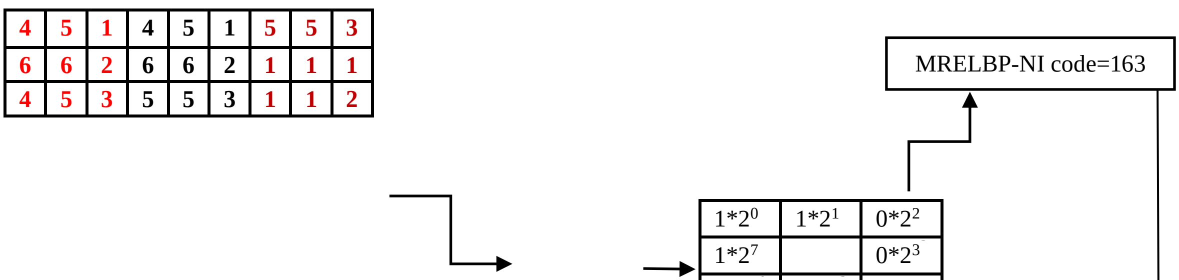


Figure 5. VELBP example



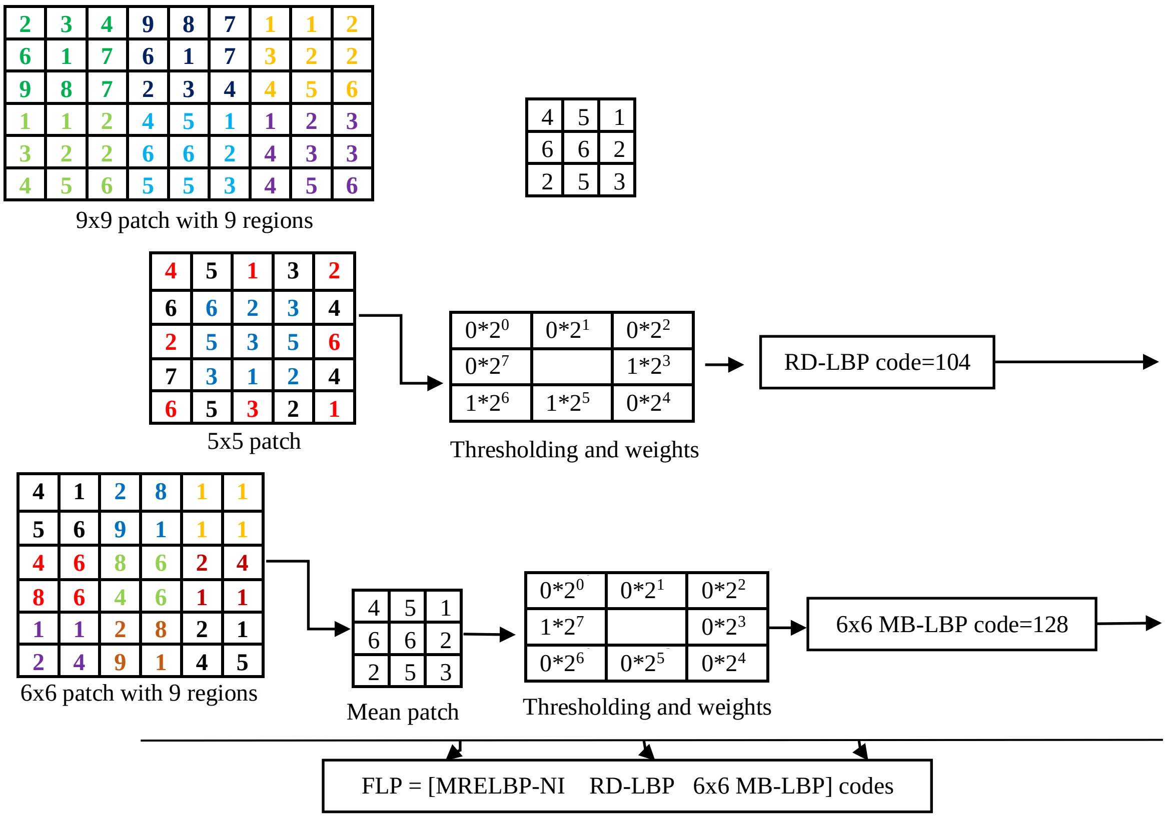


Figure 6. FLP illustration for single position

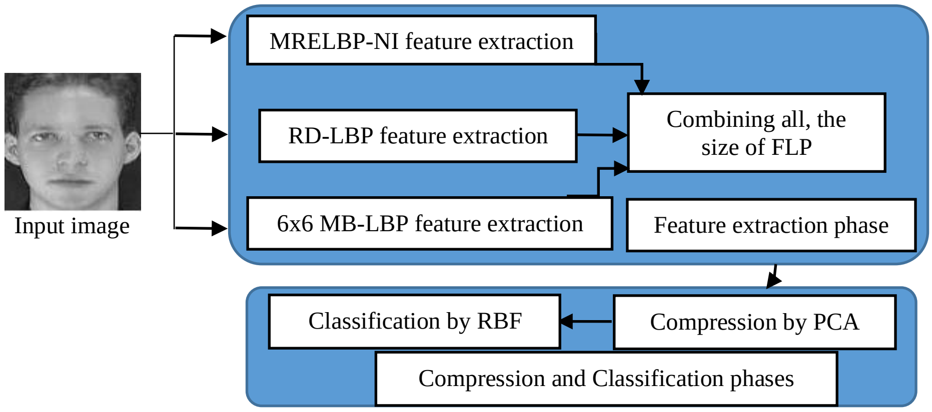


Figure 7. Architecture of FR invented in [1]

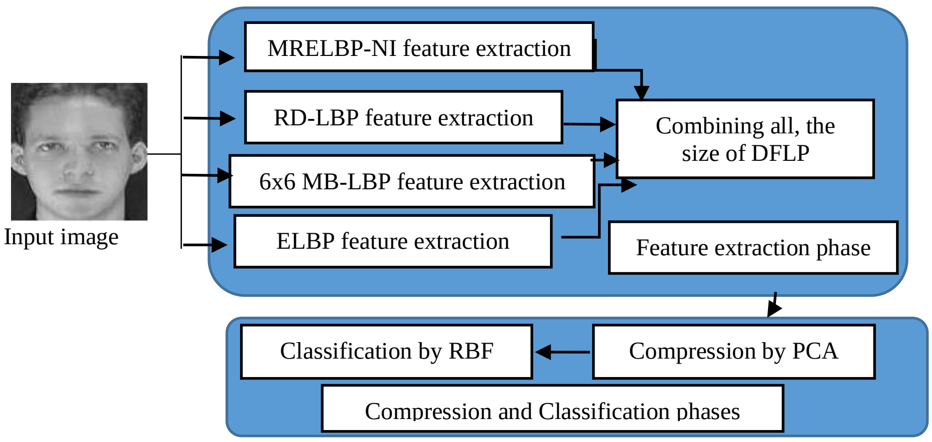
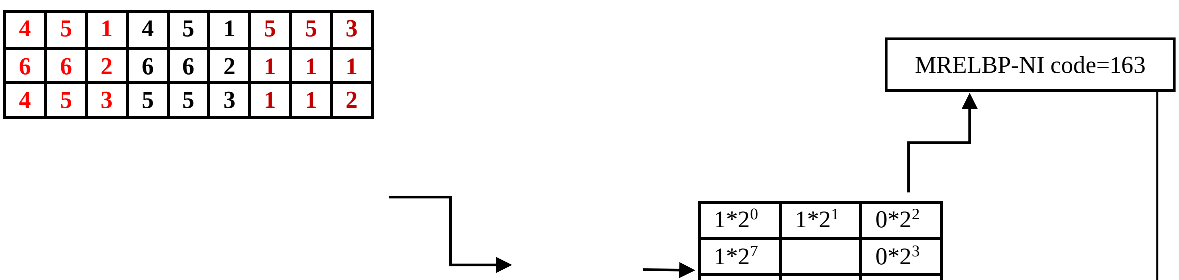


Figure 8. The proposed FR framework block diagram



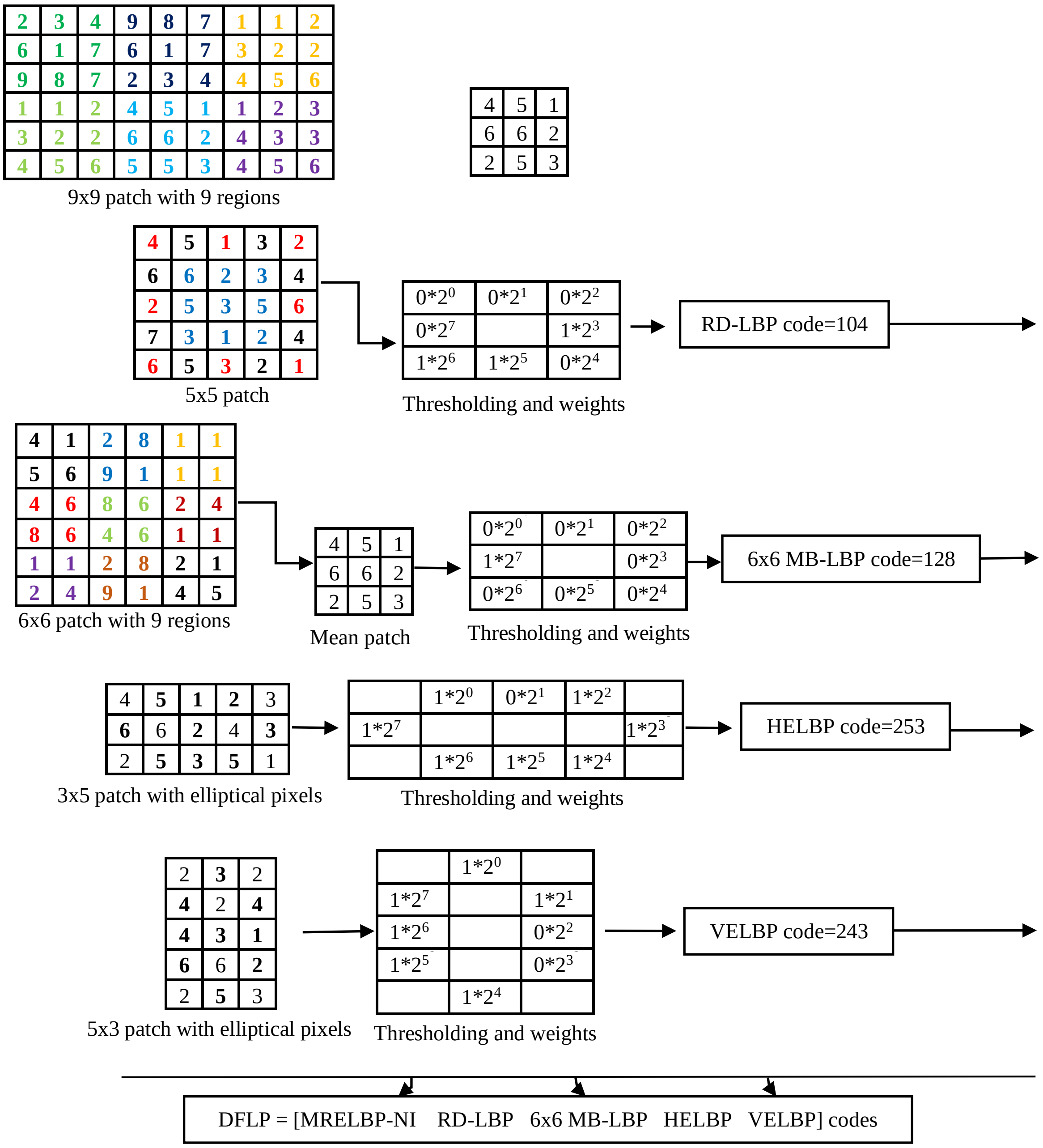
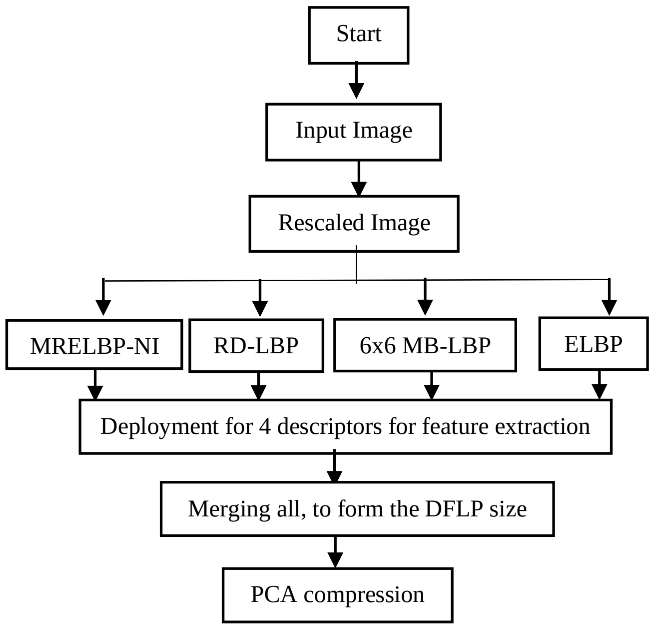


Figure 9. DFLP illustration for single position



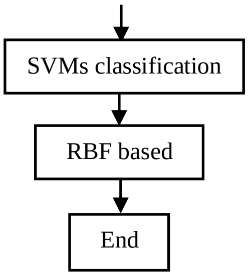


Figure 10. The flow chart of the proposed work

B. Feature size specifications

Results are conducted on gray format and ORL possesses gray scale images. ORL possesses large feature size therefore it cannot be used straight way for feature extraction. Because large feature size, if used takes much time for execution. To save the computational complexity, the samples are shortened to size of 52x48. Then 6 descriptors are imposed and these are MRELBP-NI, RD-LBP, 6x6 MB-LBP, ELBP, FLP and DFLP. ELBP size is created by joining features of HELBP and VELBP. FLP size is formed by joining the features of first three descriptors and DFLP size is formed by joining the features of first four descriptors. The last one is invented descriptor and remaining are the compared ones. The feature size formed from these are 256, 256, 256, 512, 768 and 1280. PCA is deployed to all for the feature compression. Therefore after PCA the classifier takes the size of 25 for getting the performance. The reduced size is put similar for all the descriptors for fair comparison among all. The matlab environment used for the evaluation is 2021a. The system specifications are as defined: It contains 6 GB of RAM with 64 bit windows 10 pro operating system.

C. Generation of accuracy

The accuracy is the performance metric, which has been taken for evaluating all the descriptors. Most of the literature work implement and evaluate their methods by measuring the accuracy of their methods. Therefore the performance metric accuracy has been utilized in the proposed work. The formula for accuracy generation is displayed in eq. 8. The elements used in eq. 8 are ACC, FC and TE. The specification of these parameters are accuracy, false counts and test size. The remaining element TG used for the description of training size.

Some examples of ACC computation is defined as: When 1 sample TG value is used for each then 9 samples remains for TE. Which means 40 are TG and 360 are TE. As ACC is estimated on TE and if the FC produced are 10 then ACC = (360-10)/360=97.22. When 2 samples TG value is used for each then 8 samples remains for TE. Which means 80 are TG and 320 are TE. As ACC is estimated on TE and if the FC produced are 7 then ACC = (320-7)/320=97.81. When 3 samples TG value is used for each then 7 samples remains for TE. Which means 120 are TG and 280 are TE. As ACC is recorded on TE and if FC produced are 2 then ACC = (280-2)/280=99.28. In similar way the ACC is computed on every taken subset.

$$ACC = \frac{TE-FC}{TE} * 100 \tag{8}$$

On ORL, the TG=1:3 and TE=9:7. The three subsets formed from these are (1/9, 2/8 and 3/7). For 1 sample TG value, the 9 samples are evaluated for TE. For 2 samples TG values, the 8 samples are evaluated for TE and for 3 samples TG values, the 7 samples are evaluated for TE. The ACC is analyzed on these three subsets. The supreme/finest ACC is estimated on every subset after the running of classifier 32 times. All obtained ACC is displayed in table 1. Table 1 shows that DFLP is the most discriminant among all. DFLP beats ACC of all the other 5 compared ones. DFLP achieves the ACC of [88.88% 93.75% 98.21%] on TG=1:3. These ACC are much higher and better than the compared ones. The compared descriptors achieves the ACC of [67.77% 83.43% 88.57%], [68.88% 82.18% 89.28%], [66.94% 80.31% 89.28%], [72.22% 84.37% 91.07%] and [86.11% 92.81% 96.78%]. The chronological order of these are same as mentioned earlier. The ACC investigation through graph is displayed in figure 12.

The matching algorithm used for evaluating all descriptors is SVMs (RBF). SVMs is very effective technique and used in many applications to evaluate the results therefore SVMs is considered for the evaluation purpose. The holdout method is used for partitioning of TG and TE sizes and coding strategy used is one vs all. For creating multiclass models there is the requirement of some technique which creates these models and the best model for that is ECOC. Therefore multiclass models are generated by using ECOC. ECOC is also very effective method. Results clearly indicates that by merging four descriptors (DFLP), much better facial descriptor is achieved as compared to the work launched in [1], the FLP descriptor. FLP is formed by merging three descriptors. If more than four descriptors has been used then the ACC improvement is much better than the others.

D. Accuracy comparison against literature techniques

The techniques which are compared are the 12. These techniques follows the same evaluation settings as DFLP possesses. Although they are local and non-local based techniques. The idea is to compare the ACC of different set of techniques on the considered subsets of training and test size. Their ACC illustration is defined as. IGFC [29], CLBP [29], MLDP [30], SRRS [30] and RSLDA [30] procure the ACC rate of 88.57%, 73.93%, 89.29%, 85.36% and 88.93% on TG=3. ND-LBP+NM-LBP [15], CNN-LCDRC [32] and LCDRC [32] secures the ACC rate of [84.68% 89.64%], [83.65% 90.27%] and [74.47% 80.18%] on TG=2:3. ILBP

[31], DLBP [31], GBSBP [33] and GBSBP++LPQ [33] procures the ACC rate of [61.38% 80.00% 88.21%], [72.22%

87.18% 93.57%], [70.83% 84.06% 93.21%] and [73.88% 86.56% 94.28%] when TG=1:3. The ACC off all 12 techniques are outclassed completely by DFLP. DFLP proves out better than all the techniques. So DFLP proves out as the efficient descriptor in front of the literature techniques also. Table 2 communicates the ACC comparison.

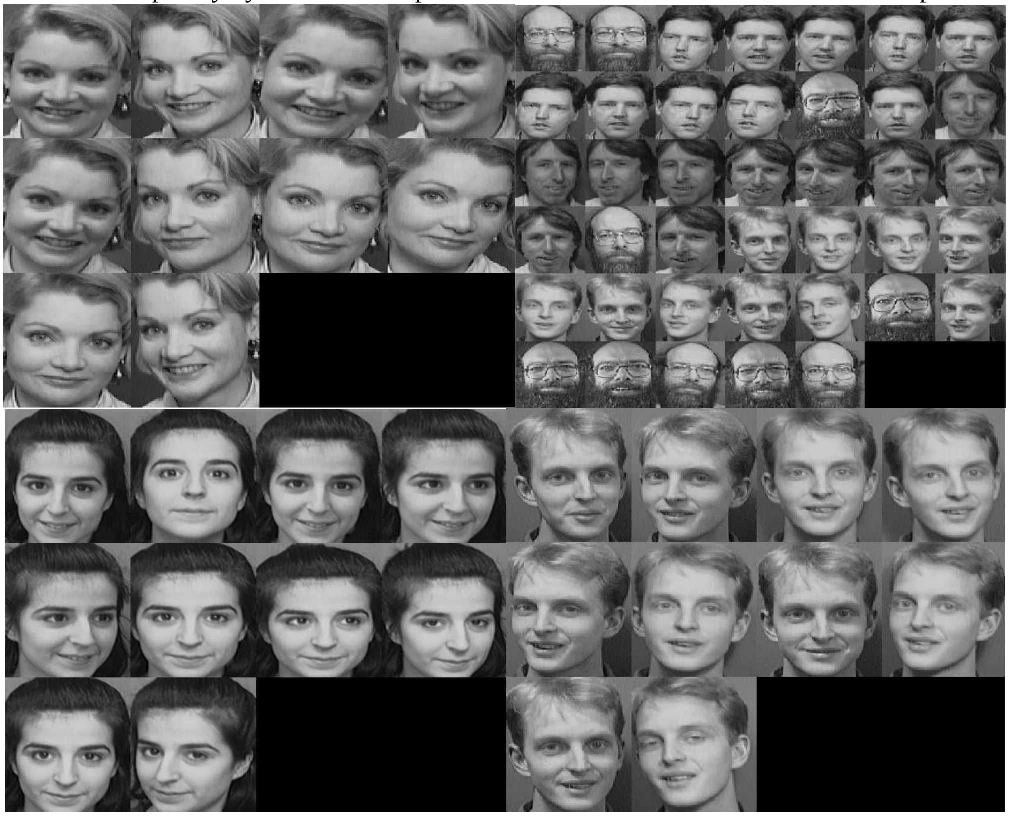


Figure 11. Some ORL images

Table 1. Analysis of ACC on ORL

	SVM (RBF) classifier		
	TG details		
	TG=1	TG=2	TG=3
Descriptors	ACC in %		
MRELBP-NI	67.77	83.43	88.57
RD-LBP	68.88	82.18	89.28
6x6 MB-LBP	66.94	80.31	89.28
ELBP	72.22	84.37	91.07
FLP	86.11	92.81	96.78
DFLP	**88.88**	**93.75**	**98.21**

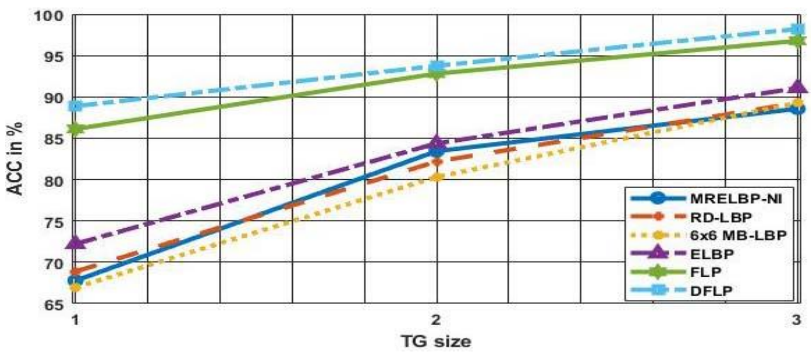


Figure 12. Graph analysis

Table 2. ACC comparison on ORL

	Training size details		
	TG details		
	TG=1	TG=2	TG=3
Techniques	ACC in %		
IGFC [29]	A	A	88.57

CLBP [29]	A	A	73.93
ND-LBP+NM-LBP [15]	A	84.68	89.64
MLDP [30]	A	A	89.29
SRRS [30]	A	A	85.36
RSLDA [30]	A	A	88.93
ILBP [31]	61.38	80.00	88.21
DLBP [31]	72.22	87.18	93.57
CNN-LCDRC [32]	A	83.65	90.27
LCDRC [32]	A	74.47	80.18
GBSBP [33]	70.83	84.06	93.21
GBSBP+LPQ [33]	73.88	86.56	94.28
DFLP	**88.88**	**93.75**	**98.21**
A-Absent			

V. Discussions

In literature several multiple features are integrated to develop the discriminant FR descriptor in pose variations. These descriptors attains good results with respect to the challenge they were implemented. Motivated from that the proposed work develops the novel local descriptor called as DFLP. Precisely, the DFLP, is the advancement of FLP developed in [1]. The limitation of FLP is that it uses only 3 features (integration) for forming the FLP size. These 3 features are MRELBP-NI, RD-LBP and 6x6 MB-LBP. If one or more features are appended to these then the accuracy improvement is guaranteed. Therefore in proposed work, the DFLP size is formed from 4 descriptors and these are MRELBP-NI, RD-LBP, 6x6 MB-LBP and ELBP. The results are conducted on ORL dataset. Results shows that DFLP is best among all the descriptors. It beats the results of the alone 4 descriptors and FLP.

The accuracy attains by DFLP is [88.88% 93.75% 98.21%], which is much higher than the other compared ones. This proves the DFLP potent as compare to the other descriptors. The compared descriptors achieves the ACC of [67.77% 83.43% 88.57%], [68.88% 82.18% 89.28%], [66.94% 80.31% 89.28%], [72.22% 84.37% 91.07%] and [86.11% 92.81% 96.78%]. The chronological order of these are same as mentioned earlier. The matlab environment used for evaluation is R2021a. DFLP also beats the results of several literature techniques. Total 12 techniques from the literature are outclassed by DFLP. This proves the DFLP potent as compare to the other techniques. For compaction and matching PCA and SVMs are used. SVMs is very effective technique and used in many applications to evaluate the results therefore SVMs is considered for the evaluation.

VI. Conclusions and Future prospect

This paper launch the DFLP descriptor under the challenge pose variations. In [1] Karanwal et al. imposed the novel local descriptor for face analysis called as Fused Local Pattern (FLP). FLP build its size by merging features of MRELBP-NI RD-LBP and 6x6 MB-LBP. FLP outperforms various individual and the several benchmark methods. After evaluating carefully the descriptor launched in [1], the one major shortcoming which is observed is that FLP builds its size by integrating only 3 descriptors. If one or more descriptors are added then discriminancy of the descriptor is assured.

With this note the proposed work makes use of 4 descriptors and develops novel and discriminant descriptor called as DFLP. First 3 descriptor remains same as used earlier. The additional descriptor which is appended to these 3 is ELBP. Therefore DFLP feature size is formed from MRELBP, RD-LBP, 6x6 MB-LBP and ELBP, by merging the features of all. Compression and matching was done by PCA and SVMs. SVMs is very effective technique and used in many applications to evaluate the results therefore SVMs is considered for the evaluation purpose. The holdout method is used for partitioning of TG and TE sizes and coding strategy used is one vs all. The multiclass models are generated by using ECOC. ECOC is also very effective method. For evaluating descriptors ORL dataset is used. Experiments suggests that accuracy enhancement is achieved by using DFLP, which beats the performance of the individually evaluated descriptors and FLP. DFLP also beats the performance of various literature techniques. The accuracy achieved by DFLP is [88.88% 93.75% 98.21%], which is much higher than the compared ones. The compared descriptors achieves the ACC of [67.77% 83.43% 88.57%], [68.88% 82.18% 89.28%], [66.94% 80.31% 89.28%], [72.22% 84.37% 91.07%] and [86.11% 92.81% 96.78%]. The chronological order of these are same as mentioned earlier. The matlab environment used for evaluation is R2021a.

The proposed work can be extended to future research in variety of ways: (i) the regional feature extraction is not conducted in the presented research. If regional wise extraction of feature is used then accuracy improvement is assured, (ii) the testing is not conducted on the large scale datasets. In future some large scale datasets will be used, (iii) the development of more robust and discriminant face descriptor. In future the development of novel local descriptor is guaranteed. Additionally some other applications will also be considered for evaluation. The inclusion of other applications give new directions to the proposed work.

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