Convolutional neural network-based face recognition using non-subsampled shearlet transform and histogram of local feature descriptors

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Article Info

ABSTRACT

Face recognition has been using in a variety of applications like preventing retail crime, unlocking phones, smart advertising, finding missing persons, and protecting law enforcement. However, the ability of face recognition techniques reduces substantially because of changes in pose, illumination, and expressions of the individual. In this paper, a novel face recognition approach based on a non-subsampled shearlet transform (NSST), histogram-based local feature descriptors, and a convolutional neural network (CNN) is proposed. Initially, the Viola-Jones algorithm is used for face detection and then the extracted face region is preprocessed by image resizing operation. Then, NSST decomposes the input image into a low and high-frequency component image. The local feature descriptors such as local phase quantization (LPQ), pyramid of histogram of oriented gradients (PHOG), and the proposed CNN are used for extracting features from the low-frequency component of the NSST decomposition. The extracted features are fused to generate the feature vector and classified using support vector machine (SVM). The efficiency of the suggested method is tested on face databases like Olivetti Research Laboratory (ORL), Yale, and Japanese female facial expression (JAFFE). The experimental outcomes reveal that the suggested face recognition method outperforms some of the state-of-the-art recognition approaches.

Keywords:
Convolutional neural network
Face recognition
Feature extraction
Histogram
Non-subsampled shearlet transform

1. INTRODUCTION

Face recognition has grabbed noticeable attention in several areas like surveillance, information security, and entertainment [1]-[3] due to its uniqueness, low-cost, and easy accessibility compared to other biometric approaches. Face recognition is a process of recognizing an individual from the available face database [4]. A general face recognition methodology comprises pre-processing, extracting features, and classification stages. The pre-processing step involves operations like image de-noising, scaling, image registration, face detection, and normalization. In the feature extraction phase, features are obtained for efficient image representation and visual description. Feature extraction plays a major role in computer vision applications like face recognition [5]-[7], texture analysis [8], [9], and sketch synthesis [10]-[12]. A precise image feature should be both robust and discriminative to distinct variations like noise and illumination changes. The last step of the face recognition system is the classification which incorporates robust classifiers.
namely K-Nearest neighbors (KNN), support vector machine (SVM), and extreme learning machine (ELM), to recognize the input face.

Recently, several face recognition methods have been developed with a good recognition rate under certain constraints [13]. However, in practice, the face recognition process is affected by some external factors like illumination, conclusion, and imaging equipment, which leads to a reduction in the efficiency of the recognition system. Therefore, face recognition is still a challenging task [14].

2. RELATED WORK

From the last few decades, several methodologies were developed to identify the faces in an image. Among all these methods feature extraction plays a major role. Typically, feature extraction techniques are categorized into subspace learning [5]-[7] and local feature descriptors [8], [9], [15], [16] methods. Principle component analysis (PCA) and fisher linear discriminant analysis (FLDA) are conventional subspace learning approaches. Local linear embedding (LLE) [17], isometric feature mapping [18], Laplacian Eigenmap [19] are different manifold learning techniques to unwrap the intrinsic low-dimensional representation. Abusham et al. [20] demonstrated an approach to face recognition by integrating PCA and LLE. An and Ruan [21] propounded Enhanced fisher’s linear discriminant (EFLD) method and it outperforms the earlier algorithms. PCA reduces the dimension and eliminates correlation, however, it is not appropriate for classification [22]. Zhou et al. [23] introduced a face recognition method depending upon PCA image reconstruction and linear discriminant analysis. But the above-mentioned methods are computationally expensive since they deal with the Eigen decomposition and also require a lot of memory.

Compared to subspace learning methods, local feature descriptors are more efficient and robust. Further, they can be classified into handcrafted and learning-based descriptors. Local binary patterns (LBP) and Gabor wavelets are two typical handcrafted features. Ahonen et al. [24] primarily used LBP in face recognition and they attained promising results due to its effectiveness and simplicity [25]. Owing to this idea, several LBP approaches have been evolved [26]-[28]. However, the handcrafted features are sensitive to illumination variations, and also lose some texture information under specific conditions. These problems are resolved by learning-based descriptors. Among them, local quantized patterns [29] and discriminant face descriptors [30] staging a good performance.

Dai et al. [31] manifested a decorrelated 2D-feed-forward neural network ensemble with random weights for face recognition. Chen et al. [32] addressed the problem of multi-pose classification using 2D-gabor features and the Deep Belief Nets. Muqet et al. [33] utilized LBP and directional wavelet transform for face recognition. Tai et al. [34] proposed the orthogonal procrustes problem (OPR) as a framework to recognize pose varying faces. Li et al. [35] introduced a new method to estimate the low-rank representation for image classification. Khan et al. [36] proposed a system that can recognize faces with varying illumination and expressions by employing particle swarm optimization (PSO). Lin et al. [37] propounded a new dictionary learning approach for face recognition. In recent years convolutional neural network (CNN) methods have grabbed substantial attentiveness in face recognition. The CNNs considerably enhances the model generation ability by establishing effective regularization strategies such as dropout [38]. The research group at Facebook developed a deep learning facial recognition system named DeepFace [39], Sun et al. [40] proposed a CNN-based face representation named deep hidden IDentity feature (DeepID), whose features are learned by training a group of small CNNs. Features extracted from all the CNNs are concatenated to form a powerful feature. Yin and Liu [41] proposed multi-task learning for face recognition with the illumination, expression, and pose estimation as the side tasks. Görgel and Simsek [42], deep stacked denoising and sparse autoencoders (DSDSA) were used for face recognition. In this paper, a new face recognition technology is introduced by utilizing non-subsampled shearlet transform (NSST), histogram-based local feature descriptors, and CNN.

The remainder of the paper is planned as: we discuss the proposed face recognition method in section 3. Experimental outcomes are demonstrated in section 4. Section 5 consists of the conclusion of the paper.

3. PROPOSED WORK

The proposed approach consists of five major phases, detecting a face from the input image, pre-processing, NSST decomposition, extracting features, and classification. Face detection removes unwanted parts like hands, neck, and surroundings from the images, and gives the region of interest. Here Viola-Jones [43] algorithm is utilized for face detection. After the detection of the face region, the image resizing pre-processing operation is performed. Later, NSST is applied to the preprocessed image, and features are extracted by using LPQ, pyramid of histogram of oriented gradients (PHOG), and the proposed
CNN. The extracted features are fused to obtain a hybrid feature vector. Finally, SVM is employed as a classifier to recognize the face images. The whole process is shown in Figure 1.

3.1. Non-subsampling shearlet transform

Traditional multiscale methods like wavelets, curvelets, and contourlet transforms are unable to capture the anisotropic features in multidimensional data. These problems are overcome by shearlets since they can efficiently represent the data in multidimensional phenomena [44]. Let dimension \( n = 2 \), the discrete shearlet transform can be given as (1),

\[
\{ \psi_{p,q,r}(x) = |\det M|^{p/2} \psi(S^q M^p x - r) ; p,q \in Z, r \in Z^2 \}
\]

where \( \psi \) is a group of basis functions that satisfy \( \psi \epsilon L^2(R^2) \), \( M \) indicates the anisotropy matrix, \( S \) is a shear matrix, \( p, q, r \) are scale, dimension, and shift parameters. Both \( M \), and \( S \) are invertible matrices with size \( 2 \times 2 \) and \( |\det S| = 1 \). For each \( k > 0 \) and \( s \in R \), the matrices \( M \) and \( S \) are given by (2),

\[
M = \begin{pmatrix} k & 0 \\ 0 & \sqrt{k} \end{pmatrix}, S = \begin{pmatrix} 1 & s \\ 0 & 1 \end{pmatrix}
\]

the matrix \( M \) controls the scaling of shearlet and \( S \) controls the orientation of shearlet. For \( k = 9, s = 1 \), (2) becomes

\[
M = \begin{pmatrix} 9 & 0 \\ 0 & 3 \end{pmatrix}, S = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix}
\]

the basic function \( \hat{\psi}^{(0)} \) for shearlet transform, for any \( \beta = (\beta_1, \beta_2) \in R^2, \beta_1 \neq 0 \) is given by (4),

\[
\hat{\psi}^{(0)}(\beta) = \hat{\psi}_1(\beta_1) \hat{\psi}_2(\beta_2/\beta_1)
\]

here \( \hat{\psi} \) is the Fourier transform of \( \psi, \hat{\psi}_1 \in C^\infty(R), \hat{\psi}_2 \in C^\infty(R) \) are both wavelets.

The NSST decomposition consists of multi-scale and multi-directional factorization steps. To achieve multiscale factorization, the non-subsampling laplacian pyramid (NSLP) is utilized and it consists of a dual-channel non-subsampling filter bank to ensure multi-scale property, which separates the input image into low and high-frequency components. Implementation of successive NSLP decomposition is done to decompose the low-frequency component repeatedly and hence singularities in images are found. Similarly, to realize, multi-directional factorization improved shearing filters are used. In our proposed approach, initially, we detect the face region and then resize it to 64×64 and then NSST is applied to it. Figure 2(a) shows the input face image, Figure 2(b) gives the detected face region, and the low-frequency sub-band component from the NSST is shown in Figure 2(c).
3.2. Local phase quantization

LPQ is a well-known local texture feature descriptor and used to extract the textual details, which are robust to blurring [45]. Initially, LPQ performs short time Fourier transform (STFT) to obtain the phase details for every pixel of the source image and then encrypts the corresponding phase information. Finally, estimates the distribution of the encrypted details to get the LPQ features. The mathematical description of LPQ is described as:

Let us assume that \( p(m, n) \) be an original image. Then the spatial invariant blurring of the image \( p(m, n) \) is obtained by a convolution operation (5):

\[
q(m,n) = p(m,n) \otimes h(m,n)
\]  

(5)

where \( q(m,n) \) is a blurred image, \( h(m,n) \) is the point spread function (PSF) and \( \otimes \) represents the convolution [46].

The Fourier representation of (5) is given by (6),

\[
Q(u,v) = P(u,v) \cdot H(u,v)
\]  

(6)

where \( Q(u,v) \), \( P(u,v) \), and \( H(u,v) \) are the Fourier transforms of \( q(m,n) \), \( p(m,n) \), and \( h(m,n) \) respectively. After that, the phase information of the blurred image is attained by the following expression,

\[
\angle Q(u,v) = \angle P(u,v) + \angle H(u,v)
\]  

(7)

where \( \angle Q(u,v) \), \( \angle P(u,v) \), and \( \angle H(u,v) \) are the phases of \( q(m,n) \), \( p(m,n) \), and \( h(m,n) \) respectively. When the PSF, \( h(m,n) \) is centrally symmetric, its phase has only two values and is represented by (8),

\[
\angle H(u,v) = \begin{cases} 
0, & \text{if } H(u,v) \geq 0 \\
\pi, & \text{otherwise}
\end{cases}
\]  

(8)

thus, the phase invariance between \( Q(u,v) \) and \( P(u,v) \) is obtained as (9),

\[
\angle Q(u,v) = \angle P(u,v), \quad \text{for all } H(u,v) \geq 0
\]  

(9)

However, in LPQ the phase details are evaluated over the \( M \times M \) neighborhood region of image \( q(m,n) \). To obtain these local spectra features estimate the STFT by (10),

\[
Q(u,v) = \sum_{m \in N_m} \sum_{n \in N_n} q(m,n) e^{-j2\pi(um+vn)/M}
\]  

(10)

where \( N_m \) and \( N_n \) indicate the neighborhood region. LPQ finds the phase detail at frequency points \( z_1 = (a, 0), z_2 = (0, a), z_3 = (a, a), z_4 = (a, -a) \) using STFT, where \( a \) is a small integer that obeys (9). The acquired results are arranged as (11)

\[
V = [Q(z_1), Q(z_2), Q(z_3), Q(z_4)]
\]  

(11)

Figure 2. (a) input face image, (b) detected face region, (c) NSST low-frequency sub-band component
and

\[
W = [Re(V), Im(V)]
\]  
(12)

where \(Re[V]\) represents the real part of \(V\) and \(Im[V]\) denotes the imaginary part of \(V\). The textural details can be obtained by encrypting the elements in \(W\) as (13),

\[
c = \sum_{i=1}^{8} k_i 2^{l-1}
\]  
(13)

where \(k_i\) is the quantization of the \(i^{th}\) element in \(W\), given by (14)

\[
k_i = \begin{cases} 
1, & \text{if } W_i \geq 0 \\
0, & \text{otherwise} 
\end{cases}
\]  
(14)

Finally, the LPQ is obtained by detecting the distribution histogram of the encoded values \(c\). In the proposed method, after applying NSST on the face detected image, the obtained low-frequency sub-band component is applied to LPQ to obtain the blur insensitive texture features. The detected face region from the input face image is given in Figure 3(a), and Figure 3(b) represents the NSST low-frequency sub-band component. Figure 3(c) and Figure 3(d) show the LPQ descriptor image and the corresponding histogram.

![Figure 3. (a) detected face region, (b) NSST low-frequency sub-band component, (c) LPQ descriptor image, (d) histogram of (c)](image)

### 3.3. Pyramid of histogram of oriented gradients

For effective face recognition, we require shape information along with texture details. To obtain such shape information we apply the PHOG descriptor which is built by utilizing the histogram of oriented gradients (HOG) features and pyramid representation of the images [47]. HOG descriptor is used to find the local shape of the objects in images and pyramid representation addresses spatial structure. The image is split into tiny regions (cells) and HOG features [48] are computed for every spatial region. The cells are split recurrently to maintain the local shape information completely. The extracted features from all the cells are integrated to form the final HOG features and they are concatenated with the pyramid structure to incorporate the details associated with the spatial design. Canny edge detection algorithm was utilized to identify the edges in the face image, and then the face image is split into cells by following the quad-tree concept. Let the \(M\) be the number of levels, and \(N\) be the number of bins for HOG features, then the dimension for PHOG descriptor is given by \(N \times \sum_{k=0}^{M} 4^k\). In this work, we choose \(3(M = 0,1,2)\) number of levels and the number of bins as 8, then the resultant feature vector has a size 168. Figure 4(a) shows the detected face image and Figure 4(b) represents the NSST low-frequency sub-band component. The PHOG descriptor image and the final histogram of the PHOG for the corresponding input face image are given in Figure 4(c) and Figure 4(d) respectively.
3.4. Proposed convolutional neural network

Convolutional neural networks have attained noticeable progress in image classification and they have been utilized in face recognition applications because they can extract robust facial features. The CNNs are generally made up of three types of layers namely, convolutional, pooling, and fully connected layers. A convolutional layer includes many convolutional kernels that are utilized to generate different feature maps. After each convolutional layer, a pooling layer is utilized that decreases the dimension of the feature maps and thus reduces the computational complexity of the CNN model. A fully connected layer considers all the neurons in the previous layer and associates them with every neuron of the current layer.

The architecture of the proposed CNN is shown in Figure 5. The proposed convolutional neural network contains three convolutional, three pooling, and two fully connected layers. The input to the proposed CNN is a 64x64x1 grayscale image. The first convolutional layer has six 5x5 filters and the convolution stride is set to one pixel. Thus, the output of the first convolutional layer contains six feature maps with size 60x60. Here, ReLU non-linear activation function is used in the convolutional layer. After each convolutional layer, max-pooling is accomplished over a 2x2 window, with stride two. Hence, the outcome of the maxpooling1 is feature maps with a 30x30 dimension. In each convolutional layer, the stride is considered as one whereas for max-pooling layers it is taken as two. The depth of the second and third convolutional layers is eight and ten, with output feature map dimensions 26x26x8 and 9x9x10 respectively. Maxpooling2 and maxpooling3 layers generate an output of 13x13x8 and 5x5x10 respectively. The last two layers are fully connected layers with 200 and 120 hidden units.

4. EXPERIMENTAL RESULTS AND DISCUSSION

The capability of the suggested method, with different filters for the Laplacian pyramid decomposition [49], is tested using three face databases: i) ORL [50], ii) Yale [51], and iii) Japanese female facial expression (JAFFE) [52]. In every class of the database, 70% of images were utilized for training and the rest of the images were used for testing. While training the proposed CNN, stochastic gradient descent has been used for optimization with a base learning rate of 0.0001, and the maximum number of epochs as 20. Each experiment was done 10 times with the chosen datasets and the average recognition rate was given.

The ORL database comprises 40 different subjects. Each subject contains ten different images with distinct lighting environments, facial expressions, and attributes. In total ORL database includes 400 images each with 112x92 image resolution. The Yale face database includes a total of 165 face images of 15 subjects with 11 images per class. These images are considered under different configurations such as normal, happy,
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is 3.24 minutes, 1.56 minutes, and 2.35 minutes respectively. The execution time required to recognize the probe image of ORL, Yale, and JAFFE databases is 2 seconds, 1.2 seconds, and 1.6 seconds respectively.

### Table 1. Recognition rate (%) for the proposed method with ‘kos’ filter

| Database | ORL | Yale | JAFFE |
|----------|-----|------|-------|
| Classifier | KNN | SVM | KNN | SVM | KNN | SVM |
| LPQ | 94.32 | 95.78 | 93.42 | 94.64 | 93.71 | 94.17 |
| PHOG | 92.72 | 93.52 | 92.33 | 93.76 | 92.41 | 92.32 |
| CNN | 94.54 | 96.31 | 95.56 | 96.37 | 95.28 | 96.84 |
| LPQ+PHOG | 95.46 | 95.92 | 94.37 | 95.27 | 93.36 | 94.58 |
| LPQ+CNN | 97.16 | 97.43 | 96.28 | 97.63 | 97.38 | 98.49 |
| PHOG+CNN | 96.46 | 96.87 | 96.15 | 97.26 | 96.27 | 97.92 |
| Proposed | 97.45 | 97.61 | 96.52 | 97.88 | 97.48 | 98.75 |

### Table 2. Recognition rate (%) for the proposed method with ‘pyr’ filter

| Database | ORL | Yale | JAFFE |
|----------|-----|------|-------|
| Classifier | KNN | SVM | KNN | SVM | KNN | SVM |
| LPQ | 95.36 | 96.78 | 93.61 | 94.24 | 93.32 | 93.85 |
| PHOG | 93.53 | 94.52 | 92.43 | 93.66 | 92.42 | 92.25 |
| CNN | 96.43 | 97.91 | 96.21 | 96.35 | 96.72 | 97.41 |
| LPQ+PHOG | 96.28 | 96.39 | 94.86 | 95.29 | 94.78 | 94.84 |
| LPQ+CNN | 98.22 | 98.57 | 97.48 | 98.35 | 98.25 | 98.72 |
| PHOG+CNN | 97.24 | 98.82 | 96.47 | 97.38 | 98.14 | 98.26 |
| Proposed | 98.67 | 99.32 | 97.85 | 98.72 | 98.54 | 99.45 |

### Table 3. Recognition rate (%) for the proposed method with ‘pyrex’ filter

| Database | ORL | Yale | JAFFE |
|----------|-----|------|-------|
| Classifier | KNN | SVM | KNN | SVM | KNN | SVM |
| LPQ | 94.36 | 93.88 | 93.51 | 94.78 | 93.81 | 93.71 |
| PHOG | 93.42 | 94.53 | 92.33 | 93.56 | 92.43 | 92.25 |
| CNN | 96.25 | 96.58 | 95.24 | 96.34 | 96.29 | 95.62 |
| LPQ+PHOG | 95.38 | 96.51 | 94.38 | 95.54 | 94.47 | 94.48 |
| LPQ+CNN | 97.65 | 97.16 | 96.58 | 97.43 | 97.58 | 98.51 |
| PHOG+CNN | 97.29 | 96.97 | 96.14 | 97.23 | 97.36 | 97.46 |
| Proposed | 97.78 | 97.94 | 97.28 | 97.87 | 97.67 | 98.87 |

### Table 4. Recognition rate (%) for the proposed method with ‘maxflat’ filter

| Database | ORL | Yale | JAFFE |
|----------|-----|------|-------|
| Classifier | KNN | SVM | KNN | SVM | KNN | SVM |
| LPQ | 94.66 | 95.31 | 93.71 | 94.93 | 93.65 | 93.21 |
| PHOG | 93.52 | 94.82 | 92.63 | 93.65 | 92.47 | 92.14 |
| CNN | 96.23 | 97.23 | 95.84 | 96.34 | 96.14 | 96.95 |
| LPQ+PHOG | 95.45 | 96.81 | 94.75 | 95.96 | 94.25 | 94.28 |
| LPQ+CNN | 96.67 | 97.42 | 96.82 | 97.31 | 97.34 | 97.64 |
| PHOG+CNN | 96.45 | 97.24 | 96.26 | 96.93 | 97.19 | 97.28 |
| Proposed | 97.13 | 97.83 | 97.24 | 97.92 | 98.45 | 98.95 |

From the values of Tables 1-4, it is inferred that the proposed technique achieves a maximum face recognition rate of 99.32%, 98.72%, and 99.45% on ORL, Yale, and JAFFE databases respectively with ‘pyr’ filter. The comparison of the recognition rate for the proposed face recognition system on the ORL, Yale, and JAFFE databases with some of the existing methods shown in Table 6 appendix, to show its effectiveness.

### Table 5. Performance metrics for the proposed method with ‘pyr’ filter

| Database | ORL | Yale | JAFFE |
|----------|-----|------|-------|
| Classifier | KNN | SVM | KNN | SVM | KNN | SVM |
| Precision | 0.9833 | 0.9916 | 0.9812 | 0.9833 | 0.9925 | 0.9937 |
| Recall | 0.9809 | 0.9904 | 0.9793 | 0.9777 | 0.9912 | 0.9916 |
| Specificity | 0.8678 | 0.9334 | 0.9632 | 0.9761 | 0.9873 | 0.9752 |
| F1-Score | 0.9821 | 0.9909 | 0.9758 | 0.9804 | 0.9895 | 0.9926 |

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Figure 7. ROC curves for the proposed method on; (a) ORL, (b) Yale, and (c) JAFFE databases

5. CONCLUSION

A reliable and effective face recognition system using the NSST, the histogram of local feature descriptors, and CNN is proposed. The significant contribution of this work is presenting a novel method using histogram-based local feature descriptors, and CNN features on a transformed image for robust face recognition. NSST decomposes the input face image, into low and high-frequency sub-band components using the Non-Subsampled Laplacian Pyramid. Histograms of the local feature descriptors namely LPQ, PHOG, and the deep features from CNN are obtained from the low-frequency sub-band component and concatenated to form the feature space. In our proposed method compared to KNN classifier SVM produces better results on the chosen face databases. The experimental results reveal that the suggested method effectively recognizes the faces with different illuminations, poses, and expressions. Compared to some of the existing approaches, the proposed method achieves a better recognition rate.
APPENDIX

Table 6. Comparison of recognition rate (%) of the proposed method with some of the existing methods

| Method                                      | ORL  | Yale | JAFFE |
|---------------------------------------------|------|------|-------|
| PCA [21]                                    | 89.50|      |       |
| EFLDA [21]                                  | 93.00|      |       |
| CLDA [21]                                   | 94.06|      |       |
| PCA image reconstruction+LDA+SVM [23]       | 97.48|      |       |
| GFDBN [32]                                  | 94.98|      |       |
| DIWTLBP [33]                                | 97.00|      |       |
| DSDSA [42]                                  | 98.00|      |       |
| Proposed                                    | 99.32|      |       |
| OPR [34]                                    | 94.15|      |       |
| PLR [35]                                    | 96.23|      |       |
| Yin [41]                                    | 95.02|      |       |
| RDCDL [38]                                  | 97.22|      |       |
| DSDSA [42]                                  | 98.16|      |       |
| Proposed                                    | 98.72|      |       |
| FLLEPCA [20]                                |      | 94.98|       |
| Single 2D-NNRW [31]                         |      | 97.00|       |
| PSO [36]                                    |      | 98.80|       |
| Proposed                                    |      | 99.45|       |

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