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LWKPCA: A New Robust Method for Face Recognition Under Adverse Conditions

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ABSTRACT Over the last two decades, face recognition (FR) has become one of the most prevailing biometric applications for effective people identification as it offers practical advantages over other biometric modalities. However, current state-of-the-art findings suggest that FR under adverse and challenging conditions still needs improvements. This is because face images can contain many variations like face expression, pose, and illumination. To overcome the effect of these challenges, it is necessary to use representative face features using feature extraction methods. In this paper, we present a new feature extraction method for robust FR called Local Binary Pattern and Wavelet Kernel PCA (LWKPCA). The proposed method aims to extract the discriminant and robust information to minimize recognition errors. This is obtained first by the best use of nonlinear projection algorithm called RKPCA. Then, we adapted the algorithm to reduce the dimensionality of features extracted using the proposed Color Local Binary Pattern and Wavelets transformation called Color LBP and Wavelet Descriptor. The general idea of our descriptor is to find the best representation of face image in a discriminant vector structure by a novel feature grouping strategy generated by the Three-Level decomposition of Discrete Wavelet Transform (2D-DWT) and Local Binary Pattern (LBP). Extensive experiments on four well-known face datasets namely ORL, GT, LFW, and YouTube Celebrities show that the proposed method has a recognition accuracy of 100% for ORL, 96.84% for GT, 99.34% for LFW, and 95.63% for YouTube Celebrities.

INDEX TERMS Face recognition, RKPCA algorithm, local binary pattern, local binary pattern and wavelet kernel PCA, color LBP and wavelet descriptor.

I. INTRODUCTION

Facial biometrics systems are one of the most important in many socio-economic fields. Indeed, it's involved in multiple security applications like access control applications in authorized areas, personal computers, airports, and surveillance systems [1], [2]. From face images these biometric technique capable of providing lots of useful information including human sex, facial expressions, age. Also, due to uniqueness of a person's face makes the recognition of it a good alternative for security insurance as well as automatic person identification across a system of multiple cameras. Many FR methods have been discussed and applied by several research and development structures. However, these techniques suffer from several challenges such as difficult illuminations, pose variation, facial expressions, and low-resolution images. These unfavorable conditions remain a complicated problem that considerably decreases the recognition performance of modern FR systems especially when a real-time analysis is required.

To solve these weaknesses, a large number of approaches have been discussed in order to propose effective face descriptors. The application of these descriptors still not accurate to produce optimal and discriminating features. For example, in [3] the authors propose an efficient FR method under adverse conditions based on the Gabor wavelet. In another work, Gabor filters, PCA and ICA are used for FR [4]. The covariance matrix, which is a multivariate model, was also used in [5] where the obtained results using it are promising. For image recognition, covariance-based models

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are expoilted including the Gaussian mixture model and gaussian model. In the same context, a local descriptor with the nearest neighbor classifier incorporating the Hellinger distance were exploited to analyze features vectors for FR [6]. LBP is another descriptor that has been used for face recognition, due to it simplicity of implementation as well as useful for lighting changes. However LBP-based technique has some limitations like limited discriminative capacity [7]. However, LBP is used widely for face recogntion like in [8] while the authors used PCA to reduce the features obtained using their two descriptors based on LBP called CZZBP and CMBZZBP. The basic idea of these two descriptors is to exploit the ZigZag features of three RGB components to extract representative information. The results of simulations on GT and Faces94 show the efficiency of the proposed descriptors in terms of recognition rate. In 2021, the same authors propose a series of descriptors based on LBP method in order to minimize the effect of face image variations. These descriptors are: NCDB-LBP [9], DCD [10], OD-LBP [11]. In the same context we propose, in this paper, a robust FR method based on a new efficient face descriptor combined with a recent robust nonlinear projection learning algorithm to obtain better face recognition performance. The major contributions of our proposed approach are summarized as follows:

- A novel face descriptor called Color LBP and Wavelet based on a new feature grouping strategy generated by the three-level decomposition of 2D-DWT. An empirical study is carried out to fix the parameters related of our descriptor to obtain better recognition accuracy.
- We have proposed a robust FR method under adverse conditions called LWKPCA with the exploitation of non-linear subspace learning algorithm to extract the discriminant and robust information contained in the feature space produced by the proposed descriptor.
- A comparison of the obtained results with the state-fo-the-art methods on four well-known face image datasets, such as GT, ORL, LFW, and YouTube Celebrities.

The remainder of this paper is organized as follows. Section 2 reviews some related FR models. Section 3 presents a background on 2D-DWT and LBP, PCA and KPCA using RRQR factorization. Section 4 details the proposed LWKPCA method. Section 5 presents the experimental results of our method on four representative face-datasets. Finally, brief-conclusions are summarized in Section 6. The paper contains alot of abreviations, for that Table 1 shows the meaning of each acronyms used in this paper.

TABLE 1. Acronyms used in this paper.

Acronym	Meaning
CLWD	Color LBP and Wavelet Descriptor
CZZBP	Color ZigZag Binary Pattern
CMBZZBP	Color Median Block ZigZag Binary Pattern
CLBP	Compound Local Binary Pattern
DWT	Discret Wavelet Transform
DCD	Discriminative Color Descriptor
FR	Face Recognition
GT	Georgia Tech
ICA	Independent Component Analysis
KPCA	Kernel Principal Component Analysis
LBP	Local Binary Pattern
LDA	Linear Discriminant Analysis
LFW	Labeled Faces in the Wild
LWD	LBP and Wavelet Descriptor
LWKPCA	LBP and Wavelet KPCA
MSPP	Multiple Samples Per Person
NCDB-LBP	Neighborhood and Center Difference-LBP
N/A	Not Available
OD-LBP	Orthogonal difference-LBP
PCA	Principal Component Analysis
PCA-L_1	PCA using L_1-norm maximization
RRQR	Rank Revealing QR
RR	Recognition Rate
RBF	Radial Basis Function
RKPCA	Robust Kernel PCA
RWLDA	Relevance Weigthed LDA
SVD	Singular Value Decomposition
STD	Standard deviation
TT	Training Time
WKPCA	Wavelet KPCA
WTPCA-L_1	Wavelet Transformation PCA-L_1
2DPCA	Twodimensionnal PCA
2DLDA	Twodimensionnal LDA

II. RELATED WORKS

The human face is one of the most used biometric features in computer authentication applications such as video surveillance and security cheking. The purpose of FR is to identify the face-image against facial samples saved in a dataset. However, the performance of FR is yet not very satisfying when the face image is under complex environments. This is mainly due to the variation of facial images in terms of expressions, and poses. Many methods have been proposed for tackling this challenges including Wavelets-based methods [12], LBP-based methods [13], Deep-Rooted Learning Algorithm [14], and deep FR learning models [15]. In addition, several research studies have been carried out on other FR problems [16] like uneven illumination and its negative impact on the performance of FR algorithms. For example, Pilchoski *et al.* [17] exploited histogram equalization on Wavelet transformation domain to minimize the influence of uneven illumination. In [18], the authors propose a new adaptive illumination normalization based on a nonlinear modifier. All these variations contained in face images represent great challenges for FR algorithms. Many sub-space learning approaches based on PCA have been successfully used to mitigate the influence of these variations. Basically, PCA seeks for a projection matrix which minimizes the reconstruction error in a sense of least squares. However, several research works have proven a high sensitivity of these algorithms to Gaussian noise.

Several robust variants of PCA have been proposed for face recognition over the past ten years. It can be classified into two main classes. Methods based on a novel PCA formulation and methods that use pre-processing to improve PCA performance. The techniques based on a novel PCA fomulations rely on the use of different norm maximization [19]–[21]. While the pre-processing based on PCA techniques aim to improve the performance of feature extraction by the combination of PCA with other facial features. For example,

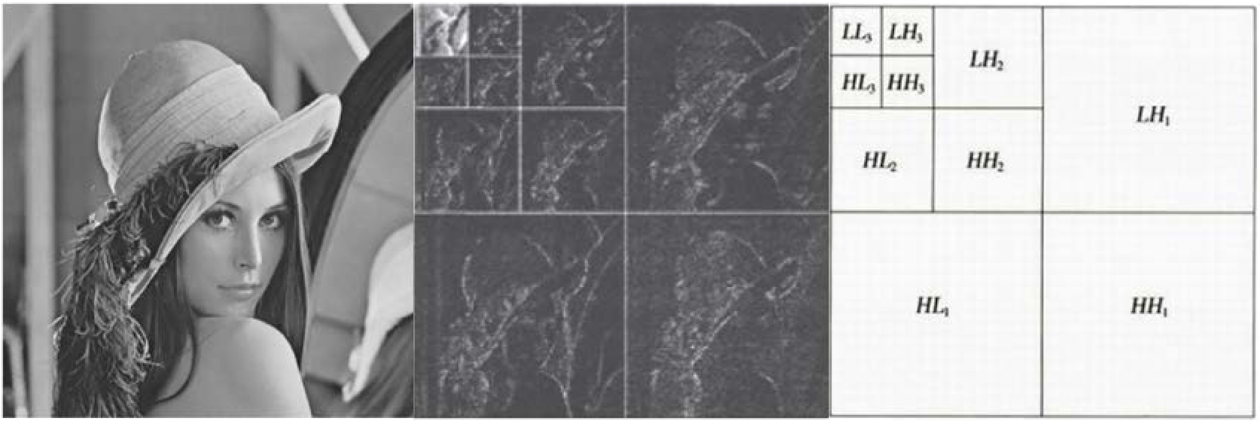


FIGURE 1. Lena image decomposed using three-level discrete wavelet transform.

the authors in [22] exploited the gradient orientation to calculate the PCA subspace using the Schur decomposition [23]. The earest neighbour classifier [24] is used to prove the robustness of their proposed method. In the same context, Elmahmudi *et al.* [25] proposed an efficient face features extraction method called BiPCA. BiPCA exploits the Biharmonic operator in face images as a preprocessing method. The results of the application of BiPCA on three face databases namely ORL [26], Face95 [27], and Face96 [27] shows the effectiveness of the proposed method in terms of the average percentage error rate. Also, a deep learning method has been proposed in [28]. However, even the use of deep learning face under extreme conditions still represent a challenges for all types of methods. Therefore, various hybrid systems have been proposed recently to face these challenges. The general idea of hybrid systems is to combine face features generated by several feature extraction methods in order to minimize the effect of these variations as much as possible to have the best recognition rates. For exemple, the authors in [29] proposed a fusion method of two efficient dimensionnality-reduction techniques in discrete wavelet-transform domain. The application of this fusion with Min-Max as a method of normalization on two face datasets gives convincing results. Also, in [30] a new features-based deep lerning architecture generated by WTPCA-L_1 norm maximization method called DeepWTPCA-L_1 is proposed. Hassan *et al.* [31] proposed a FR method based on Gabor Feature Extraction [32] then used FastICA [33], [34]. All these hybrid systems attempted to solve all these constraints. However, it does not perform well under adverse and challenging conditions. Therefore, we proposed a robust FR method based on a novel features grouping strategy combined with a recent nonlinear projection learning algorithm. A description of the proposed method will be presented in details in the following sections.

III. BACKGROUND

In this section, we present the theoretical concept on 2D-DWT, LBP, PCA and KPCA using RRQR factorization methods. These methods are the preliminary ones for construction of our proposed method.

A. DISCRETE WAVELET TRANSFORM

2D-DWT is a feature extraction method popular in image processing [35], [36], which has been used in many fields, such as pattern recognition, image encryption, reversible data hiding, ect. After the level-decomposition, 2D-DWT uses the high pass filter and the low pass filter to decompose the input image into four approximation sub-images or sub-bands, named LL, HL, LH, and HH. These sub-images are obtained by using a low pass filtering in horizontal direction and high pass filtering in vertical direction for each-level of decomposition. The spatial orientation information is stored in sub-images LH, HL and HH. The LL image contains the maximum of the discriminating features and represents the approximate coefficients. Also this image can be exploited to produce the next level decomposition. In this paper, we use the Daubechies wavelet into Three-level decomposition to produces the four (LL_3, LH_3, HL_3 and HH_3) sub-images. In our proposed method, We are only interested in the LL_3 band to represent the facial image. The Three-level decomposition method is depicted in Figure 1.

B. LOCAL BINARY PATTERN

The LBP [37] is one of the non-parametric descriptors for extracting the image local information. It is implicitly defined at the position of the pixel, LBP operator is expressed by a sequence of binary values obtained by comparing the central pixel with its neighbors in a circular manner. For this, all the pixels of the image take an operator value which is calculated as a function of the P neighborhood pixels and the neighborhood threshold which is based on the central pixel. The pixel less than to the central pixel are given the binary value 0 and 1 otherwise. Then all the calculed binary values are concatenated, and the decimal value equivalent to the binary code represents the LBP-label. This is defined

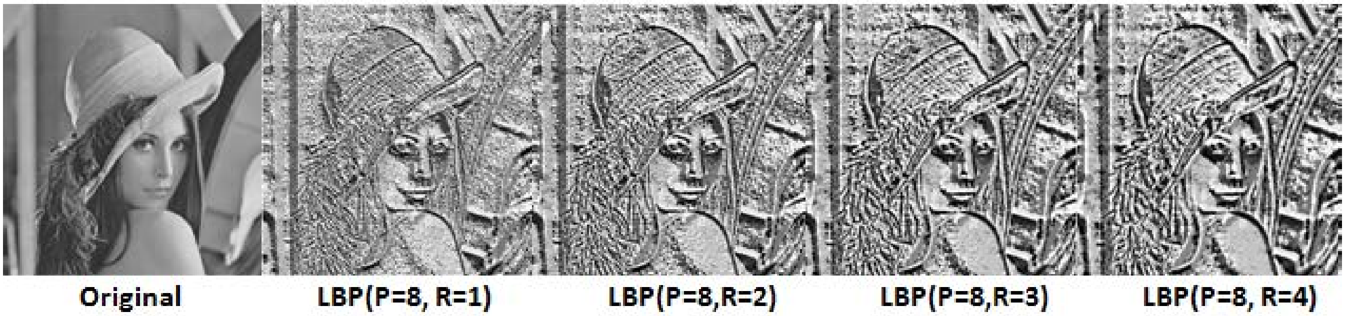


FIGURE 2. The lena images by: original, LBP (R = 1, 2, 3, 4) descriptors.

mathematically by the following expression:

$$LBP_{P,R} = \sum_{k=0}^{P-1} S(g_k - g_c)2^k \tag{1}$$

where g_k is the pixel value of the neighbors and g_c is the center pixel value. The P and R represent the number of neighborhoods and radius, and function $S(x)$ is defined as:

$$S(x) = \begin{cases} 1, & x > 0 \\ 0, & otherwise \end{cases} \tag{2}$$

In this work, we have fixed the neighborhood value $P = 8$ and we vary R by these values $R = 1, 2, 3, 4$. Figure 2 shows the LBP descriptors for each R-value of Lena image.

C. PCA AND KPCA USING RRQR FACTORIZATION

PCA is a linear statistical feature extraction and dimensionality reduction method widely used primarily in computer vision applications. Its main purpose is to extract the discriminative features contained in the initial face dataset $X = \{x_i\}_{i=1}^n$ with $x_i \in \mathbb{R}^d$. This is done mathematically by the search for a projection matrix $\Psi = [\psi_1, \psi_2, \ldots, \psi_{\tilde{d}}] \in \mathbb{R}^{d\times\tilde{d}}$ which maximizes the data variance $H = \{h_i\}_{i=1}^n$, where $h_i = x_i - m$ and $m = \frac{1}{n}\sum_{i=1}^n x_i$ by the following equation:

$$\Psi = arg \max_{\Psi^T\Psi = I_{\tilde{d}}} \sum_{i=1}^n \|\Psi^T h_i\|_2^2 = arg \max_{\Psi^T\Psi = I_{\tilde{d}}} tr(\Psi^T C_r \Psi), \tag{3}$$

where $C_r = \frac{1}{n}HH^T$ is a covariance matrix. The Eq. (3) admits a classical solution defined by the eigenvectors set of C_r associated to first $\tilde{d}$ largest eigenvalues. The strength of conventional PCA in human FR is its better recognition performance in ideal face-dataset. However, its main limitation is the very high computational complexity of the projection matrix. To address this weakness, many methods have been proposed. Turk & Pentland [38], [39] have proposed an intelligent technique to speed up the computation of the needed values from $\tilde{C_r} = \frac{1}{n}H^T H$. It is clear that the two matrix C_r and $\tilde{C_r}$ are defined by the same eigenvalues $\lambda_i \neq 0$. Therefore the normalized eigenvectors which form the projection matrix are calculated by this formulation $\psi_i = \frac{1}{\sqrt{\lambda_i}}Hv_i$. Such that v_i are the normalized-eigenvectors of $\tilde{C_r}$. Another variant of PCA based on SVD [40] (SVD PCA) is proposed in order to minimize the computational process of the conventional version. In order to improve the performance of SVD PCA algorithm. A. Sharma *et al.* [41] have suggested a new technique based on QR decomposition called QR PCA. The general idea of QR PCA is to use Householder QR decomposition instead of using SVD in order to speed up the process of computation PCA. In the same context, the authors in [42] propose a new extension of PCA based on the economic RRQR factorization called RRQR PCA. RRQR perfectly accelerates the computation of the projection bases. The second limitation of PCA-based FR models is that PCA is a linear technique whereas human faces are not linearly separable in raw input space. Therefore, the application of linear PCA as a face feature extraction process can lead to degradation of recognition rates. For this, many approaches have been developed to address this weakness, such as kernel-based PCA [43], [44]. Recently, in [42] the authors proposed a nonlinear extension of RRQR PCA called RKPCA to take into account the data nonlinearity criterion. The general concept of RKPCA is first to map the input space into a feature space via nonlinear mapping, and then to compute the projection matrix into that feature space using RRQR factorization. Similar to RRQR PCA, RKPCA seeks a discriminant solution of the F_{RKPCA} objective function in order of find the projection matrix or projection bases of the feature space **F**.

$$F_{RKPCA}(\psi) = arg \max_{\psi^T\psi = I_{\tilde{d}}} tr(\psi^T C_\phi \psi), \tag{4}$$

where $C_\phi = \frac{1}{n}\sum_{i=1}^n \phi(x_i)\phi(x_i)^T$ is a covariance matrix in the feature space **F** and $\phi(x_i)$ is the i_{th} sample defined in F with zero mean and unit variance and n denotes the sample size. The eigenvectors v associated to the largest eigenvalues λ are considered as the projection bases in the feature space. Based on last equation, $C_\phi v$ can be formulated mathematically as follows:

$$\begin{aligned} C_\phi v &= \left(\frac{1}{n}\sum_{i=1}^n \phi(x_i)\phi(x_i)^T\right)v \\ &= \frac{1}{n}\sum_{i=1}^n \langle\phi(x_i), v\rangle\phi(x_i), \end{aligned} \tag{5}$$

where $\langle x, y\rangle$ denotes the dot product between x and y. For this, all the solutions v with $\lambda \neq 0$ are defined in $\{\phi(x_i)\}_{i=1}^{n}$. The implies that $\lambda v = C_\phi v$ is equivalent to

$$\lambda\langle\phi(x_k), v\rangle = \langle\phi(x_k), C_\phi v\rangle, \quad k = 1, \ldots, n, \tag{6}$$

and there exist expansion coefficients $\{\alpha_i\}_{i=1}^{n}$ such that,

$$v = \sum_{i=1}^{n}\alpha_i\phi(x_i). \tag{7}$$

By replacing Eq (7) in (4), we obtain an equivalent eigenvalue problem

$$(I_n - \frac{1}{n}1_n)K(I_n - \frac{1}{n}1_n)^T\alpha = \lambda\alpha, \tag{8}$$

where I_n is the identity-matrix of size $n \times n$, 1_n is an $n \times n$ matrix of which all the elements are equal to 1, and K is the Gram matrix defined by

$$K = \begin{bmatrix} \phi_1^T\phi_1 & \cdots & \phi_1^T\phi_n \\ \vdots & \ddots & \vdots \\ \phi_n^T\phi_1 & \cdots & \phi_n^T\phi_n \end{bmatrix} = \begin{bmatrix} k(x_1, x_1) & \cdots & k(x_1, x_n) \\ \vdots & \ddots & \vdots \\ k(x_n, x_1) & \cdots & k(x_n, x_n) \end{bmatrix} \tag{9}$$

where k is the kernel function. For more technical details on the classical solution of Eq. (8) can be referred to [45]. The most adapted kernel functions is the RBF which is given by $k(x_i, x_j) = \exp(-\frac{\|x_i - x_j\|_2^2}{2\sigma^2})$. However, the authors [42] have proposed a new kernel function called robust RBF L_p-norm kernel, expressed mathematically by Eq (10). This function exploits the robustness of the L_p-norm, $0 < p < 2$ to minimize the effect of outliers and extreme noise added in raw face images.

$$K_p = k_p(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|_p}{2\sigma^2}\right) \tag{10}$$

where, σ^2 means the Gaussian function width, common to all kernels, is fixed-empirically by the user. Therefore, Hala M. Ebied [46] shows that the classical Gaussian-KPCA gives the best face recognition rate with $\sigma = 3000$. Recently, the authors [42] have proposed a new solution of Eq (8). This solution is expressed by the decomposition of matrix K using cholesky decomposition $K = K_cK_c^T$, because the matrix K is symmetry and positive definite. This is defined mathematically by

$$\begin{aligned}\lambda\alpha &= [(I_n - \frac{1}{n}1_n)K_c][K_c^T(I_n - \frac{1}{n}1_n)^T]\alpha \\ &= [(I_n - \frac{1}{n}1_n)K_c][(I_n - \frac{1}{n}1_n)K_c]^T\alpha \\ &= \tilde{K_c}\tilde{K_c}^T\alpha \end{aligned} \tag{11}$$

where $\tilde{K_c} = (I_n - \frac{1}{n}1_n)K_c$. The main steps of RKPCA is summarized in Algorithm 4. This algorithm has proven a great performance for robust FR. Its main purpose is to extract the raw features contained in ORL and FERET face datasets. In this article, we treat the problem of facial images under extreme adverse conditions and its negative impact on FR algorithms. For this, we propose an extended version of RKPCA called LWKPCA. The key idea of our proposal is to exploit RKPCA to extract the discriminating and robust information contained in the face feature space generated by our proposed Color LBP and Wavelet Descriptor.

Algorithm 1 RKPCA Algorithm

Input: Data matrix $X = \{x_i\}_{i=1}^{n} \in \mathbb{R}^{d\times n}$, $\tilde{d}$: number of features, p.
Output: Projection matrix $\Psi = \{\psi_i\}_{i=1}^{\tilde{d}}$
Using Eq. (10) compute K_p.
Using Cholesky factorization of K_p matrix, compute K_c by $K_p = K_cK_c^T$.
Compute $\tilde{K}_c$ as $\tilde{K}_c = (I_n - \frac{1}{n}1_n)K_c$.
Using economic *RRQR* factorization of $\tilde{K}_c$, compute Q and R.
Using economic SVD of R^T, compute diagonal-matrix D, and the two orthogonal matrices: U, V by $R^T = UDV^T$.
for $i = 1, 2, \ldots, \tilde{d}$ **do**
  $\tilde{V}^T(:, i) = \frac{1}{D(i,i)}V^T(:, i)$
end for
Compute RKPCA-transform $\Psi = Q\tilde{V}^T$
return Ψ

Algorithm 2 CLWD

Input: Facial Image I, Radius r, Number of DB wavelet transform levels k.
Output: Feature vector F_v
1. Apply 2D-DWT & LBP feature extraction
$R = LL_3(I(:, :, 1), k)$; $[l, c] = size(R)$;
$Data = zeros(l \times c, 3)$; $Data(:, 1) = R(:)$;
$G = LL_3(I(:, :, 2), k)$; $Data(:, 2) = G(:)$;
$B = LL_3(I(:, :, 3), k)$; $Data(:, 3) = B(:)$;
$H_r = imhist(LBP(rgb2gray(I), r))$;
2. Concatenating all the four feature vectors
$D_v = Data(:)$;
$F_v = zeros(length(D_v) + length(H_r), 1)$;
$F_v(1 : length(D_v)) = D_v$;
$F_v(length(D_v) + 1 : length(IO)) = H_r$;
3. return F_v

IV. PROPOSED METHOD

In this section, a detailed description of the proposed approach is presented. Like illustrated in Figure 3, the proposed method consist of two main steps. The first one is the operation of extracting the discriminating features followed by the exploitation of RKPCA algorithm to reduce the dimensionality of the features extracted by our Color LBP and Wavelet descriptor. The second step is to classify the feature vector of input facial image with the feature vectors

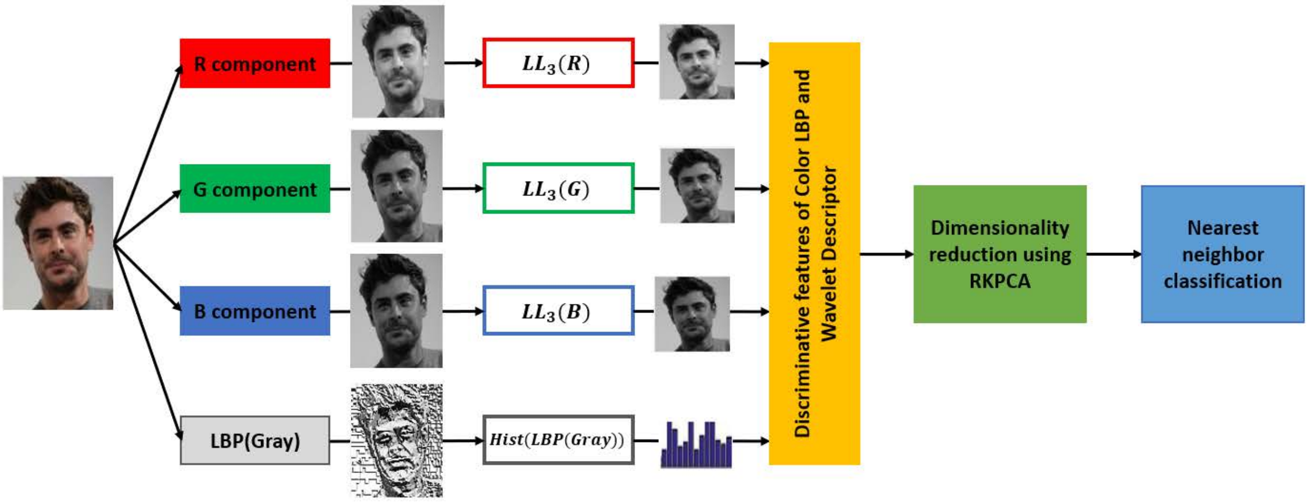


FIGURE 3. Flowchart of the proposed LWKPCA method. The first part of the diagram is feature extraction step from Color LBP and wavelet feature. The second part is the classfication part wich is made using nearest neighbor method.

of face dataset which is performed via the nearest neighbor classification algorithm using the Euclidean distance. The following subsection demonstrate the obtained results of the proposed Color LBP and Wavelet Descriptor comparing with the state-of-the-art methods.

A. PROPOSED COLOR LBP AND WAVELET DESCRIPTOR

Initially, we exploited the three components of the input color image such as R, G, and B. For each component, the three-level decomposition of 2D-DWT; Daubechies (DB) from DB1 to DB4 transformation are adapted. 2D-DWT calculates the LL_3 sub-band. Then, these three bands $LL_3(R)$, $LL_3(G)$, and $LL_3(B)$ are converted into a vector structure by this strategy,

$$LL_3(R) = \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{bmatrix} \Rightarrow LL_3(R)_v = \begin{bmatrix} r_{11} \\ \vdots \\ r_{m1} \\ \vdots \\ r_{1n} \\ \vdots \\ r_{mn} \end{bmatrix} \quad (12)$$

These three vectors structures such as $LL_3(R)_v$, $LL_3(G)_v$, $LL_3(B)_v$, and H_r are concatenated to generate the feature vector F_v of the proposed CLW Descriptor. $H_r = Hist(LBP(Gray, r))$ is the histogram of LBP operator of the grayscale version of the input color image, with r is the radius of the LBP operator. This is expressed by the following formulation,

$$F_v = LL_3(R)_v \oplus LL_3(G)_v \oplus LL_3(B)_v \oplus H_r, \quad (13)$$

where $\oplus$ is the concatenation operator, *imhist* is a matlab function capable of producing the histogram of generated by LBP operator. If the input image *Im* is in gray-scale, the LBP and Wavelet Descriptor concatenates only the vector stucture of $LL_3(Im)_v$ sub-band extracted by 2D-DWT and the histogram H_r of LBP operator. This is expressed by,

$$F_v = LL_3(Im)_v \oplus H_r \quad (14)$$

Ultimately, we exploit the F_v of each image to build the training space of the recognition model. Algorithm 2, 3 summarize the main steps developed under Matlab platform the discriminating features generated by the proposed descriptorwhile color and gray-scale images formulated by Eq.(13) and Eq.(14) respectively. An empirical study is carried out to select the appropriate radius R of LBP operator for each face dataset. We also tested the DB1 to DB4 transforms to obtain improve the FR accuracy. After applying our CLWD to raw facial images, we perform a non-linear dimensionnality reduction of the features generated by the proposed descriptor using RKPCA algorithm [42]. The proposed method does not admit a normalization module before the dimensionality reduction step. The features normalization generated by CLWD is achieved by forming the matrix K. The L_p-norm RBF kernel $k_p(x_i, y_i)$ is not only produces a mapping to construct the feature space $\mathbf{F}$, but also implicitly normalizes the idea of grouping two forms of features generated by two different feature extraction methods. Therefore, the proposed LWKPCA method mainly aims to find the discriminating nonlinear information in Color LBP and Wavelet feature space by applying Algorithm 4. For the recognition step, we exploited the nearest neighbor classifier based on Euclidean distance to validate the robustness of the proposed method.

V. EXPERIMENTAL RESULTS AND DISCUSSION

This section provides a demonstration of the experimental results of the proposed method on various datasets under

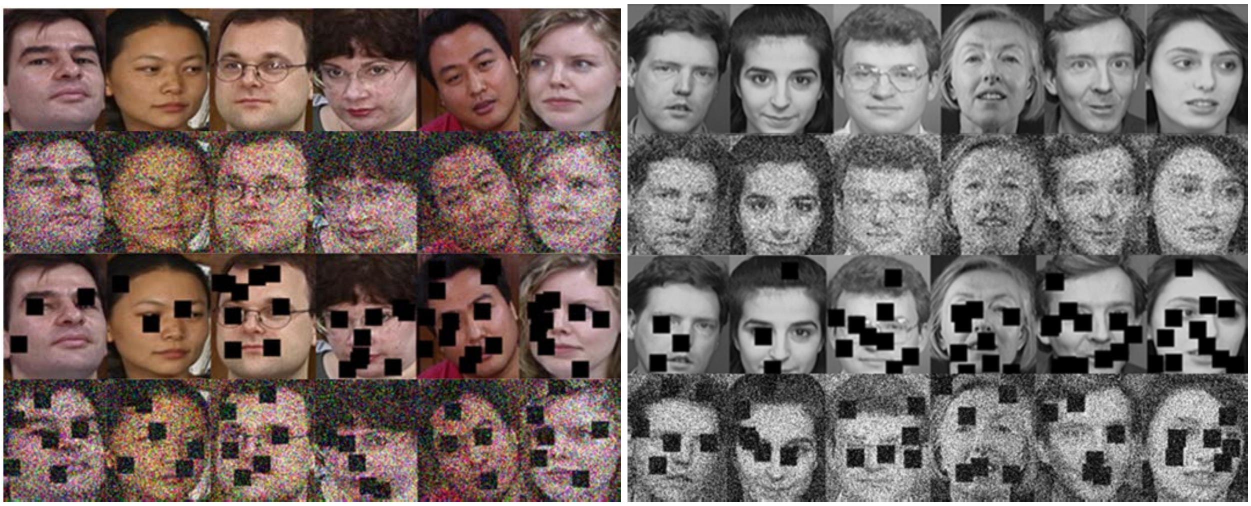


FIGURE 4. Example of some samples of facial images (original, Gaussian noise, and missing partial) on GT (left) and on ORL (right) face datasets. The first row illustrates the original images. The second row shows noisy images with Gaussian noises. The third row contains images with missing random parts, and the fourth row shows noisy images with missing six black blocks.

Algorithm 3 LWD

Input: Facial Image I, Radius r, Number of DB Transformation k.

Output: Feature vector F_v

1. Apply 2D-DWT & LBP feature extraction

$IW = LL_3(I, k)$; $LLv = IW(:)$;

$H_r = imhist(lbp(Im, r))$;

2. Concatenating all the two feature vectors

$F_v = zeros(length(LLv) + length(H_r), 1)$;

$F_v(1 : length(LLv)) = LLv$;

$F_v(length(LLv) + 1 : length(IO)) = H_r$;

3. return F_v

Algorithm 4 The Proposed LWKPCA Method

Input: Data matrix X, Facial test image T, Radius R, Number of features d, $\sigma = 3000$ [46], Number of DB Transformation $k.\ p$.

Output: Feature vector F

if $(size(T, 3) \neq 3)$ **then**

$I =$ LWD (T, R, k) using Algorithm 3

for $i = 1, 2, \ldots, n$ **do**

$X_{Training}(:, i) =$ LWD $(X(:, i), R, k)$ using Algorithm3

end for

end if

if $(size(T, 3) == 3)$ **then**

$I =$ CLWD (T, R, k) using Algorithm 2

for $i = 1, 2, \ldots, n$ **do**

$X_{Training}(:, i) =$ CLWD $(X(:, i), R, k)$ using Algorithm 2

end for

end if

$\Psi = RKPCA(X_{Training}, d, p)$ using Algorithm 1

for $i = 1, 2, \ldots, n$ **do**

$K(i) = \exp\left(-\frac{\|(X_{Training}(:, i) - I)\|_p}{2\sigma^2}\right)$

end for

Compute LWKPCA-Transform $F = \Psi^T K$

return F

TABLE 2. Facial data sets and its adverse-factors to FR.

Database	Adverse-factors
ORL	Face expression, Slight head movement.
GT	Pose, Illumination, Scale variations.
YouTube	MSPP, large-varying pose, low-resolution.
LFW	Large-varying pose.

unfavorable conditions. For this, we exploited several face datasets such as: ORL [26], GT [47], YouTube celebrities face dataset [48], and LFW [49]. All this experiments are implemented using a machine with a 2.00 GHz i7 processor, 8 GB of RAM and MATLAB and Python as development environment. Table 2 illustrates these facial datasets and their adverse factors.

A. EXPERIMENTS ON GT AND ORL FACE DATA SETS

First, we started by exploiting the original images of GT and ORL face dataset to define the best parameters (R value and the adequate DB transformation type) of the LWKPCA method.

GT face data set contains 50 classes of individuals, each class is defined by 15 samples. These samples are captured with different lighting conditions, variations in pose, and rotations. All facial images are resized to 192 × 92. Also, we have exploited the first 10 face samples for each class to build the training set and we used the rest of samples for testing.

ORL face data set contains 40 classes of individuals. Each individual is represented by 10 different samples. In general this dataset contains 400 grayscale images with a constant resolution of 112 × 92 pixels. All the samples were taken against a dark homogeneous background with the subjects

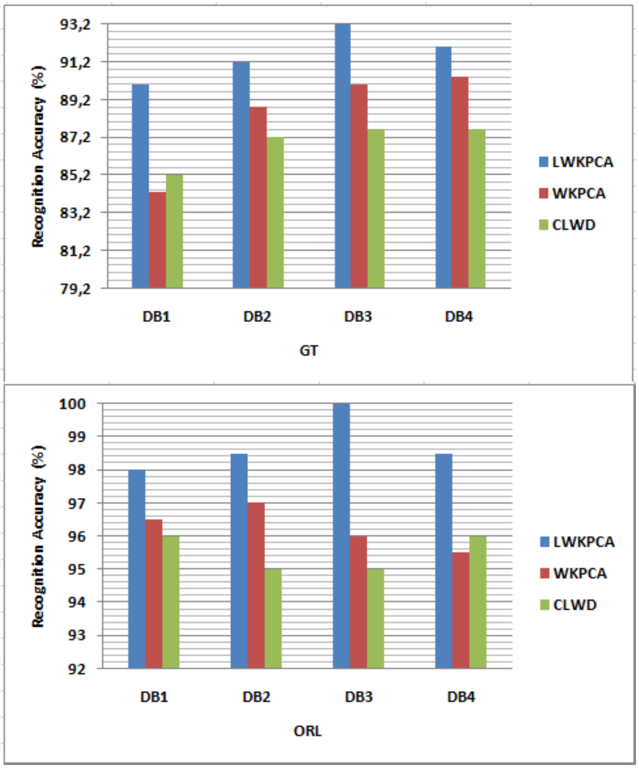


FIGURE 5. Analysis of the proposed method on ORL and GT face datasets.

TABLE 3. RR (%) of the proposed method with R = 1 for GTFD and R = 3 for ORL.

Number of features	Dataset	RKPCA		LWKPCA			
		p=1.0	*p=0.5*	DB1	DB2	DB3	DB4
10	ORL	85.0	86.0	87.5	92.5	93.0	93.5
40	GT	76.0	78.4	88.8	90.4	90.8	90.8
30	ORL	90.0	93.0	94.5	95.5	96.0	95.5
90	GT	77.2	79.6	89.6	91.6	91.6	91.6
50	ORL	93.0	93.0	95.0	96.0	96.5	96.0
140	GT	78.4	80.8	88.8	91.2	92.4	90.0
70	ORL	92.0	93.5	96.5	96.0	96.5	96.0
190	GT	78.4	80.0	89.2	90.8	92.0	90.4
90	ORL	92.5	94.5	96.5	97.0	96.5	96.0
240	GT	79.6	81.6	90.4	90.4	91.6	89.6
110	ORL	93.5	94.0	96.5	97.0	97.5	96.0
290	GT	78.8	80.8	88.8	90.4	91.6	88.8
130	ORL	95.5	95.5	98.0	98.0	98.0	96.5
340	GT	78.0	80.8	89.6	90.0	90.8	87.2
150	ORL	95.5	95.5	97.0	97.5	99.5	98.0
390	GT	78.0	80.4	89.6	90.0	91.6	87.2
170	ORL	95.0	95.5	98.0	98.5	**100.0**	98.5
440	GT	78.0	80.4	89.2	90.0	91.2	86.4
190	ORL	95.5	96.0	97.5	98.5	99.0	98.5
490	GT	78.8	81.2	90.0	91.2	**93.2**	92.0

in an upright, frontal position with tolerance for some side movement. No preprocessing is carried out in the validation experiments. The first 5 samples of each class are selected for the training set, and the rest for the testing set. We test the impact of the DB type in the LWKPCA proposed method on the recognition rate. This is achieved by testing DB1, DB2, DB3, and DB4 respectively. Table 3 show the recognition rate of RKPCA methods ($p = 1.0$ & $p = 0.5$) and our LWKPCA method on GTFD by varying the number of features from 40 to 490, and from 10 to 190 for ORL. From Table 3, we can see that on DB3 type reached 93.20%

TABLE 4. Impact of R value on the recognition accuracy (%) on the ORL and GT datastes.

Dataset	R=1	R=2	R=3	R=4	$R_{\oplus}$
ORL	98.0	99.0	**100.0**	98.0	99.0
GT	**93.2**	93.0	92.8	92.4	90.5

for GT and 100% for ORL as the best RR. Then we test the impact of the LBP Operator's Radius value on the recognition performance of the proposed LWKPCA method. The value of R is set to 1, 2, 3, 4, and $R_{\oplus}$ respectively. While $R_{\oplus}$ is a concatenation of features of different radius. The Recognition Rates for this experience are shown in Table 4. From the table, we can clearly see that the value $R = 1$ and $R = 3$ offers the best recognition rate for GT and ORL respectively. Figure 5 presents an analysis of the proposed method. This is done by comparing the recognition accuracies of the proposed method (LWKPCA) with and without LBP features (WKPCA), also with the proposed descriptor (CLW) without dimensionality reduction. From the recognition details presented in this figure, we can clearly note two main remarks:

1) The positive impact of the LBP method to extract discriminating features to minimize recognition errors in the two facial databases.
2) The DB3 transformation contributes perfectly to improve the recognition accuracy, such as the recognition accuracy goes from 95% for CLW to 100% for the proposed method, which offers an improvement of 5% for ORL. Same remark for GT, with a gain of +5.6%. This proves the adaptation efficiency of the RKPCA algorithm to extract the robust and discriminating information contained in the CLW space.

The proposed method evaluated also with facial images under partial oclussion conditions. This is achieved by adding a number N of missing random blocks to images of testing set. The size of the black blocks is fixed 15×15. The number of blocks N is set to 3, 6, 9, 12. Each trials are repeated 10 times, and then the average recognition rates are taken to compare the degree of recognition of our approach with a set of state-of-the-art (SOTA) methods including PCA [50], 2DPCA [51], PCA-L_1 [52], LDA [53], 2DLDA [54], WTPCA-L_1 [52], $L_{2,p}$-norm PCA [21], Discriminative PCA [55], RKPCA [42], and DeepWTPCA-L_1 [30]. Figure 4 shows some examples of partial missing image, noisy images, and noisy image with 6 random block missing. The first line shows some original images from GT and ORL. The second line depicts Gaussian noisy images, whereas the third line shows corresponding images with random block missing. The fourth line shows the noisy images with 6 missing random blocks.

Table 5 illustrates the impact of random images missing on RR and TT of the proposed method on ORL and GT. From Table 5, we can clearly observe that the number of random blocks added gradually increases, the recognition rates of all methods are gradually reduced for both face data sets. Also Table 5 lists the training times of the face feature extraction méthodes used for the comparison. From these

TABLE 5. Impact of random missing blocks on RR ± STD & TT ± STD of the proposed method on GT and ORL datasets.

Methods	Dataset	Number of random missing block					TT
		N=3	N=6	N=9	N=12	Avg	(second)
PCA [50]	GT	76.60 ± 0.63	75.96 ± 0.47	75.52 ± 0.99	74.32 ± 0.49	75.6 ± 0.64	5.09 ± 0.68
	ORL	87.25 ± 1.06	84.05 ± 1.23	79.20 ± 2.12	76.72 ± 2.11	81.80 ± 1.63	4.13± 0.51
2DPCA [51]	GT	78.20 ± 0.57	78.16 ± 0.73	77.32 ± 0.37	75.56 ± 1.21	77.31 ± 0.72	**2.13 ± 1.34**
	ORL	88.10 ± 1.57	85.50 ± 1.73	82.35 ± 2.21	74.70 ± 1.97	82.66 ± 1.87	**1.41 ± 0.29**
PCA-L_1 [19]	GT	76.90 ± 0.54	76.40 ± 1.04	75.78 ± 1.28	74.40 ± 1.20	75.87 ± 1.01	17.56 ± 2.67
	ORL	87.90 ± 0.54	85.90 ± 2.04	81.20 ± 2.28	74.40 ± 2.20	82.35 ± 1.76	10.65 ± 0.84
WTPCA-L_1 [52]	GT	81.73 ± 0.23	81.33 ± 0.46	80.53 ± 0.46	79.88 ± 0.80	80.86 ± 0.48	9.56 ± 0.1
	ORL	91.65 ± 0.78	88.55 ± 1.34	85.50 ± 1.66	82.90 ± 1.26	87.15 ± 1.26	1.9 ± 0.01
LDA [53]	GT	76.72 ± 1.39	75.84 ± 0.60	75.44 ± 0.96	74.16 ± 1.56	75.54± 1.12	22.07 ± 1.62
	ORL	85.95 ± 1.75	82.85 ± 1.98	77.70 ± 2.23	75.55 ± 1.51	80.51 ± 1.86	12.28 ± 0.55
2DLDA [54]	GT	77.96 ± 0.35	77.88 ± 0.71	76.84 ± 0.82	77.72 ± 0.43	77.60 ± 0.57	9.05± 3.31
	ORL	91.90 ± 0.77	88.50 ± 1.37	85.25 ± 1.06	78.60 ±1.39	86.06 ± 3.85	3.54 ± 1.79
RKPCA ($p = 0.5$) [42]	GT	84.20 ± 0.60	84.13 ± 0.54	84.08 ± 0.64	84.00 ± 0.65	84.10 ± 0.6	3.69 ± 0.001
	ORL	96.05 ± 0.36	95.65 ± 0.62	95.55 ± 0.64	94.85 ± 0.78	95.52 ± 0.6	1.67 ± 0.01
$L_{2,p}$ norm PCA ($p = 0.5$) [21]	GT	83.26 ± 1.93	82.74 ± 1.64	80.09 ± 1.37	78.94 ± 1.37	81.25± 1.57	14.72 ± 0.84
	ORL	92.74 ± 0.96	89.12 ± 1.08	84.68 ± 0.47	81.02 ± 0.61	86.89 ± 0.78	9.05 ± 0.27
Discriminative PCA [55]	GT	77.24 ± 0.84	76.24 ± 1.28	76.09 ± 1.47	75.86 ± 1.04	76.35 ± 1.15	4.74 ± 0.51
	ORL	88.45 ± 0.35	86.37 ± 0.89	80.21 ± 1.75	77.09 ± 0.45	83.03 ± 0.86	3.02 ± 1.02
DeepWTPCA-L_1 [30]	GT	92.90 ± 0.64	92.05 ± 0.64	91.30 ± 0.48	91.14 ± 0.82	91.84 ± 0.64	669 ± 5.1
	ORL	98.45 ± 0.82	97.05 ± 0.74	96.30 ± 0.38	95.30 ± 0.90	96.77 ± 0.71	483 ± 3.2
LWKPCA (Ours)	GT	**93.12 ± 0.25**	**93.04 ± 0.38**	**92.84 ± 0.29**	**91.78 ± 0.20**	**92.69 ± 0.28**	5.10 ± 0.13
	ORL	**98.60 ± 0.56**	**97.80 ± 1.00**	**97.35 ± 0.62**	**97.10 ± 0.73**	**97.71± 0.72**	2.14 ± 0.29

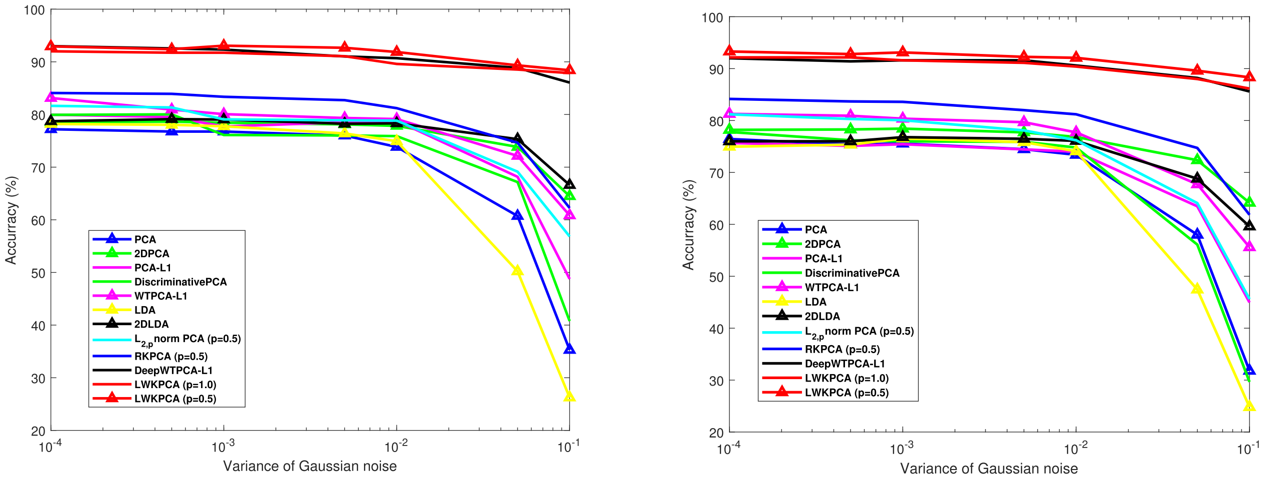
temporal results, we can clearly notice that the learning time of our method is reasonable compared to the fast techniques including 2DPCA, 2DLDA, and RKPCA. The recognition rate of the proposed LWKPCA method is always higher than that of other methods, which proves that our proposed method has a high efficiency. We have also validated the degree of robustness of our method to the two forms of noise. The first one we added a Gaussian noise of zero mean and a variable variance. The noise variance is set to 10^{-4}, 5×10^{-4}, 10^{-3}, 5×10^{-3}, 10^{-2}, 5×10^{-2}, and 10^{-1} respectively in all the images of GT and ORL. The second we added to the noisy images 6 missing random blocks. Line 2 and 4 of the figure shows samples of these two forms of noise respectively. Figure 4 show the effect of these two forms of noise on recognition performance. From this figure, we can see that with increasing noise variance, the recognition accuracy of all methods decreases. However, the recognition performance of our method is always the highest, which shows the robustness of our feature extraction method. The recognition rate of the LWKPCA method are compared with several recent advanced face recognition methods. Table 6 displays the recognition rate of our proposed approach compared with several recent face recognition methods including DIWTLBP [56], CFLDA [57], WTPCA-L1 [52], Gabor + SRC [58], LDA + SRC [58], DWT(SVD/LR + RWLDA/QR) [29], RKPCA [42], 2D-DMWT [59], IKLDA + PNN [60], DCT + VQ [61], Gabor + FastICA + LDA [31]. The proposed method adopts the same experimental-protocol of these methods. From Table 6, we can notice that the accuracy performance of our LWKPCA method is better than the other methods. Our proposed approach provides the highest recognition accuracy of 100%. This proves that our approach is very robust and provides better FR performance. Table 7 displays the recognition rate of our proposed approach compared with several recent face recognition methods including ESGK [62], Gabor filter (5 × 8) + MDC [62], LDA + MDC [62], NCDB-LBPc [9], DCD [10], Gabor + FastICA + LDA [31], Joint Collaborative [63], TPWELRMC [64]. CZZBP [8], CMBZZBP [8], CLBP [65], 6 × 6 MB-LBP [65], SAPFR-1 [66], INNC [67], SVD based VR [67], WTPCA-L1 [52], Naive CR [68], Method based on CR [68], RNLRLSR [69], CLSR [69], DWT(SVD/LR + RWLDA/QR) [29], DeepWTPCA-L_1 [30]. From this Table, we can notice that the proposed method LWKPCA achieved high recognition rates compared with the other methods. while LWKPCA reached an accuracy of 96.84% which is beter with 2.4% achieved using Gabor + FastICA + LDA method.

TABLE 6. Performances comparison on ORL.

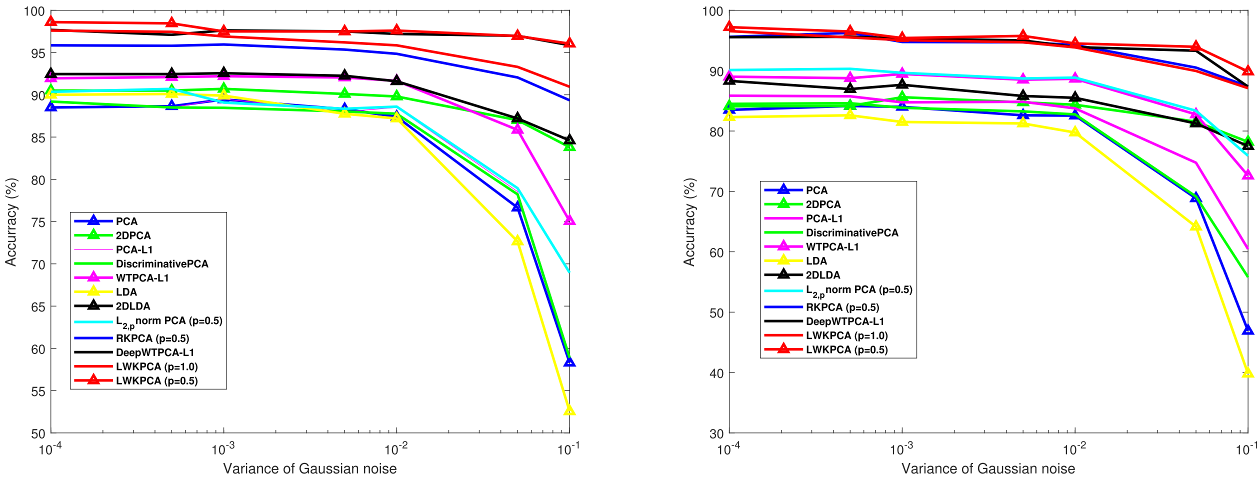
Method	Training images/ person	RR (%)
DIWTLBP (2019) [56]	5	97.00
CFLDA (2017) [57]	5	97.85
WTPCA-L1 (2019) [52]	5	96.70
Gabor+SRC (2019) [58]	5	97.50
LDA+SRC (2019) [58]	5	97.50
DWT(SVD/LR+RWLDA/QR) (2019) [29]	5	97.75
RKPCA (2021) [42]	5	97.75
Gabor+FastICA+LDA (2021) [31]	5	99.10
LWKPCA (Ours)	**5**	**99.25**
2D-DMWT (2017) [59]	8	97.50
IKLDA+PNN (2020) [60]	8	97.22
DCT+VQ (2016) [61]	8	98.75
Gabor+FastICA+LDA (2021) [31]	8	99.88
LWKPCA (Ours)	**8**	**100.00**

B. EXPERIMENTS ON LFW AND YouTube CELEBRITIES DATA SETS

YouTube Celebrities and LFW are two large-scale dataset with variable pose facial have been used for evaluating



(a) GT



(b) ORL

FIGURE 6. Impact of Gaussian noise only (left) and Gaussian noise with six missing black blocks (right), on recognition accuracy for GT and ORL datasets.

the proposed method. Before presenting these two datsets, we performed the same steps as GT and ORL to set our proposed method parameters. The parameters used in this experiment are the same adapted for GT i.e. $R = 1$, DB3, 170 fetaures are generated by our approach for both datasets.

LFW face dataset is defined by 5749 classes of people with 13233 samples in total. Among the constraints of this database is that the number of samples is not homogeneous. This complicates the task of training processing algorithms. We measured the recognition accuracy of the LWKPCA method proposed by this experimental protocol [3].

YouTube Celebrities is among the large scale facial databases collected from YouTube. It is designed to evaluate the robustness of face recognition models on the large variable pose condition. It is characterized by 1910 video clips of 47 people. Each clip is defined by hundreds of compressed images with different poses. This facial dataset is more complex than LFW in terms of the variability contained in the face images. For this, we adapted the same experimental protocol used by this recent empirical study [3] in order to compare the LWKPCA proposed method with SOTA techniques including LBP [70], LGBPHS [71],

(a) LFW

(b) YouTube Celebrities

FIGURE 7. Some face images from LFW and Youtube Celerities datasets.

TABLE 7. Performances comparison on GT.

Method	Training images/ person	RR (%)
ESGK (2017) [62]	8	79.72
Gabor filter (5×8)+MDC (2017) [62]	8	70.00
LDA+MDC (2017) [62]	8	59.43
NCDB-LBPc (2021) [9]	8	87.14
DCD (2021) [10]	8	92.57
Gabor+FastICA+LDA (2021) [31]	8	92.80
LWKPCA (Ours)	**8**	**95.37**
Joint Collaborative (2019) [63]	9	71.70
TPWELRMC (2019) [64]	9	82.33
CZZBP (2021) [8]	9	81.66
CMBZZBP (2021) [8]	9	87.00
CLBP (2021) [65]	9	90.00
6×6 MB-LBP (2021) [65]	9	82.28
NCDB-LBPc (2021) [9]	9	90.00
SAPFR-1 (2020) [66]	9	91.83
DCD (2021) [10]	9	93.33
LWKPCA (Ours)	**9**	**95.83**
INNC (2018) [67]	10	63.60
SVD based VR (2018) [67]	10	64.40
WTPCA-L1 (2019) [52]	10	85.00
Naive CR (2020) [68]	10	64.00
Method based on CR (2020) [68]	10	74.40
RNLRLSR (2020) [69]	10	72.00
CLSR (2020) [69]	10	65.60
DWT(SVD/LR+RWLDA/QR) (2019) [29]	10	89.24
CMBZZBP (2021) [8]	10	91.20
DeepWTPCA-L_1 (2021)[30]	10	93.89
Gabor+FastICA+LDA (2021) [31]	10	94.44
LWKPCA (Ours)	**10**	**96.84**

TABLE 8. Performances comparison on LFW and YouTube celebrities data sets.

Method	LFW	YouTube
LBP [70] (2006)	73.70	81.29
LGBPHS [71] (2005)	81.68	81.29
PCANet [72] (2015)	N/A	81.98
VGGFace [73] (2015)	98.95	84.91
SENet+LBP [74] (2018)	99.31	95.00
Light-CNN [75] (2018)	98.93	N/A
LCMoG-LWPZ [3] (2021)	83.88	84.35
LCMoG-CNN [3] (2021)	72.53	87.05
LCMoG-(LWPZ+CNN) [3] (2021)	87.23	95.32
LWKPCA (Ours)	**99.34**	**95.63**

PCANet [72], VGGFace [73], SENet + LBP [74], Light-CNN [75], LCMoG-LWPZ [3], LCMoG-CNN [3], LCMoG-(LWPZ + CNN) [3]. The recognition performance of this comparison are illustrated in Table 8. Figure 7 displays some samples of two individuals from LFW and YouTube Celebrities. From the recognition rates displayed in Table 8, we can clearly notice that our approach offers the best recognition performance and outperforms other techniques. The proposed LWKPCA method reached the highest recognition accuracies of 99.34%, 95.63% for LFW and YouTube Celebrities respectively.

VI. CONCLUSION

In this paper, a new robust feature extraction method called LWKPCA has been proposed for face recognitiom under different adverse conditions. The proposed method has two main phases: (1) Pre-processing phase (2) Training phase. The first phase is dedied to find the best face image representation in an discriminant vector structure. This is achieved using the proposed Color LBP and Wavelet Descriptor. Our descriptor is based on a new strategy of grouping the face features produced by 2D-DWT and LBP methods. Then we exploited the RKPCA nonlinear projection learning algorithm for extracting the robust information contained in Color LBP and Wavelet feature space. To deal with complicated real-world situations, we measured the degree of recognition robustness of the proposed LWKPCA method in several experiments with face images (normal, noise, and occlusion). Compared with several recent advanced face recognition methods, experimental results are more stable and offers the best recognition rates for different challenges related to face recogntion.

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