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Face recognition system based on the multi-resolution singular value decomposition fusion technique

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A B S T R A C T

This study proposes a Fusion, Feature-Level, Face Recognition System (FFLFRS) that is based on the Multi-Resolution, Singular Value Decomposition (MSVD) fusion technique. Face recognition in the FFLFRS is achieved via four processes: face detection, feature extraction, feature fusion, and face classification. In this system, the most significant face features (that is, the eyes, nose, and mouth) are first detected. Then, local and global features are extracted by the Local Binary Pattern (LBP) and Principal Component Analysis (PCA) extraction approaches. Afterwards, the extracted features are fused by the MSVD method and classified by the Artificial Neural Network (ANN). The proposed FFLFRS was verified on 10,000 face images drawn from the face images database of the Olivetti Research Laboratory (ORL). Face recognition performance of this system was contrasted with levels of performance of three state of the art, fusion-level, face recognition systems (FRSs) depending on the Frequency Partition (FP), Laplacian Pyramid (LP), and Covariance Intersection (CI) fusion methods. Ten-thousand images were employed to test the proposed model and assess its performance, which was evaluated in terms of changes in pose, illumination, and expression, besides low resolution and presence of occlusion. The face recognition results of the proposed FFLFRS are encouraging. This system proved to be effective in dealing with images having challenges to face recognition and it could achieve a recognition accuracy as high as 97.78%.

1. Introduction

Research into face recognition started in the late 1970s. It has then grown into a highly interesting and active research area in the information technology and computer science fields since 1990 (Huang et al., 2004). In general, the Face Recognition System (FRS) is a computer application that identifies and/or validates a human face automatically by utilizing characteristic face traits (DeCarrera & Marques, 2010). Such method may be employed for a variety of goals that encircle (i) recognition of patterns, (ii) checking criminal records, (iii) development of security by utilize of surveillance cameras linked with FRS, (iv) early notification if Very Important Person (VIP) is entering a place (e.g., mall or hotel), (v) finding lost children by utilizing images captured by cameras that are fixed in public places, and (vi) detection of criminals in any public places. Moreover, the FRSs can be employed in several science fields for the purpose of comparing entities of interest with collection of entities (Annu & Sharma, 2016; Priya 2014).

Typically, recognition by the FRS is achieved by implementation of three successive processes: image preprocessing and face detection, feature extraction, and face recognition. In the first process, quality of the face image is often improved by removal

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of noise and any unnecessary information from the scanned face so as to specify its right location and distinctive features (Al-Allaf, 2014). In the feature extraction process, the face features are extracted locally and/or globally (Ding 2016; Nguyen 2014). The global features relate to the overall texture of the features of the face whereas the local features are the fundamental internal face features, namely, the mouth, nose, and eyes (Ding, 2016; Nguyen, 2014). Once these two processes are implemented, the extracted features are subjected to classification by means of machine learning classifiers such as the Artificial Neural Network (ANN), Support Vector Machine (SVM), and the *k*-Nearest Neighbor (*k*NN) classifier (Dhriti & Kaur, 2012; Le, 2011).

One of the major challenges to successful face recognition is describing efficient, distinctive descriptors of appearance of the face that can assimilate the variations in illumination, face expressions, pose, occlusions, and resolution, amongst other challenges. Most of the current FRSs utilize one sort of feature only. However, for complicated tasks, of which face recognition is an example, it is of common occurrence that modality of a feature is not rich enough to allow for detection of the entire classification information that exist in the image (Štruc et al., 2013; Tan & Triggs, 2007; Zhao et al., 2003). To overcome the aforementioned challenges to face recognition, there is a bad need for fusion of information at the level of the feature in the FRSs.

For face recognition, fusion of information may either be conducted at the feature level or at the decision level (Jagalingam & Hegde, 2014; Wang et al., 2018). The feature-level approaches combine numerous input feature groups into a single, fused set that is then utilized in any conventional classifier however the decision-level approaches combine numerous classifiers, founded on distinctive features, for example, in order to eventually generate a robust classifier (Štruc et al., 2013; Kittler et al., 1998; Singh et al., 2019). These methods are characterized by a number of advantages that include (i) simple training because only one phase of training is needed on the integrated feature vector and (ii) ability to exploit the associations of varied features on an early phase. But these approaches necessitate presenting the features that should be fused in the same format before their fusion (Wang et al., 2018; Singh et al., 2019). In view of this, in this paper, the researcher suggests a Fusion, Feature-Level, Face Recognition System (FFLFRS) that is based on the Multi-Resolution, Singular Value Decomposition (MSVD) fusion method. The local and global face features are extracted by Local Binary Pattern (LBP) extraction and Principal Component Analysis (PCA), respectively. Thereafter, the feature vectors that have been fused by MSVD are classified by a Multi-Layer Perceptron (MLP) ANN. Performance of the proposed FFLFRS was then verified on 10,000 gray-scale images that have been obtained from the face images database of the Olivetti Research Laboratory (ORL). Afterwards, performance of the FFLFRS in terms of the face recognition accuracy was compared with the corresponding recognition accuracies of state-of-the-art FRSs, one based on Laplacian Pyramid (LP), one based on Covariance Intersection (CI) fusion, and one based on Frequency Partition (FP) fusion (Nusir, 2018; AL-Shatnawi et al., 2021; El-Bashir et al., 2021). In all cases, performance was evaluated in terms of the ability of the FRS to deal with the challenges to face recognition of change in pose, illumination, and expression, as well as low image resolution and the presence of occlusion.

The major contribution of this work is that it illustrates how to integrate the local and global feature extraction methods correctly so as to reach credible and reliable face recognition results. The contributions of this work may be summarized in few points as follows: (i) development of FFLFRS that is based on MSVD fusion; (ii) confirmation of good recognition performance of the proposed FFLFRS under the conditions of the image limitations of expression, illumination, occlusion, pose, and low resolution; and (iii) comparison of the performance of this FFLFRS in terms of recognition accuracy with the corresponding accuracies of state-of-the-art models depending on FP, LP, and CI fusion.

The rest of this paper is structured in five sections. Section 2 reviews previous studies on the fusion methods employed in face recognition. Section 3 presents the suggested FFLFRS. Section 4, then, illustrates and discusses the experimental results. Thereafter, Section 5 lists conclusions of the study and gives recommendations for the related future research.

2. Related Works

Image fusion can be defined as the process of integration of appropriate information from 2 or more images into a single image (Zhang et al., 2015). The fused image needs to have complete information and be more suitable than the source images for accurate and adequate visual recognition and perception. In the process of face recognition, fusion may be achieved at either the feature level or the decision level (Jagalingam & Hegde, 2014).

Until now, many methods of, and systems for, face recognition have been proposed based on decision-level fusion (e.g., Štruc et al., 2013; Zhang et al., 2015). In decision-level image fusion, different classifiers are frequently used so as to obtain scores depending on individual local features. Afterwards, the local decisions are united in order to develop the final decision (Wang et al., 2018; Singh et al., 2019). Usually, fusion of images at the decision level is a combination of the output scores that are derived from the classifiers (Wang et al., 2018; Singh et al., 2019). Fusion of Gabor features, pixel scores, and LBPs was conducted by Štruc et al. (2013) and normalization was implemented as a post processing step. Taigman et al. (2009) employed the same local descriptors to fuse varied LDA-depending on one-shot scores of similarity. Likewise, Wolf et al. (2010) applied local descriptors on extra Gabor features. They utilized a combination of Hellinger distance, one-shot distance, two-shot distance, and ranking-depending on distance in an attempt to get high classification accuracy (Wang et al., 2018).

In the case of feature-level fusion, the extracted features are first concatenated into a single feature vector and passed, then, to a certain classifier (Wang et al., 2018). Liu et al. (2012) proposed a novel approach to classification of textures through a generalization of the LBP technique. In this approach, two kinds of features, namely, pixel variances and pixel intensities, were extracted from local patches. These researchers conducted large experiments on three, quite challenging texture datasets; the Outex, CUReT, and KTHTIPS2b datasets. The best classification outcomes which this technique generated were associated with the KTHTIPS2b dataset.

Tran et al. (2014) presented a new method that uses LBP and Local Ternary Pattern (LTP) descriptors for face image representation. In addition, it employs a feature-based similarity selection and classification algorithm to improve the accuracy of recognition. The image of the face is first divided in this method into small parts wherefrom the LBP and LTP histograms are plotted and concatenated into a single-feature vector. Experiments were run on the ORL face image database and the Extended Yale Face Database B. The results of experiments confirm the superiority of this algorithm over the other algorithms.

Tan and Triggs (2007) proposed a fusion FRS at the feature level that extracts two feature sets by using the Gabor wavelet and LBP local appearance descriptors. Then, the Kernel Discriminative Common Vector method was verified to the integrated feature vector to get discriminating, non-linear features for face classification. Performance of this method was evaluated on three, challenging face datasets: FRGC 2.0.4, FERET, and FRGC 1.0.4.

Mirza et al. (2013) studied fusion of the global and local features for gender classification. They extracted the local features using the LBP method augmented with two-dimensional, Discrete Cosine Transform (DCT) and extracted the global features by PCA and DCT. Experiments on the FERET dataset were conducted to assess performance of this system. The results pointed out that this method had 98.16% recognition accuracy.

Nusir (2018) proposed face recognition system that is based on the FP method besides feature-level fusion. They joined the global and local features by PCA and LBP, respectively. Performance of this proposed system was evaluated by experimenting on the ORL face image database. The results of the experiments showed that this system has higher recognition accuracy and is more robust than the single-feature method that is based on PCA and LBP.

Guo et al. (2010) developed a method integrating the expectation-maximization (EM) algorithm with the CI principle as a new approach to image fusion. Contrary to other methods of fusion, this suggested method considers cross-correlations among the data sources and, therefore, provides accurate and consistent estimates via convex combinations. Owing to that the covariance information is often not known practically, the EM algorithm is employed to give a maximum likelihood estimate (MLE) of the covariance matrix.

Al-Shatnawi et al. (2021) proposed a system for face recognition on the basis of feature-level fusion by the Laplacian Pyramid (LP) approach and integration of the local and global features. The LBP method and PCA were employed for extraction of the local and global features, respectively. This model was examined on the ORL dataset of face images by using MLP ANN. The results of experiments indicated that this FRS produces better face recognition outcomes than the recognition system that is based on the PCA and LBP under the circumstances of varying facial expressions and illumination and in presence of occlusions. In other respects, a FRS founded on the CI method and feature-level fusion was suggested by El-Bashir et al. (2021). This system was tested on the ORL face image dataset by using MLP ANN. The assessment results confirmed the effectiveness of this FRS and that it performs better than some state-of-the-art systems.

3. The Proposed Model

This study proposes a FFLFRS on the basis of the MSVD method of fusion. The proposed system achieves face recognition via four successive processes: detection of the face, extraction of the face features, fusion of the extracted features by MSVD, and classification of the face by MLP ANN (Fig. 1). The first step in the recognition process is detection of the face on the basis of its distinctive features (that is, the eyes, nose, and mouth) through the Haar Cascade method. After that, the local and global features are extracted by use of the LBP and PCA methods, respectively. Afterwards, these extracted features are fused by MSVD. The feature vectors that have been fused are then input to the MLP ANN for the purpose of classification of the face. The architecture of this suggested system is displayed in Fig. 1 and the major processes involved in this FRS are discussed in the sequent sub-sections.

3.1 Face Detection by the Haar Cascade Method

The Haar Cascade method was originally designed by Viola and Jones (De Carrera & Marques, 2010; Zhao et al., 2003; Viola & Jones, 2001). It detects the face based on its appearance. So, it is commonly employed for detection of the characteristic face features, namely, the nose, eyes, and mouth. This method performs classification of the face Haar based on Haar-like features rather than on pixel analysis (Viola & Jones, 2004). The Haar-like characteristics are rectangular-shaped features of relevant characteristics that are representative of the objects of interest (Viola & Jones, 2004), which are extracted commonly by use of such methods as the integral image, Adaptive Boosting (AdaBoost), and the attentional cascade methods

(Wang, 2014). The present study uses Wang's (Wang, 2014) modification of the Viola-Jones Haar Cascade method to detect four patches of face features; the face, eyes, mouth, and nose.

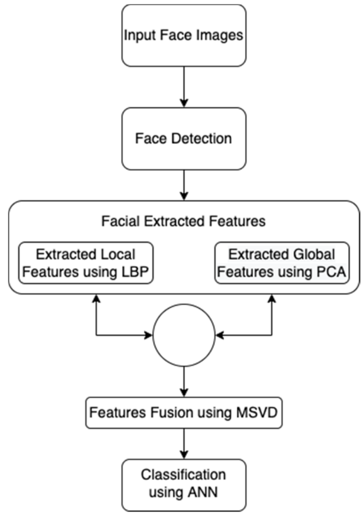

Fig. 1. Architecture of the FFLFRS

3.2 Local and Global Feature Extraction

In the process of face recognition, the most important step is extraction of features. The best recognition is actually dependent on the success of feature extraction (Jafri & Arabnia, 2009; Zhao et al., 2003). The purpose of feature extraction is to give an efficient representation of the face image by utilizing some of its distinctive features (Jafri and Arabnia, 2009; Zhao et al., 2003). The features of the face may be extracted globally or locally using the PCA and the LBP method, respectively, so that those extracted features can be fused by the MSVD method in the subsequent step. Feature extraction is illustrated in the two sequent sub-sections.

3.2.1 Global Feature Extraction Using Principal Component Analysis

Principal Component Analysis (PCA) is classical statistical linear transform that is widely used in different applications of pattern recognition such as face recognition (e.g., Bansal, et al., 2012) and character recognition (e.g., Al-Saqqar et al., 2019). In the process of extraction of features, the PCA, which was originally developed by Pearson (1901), is used to choose and extract global features of the face so that they can be fused with the local features that had been extracted by applying the MSVD method of feature fusion, which is demonstrated in the following sub-section.

The PCA is frequently used as a method of feature extraction to lower the image feature dimensionality. First, this analysis calculates the data matrix mean. Then, it computes its covariance. Afterwards, eigenvalues and eigenvectors are computed (Balola and Shaout, 2016). The main objective of PCA is identification of the space that characterizes the direction of the maximum variance of the data of interest. It produces low dimensional space or PCA space (W) that is used then to convert the data ($X = \{x_1, x_2, \ldots, x_N\}$) from high-dimensional space to a space with lower dimensionality, where N is the number of the samples, or observations, and x_i expresses the i^{th} pattern, observation, or sample (Tharwat, 2016; AL-Shatnawi et al., 2021).

3.2.2 Extraction of the Local Face Features Using the LBP Method

The LBP method is used to extract local face features. It was originally developed by Ojala, et al. (1996) for analysis of texture. It is frequently used as a statistical method for extraction of local features of the face from face images so that the extracted features are then fused with global features that had been extracted using the MSVD technique, which is illustrated in the following sub-section.

The process of extraction of the local features of the face operates basically by a determination of the focal pixel of (3x3) pixel block of the image and computation of the values of the features based on a certain pixel threshold. Thereafter, the whole image of the face is presented as a feature vector in decimal values (Nusir, 2018).

3.3 Feature Fusion Using Multi-Resolution Singular Value Decomposition

The MSVD fusion method, which was originally developed by Naidu (2011), was used in the current study to fuse the extracted local and global features of the face. In the next step, the combined fused features were presented as recognized feature vectors using MLP ANN.

The MSVD method of fusion of Naidu (2011) was designed based on the SVD method. It consists of two functions; reduction function and expansion function. These two functions are disintegrated various times in this fusion method so as to enhance face image resolution (Naidu, 2011). The MSVD method compares with wavelet transform in that signals are filtered by use of low/high pass Finite Impulse Response (FIR) filter and the resultant of every filter is decimated by factor of 2 so as to obtain the first stage of decomposition. The decimated, low-pass, filtered output is independently filtered by high pass and low pass filter and, then, decimated by factor of two in order to produce the second stage of decomposition. In the present study, the MSVD method, rather than FIR filter, was employed for decomposition of the image of the face several times. Within this context, decomposition of image of the face by the MSVD method progresses as follows:

Step 1: Split the image of interest into non-overlapping blocks.
Step 2: Organize every block into 4x1 vectors. This is achieved by stacking the columns to create a data matrix. The resulting blocks are scanned by a transpose raster scan, proceeding downwards then right.
Step 3: Eigen decomposition of the scatter matrix is calculated according to the following equation:

$$T1 = X1X1^T = U1S1^TU1^T \tag{1}$$

where *Ui* is Eigenvector and $S1^2$ is the diagonal matrix which includes squares of the singular values.

$$S1^2 = \begin{bmatrix} S1(1)^T & 0 & 0 & 0 \\ 0 & S1(1)^T & 0 & 0 \\ 0 & 0 & S1(1)^T & 0 \end{bmatrix} \tag{2}$$

The singular values are commonly organized in descending order:

$$S1(1) \geq S2(1)) \geq S3(1)) \geq S4(1) \tag{3}$$

Step 4: Assume that

$$X1 = X1U1^T \tag{4}$$

The first row in the *X1* matrix has the highest eigenvalues and is regarded as its Approximation Component (AC) whilst the remainder rows *X1* contain the Details Component (DC), which pertains to the image texture or edges.
Step 5: Re-order the elements in every row so as to create matrix having the size. $\frac{M}{2} \times \frac{N}{2}$
Step 6: Assume that a1 refers to the $\frac{M}{2} \times \frac{N}{2}$ matrix that is obtained by re-ordering of the top row of the matrix X1 via filtration of columns followed by rows. The top row of this matrix is expressed as: $X1(1,:)$. It includes the AC. Likewise, the three remaining rows $X1(2,:), X1(3,:)$ and $X1(4,:)$ are organized in $\frac{M}{2} \times \frac{N}{2}$ matrices that include the DC. These matrices are respectively denoted as: $B1^V, B1^H, and\ B1^D$.
Step 7: The next decomposition level of is obtained by replacement of the X matrix with a1 and reiteration of this producer. The L level of decomposition is expressed as follows:

$$X \rightarrow \{al, \{B1^V, B1^H, B1^D\}^l i = 1, \{\mathrm{U1}\}^l i = 1\} \tag{5}$$

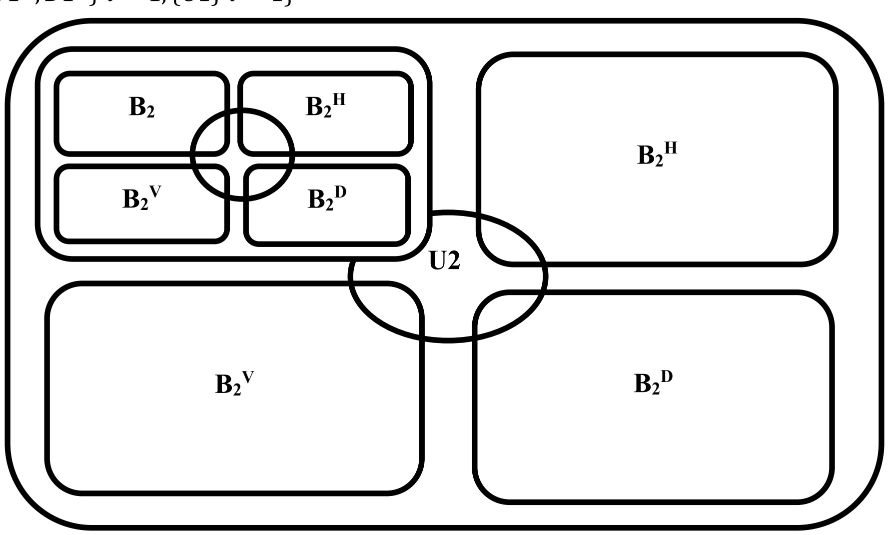

Fig. 2. Structure of the MSVD (Naidu, 2011).

The original structure of the image may be restored from the right side. The two-dimensional (2D) structure of MSVD with three levels of decomposition is displayed in Figure 2.

Fusion of the $_{l1}$ image with the l_2 image using the MSVD method is performed in the present study according to the following steps:

Step 1: Decompose those images that should be fused into the $L(i = 1,2,3, \dots\dots, L)$ levels.

Step 2: The rules for fusion on every decomposition level $L(i = 1,2,3, \dots\dots, L)$ are illustrated **in Step 3.**

Step 3: Choose the highest absolute value of a couple of DC coefficients, recalling that the DC coefficient represents sharper changes in brightness in the image, e.g., object boundary and edges. Values of these DCs fluctuate about zero. The rule for fusion of the procedure of selection is acquired according to Eq. (6),

$$\{B^V i\}^f = \max\left(|\{B^V i\}^1, \{B^V i\}^2|\right)$$

$$\{B^H i\}^f = \max\left(|\{B^H i\}^1, \{B^H i\}^2|\right) \tag{6}$$

$$\{B^D i\}^f = \max\left(|\{B^D i\}^1, \{B^D i\}^2|\right)$$

Step 4: On the coarsest level$(i = L)$, the fusion rule selects the mean of the values of the MSVD AC coefficient. In addition, on this level, the AC coefficient is a smoothed and sub-sampled version of the source image. Fusion of any two AC coefficients is computed as follows:

$$aL^f = average\ (aL^1, aL^2) \tag{7}$$

Step 5: On every level of decomposition, $L(i = 1,2,3, \dots\dots, L)$, the rule for fusion is gained by computing the mean of two Eigen matrices of the MSVD as shown in Eq. (8),

$$Ui^f = average\ (Ui^1, Ui^2) \tag{8}$$

Step 6: The fusion image lf is acquired using Eq. (9),

$$\text{lf} \leftarrow \{\{al\}^f, \{\{B^V i\}^f \{B^H i\}^f, \{B^D i\}^f\}^l i = 1,\ \{\{U1\}^f\}^l i = 1\} \tag{9}$$

The general scheme of MSVD fusion of images is presented in Fig. 3.

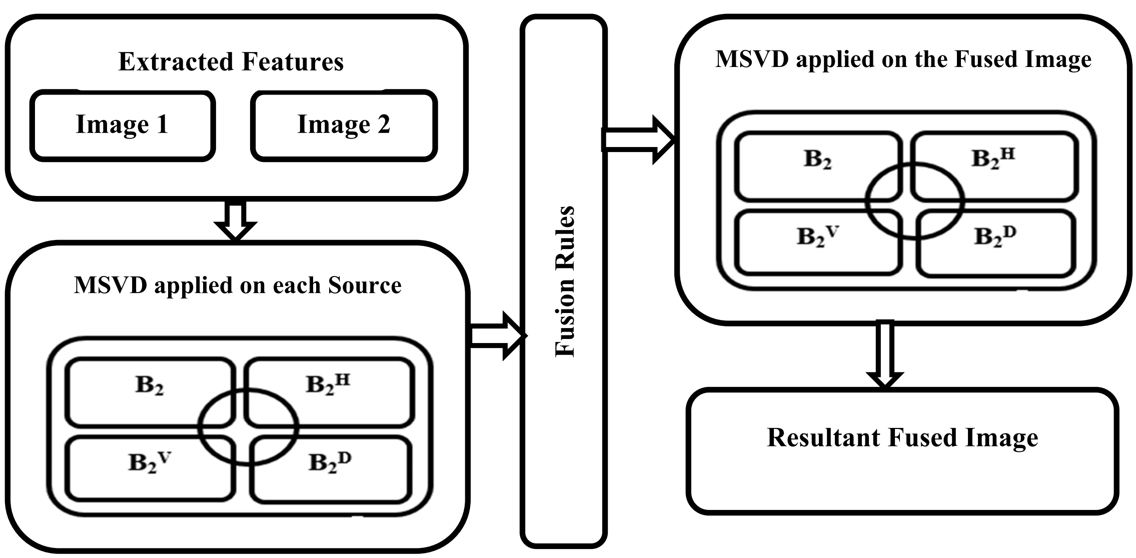

Fig. 3. General scheme of MSVD fusion of images (Naidu, 2011).

In the system proposed in the present study, the MSVD method of fusion was employed for fusing the features extracted by LBP and PCA. The features extracted by PCA were decomposed to the highest available level of decomposition by the MSVD method, which was $2^7 – 2^9$ levels. The features extracted by LBP too were decomposed into the highest available level of decomposition, which was $2^7 – 2^9$ levels, also using the MSVD method. Doing so is justified by the need for obtaining images with higher resolution than the source images. Next to decomposition of the LBP-, and PCA-extracted features, the rule for MSVD fusion was employed so as to get fused images.

3.4 Face Recognition Using the Artificial Neural Network)

The ANN can provide powerful classification. Thus far, it has been utilized for varying purposes such as approximation and pattern recognition, classification, and prediction (Gardner & Dorling, 1998; Al-Allaf 2014). In this context, the present study employed the Multi-Layer Perceptron Artificial Neural Network (MLP ANN) in the proposed FFLFRS so as to recognize faces in fused face images. Information on the usage of the ANN for classification purposes can be found in Al-Allaf (2014).

4. Experimental Results and Discussion

The suggested MSVD-based FFLFRS and the three investigated state-of-the-art FRSs were written in MATLAB@2015a platform and run on a personal computer (PC) having Intel Core i7, 2.40-GHz processor and a RAM of 8 GB.

Three state-of-the-art FRSs were chosen to compare the performance of the proposed FFLFRS with theirs. These methods are (i) fusion-level FRS that is based on the FP method, which was designed by Nusir (2018); (ii) fusion-level FRS that is based on the LP method, which was proposed by AL-Shatnawi et al. (2021); and (iii) fusion-level FRS that is based on the CI method, which was designed by El-Bashir et al. (2021).

Because, ideally, the effective FRS should address certain challenges to face recognition that encompass changes in illumination, pose, and expression; low image resolution; and presence of occlusion (DeCarrera and Marques, 2010; Al-Shatnawi et al., 2021), recognition accuracies of the FFLFRS proposed here and the three FRSs have been examined by using the MLP ANN and 10,000 images of faces obtained from the ORL dataset. The classification accuracies of these models are given in Table 1 and discussed in subsequent sub-sections.

Table 1
Classification accuracies of the proposed FFLFRS and the three FRSs under varying conditions.

	Pose change	Illumination change	Expression change	Low-resolution images	Occlusion
FRS based on FP fusion	97.02%	96.47%	97.73%	96.99%	96.18%
FRS based on LP fusion	96.14%	97.03%	98.2%	96.5%	96.2%
FRS based on CI fusion	96.23%	96.89%	97.68%	96.1%	96.84%
The proposed MSVD-based FFLFRS	96.19%	97.23%	97.78%	97.01%	96.98%

4.1 Pose Change

Quite often, change in pose occurs by effect of angles of the camera and movement of the individual during shooting (DeCarrera and Marques, 2010; Al-Shatnawi et al., 2021). It negatively impacts geometry of the features of the face in the image, hence resulting in serious misrepresentation of those features and, consequently, negatively impacts the eventual image recognition accuracy.

The performance evaluation results of the four models under consideration in terms of change in pose are listed in Table 1 and depicted in Fig. 4. It is seen in Figure 4 that the classification accuracy of the proposed FFLFRS is 96.19% while the classification accuracies of the FRSs that are based on the FP, LP, and CI fusion methods are 97.02%, 96.14, and 96.23%, respectively. As such, recognition accuracy of the FFLFRS is higher than that of the LP-based FRS but somewhat lower than the accuracies of the other two FRSs. This finding ensures the face recognition efficiency of the proposed FFLFRS under the pose change condition.

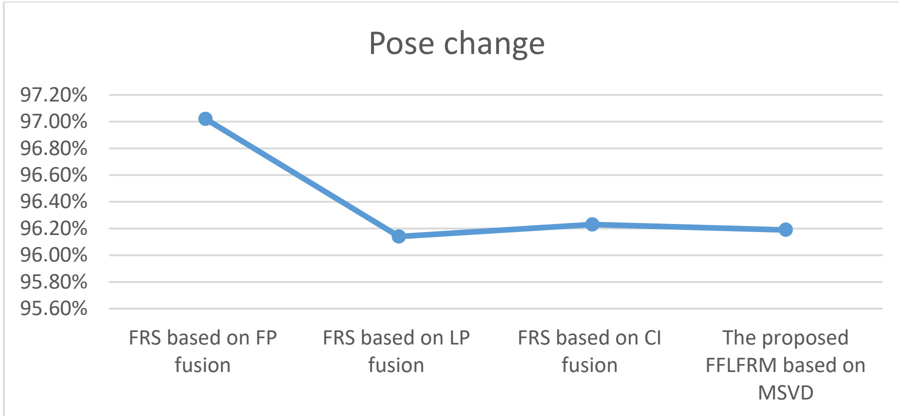

Fig. 4. Recognition accuracies of the four studied FRSs under the condition of pose change.

4.2 Illumination Change

Illumination change occurs because of differences in lighting conditions during shooting (DeCarrera & Marques, 2010; Al-Shatnawi et al., 2021). It may lead to substantial change in the face appearance, which negatively influences the overall accuracy of the process of face recognition.

The results of assessment of performance of the four models under consideration in terms of change in illumination are shown in Table 1 and Fig. 5. It can be noticed in Fig. 5 that the classification accuracy of the FFLFRS is 97.23%. Meanwhile, the classification accuracies of the FRSs that are based on the FP, LP, and CI fusion methods are 96.47%, 97.03%, and 96.89%%, respectively. In consequence, this study finds that the face recognition accuracy of the proposed FFLFRS is higher than those of all three studied systems. This result suggests that the proposed FFLFRS is efficient in face recognition under the illumination change condition.

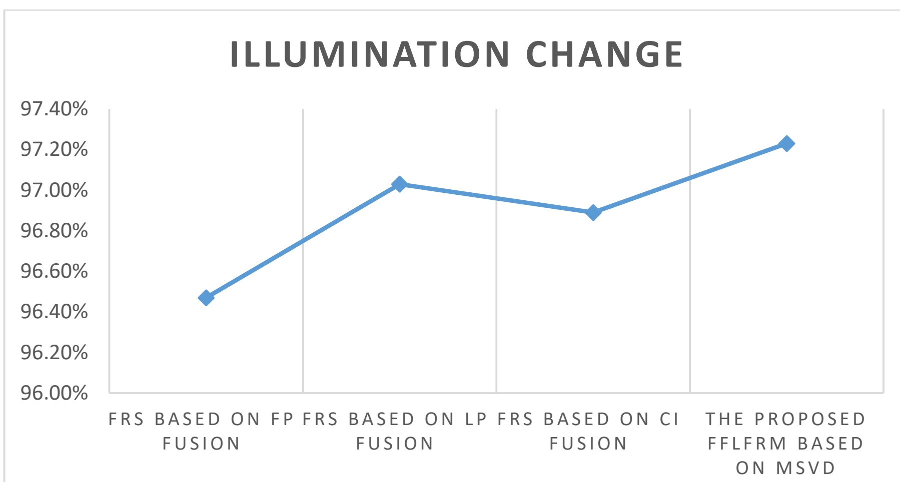

Fig. 5. Recognition accuracies of the four studied FRSs under the condition of illumination change.

4.3 Expression Change

Usually, people express their emotions through different facial expressions (DeCarrera & Marques., 2010; Al-Shatnawi et al., 2021). So, a change in expression of the face leads to a change in the shape of the feature, which brings about shifts in the locations of the features of the face in the images. This shift affects performance of the FRS.

The face recognition accuracies of the four models under consideration are provided by Table 1 and drawn in Fig. 6. This figure indicates that FFLFRS has the highest face recognition accuracy (97.78%). Classification accuracies of the FRSs based on the FP, LP, and CI fusion methods are 97.73%, 98.20%, and 97.68%, respectively. So, the FFLFRS has higher face recognition accuracy than the FRSs based on FR and IC and lower accuracy than that of the LP-based FRS. This result supports the face recognition efficiency of the herein suggested system under the condition of change in face expression.

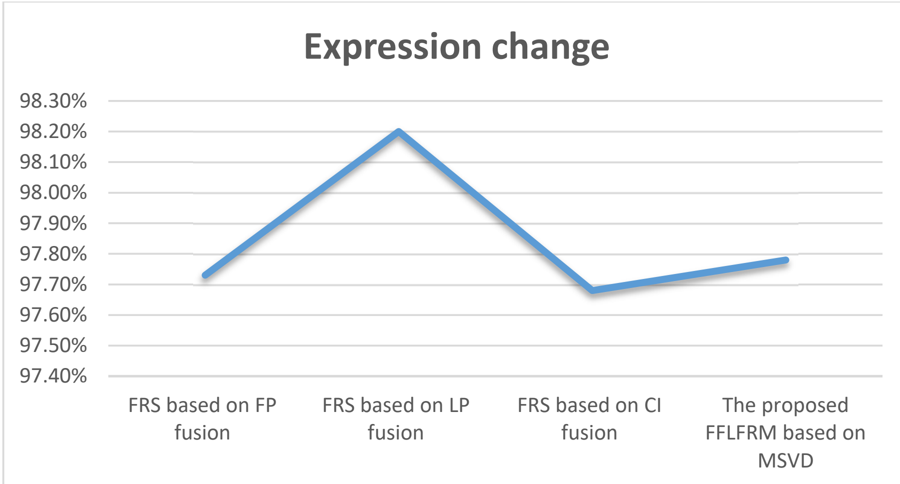

Fig. 6. Recognition accuracies of the four studied FRSs under the condition of face expression change.

4.4 Low Image Resolution

Resolution of the image depends on several factors, including the camera type and environmental conditions (DeCarrera & Marques., 2010; Al-Shatnawi et al., 2021). The low-resolution images can reduce the recognition accuracy of the FRS.

The outputs of evaluation of performance of the four FRSs under study in terms of resolution of the image are provided by Table 1 and Fig. 7. It is noticed in Fig. 7 that the classification accuracy of the system proposed by this study is 97.01%. For comparison purposes, the classification accuracies of the FP-, LP-, and CI-based FRSs are 96.99%, 96.5%, and 96.1%, respectively. Accordingly, the FFLFRS performs better than any of the three other systems under consideration. This finding confirms that FFLFRS is advantaged with noticeably high face recognition accuracy under the low image resolution condition.

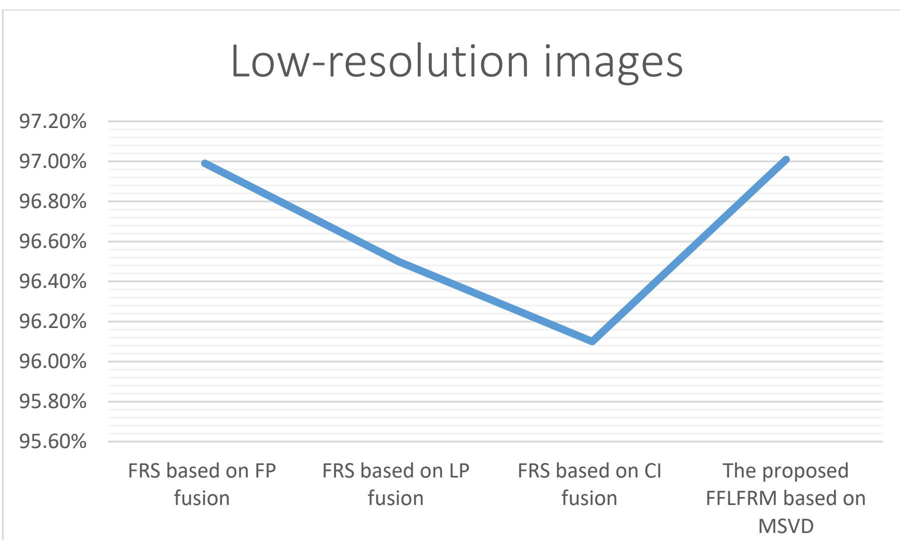

Fig. 7. Recognition accuracies of the four studied FRSs under the condition of low image resolution.

4.5 The Occlusion Challenge

Occlusion constitutes a substantial challenge to the face recognition process. It happens when the subject's face is partially or wholly covered or hidden, which makes extraction of the features a difficult task and, in consequence, it adversely affects the total accuracy of recognition (DeCarrera & Marques., 2010; Al-Shatnawi et al., 2021).

The outcomes of evaluation of the recognition accuracies of all four models under investigation in terms of occlusion of the image are presented in Table 1 and Fig. 8. This study found that FFLFRS has the highest accuracy of face recognition

(96.98%). Recognition accuracies of the systems based on the FP, LP, and CI fusion methods are, respectively, 96.18%, 96.2%, and 96.84%. On this account, it is concluded that FFLFRS has better face recognition performance than the other investigated FRSs. This result supports efficiency of FFLFRS in recognition of faces in presence of occlusion in the source images.

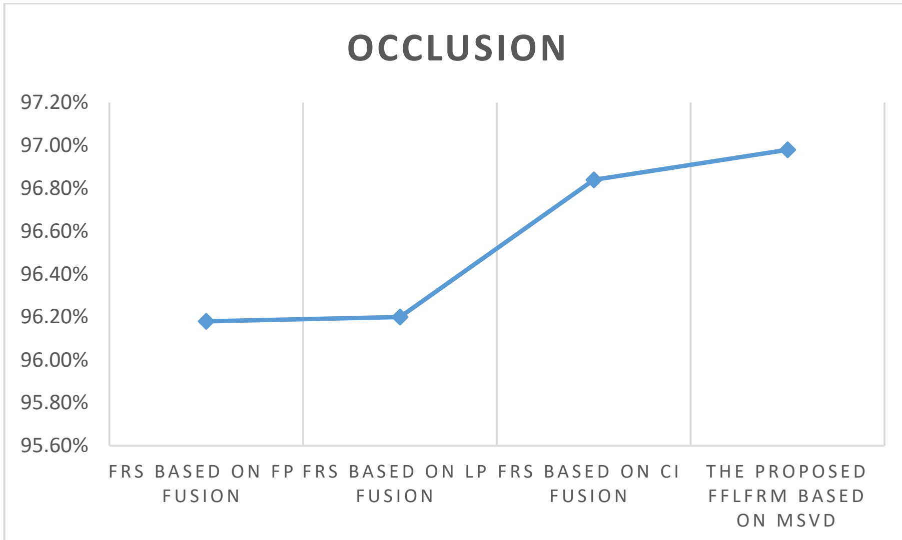

Fig. 8. Recognition accuracies of the four studied models in presence of occlusion in the face images.

5. Conclusions and Future Work

This paper developed a FFLFRS that is dependent on the MSVD fusion method. The suggested FRS performs the face recognition tasks via four procedures: face detection, feature extraction, feature fusion by the MSVD technique, and face classification by MLP ANN. Performance of the FRS suggested in this paper (i.e., the FFLFRS) was verified and its face recognition accuracy was compared with the recognition accuracies of three state-of-the-art, fusion-level FRSs that are depending on the FP, LP, and CI fusion methods. Performance of these four FRSs was evaluated using 10,000 face images produced from the ORL dataset. As well, performance of FFLFRS was compared with levels of performance of the three FRSs under the conditions of illumination change, pose change, occlusion, expression change, and low image resolution. The recognition accuracies of FFLFRS under these conditions were 97.23%, 96.19%, 96.98%, 97.78%, and 97.01%, respectively. In light of these findings, the best performance of FFLFRS was associated with illumination change, low image resolution, and presence of occlusion. These results confirm the high face recognition accuracy of the proposed system under all foregoing five challenges to the face recognition process. In effect, the face recognition outputs of this system are quite promising.

In light of the results of this study, the researcher reaches to the conclusion that better face recognition accuracies are obtained on the feature fusion level than on the level of the global or local features only. Consequently, the FFLFRS proposed by this study produces higher face recognition accuracies under varying conditions than the FRSs that are based on the FP, LP, and CI fusion methods. In the future, the researcher intends to assess the performance of FFLFRS with other classifiers like the SVM and HMM and with fusion on the decision level. Future research may consider integration of different methods for extraction of global and local features by the MSVD fusion method.

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