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Face Recognition Model based on the Laplacian Pyramid Fusion Technique

Atallah AL-Shatnawi, Faisal Al-Saqqar, Mohammad El-Bashir and Mohammad Nusir

Prince Hussein Bin Abdullah College for Information Technology
AL al-Bayt University, Mafraq, Jordan
atallah@aabu.edu.jo

Abstract

In this paper, a Fusion Feature-Level Face Recognition Model (FFLFRM) based on the Laplacian Pyramid (LP) fusion technique is proposed. The proposed FFLFRM model consists of four main processes: face detection, feature extraction, feature fusion, and face classification. In the FFLFRM model, the important characteristics of the face (i.e., the mouth, nose, and eyes) are detected, as well as, both global and local features are extracted using Principal Component Analysis (PCA) and the Local Binary Pattern (LBP) extraction methods. The extracted features are then fused using the LP fusion technique and classified using the Artificial Neural Network (ANN) classifier. The FFLFRM model was tested on 10,000 face images generated from the Olivetti Research Laboratory (ORL) database. The performance of the FFLFRM was compared with three state-of-the-art face recognition models based on local, global, and Frequency Partition (FP) fusion techniques, in terms of illumination, pose, expression, occlusion, and low image resolution challenges. The recognition results of the proposed FFLFRM were promising. Hence, it achieved up to 98.2 recognition accuracy. Thus, shows the effectiveness of the proposed model in manipulating with variant face challenges.

Keywords: *Feature Fusion; Face Recognition; Principal Component Analysis; Local Binary Pattern; Laplacian Pyramid.*

1 Introduction

The face recognition research commenced in the late 70s. Since 1990, it has become one of the highly exciting and active research domains in the computer science (CS) and information technology (IT) fields [1]. The Face Recognition System (FRS) is a computer application that automatically distinguishes or verifies the human face using certain characteristic face features [2]. This system can be used for various purposes, mainly including (i) pattern recognition, (ii) checking for criminal records, (iii) security enhancement by the use of surveillance cameras in combination with a FRS, (iv) knowing ahead if a Very Important Person (VIP) is entering hotel, (v) finding any lost children by utilization of the images received from cameras fitted in public places, and (vi) identification of criminals in public place. In addition, the FRSs may be utilized in varying science domains to compare an entity of interest with a set of entities [3, 4].

The typical FRS operates in three main phases: face preprocessing and detection, feature extraction, and face recognition [5]. In the face preprocessing and detection phase, the image of the face is usually enhanced by removing the noise and the unwanted information of the scanned face in order to detect the exact face location and characteristics, i.e., the distinctive face features [5]. In the feature extraction phase, however, the face features can be extracted globally and/or locally [6, 7]. The global features are the holistic texture of the facial features while the local features are the essential inner features of the face, that is, the eyes, mouth, and nose [6, 7]. Then, in the last stage, the extracted features are classified using variant machine learning classifiers like the Support Vector Machines, the k-Nearest Neighbor (KNN) classifier and the Artificial Neural Network (ANN) [8, 9].

A key challenge in face recognition is defining discriminative and efficient descriptors of the face appearance that are resistant to high variations in the pose, illumination, face expressions, resolution limitations, and partial occlusions, among others [10, 11, 12].

The majority of the contemporary FRSs employ only one kind of features. For sophisticated tasks like face recognition, however, it is usually the case that one feature modality is not adequately rich to detect the whole classification information that are present in the face image [10; 11, 12]. Hence, for avoiding the foregoing challenges to face recognition, information fusion at the feature level is badly needed in the FRSs.

Fusion of information for face recognition can be performed at either the decision level or the feature level [13, 14]. The feature level techniques integrate various input feature sets into one fused set that is utilized afterwards in a conventional classifier while the decision level methods integrate various classifiers (e.g., on the basis of characteristic features) to produce a powerful final classifier [10, 15, 16]. The major advantages of the feature-level fusion methods lie mainly in (i) simplicity of the training owing to that only a single phase of learning on the combined feature vector is needed and (ii) the capability of exploiting the correlations among multiple features at early stage. However, these methods require that the features to be fused are presented in the same format prior to fusion [14, 16]. Therefore, in this paper, the researcher proposes a FFLFRM model that is based on the Laplacian Pyramid (LP) fusion technique. In this model, the extracted global and local face features were fused using the LP fusion technique. Thereafter, the global and local features were extracted using the Principal Component Analysis (PCA) and the Local Binary Pattern (LBP) extraction method, respectively. Afterwards, the fused feature vectors were classified using the Multi-Layer Perceptron (MLP) ANN. Then, the proposed FFLFRM was evaluated and tested on 10,000 greyscale images that have been drawn from the Olivetti Research Laboratory (ORL) database of face images. Furthermore, performance of this proposed model was compared with the levels of performance of three state-of-the-art face recognition models based on the local, global, and Frequency Partition (FP) fusion techniques in terms of the face recognition challenges of illumination, pose, expression, occlusion, and low image resolution.

The main contributions of this study lie mainly in showing how to soundly integrate the global and local feature extraction techniques to draw reliable and credible final conclusions. These key contributions can be summarized in what follows: (i) proposing a Fusion Feature-Level Face Recognition Model (FFLFRM) based on the LP fusion technique; (ii) assessing performance of the proposed feature fusion model using the MLP ANN under the circumstances of the face image problems of illumination, pose, expression, occlusion, and low face image resolution. Performance assessment was performed using 10,000 face images that were obtained from the ORL database; and (iii) comparing performance of the proposed model with the levels of performance of three state-of-the-art models that are based on the local, global, and FP fusion techniques.

The remainder of this paper is organized as follows. Section 2 presents review of previous studies of face recognition fusion methods and models. Section 3 describes the proposed FFLFRM. Then, the experimental results are illustrated and discussed in Section 4. Lastly, Section 5 presents the conclusions of this study and suggestions for future research.

2 Related Work

Image fusion is the procedure of integrating suitable information from two images or more into one image [17]. The fused image has to encompass thorough information and be more relevant than the original image for human visual perception and object recognition. For face recognition, this process can be conducted either at the decision level or at the feature level [13].

So far, numerous face recognition methods and models have been developed on the basis of decision-level fusion (e.g., [10, 18, 19, 20, 21, 22,23,24,25, and [26]). In image fusion at the decision level, separate classifiers are employed in order to get scores on the basis of the local individual features. Then, the local decisions are integrated to make a final decision [14, 16]. Image fusion at the decision level is usually an integration of output scores obtained from classifiers [14, 16]. Fusion of LBP, pixel scores, and Gabor were carried out by [10] and normalization was performed as a post-processing step. Taigman et al. in [27] used the same local descriptors, fusing variable LDA-based one-shot similarity scores. Likewise, Wolf et al. [28] employed local descriptors on additional Gabor features. They employed combination of one-shot distance, Hellinger distance, ranking-based distances, and two-shot distance to obtain a high classification efficiency [14].

In fusion at the feature level, first, the extracted features are concatenated into one feature vector and, then, passed to a classifier [14]. In [29] Liu suggested a novel method for texture classification via generalizing the LBP method. In this method, two sorts of features (that is, pixel intensities and variances) are drawn from local patches. These researchers performed huge experiments on three challenging texture datasets (the KTHTIPS2b, Outex, and CUReT databases). The optimum classification results which this proposed technique produced was classification of the KTHTIPS2b data. The method also gave results that are comparable to the state-of-the-art results on the CUReT database by integrating variants of the LBP to produce a joint histogram.

Sanderson in [30] designed new image set-matching method that consisted of three major elements: (i) powerful descriptors of the face regions on the foundation of local features, (ii) employment of various sub-space and exemplar metrics in order to compare the concomitant face regions, and (iii) joint learning of which face parts are the most discriminative while determining the optimum mixing weights for combining the metrics. Experiments on the MOBIO, LFW, and PIE face datasets disclosed that the suggested algorithm has substantially better performance than a number of other techniques like the Kernel Affine Hull technique and the Local Principal Angle technique.

In [31] Ma designed new descriptor for the purpose of re-identification of persons that was built on late advances in fisher vectors. In specific, they developed a simple vector of the attributes that consists of pixel coordinates whose intensity was calculated for every pixel in the two-person re-identification benchmarks of VIPeR and ETHZ. This proposed descriptor achieved state-of-the art performance on the two image datasets. The local descriptors were turned into Fisher Vectors prior to their pooling so as to generate global representation of image. The resultant local descriptors that were encoded by the Fisher Vector (LDFV) were validated via experiments.

Yuan et al. [32] introduced a face recognition technique based on the LBP and Local Phase Quantization (LPQ). In this technique, the image of the face is divided into various regions. The LBP operator is employed to detect the LBP feature in the spatial area while the LPQ operator is employed to detect the LPQ feature in the frequency area. Then, the LBP and LPQ features are concatenated into an enhanced feature vector that is to be employed as a face descriptor. The simulation experiments on the AR and YALE face databases indicated that this technique has higher recognition efficiency and is quite more powerful than the single method.

In [33], Tran suggested novel technique that employs the Local Ternary Patterns (LTP) and LBP descriptors to represent the face images, in addition to feature-based similarity selection and classification algorithm in an effort to enhance the recognition efficiency. In this method, first, the face image is split into small areas from which the LTP and LBP histograms are drawn and concatenated into one feature vector. These researchers conducted experiments on the Extended Yale Face Database B and the ORL Database of Faces. Outcomes of the experiments supported superiority of this suggested algorithm over others.

Gu and Liu in [34] proposed a novel LBP feature extraction method that encodes information of both the features and the local texture. The different features are defined broadly by the Gabor wavelet features, the edges, and the color features, amongst others. In specific, a binary image is first obtained by means of extraction of the feature pixels from the image of interest. A distance vector field is then obtained via calculation of the distance vectors between every pixel and its closest feature pixel in the same binary image. The experimental eye detection results using the FERET and BioID datasets uncovered viability of the FLBP technique. Compared with a number of state-of-the-art methods, the FLBP technique had the highest accuracy of localization of the eye center.

Li in [35] derived local features like the SIFT and LBP from multi-scale, densely-sampled image spots. By linking every feature with its position, a Gaussian mixture model (GMM) was trained in order to gain the spatial distribution of the appearance of the entire face images in the training set. For verification of the face, these researchers trained SVM on the vector that concatenates the variance vectors of the entire feature pairs so as to decide if a faces/face track pair is matching or not. Moreover, they suggested joint Bayesian adaptation method for adapting universally-trained GMM to better model the differences of pose among the target faces/face track pairs. This improved the accuracy of the face verification consistently. The experiments they conducted disclosed that their suggested method does in effect outpace the state-of the-art performance in the most constricted protocol on the YouTube video face dataset and the Labeled Face in the Wild (LFW) dataset by a substantial margin.

Vu [36] suggested new technique for description of the face images by means of exploring the relations among the gradient magnitudes and orientations of varying local image structures. Besides, they presented novel technique called Patterns of Oriented Edge Magnitudes (POEM). The whitened PCA dimensionality reduction method was tested on the POD-, and POEM-based representations to obtain extra discriminative and compact face descriptors. Experiments were conducted on a number of the popular benchmarks, including the FERET dataset, both with non-frontal and frontal images, besides the somewhat challenging LFW dataset. The experimental results confirmed that the proposed technique is more efficient than the contemporary approaches as it has lower complexity and higher performance than them.

In [10], Tan and Triggs suggested feature-level, fusion, face recognition system that extracts two sets of features by utilizing the LBP local appearance and Gabor wavelet descriptors. The Kernel Discriminative Common Vector technique was then tested to the joined feature vector so as to derive discriminant non-linear features for recognition. Performance of this suggested recognition system was assessed on various challenging face databases, containing FERET, FRGC 1.0.4, and FRGC 2.0.4.

In [37], Mirza researched into fusion of both the local and global features for classification of genders. The global features were extracted by means of the Discrete Cosine Transform (DCT) and PCA. The local features, on the other hand, were extracted by the LBP approach reinforced by two-dimensional DCT. Performance of this proposed system was tested by performing extensive experiments on the FERET dataset. The results brought to surface that this approach has a recognition efficiency of 98.16% when tested to the FERET dataset.

Nusir in [38] suggested a face recognition model based on feature-level fusion and the FP method, which was actually employed to combine the global and local features by using the PCA and LBP, respectively. Experiments were performed on the ORL database of face images. The experimentation outcomes pointed out that this proposed approach has a better face recognition efficiency and is more powerful than the single approach based on the LBP and PCA.

3 The Proposed Model

In this paper, a FFLFRM based on the LP fusion technique is proposed. The model consists of four main processes: face detection, feature extraction, feature fusion using the LP method, and face classification using the MLP ANN (Figure 1). First, the face is detected based on its characteristic features, i.e., the mouth, nose, and eyes, using the Haar-cascade face detection technique. Then, both the global and local features are extracted using PCA and the LBP extraction method, respectively, in order for them to be fused using the LP fusion technique. Afterwards, the fused feature vectors are fed into the MLP ANN for face classification. Architecture of the proposed FFLFRM is shown in the Figure 1 and the main model processes are illustrated in the following sub-sections.

3.1 Face Detection Using the Haar–Cascade Technique

For face detection, the Haar-cascade face detection method is used to detect the main features of the face, that is, the eyes, mouth, and nose. This method is an appearance-based face detection technique that was developed originally by Viola and Jones [2, 12, 39]. It classifies the face Haar on the basis of the Haar-like features and is, thus, not founded on pixel analysis [40]. The Haar-like features are rectangular shape properties of appropriate features that represent the target objects [40], which are usually extracted by using the attentional cascade, the Adaptive Boosting (AdaBoost), and the integral image methods [41]. In this study, the Wang's [41] modified version of the Viola-Jones Haar-cascade face detection technique was employed for detection of four face feature patches according to the following steps:

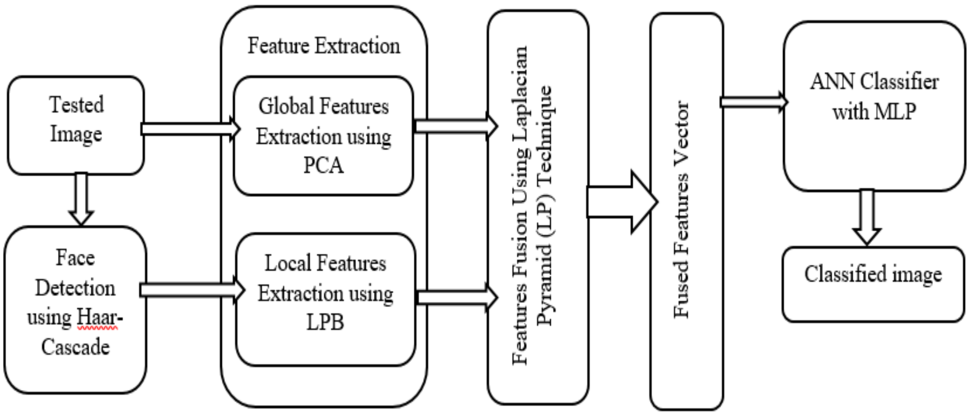
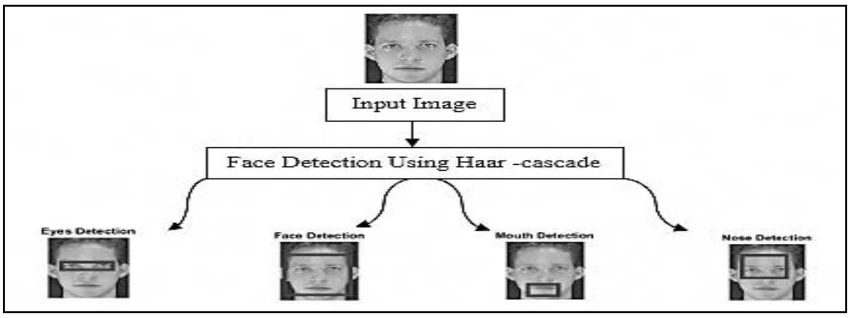


Fig. 1. Architecture of the Proposed FFLFRM.

- Identify the face and return the surrounding box that bounds the identified face (Figure 2,a).
- Recognize the nose and return the surrounding box that bounds the recognized nose (Figure 2,b).
- Detect the mouth and return the surrounding box that bounds the detected mouth (Figure 2,c).
- Recognize the eyes and return the surrounding box that bounds the recognized eyes (Figure 2,d).



(a) (b) (c) (d)

Fig. 2. Four face feature patches detected using the Haar-cascade face detection method [38].

3.2 Local and Global Feature Extraction Processes

The single most important step in the face recognition process is feature extraction. Optimum recognition depends upon success of the feature extraction method [12, 42]. The goal of feature extraction is to provide efficient representation of the image of the face by using a set of its characteristic features [12, 42]. The face features can be extracted either locally or globally and in the feature extraction process, the local and global features are extracted using LBP and PCA, respectively, in order for them to be fused in the next step using the LP feature fusion technique. The feature extraction process is explained in the following two sub-sections.

3.2.1 Global Face Features Extraction Using Principal Component Analysis

Principal Component Analysis is a traditional statistical linear transform that has been broadly employed in varying pattern recognition applications like character recognition (e.g., [43]) and face recognition (e.g., [44]). In the feature extraction process, principal component analysis, which was developed originally by Pearson [45], is employed as a statistical feature extraction technique to select and extract the global face features for those features to be fused with the local face features extracted using the LP feature fusion method, which is presented in the next sub-section.

Principal component analysis is often employed as a feature extraction method so as to reduce dimensionality of the image features. This analysis starts by calculating the mean of the data matrix, followed by calculating its covariance. Thereafter, the eigenvalues and eigenvectors are calculated [46]. The major goal of PCA is to identify the space that represents direction of the maximal difference of the data under consideration. It determines a low dimensional space or a PCA space (W) that is then employed to transform the data ($X = \{x_1, x_2, . . . , x_N\}$) from a high-dimensional space to a lower-dimensional one, where N denotes the whole number of the observations or samples and x_i expresses the i^{th} observation, sample, or pattern [47].

3.2.2 Local Face Feature Extraction Using the LBP Method

In the local face feature extraction process, the LBP method. It was developed originally by [48] for texture analysis, is employed as a statistical feature extraction technique to extract the local face features from the face image for those features to be fused with the global face features extracted using the LP feature fusion method, which is described in the next sub-section.

Basically, the local face feature extraction process operates by determining the central pixel of the 3x3 pixel block of image and computing the feature values on the basis of a pixel threshold. Then, the entire face image is presented in decimal values as a feature vector. In this process, the LBP method is employed for extraction of the local face features from the image according to the following steps [38]:

Step 1: Partition the image into a block of 3x3 pixel cells.

Step 2: Let g_c denote the threshold value and g_b express the values of its neighbors, $px_i = 0, 1, \ldots, 7$.

Texture, *T*, in the local neighborhood of pixel (x_p, y_p) can be defined as follows:

$$T = t(g_c, g_0, \ldots, g_{P-1})$$

Step 3: For all image pixel blocks, compute the LBP values by comparison of the surrounding pixel, px_i, $i = 0, 1, \ldots, 7.$, with the central pixel, px_c as shown in Equation (1):

$$LB(p_{xi} - p_{xc}) = \begin{cases} 1, & if\ p_{xi} \geq p_{xc} \\ 0, & if\ p_{xi} < p_{xc} \end{cases} \quad (1)$$

Step 4: Compute the resultant binary number from the foregoing step and transform it into a decimal form as in Equation (2).

$$LBP = \sum_{i=0}^{7} LB(p_{xi} - p_{xc}).2^i \quad (2)$$

3.3 Feature Fusion using the Laplacian Pyramid

In this study, the image fused based on the LP method, which was developed originally by Naidu and Elias [49], was employed for fusing the extracted global and local face features. The integrated fused features are presented as feature vectors that are recognized by using the MLP ANN in the subsequent step.

The LP-based fusion method of [49] was developed according to the 2D DCT method. It comprises two main functions; a reduction function and an expansion function. In this fusion method, both LP functions are disintegrated several times so as to improve the resolution of the face image [49].

The reduction function reduces the original image at the zero pyramid level, g_0, of the size *MxN* using a 2D-DCT in order to get the sequent pyramid level, g_1, of the size $\frac{M}{2} x \frac{N}{2}$, where both the spatial density and resolution are reduced. The subsequent pyramid level, g_k, is gained by iterating the same reduction procedures using 2D-DCT. The reduction function, R, is given by Equation (3) [49]:

$$g_k = R(g_{k-1}) \quad (3)$$

The expansion function expands the image of the size *MxN* at the g_k level in the pyramid to image of the size *2Mx2N* using 2D-Inverse Discrete Cosine Transformation (IDCT). The expansion function, *E*, is expressed by the Equation (4) [49]:

$$\hat{g}_k = E(\hat{g}_{k+1}) \quad (4)$$

With reference to [49], the LP is built and rebuilt by using the two following steps:

Step 1: Construction of LP is achieved according to Equation (5) and Equation (6):

$$g_{k+1} = R(g_k) \quad (5)$$

$$i_k = g_k - E(g_{k+1}) \quad (6)$$

Where $I_0, I_1, \ldots, I_{k-1}$ are the laplacian image pyramids that include the Band Pass Filter (BPF). Further, these LP images transfer frequency within a distinct range and reject frequencies falling outside of this particular range. Additionally, they save a record of the errors that are later utilized by the reconstruction producer. It should be noted that g_k is the image of the coarser level. The *k* level of image in the LP is represented by Equation (7):

$$P_k \rightarrow \{g_k, i_0, i_1, \ldots, i_{k-1}\} \quad (7)$$

Step 2: Reconstruction of the LP is achieved by use of the following Equation (8):

$$\hat{g}_{k-1} = I_{k-1} + E(\hat{g}_k) \quad (8)$$

In this study, the extracted global and local image features are fused by use of the LP fusion method according to the following steps:

Step 2.1: Let x_1 and x_2 express the PCA and LBP images, respectively.

Step 2.2: Using the LP method, the extracted image features x_1 and x_2 are disintegrated into the maximal available decomposition levels, which will be 28 levels in the present case, so as to obtain images of maximum resolution. The two images are established *k* times. Thereupon, its pyramid results are expressed by use of the two equations Equation (9) and Equation (10).

$$P_k^{\ 1} \rightarrow \{g^1{}_k, i_0{}^1, i_1{}^1, \ldots, i_{k-1}{}^1\} \quad (9)$$

$$P_k^{\ 2} \rightarrow \{g^2{}_k, i_0{}^2, i_1{}^2, \ldots, i_{k-1}{}^2\} \quad (10)$$

Step 3: The two decomposed x_1 and x_2 image features are fused by use of the LP fusion method. Fusion is established using the Equation (11) and Equation (12):

$$\textit{At k level:} \qquad g^f{}_k = \frac{g^1{}_k + g^2{}_k}{2} \quad (11)$$

$$\textit{For } k-1 \textit{ to } 0 \textit{ levels}$$

$$g^f{}_{k-1} = i_{k-1}{}^f + E(g_k{}^f),$$

$$\textit{where}$$

$$i_{k-1}{}^f = \begin{cases} i_{k-1}{}^1 \textit{ if } \left|i_{k-1}{}^1\right| \geq \left|i_{k-1}{}^2\right| \\ i_{k-1}{}^2 \textit{ if } \left|i_{k-1}{}^1\right| < \left|i_{k-1}{}^2\right| \end{cases} \quad (12)$$

Therefore, comparison is made on the concomitant pixel. Lastly, the fused image is provided by Equation (13):

$$I_f = {g_0}^f \qquad (13)$$

3.4 Face Recognition using Artificial Neural Network)

ANN is a robust classification tool that has been so far applied to broad variety of tasks like approximation, pattern classification, and prediction [50, 5]. In face recognition using the ANN, the multi-layer perceptron artificial neural network (MLP ANN) was employed in the current study to recognize the face images based on the fused face images. Further details about use of the ANN in classification can be found in [5].

4 Experimental Results and Discussion

The proposed FFLFRM, which is based on the LP fusion technique, as well as the state of the art models, have been implemented using the MATLAB@2015a programming language in a personal computer with Intel Core i7 processor running at 2.40 GHz and 8 GB of RAM.

Three face recognition state-of-the-art models have been selected in order to compare performance of the proposed model with that of each of them. These models were (i) a face recognition model based on extracting local features using the LBP technique; (ii) a recognition model based on extracting global features using the PCA technique; and (iii) a fusion-level face recognition model based on the FP technique that was developed by [38].

Due to the fact that the effective face recognition model should ideally deal with a number of challenges. It basically include pose, illumination, expression changes, occlusion, and images with low resolution ([2]et al., 2010), the proposed model and the three state-of-the-art models have been tested using the MLP ANN on 10,000 face images drawn from the ORL database. The comparative performance results of these four models, in terms of the classification efficiency are summarized in Table 1 and discussed in the following sub-sections.

4.1 Pose Change

Pose change usually takes place because of the camera angles and individual's movement during image capture [32]. It affects the geometry of the facial features in the shot image, thus leading to serious misrepresentation of the face features and, hence, negatively affects the overall accuracy of image recognition. The comparative performance results of the proposed model and the three state-of-the-art models in terms of pose change are shown in Table 1 and presented graphically in Figure 3.

Table 1: Comparative performance results of the proposed model (FFLFRM) and the three state-of-the-art models in terms of the classification efficiency.

	Pose change	**Illumination change**	**Expression change**	**Low-resolution images**	**Occlusion**
Local based on LBP	**95.15%**	**95.27%**	**96.24%**	**95.06%**	**95.75%**
Global based on PCA	**95.3%**	**95.81%**	**96.99%**	**95.46%**	**95.55%**
FRS based on FP fusion [39]	**97.02%**	**96.47%**	**97.73%**	**96.99%**	**96.18%**
The proposed FFLFRM	**96.14%**	**97.03%**	**98.2%**	**96.5%**	**96.2%**

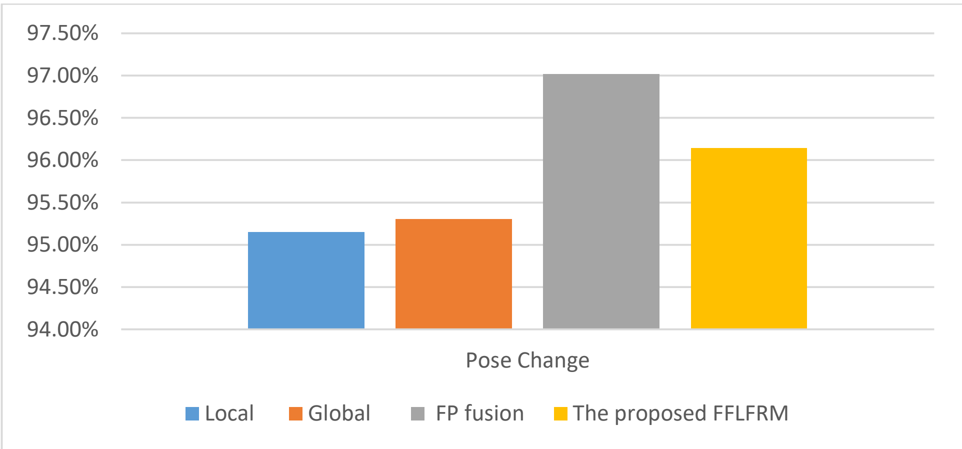


Fig. 3. Comparative performance results of the proposed model (FFLFRM) and the three state-of-the-art models in terms of the pose change.

Figure 3 points out that the proposed model has a classification efficiency of 96.16% whereas the classification efficiencies of the other three models were 95.19%, 95.30%, and 97.02%, respectively. The performance of the proposed model is better than that of model based on the LBP and the one based on PCA but only slightly lower than that of the model based on FR. This confirms effectiveness of the FFLFRM in face recognition under the condition of pose change.

4.2 Illumination Change

Change in illumination takes place as a result of diversity of the lighting conditions [32] and can result in dramatic change in appearance of the face, thus affecting the overall accuracy of the face recognition process. The comparative performance results of the proposed model and the three state-of-the-art models in terms of illumination change appearing in Table 1 are graphically presented in Figure 4.

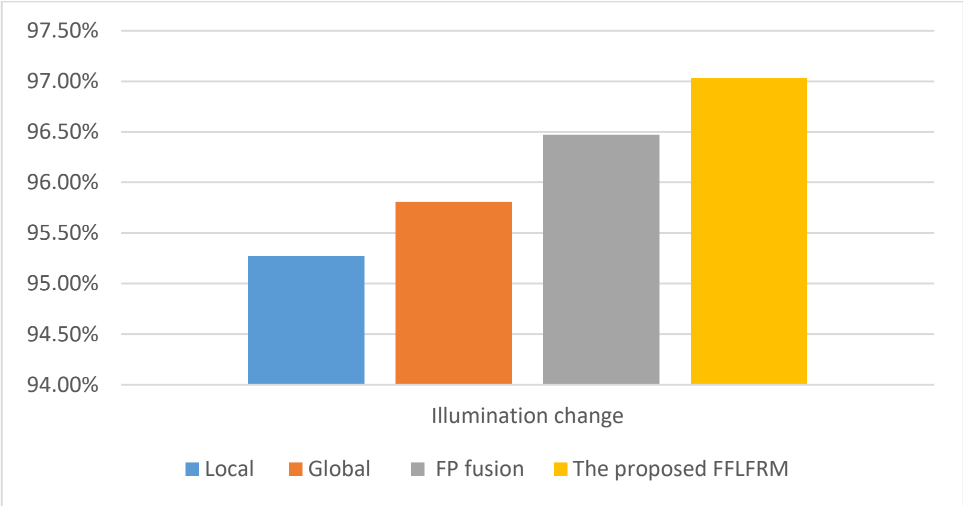


Fig. 4. Comparative performance results of the proposed model (FFLFRM) and the three state-of-the-art models in terms of illumination change

Figure 4 indicates that the proposed model has a classification efficiency of 97.03% while the classification efficiencies of the three other models were 95.27%, 95.81%, and 96.74%. Performance of the proposed model is better than that of any of the three investigated models. This ensures effectiveness of the FFLFRM in face recognition under the condition of illumination change.

4.3 Expression Change

The humans usually express their temper or emotion by using varying facial expressions [32]. Thereupon, when the face expression changes, so does the shape of the feature, thus leading to shift in locations of the face features, which is a shift that influences performance of the FRS. Results of comparisons in performance between the proposed model and the three state-of-the-art models in terms of change in face expression that are listed in Table 1 are depicted in Figure 5.

Figure 5 highlights that the proposed FFLFRM had the highest classification efficiency (98.20%). The classification efficiencies of the three other models were 96.24%, 96.99%, and 97.73%. Thus, performance of the proposed model proved to be higher than that of any of the three investigated models. This supports effectiveness of the FFLFRM in face recognition under the condition of face expression change.

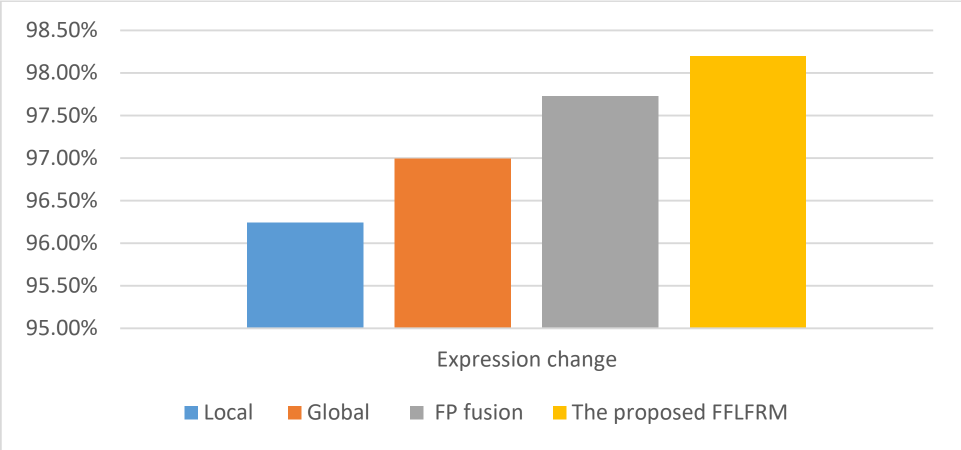


Fig. 5. Comparative performance results of the proposed model (FFLFRM) and the three state-of-the-art models in terms of change in face expression.

4.4 Low-Resolution Images

Image resolution is a function of a number of factors, including camera sort and environmental conditions [32]. Images of low resolution can lower the overall recognition accuracy. Outcomes of comparisons in performance between the proposed model and the three state-of-the-art models in terms of image resolution (Table 1) are displayed in Figure 6.

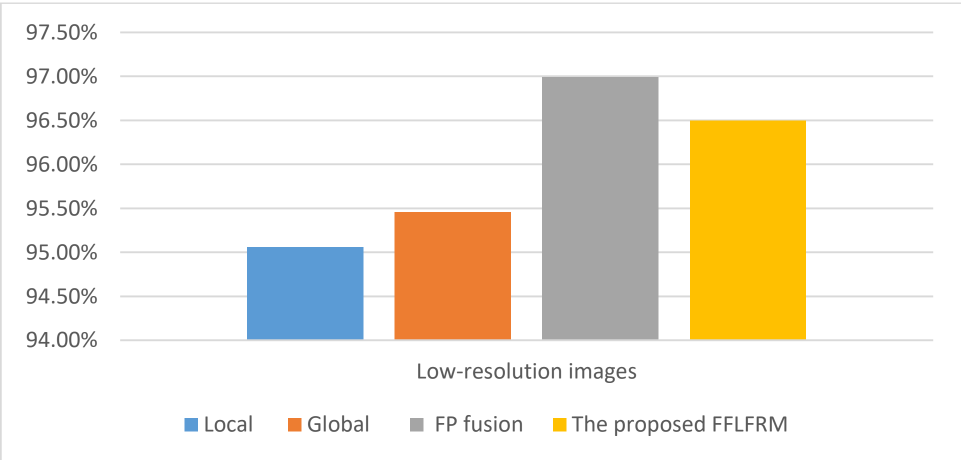


Fig. 6. Comparative performance results of the proposed model (FFLFRM) and the three state-of-the-art models in terms of image resolution.

Figure 6 underlines that the proposed FFLFRM had the second best classification efficiency (96.50%) next to the FP, which has a classification efficiency of 96.99%. The classification efficiencies of the models based on PCA and LBP were 95.06%

and 95.46%, respectively. So, performance of the proposed model is higher than that of the model based on PCA and the one based on LBP and is almost similar to that of the model based on the FP. This emphasizes effectiveness of the FFLFRM in face recognition under the condition of low image resolution.

4.5 Occlusion Challenge

Occlusion is a serious challenge to face recognition. It takes place when the face is fully or partially hidden or covered, which makes feature extraction a difficult task. Hence, occlusion affects the overall face recognition process [32]. The results of comparisons in performance between the FFLFRM and the three state-of-the-art models in terms of occlusion that are given in Table 1 are presented in Figure 7.

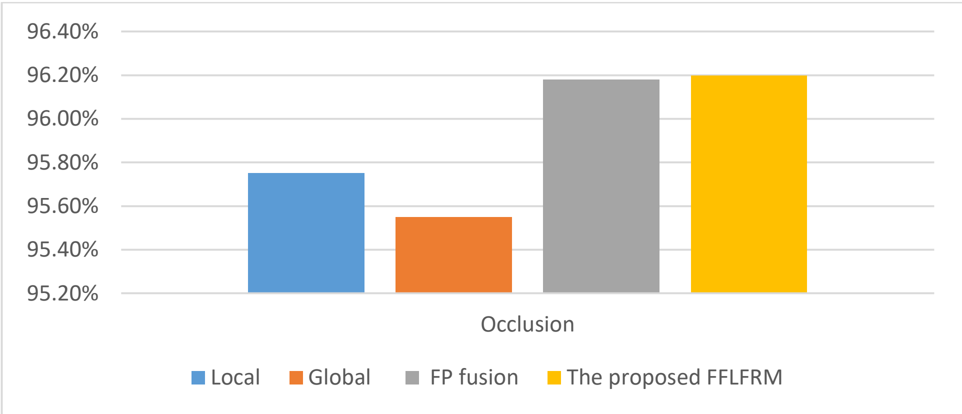


Fig. 7. Comparative performance results of the proposed model (FFLFRM) and the three state-of-the-art models in terms of occlusion

Figure 7 brings to surface that the proposed FFLFRM had the highest classification efficiency (96.20%). The classification efficiencies of the three considered models were 95.75%, 95.55%, and 96.18%. Therefore, performance of the proposed model is better than that of any of the three investigated models. This finding confirms effectiveness of the FFLFRM in face recognition under the condition of occlusion.

5. Conclusions and Future Directions

This paper proposes a FFLFRM based on the LP fusion technique. The proposed model consists of four main processes: face detection, feature extraction, feature fusion using the LP method, and face classification using the MLP ANN. In the first step, the face with its distinctive characteristics (i.e., mouth, nose, and eyes) were detected using the Haar-cascade face detection technique. In the second step, both the global and local features were extracted using PCA and the LBP method, respectively, in order for these features to be fused using the LP fusion technique in the third step. Lastly, the fused feature vectors were fed into the MLP ANN for face classification.

The proposed model was tested and its recognition performance was compared with the levels of performance of three state-of-the-art models that are based on local features using the LBP technique, global features using PCA, and fusion-level face recognition model based on the FP. Model testing and performance evaluation were conducted on 10,000 images obtained from the ORL database of face images. The performance results of the proposed model were compared with three state-of-the-art models using the MLP ANN on the ORL database under the conditions of pose change, illumination change, expression change, low image resolution, and occlusion. Under these circumstances, the classification efficiencies of the proposed model were 96.14%, 97.03%, 98.2%, 96.5%, and 96.2, respectively. Accordingly, the proposed FFLFRM had the best performance with illumination change, expression change, and occlusion. The results of this study confirm effectiveness of the proposed model in working properly with the five above-mentioned face recognition challenges. Indeed, its face recognition results are much promising.

In view of the study results, the researcher concludes that face recognition at the feature fusion level produces better results than recognition based on local or global features only. Thereupon, the proposed model has higher face recognition accuracy than the models based on LBP and PCA. Moreover, for future directions the researcher plans to test performance of the proposed model (FFLFRM) using different classifiers such as HMM and SVM, as well as its performance with decision-level fusion. It will be interesting for future works to fuse different local and global feature extraction methods using the LP fusion technique.

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Notes on contributors

Atallah Al-Shatnawi is an associate professor at the Department of Information Systems, Prince Hussein Bin Abdullah College for Information Technology, Al Al-Bayt University (Jordan). His research interests include: Pattern Recognition, Image Analysis and Processing, Machine learning as well as Modal logic verification and validation.

Faisal AL-saqqar is an assistant professor at the Department of Computer Science department, Prince Hussein Bin Abdullah College for Information Technology, Al Al-Bayt University (Jordan). His research interests include: Pattern Recognition, Modal logic verification and validation, Image Analysis and Processing as well as Machine learning.