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Face Recognition under varying Expressions and Illumination using particle swarm optimization

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Abstract

Social networks generate enormous amounts of visual data. Mining of such data in recommender systems is extremely important. User profiling is carried out in recommender systems to build the holistic persona of the user. Identification and grouping of images in these systems is carried out using face recognition. It is one of the most appropriate biometric features in such situations. Ever since the first use of face recognition in security and surveillance systems, researchers have developed many methods with improved accuracy. Face recognition under variant illumination is still an open issue and diverging facial expressions reduces the accuracy even further. State of the art methods produced an average accuracy of 90%.In this study, a computationally intelligent and efficient method based on particle swarm optimization (PSO) is developed. It utilizes the features extracted from texture and wavelet domain. Discrete Wavelet Transform provides the advantage of extracting relevant features and thereby reducing computational time and an increase in recognition accuracy rate. We apply particle swarm optimization technique to select informative wavelet sub-band. Furthermore, the proposed technique uses Discrete Fourier Transform to compensate the translational variance problem of the discrete wavelet transform. The proposed method has been tested on the CK, MMI and JAFFE databases. Experimental results are compared with existing techniques and the results indicate that the proposed technique is more robust to illumination and variation in expressions, average accuracy obtained over the CK, MMI and JAFFE datasets is 98.6%, 95.5%, and 98.8% respectively.

Keywords: Face Recognition, Face Expressions, Local Binary Pattern, Wavelets, variant illumination, particle swarm optimization.

1. Introduction

Face Recognition (FR) is a biometric solution that is used for the identification or authentication of a human from a video or image source. It has been successfully utilized in a variety of domains. Key application areas of facial recognition include augmented reality, retailed marketing industry, gaming, security, forensics, video conferencing, smart meetings, visual surveillance and anti-terrorism. It is a process in which the unique facial characteristics of a person are matched with the templates stored in a facial database [1].

Finding an automated solution for the face recognition problem is not a trivial task due to various factors including variable lighting effects [2], different facial expressions and postures [3] in different images of the same person. Face recognition techniques can be classified into three groups; feature-based, holistic, and hybrid of these two [1].

In face recognition process, facial features' extraction process plays an important role and it involves a number of decisions like the selection of appropriate features, description, and representation of these features. The fundamental goal is to represent patterns with the most significant features from the feature set yet with minimal loss of important facial information [4]. The FR methodology is highly dependent on the quality of such feature selection that serves as an input to the classifier. A feature extractor of good quality must be capable of extracting the discriminant features in unconstrained situations like outdoors, variable illumination, variation in poses, and facial expressions etc. Majority of the holistic feature extraction technique uses a combination or variations of Neural Networks, Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) [5] etc. PCA-based face recognition has the advantages of simplicity and efficiency but is vulnerable in the presence of different lighting conditions, translation-variance, and different poses [6]. LDA-based techniques are suitable candidates for feature extraction and dimensionality reduction. These are generally considered better than the conventional PCA-based techniques and are also able to solve the illumination problem [7].

Transform domain-based techniques extract the major features of a facial image by performing the transformation from one coordinate system to a new orthogonal coordinate system resulting in the reduction of dimensionality and compact representation of data.

Shah et al. [8] have proposed a novel technique where they first cater for the problem of changes in textual values that occur due to illumination normalization and then the false positive rate is reduced. They have used LDA and KLDA to represent the features. Euclidian distance is used to check the similarity between two images. Seal et al. [9] performed a comparative analysis of thermal face recognition using local binary pattern and wavelet-based features extraction process. PCA is used after feature extraction step in order to reduce the data dimensions. Lee & Lee [10] used multi-scale morphological techniques to compensate illumination effects while extracting texture information and small-scale features. They have first enhanced the texture information and then performed illumination estimation in the second step. A spatiotemporal RBM-based model is proposed in [11] to find the relationship between different image pair of different expressions. Proposed model shows superior performance after comparison with state of the art techniques. Mistry et al. [12] conduct the comparison of vertical and horizontal features by employing modified local binary pattern. Then, features optimization is performed with micro-genetic algorithm. Experiments have been performed on MMI and CK database.

Pose-invariant face recognition (PIFR) techniques have been discussed comprehensively in a survey provided by Ding et al. [13]. PIFR current techniques can be categorized into four types namely face synthesis methods, robust pose based feature extraction techniques, multi-view subspace learning methods and hybrid techniques. Techniques falling into the category of face synthesis perform face synthesis by computing the wraps across poses for every pixel value. The weakness of this method is the loss of significant texture features which can be further useful for classification [13].Robust pose based feature extraction techniques are based on learning and sometimes are called engineered features. These engineered techniques use models developed using machine learning methods and can also be designed manually. However, these methodologies are only being used for solving PIFR problems. Multi-view subspace learning methodology transforms input features to pose specific features which reduce the gap between numerous poses. However, it requires a lot of training input data and is considered a shortcoming of this methodology. It also increases computational complexity as a large number of parameters are required to tune during the learning process.

Keeping in view of the pros and cons of the above-mentioned techniques, we propose a novel methodology for solving one of the most challenging problems of facial expression classification. Following the major contribution of the proposed technique: -

- A novel hybrid solution is proposed that is capable of handling the complex variations of the real-world facial images.
- LBP descriptor containing the local texture information, convert the input image into LBP image. It avoids the construction of histogram which results in a significant reduction of data dimensions.
- DWT is used in order to achieve the multi-scale analysis.
- As the translated image of DWT is different from the original DWT image which undermines the performance so DFT has been utilized to overcome the translation variance problem of DWT.
- PSO algorithm is utilized for selection of optimal features from wavelet sub-bands.

This paper is organized as follows:
In section 2, material and methods are briefly discussed. Overview of the proposed framework is presented in section 3. Section 4 presents the simulation and results followed by conclusion and future work in section 5.

2. Materials and Methods

2.1. Local Binary Pattern (LBP)

Local Binary Pattern [14] is a simple and efficient technique that is used for the extraction of significant information. It uses pixel-level intensity distributions in the image and generates a binary pattern from which the histograms of these intensities are generated. LBP is a well-known practical technique for effective texture classification. LBP operator generates a new representation of the grey level intensities which is robust against variations. LBP operator uses 3X3 neighborhood having K sampling points (S_N ε (0… K-1) for comparison while the central pixel value g_c has radius R. The equation of LBP is

$$LBP_{K,R} = \sum_{k=0}^{k-1} Vs(g_k - g_c)2^k \text{ Where } V_s(v) = \begin{cases} 1, (v \geq 1) \\ 0, (v < 0 \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Generally, uniform binary patterns are used which are the patterns that have no more than two bitwise transitions.

2.2. Discrete Wavelet Transform (DWT)

DWT represents an image as a summation of wavelet functions. Each wavelet represents unique characteristics of a particular image. One can use different wavelets depending on the usage and applicability[15]. Short basis functions and long basis functions are mostly used for the analysis of frequency. It highlights discontinuities in signals. This can be achieved by applying short high frequency and long low-frequency basis functions. We can easily identify evident discontinuities and variations by using wavelet basis vectors.
Wavelets divide the input image into four bands as shown in Figure 1. The cA sub-band contains global information of the image having high variance.

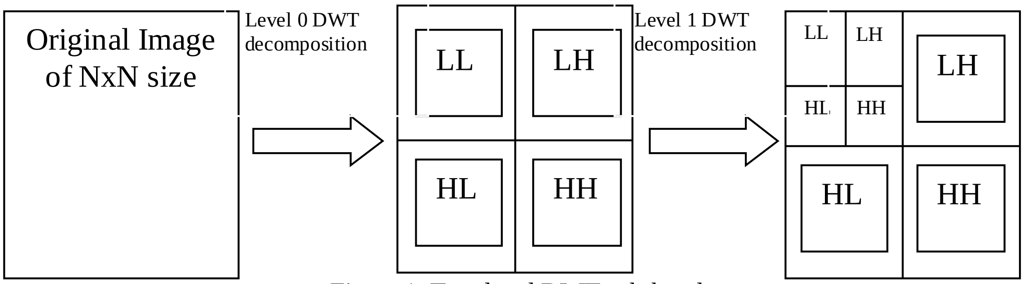

Figure 1. Two level DWT sub-bands

2.3. Particle Swarm Optimization (PSO)

Kennedy and Elberhart[16] basically presented the idea of PSO which is inspired by the behavior of bird flocking or fish schooling. In PSO, each particle is used to keep track the best solution. Initially, a random population of particles is generated and then search for the best solution. Position and velocity is associated with each particle. $V_i = (v_1^i, v_2^i, \ldots \ldots . v_m^i)$ and $X^i = (x_1^i, x_2^i, \ldots \ldots . x_m^i)$ represent the velocity and position of each particle in the search space. The personal best at time t can be represented as $P_t^g = (p_{g1}, p_{g2}, \ldots \ldots p_{gm})$. Equation 2is used to compute the new position of the particle in the search space.

$$X_{t+1}^i = X_t^i + w_t v_t^i + c_1 r_1 (P_t^i - X_t^i) + c_2 r_2 (P_t^g - X_t^i) \ldots\ldots\ldots (2)$$

In equation 1, $c_1$and c_2 denote cognitive and social parameter. w is inertia weight and $r_1$and $r_2$are random numbers uniformly distributed between 0 and 1. Global solution is considered as the final output at the end of the search.

2.4. Discrete Fourier Transform(DFT)

Frequency analysis can be effectively done by the DFT [17] technique. It exhibits the properties of symmetry and translation invariance. These properties can be very useful for facial feature extraction. When we apply DFT, the spectrum is invisible. To make this spectrum visible we have to shift it to the center. In this way, the first quadrant gets swapped with third and fourth is swapped with the second respectively.

2.5. Classifiers

In our work, Euclidean distance classifier has been used to measure the similarity between reference vectors and test vector in the gallery. It can be calculated as the distance between two points in a straight line. Euclidean distance can be calculated for two points $p_i$and $q_i$by the following equation 3;

$$D = \sqrt{\sum_{i=1}^{N} (p_i - q_i)^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

K-nearest Neighbors (KNN):

KNN is a simple and efficient instance based learning method used for classification. It uses some distance measure to calculate the distance of new unknown sample among the existing samples. The value of distance with all other available samples is sorted and output of the k data sample having least distance i.e. nearest neighbors, are considered for classification. Varying the value of k affects the performance of classifier. Value of K is set after checking the results and results having best performance with k value is set for testing data sample. Mostly Euclidean distance is used; however Manhattan and city block distance measures are also used.

Sequential Minimal Optimization (SMO):

SMO is a fast learning algorithm which provides solutions for the optimization problems [18]. It divides a larger problem into a series of smaller problems. These small sub-problems are then solved systematically.

3. Proposed Method

The major aim of our proposed frame work is to develop an efficient technique for face recognition that is not vulnerable to illumination and variations in facial expressions. Facial recognition problem has been solved by using Haar wavelet Transform and Local Binary Pattern (LBP) [9]. Translation variance is considered to be the common limitation of wavelet-based technique. LBP is a powerful descriptor which is capable of storing texture information but it requires more space. Due to large feature vector lot of redundant features exists. It results in reduced recognition performance. This problem further increases when using block-based approach. This approach favors to preserve the local information but it increases the computational cost as the features are concatenated from each block. If a block size of 4x4 is used, then the length of the feature vector (Histogram Bins) jumps from 59 to 944 for a single image as shown in figure 2.

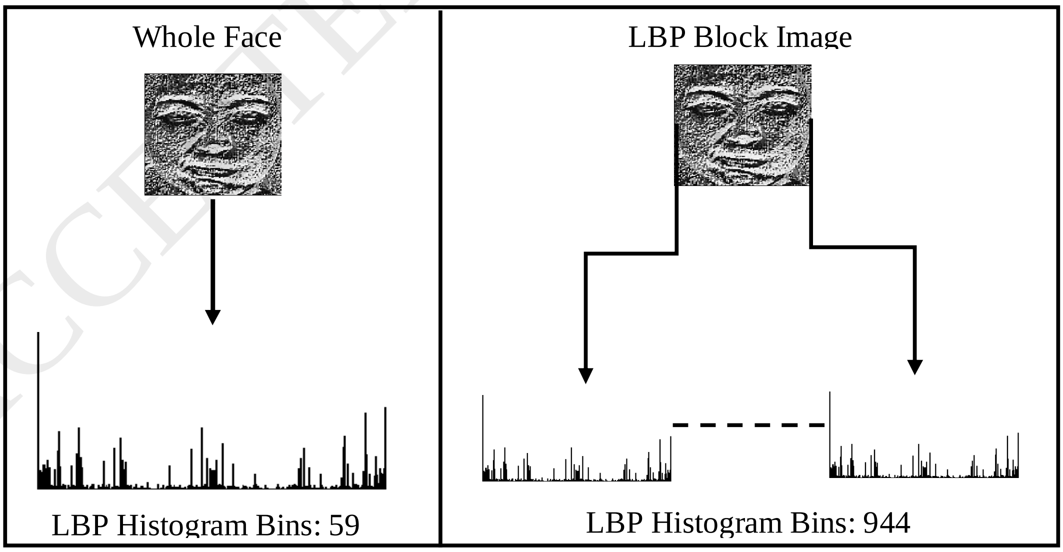

Figure 2. Histogram bins generation from LBP image

Proposed LBP-DFT technique utilizes LBP operator to calculate the value of each and every pixel and thus forms an LBP image. These LBP images are used to extract features. The histogram is not required in this process. It results in a reduction of computational cost because of reduced dimension. DWT is used for multi-scale image analysis. In order to avoid translation variance problem, we have used DFT. A detailed description of our proposed methodology is given below;

In the preprocessing step, we have applied state of the art face detection techniques and have used normalization to handle variations in illumination.

First, the face portion is detected and extracted by using Viola and Jones method [19] and then Gamma Correction is used to enhance the dynamic range of the input image. The spatial representation of the image is obtained using LBP. LBP is invariant to monotonic gray level changes and is also computationally efficient. The LBP image contains texture and geometric information of an image.

DWT is then employed in the next step which keeps the spatial relation of the pixels intact and represents the image with frequency components. DWT decomposes an input LBP image into four reduced images: diagonal [cD], vertical [cV], approximation [cA], horizontal [cH] component. The [cA] sub-band contains more information as compared to other sub-bands and basically is a reduced version of the original image. As the DWT is applied on LBP at several levels due to which the number of sub-bands increase. As stated previously, the wavelet sub-band carries different type of information which is important for classification. So in order to select the important features from different sub-bands at different levels, Sub-band important feature selection process is performed for each of the two wavelet decomposition levels. The goal of the feature selection is to store and detect only those sub-bands feature which contain relevant and compact representation of face image and also reduce the computation time.

In this study, we used binary Particle swarm optimization (BPSO) algorithm for optimal feature selection from the DWT-based extracted feature space. Unlike other algorithms (Genetic algorithm) PSO do not use evolution operators like mutation and cross-over which can make the searching operation of PSO faster.

BPSO is originally developed by Kennedy and Eberhart [20] in 1997. Numerous studies [21] show the effective use of BPSO for optimal feature selection. Each particle of PSO represents a candidate solution in the search space. The initial population for PSO is randomly generated where each particle is coded as $P = FV_1, FV_2, FV_3, \ldots..FV_n$ binary alphabet string; where n is the length of the feature vector (FV) extracted in the wavelet domain. The corresponding feature vector is selected the bit value is one "1" otherwise reject. For example, if the string of 20 data dimension ($P = FV_1, FV_2, FV_3, \ldots\ldots FV_{20}$) is analyzed for possible feature subset selection, then PSO can chose a random set of discriminative features like $FV_1, FV_3, FV_5, FV_7, FV_9, FV_{11}$by setting the 1, 3, 5, 7, 9 and 11 on in PSO. DFT is applied in next step which results in a spectrum of frequency. Euclidean distance classifier is used to measure the similarity index between reference image and input test image. Figure 3 illustrates the flow of our proposed technique.

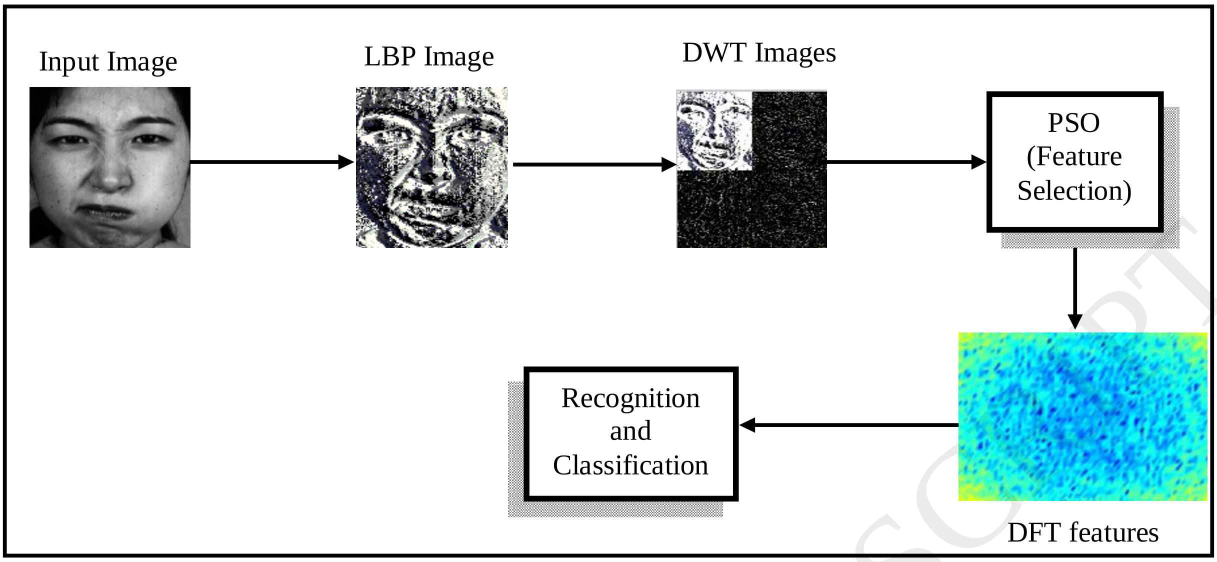

Figure 3. Architecture of the proposed system

4. Experimental Setup Results & Discussion

In order to demonstrate the efficiency and performance of our proposed technique, we have tested our framework with the well-known Cohn-Kanade (CK), MMI and JAFFE databases. Figure 4provides some sample images of CK, MMI and Japanese Female Face Expression (JAFFE) database. Face images of size 256x256 are passed to face extractor to get the cropped face. To normalize the lighting conditions, we have applied Gamma Correction to the extracted face images. We then use a uniform binary operator to compute LBP image of the input image. We have intentionally avoided the computation of LBP histogram as it increases the computational cost. All the images in the spatial domain posse's redundant features which can adversely affect the recognition accuracy rate. Only a subset of transformed features preserves the discriminative power to recognize the face image and increase the recognition accuracy rate. Then, Haar wavelet transform is applied and all the LBP images are decomposed into four new images. Haar wavelet is one of the simplest and effective transformation techniques which decomposes input image into a pair of low pass and high pass filter independently. It utilizes low pass filter by taking the average value of two consecutive pixels of input image and difference between two consecutive pixel values is used for high pass filtering. The four-level wavelet decomposition results in highest discriminative features, however, the total number of sub-bands increases due to multiple wavelet decompositions.
In order to select the optimal features from wavelet sub-band, we have applied BPSO.BPSO is run for 100 iterations with an initial population size of 60, cognitive parameter c_1=2, social parameter c_2=2 and inertia weight ω is 0.6. The N-bit binary string is used as swarm where N represents the number of selected feature at any decomposition level. The histogram of each sub-band feature is used as a fitness measure. The evolutionary process of PSO stops if the fitness stops improving after 15 iterations.

DWT suffers from the translation variance problem. This problem is not inherent in DFT. DFT descriptor is then applied to the features of the DWT and the resultant highly discriminative features are stored in vector form.

We used Sequential Minimal Optimization (SMO) and K-nearest neighbors (KNN) for training and testing.

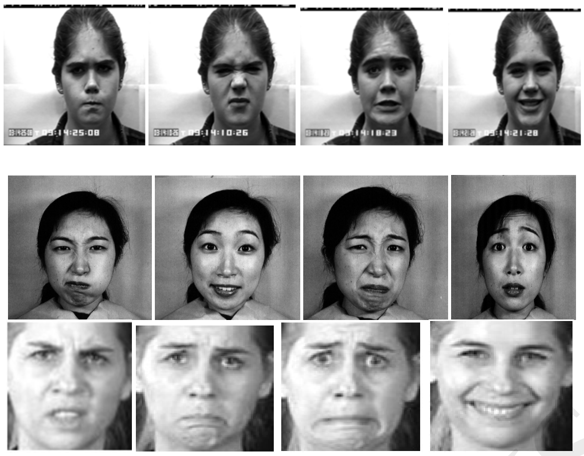

Figure.4. A sample images of CK, MMI and JAFFE database.

4.1 Experiments on Cohn–Kanade (CK) dataset:

CK dataset [22] consists of 8795 face images of six universal facial expressions (sad, disgust, anger, surprise, fear and happy) from 97 different subjects. It is a popular face image dataset that is used for testing the face recognition rate under varying expressions. We have compared our results with those techniques which used the same CK dataset as shown in table 1. A Total of 4050 images have been used for our experiments. For training purpose, we have selected 60% of the images while the remaining serves as the test dataset. It is evident that the proposed technique is more accurate as compared over other dataset even in the case when same number of training images is used for experiments.

Table 1. Comparison with Other techniques using CK database

Reference	Number of training images per person	Recognition Accuracy Rate %
[23]	5	95.47
[24]	5	97.16
[25]	10	83.7
[26]	--	91.3
[27]	--	95.37
[28]	--	89.6
Proposed	5	**98.6**

4.2 Experiments on Japanese Female Face Expression (JAFFE) dataset:

JAFFE [29] is the abbreviation of Japanese female facial expression. The JAFFE database includes a total of 213 images of six basic facial expressions namely happy, anger, sad, disgust, surprise, fear and the neutral expression. Ten Japanese female models were used to acquire the images for the database. The images of sixty Japanese volunteers were used to test the expressed expressions subjectively in each image. The accuracy rate of our proposed technique is compared with existing techniques and is provided in table 2. In case of JAFFE database, proposed technique provides better results with a lesser number of training images.

Table 2. Comparison with Other techniques using JAFFE database

Reference	Number of training images per person	Recognition Accuracy Rate %
[30]	10	84.90
[31]	4	95.12
[32]	18	93.93
[33]	100	83
[34]	10	93
[35]	15	80
Proposed	5	98.8

4.3 Confusion matrix for CK and JAFFE database Expression classification:

Table 3 provides the confusion matrix for different expression classification of JAFFE database. Unlike other expressions, neutral, disgust, anger and happy recognition accuracy rate is better. Due to some structure similarities, the sadness and happiness expression is misclassified with each other. Furthermore, fear expression is also misclassified with sad expression. The average recognition accuracy rate is 94.6 for different expressions.

Table 3: Confusion matrix for the classification results on JAFFE database

	Neutral	**Surprise**	**Anger**	**Fear**	**Happy**	**Sad**	**Disgust**
Neutral	30	0	0	0	0	0	0
Surprise	0	28	0	0	2	0	0
Anger	0	0	29	0	0	0	1
Fear	1	1	0	30	0	0	0
Happy	0	0	0	0	30	1	0
Sad	0	0	0	2	1	27	0
Disgust	0	0	1	0	0	0	28

Table 4 illustrates the confusion matrix for CK database expression classification. The Average recognition accuracy rate that we achieved is 98.3%. We used 90 images for each expression.

Table 4: Confusion matrix for the classification results on CK database

	Happy	**Sad**	**Surprise**	**Anger**	**Disgust**	**Fear**
Happy	89	0	0	0	1	0
Sad	0	85	0	3	2	0
Surprise	0	0	90	0	0	0
Anger	0	0	0	89	0	1
Disgust	0	0	0	1	88	1
Fear	0	0	0	0	0	90

4.4 Experiments on MMI database:

Performance of the proposed model has also been evaluated on MMI dataset [36] that typically provides more challenging cases for Face Recognition. This dataset includes 213 sequences with six basic expressions of 30 subjects ranging from 19 to 62 years old. Each sequence consists of single expression starting from neutral expression and ending with offset. We extracted five frames from each video sequences and thus a total of 273 frames were produced for the experiments. For benchmarking, 10 fold cross validation has been performed for all experiments. Due to unseen data, experiments on MMI dataset simulate the real-life situation. The average recognition rates of 95.5% and 94% have been obtained with SMO and KNN classifiers respectively. One of the interesting aspects of the proposed technique is that it produces better results for a simple classifier like KNN. Table 5 provides the confusion matrix of different expressions for SMO classifier.

Table 5: Recognition accuracy rate for each expression on MMI database

	Neutral	**Surprise**	**Anger**	**Fear**	**Happy**	**Sad**	**Disgust**
Neutral	36	0	0	0	0	0	0
Surprise	1	36	0	1	0	1	0
Anger	1	0	43	0	0	0	1
Fear	1	1	0	38	1	0	0
Happy	0	0	0	0	39	0	0
Sad	0	0	0	1	0	33	0
Disgust	0	0	0	2	1	2	34

Classification accuracy rate of different expressions has also been compared with state-of-art technique in table 6.

Table 6. Comparison with Other techniques using MMI database

Reference	Recognition Accuracy Rate %
Elaiwat et al. [11]	81.63
Mistry et al. [12]	94.66
Liu et al. [37]	74.59
Wang et al. [38]	59.7
Proposed	95.5

4.5 Results Comparison with traditional techniques:

To prove the efficacy of our proposed technique, we have also compared the results of different well-known methods with our proposed framework namely Weber Local Descriptor (WLD) [39], Discrete Wavelet Transform (DWT) [40], Discrete Cosine Transform (DCT) [41] and Principle Component Analysis (PCA) [42].
Cohn–Kanade (CK) [22] dataset has been used for all experiments. We provide the comparison of the average classification accuracy rate of these methods with our proposed method in Figure 5. The results indicate that the proposed method outperforms other feature extraction techniques in terms of average classification accuracy rate. We also observed from the results that

performance of the descriptor get degraded if it is utilized on the global face image. On the other hand, the traditional descriptors cannot preserve sufficient texture information due to variations in illumination and expressions of the face image.

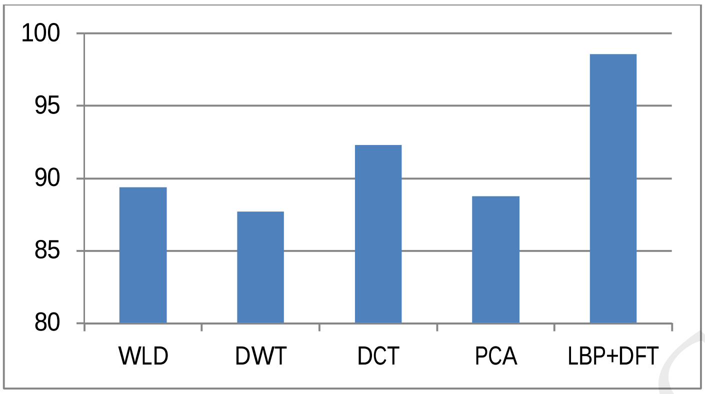

Figure.5. Proposed Technique comparison with other methods

5. Conclusion and Future Work

In this paper, the problem of face recognition under varying illumination and expressions has been investigated. A novel framework has been introduced to efficiently recognize the face images. LBP is used to preserve the local variations in the spatial domain. Discrete Wavelet Transform plays an important role in efficient feature extraction and multi-resolution analysis. PSO is utilized to select the optimal sub-band of DWT. The DWT translation variance problem is handled by applying DFT. The proposed technique provides good results and is also efficient for the images with variations in expression and illumination. Experiments on facial expression databases (CK, JAFFE, and MMI) demonstrate the effectiveness of proposed framework.
Although proposed framework exhibits good performance, there is still room for improvement especially for the images captured in an unconstrained environment containing different types of noise.

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