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NOISE ROBUST ILLUMINATION INVARIANT FACE RECOGNITION VIA BIVARIATE WAVELET SHRINKAGE IN LOGARITHM DOMAIN

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Abstract

Recognizing faces under various lighting conditions is a challenging problem in artificial intelligence and applications. In this paper we describe a new face recognition algorithm which is invariant to illumination. We first convert image files to the logarithm domain and then we implement them using the dual-tree complex wavelet transform (DTCWT) which yields images approximately invariant to changes in illumination change. We classify the images by the collaborative representation-based classifier (CRC). We also perform the following sub-band transformations: (i) we set the approximation sub-band to zero if the noise standard deviation is greater than 5; (ii) we then threshold the two highest frequency wavelet sub-bands using bivariate wavelet shrinkage. (iii) otherwise, we set these two highest frequency wavelet sub-bands to zero. On obtained images we perform the inverse DTCWT which results in illumination invariant face images. The proposed method is strongly robust to Gaussian white noise. Experimental results show that our proposed algorithm outperforms several existing methods on the Extended Yale Face Database B and the CMU-PIE face database.

Keywords: face recognition; dual-tree complex wavelet transforms (DTCWT); collaborative representation-based classifier (CRC); invariant features; pattern recognition; computer vision.

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1   Introduction

Face recognition is very active research area and important issue in biometrics and various other applications. Deep convolutional network (CNN) can be pre-trained as a deep stacked convolutional autoencoder (SCAE) in a greedy layer-wise unsupervised fashion for illumination invariant face recognition. The SCAE model can encode facial expression images and produce a feature vector with relatively similar illumination, regardless of the luminance level of the input image. Furthermore, one can fine-tune the stacked shallow autoencoders after each one of these is trained greedily, rather than just at the end, and show that this approach significantly improves the set of illumination invariant features learnt by the SCAE. The drawback of deep leaning for illumination invariant face recognition is that deep learning need many training samples and it is extremely slow during the training of the networks.

We briefly review many conventional methods for illumination invariant face recognition here. The first successful algorithm popular in applications is the one called Eigenfaces [2, 3] has been introduced in 1991. It is based on principal components analysis, which performs dimensionality reduction and extracts the most relevant information from face images. Another popular algorithm called Laplacianfaces [1] has been introduced in 2005. It uses locality-preserving projections. In [4] the authors applied wavelets to face recognition and showed that nonlinear approximation preserves more information than linear approximation. Lee et al. [5] investigated face recognition under physical lighting condition in such a way that studied images could form basis in the low-dimensional linear space. Region-based face enhancement was considered by Du and Wu [6], however this approach results in some defects on the boundaries between different regions. A novel robust face recognition based on sparse representation was proposed by Wright et al. [7]. They considered frontal views only but varied the expressions, occlusions, disguise and illumination and different categories were represented by the linear regression models. Chen et al. [8] introduced robust face illumination normalization by applying discrete cosine transform (DCT) to the logarithmic transformation of the face illumination images (LOG-DCT) and by zeroing low resolu-

tion DCT coefficients followed by the inverse DCT, which effectively resulted in face illumination maps invariance. Ruiz-Pinales et al. [9] introduced translation invariant support vector machine (SVM) face recognition algorithm, owing translation invariance using maximum cross-correlation in place of dot-product. Ahonen et al. [10] proposed a fast face recognition algorithm based on local binary patterns (LBP) texture features by forming a feature vector made up of LBP features extracted from different regions of the image. Chen et al. [11] introduced a log total variation model (LTV) applicable to face recognition under variable lighting conditions. One of the weaknesses of the model is its computational complexity which model owing to the need of solving differential equations. Lai et al. [12] proposed a face classification algorithm using multiscale logarithm difference model (edge maps) under variable lighting conditions. This edge-map model is better than such competing models as LOG-DCT or LTV as it removes light intensity from neighborhood pixels. Zhang et al. [13] investigated gradient-based face classification under different illuminations, however gradient-based approaches are sensitive to noise. Illumination invariant face recognition has been investigated by several researchers. Xie et al. [14] achieved good results by normalizing face illumination and used large- and small-scale features. Chen et al. [15, 16, 17] investigated several novel algorithms based on dual-tree complex wavelet transform (DTCWT) and other filters. Chen et al. [18, 19] studied hyperspectral approaches taking advantage of log-polar Fourier and other features. Illumination-invariant face recognition approaches proposed by Chen et al. favourably compared to other competing techniques and are currently the state-of-the-arts methods. Gupta et al. [20] studied the feature-based method for 2D face images. speeded up robust features (SURF) and scale-invariant feature transform (SIFT). Different combinations of SIFT and SURF features with two classification techniques such as decision tree and random forest have been implemented in their paper. Rouhsedaghat et al. [21] adopted a new machine learning technique called Successive Subspace Learning (SSL) to propose a high-performance data-efficient low-resolution face recognition model for resource-constrained environments. SSL provides an explainable non-parametric feature extraction sub-

model which flexibly trades the model size for the verification performance. Zhang and Yao [22] used the Expected Patch Log Likelihood (EPLL) technique to extract illumination weight and combined it with the Neighboring Radiance Ratio algorithm (NRR) to optimize the initial vector of the Gaussian mixture model, which makes full use of the redundant information in images. Their experiments with the extended Yale B and CMU PIE face databases demonstrated that the proposed algorithm could reduce the influence of illumination on face images. Huang and Chen [23] developed a new framework for effectively enhancing the performance of deep face recognition for low illumination images. Their feature restoration network achieves computational efficiency at the cost of only a few more parameters and FLOPs compared to the original feature extraction model. Furthermore, the training of this network does not need a very big dataset. Hussain et al. [24] developed a new algorithm for illumination invariant face recognition, which takes advantage of large-scale and small-scale components by discarding the illumination artifacts and detrimental noise using Contourlets. After discarding the unwanted components, local and global features are extracted using a convolutional neural network (CNN) model. They used three CNN models: VGG-16, GoogLeNet, and ResNet152 in their work.

In this paper, we introduce a new illumination-invariant face recognition algorithm based on the dual-tree complex wavelet transform (DTCWT) and on collaborative representation (CRC classifier). The main steps of the algorithm involve setting to zero the approximate sub-band values and thresholding the two highest frequency wavelet sub-bands by means of bivariate wavelet shrinkage in case noise standard deviation exceeds value 5. In case the latter condition is not satisfied the two highest frequency wavelet sub-bands are set to zero. Finally, we generate the illumination-invariant face images by the inverse DTCWT. Our newly proposed algorithm is strongly robust to Gaussian white noise, and it outperforms competing algorithms in experiments on the Extended Yale Face Database B and on the CMU-PIE illumination face database.

The paper is organized as follows. Section 2 our novel DTCWT based illumination-invariant

face recognition algorithm. In Section 3 we describe two face databases that contain face images with diverse illumination changes. In Section 4 we present the results of experiments conducted the Yale and CMU-PIE database face images. The conclusions and possible future extensions are presented in the final Section 5 of the paper.

2 The Proposed Method

We start with a brief survey of the Lambertian reflectance theory, DTCWT transform, bivariate wavelet shrinkage, and the CRC classifier. Following the Lambertian reflectance model the intensity image can be modeled [25] by

$$I(x,y) = R(x,y)L(x,y) \qquad (1)$$

where R and L represent the reflectance and illumination, respectively. As R depends only on the surface material of the subject, it is then intrinsic representation of the face image. To simplify computational complexity of model (1) we transform face intensity image by applying logarithm transform to it, which turns the multiplicative model to an additive one:

$$\log I(x,y) = \log R(x,y) + \log L(x,y) \qquad (2)$$

Kingsbury [26] applied dual tree wavelet filters to discrete wavelet transform and thus obtained partial redundancy (2m:1 for m-dimensional signals) and approximate shift invariance. A by-product of his modification were directionally selective filters (properties not shared by the standard wavelet transform) which kept the usual properties of perfect reconstruction and computational efficiency with well-balanced frequency responses. He also proposed a way to construct a new transform to make it shift-invariant, investigated its approximation accuracy described suitable filters having the desired properties. He introduced two different versions of the new transform: one based on odd/even and the other based on quarter-sample shift (Q-shift) filters. He then outlined the extension of the dual tree to images and other multi-dimensional signals and discussed the range of applications which could benefit from his innovative methodology.

The DTCWT transform has six directionally selective filters (See Figure 1 for an illustration),

while standard wavelet transform has only two dominant orientations. The discrete wavelet transform (DWT) is very sensitive to spatial shifts: a little shift in spatial domain will cause very different wavelet coefficients. This is the main reason why we choose the DTCWT transform in this paper.
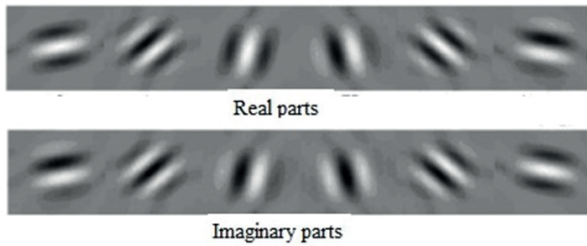

Figure 1. These are impulse responses of 2-D complex wavelet filters.

The DTCWT of a signal x is implemented by applying in parallel two critically sampled DWTs on the same data. The transformation cost because N-point signal yields 2N DWT coefficients. If the filters in the upper and lower DWTs are identical, then the new method does not offer any advantage. On the other hand, if the filters are designed in a specific way, then the sub-band signals of the upper and lower DWT can be interpreted as the real and imaginary part of a complex wavelet transform, respectively.

The two analysis filter matrices, af(1) and af(2), and synthesis filter matrices, sf(1) and sf(2), are as follows:

af(1)	
0.03516384	0
0	0
-0.08832942	-0.11430184
0.23389032	0
0.76027237	0.58751830
0.58751830	-0.76027237
0	0.23389032
-0.11430184	0.08832942
0	0
0	-0.03516384

af(2)	
0	-0.03516384
0	0
-0.11430184	0.08832942
0	0.23389032
0.76027237	0.58751830
0.58751830	-0.76027237
0.23389032	0
-0.08832942	-0.11430184
0	0
0.03516384	0

sf(1)	
0	-0.03516384
0	0
-0.11430184	0.08832942
0	0.23389032
0.76027237	0.58751830
0.58751830	-0.76027237
0.23389032	0
-0.08832942	-0.11430184
0	0
0.03516384	0

sf(2)	
0.03516384	0
0	0
-0.08832942	-0.11430184
0.23389032	0
0.76027237	0.58751830
0.58751830	-0.76027237
0	0.23389032
-0.11430184	0.08832942
0	0
0	-0.03516384

Sendur and Selesnick [27] improved the performance of image-denoising algorithms using wavelet transforms by studying the statistical dependencies among wavelet coefficients. In their previous work, a simple bivariate shrinkage rule was introduced using a coefficient and its parent. Let y_1 be the current wavelet coefficient, y_2 the parent coefficient, w_1 the denoised wavelet coefficient, σ_n the noise standard deviation of the whole image, and σ the local noise standard deviation in a

small neighbourhood of y_1. The bivariate thresholding formula is given by

$$w_1 = y_1 \cdot \left(1 - \frac{\frac{\sqrt{3}}{\sigma} \sigma_n^2}{\sqrt{y_1^2 + y_2^2}} \right)_+ \qquad (3)$$

Here $(x)_+ = \max(0, x)$. The performance was improved using simple models by estimating model parameters in a local neighborhood. They presented a locally adaptive denoising algorithm using the bivariate shrinkage function. The algorithm is illustrated using both the orthogonal and dual tree complex wavelet transforms. They also presented several comparisons with the best available methods in order to demonstrate the effectiveness of their proposed algorithm.

It is commonly believed that the l_1- norm sparsity constraint on coding coefficients plays key role in success of the sparse representation-based classifier (SRC), whereas the use of all training samples to collaboratively represent the query sample is suppressed. The authors of [28] discussed how SRC works and showed that the collaborative representation mechanism used in SRC plays key role and is primarily responsible for its success in face recognition. The SRC is a special case of the CRC, which applies different norms to coding residuals and coding coefficients. Furthermore, the l_1 or l_2 norm characterization of coding residual depends on the robustness of CRC to the outlier facial pixels, whereas the l_1 or l_2 norm characterization of coding coefficient depends on the degree of discrimination of facial features. Experiments demonstrated the accuracy and efficiency of the CRC in face recognition.

In CRC, one is required to solve the following optimization problem:

$$\tilde{\alpha}_k = \arg\min_a ||b_k - A\alpha||_2^2 + \lambda ||\alpha||_2^2 \qquad (4)$$

where λ is a parameter and $\tilde{\alpha}_k = [\tilde{\alpha}_{k1}, \tilde{\alpha}_{k2}, \ldots, \tilde{\alpha}_{k2}]$ is the coding vector associated with class k. Let A_k be the dataset of the k-th class and let each column of matrix A_k be a sample of class k. Assume that we have K classes of subjects, thus $A = [A_1, A_2, \ldots, A_k]$.

The optimization problem (4) has a closed-form solution:

$$\tilde{\alpha}_k = (A^T A + \lambda I)^{-1} A^T b_k \quad \text{with} \quad k \in [1, K], \qquad (5)$$

where A^T denotes the transpose of matrix A and K is the number of subjects. Because $(A^T A + \lambda I)^{-1} A^T$ can be computed off-line, we can speed up the calculation by $\tilde{\alpha}_k = Db_k$. Let $e_{ki} = ||b_k - A_i \tilde{\alpha}_{ki}||$ and $e_k = (e_{k1} e_{k2} \cdots e_{kC})^T$. The CRC classifies a face b_k to the class with the label $z_k = identity(b_k) = \arg\min_i\{e_{ki}\}$. The CRC chooses the class that yields the smallest reconstruction error. The speed of the CRC face recognizer is much higher than that of the SRC.

Inspired by LOG-DCT [10], we propose in this paper a new algorithm for illumination-invariant face recognition. Because of varied illumination conditions, the acquired face images can be very dark, which lowers efficiency of the existing face recognition methods. To mitigate this problem, we increase brightness of the dark region and reduce brightness of dark regions by implementing the logarithm transform. Subsequently we subject the images to DTCWT transformation followed by setting the approximation sub-band to zero, and by thresholding two highest frequency wavelet sub-bands to zero by bivariate wavelet shrinkage. Finally, an inverse DTCWT transformation is used to generate the enhanced face images, which are approximately invariant to illumination. The reason why we choose DTCWT transform is that it can represent images more accurately. Figure 2 shows the input and output of our illumination invariant face recognition algorithm: (a) the input face image, (b) the output illumination invariant face generated by the inverse DTCWT transform.

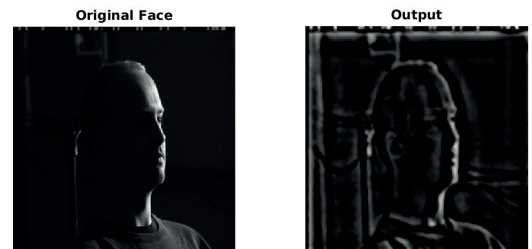

Figure 2. The input and output of our new face recognition algorithm LOG-DTCWT: (a) the input face image, (b) the output illumination invariant face image generated by inverse DTCWT transform.

We present the steps of our new algorithm for illumination invariant face recognition by using the DTCWT transform. Our algorithm is very robust to Gaussian white noise due to the bivariate wavelet

shrinkage introduced in our algorithm. Figure 3 shows the flowchart of our proposed algorithm in this paper: (a) the input face image, (b) the logarithm of the input image, (c) the DTCWT transform on the logarithm image, (d) set the approximation sub-band to zeros and threshold/set to zero values for two highest frequency wavelet sub-bands by bivariate wavelet shrinkage, (e) the output illumination invariant face image generated by inverse DTCWT transform, (f) the CRC classifier to classify the unknown faces.

This algorithm can be described as follows:

Algorithm 1. New Algorithm

1. *Initialization: $J = 4$.*

2. *Take the logarithm transform of the intensity image $I(x,y)$ as equation (2).*

3. *Normalize image $\log I(x,y)$ to the range $[0., 255]$, denoted as IM.*

4. *Perform the forward DTCWT transform to IM for J decomposition levels, denote it as $CIM = DTCWT(IM, J)$.*

5. *Set the approximation sub-band to zero values.*

6. *Noise standard deviation σ_n can be estimated as in [30].*

7. *If noise standard deviation σ_n is greater than 5, then threshold the two highest frequency wavelet sub-bands by bivariate wavelet shrinkage. Otherwise, set these two highest frequency wavelet sub-bands to zero values.*

8. *Conduct inverse DTCWT transform to the output image from Step 7) in order to obtain face image D.*

9. *Normalize D so that it has zero mean and unit variance.*

10. *Set $E = D^k$, where $k = 0.69$ is a constant.*

11. *Use CRC to classify the resulting face image to one of the known classes.*

The contributions of this paper can be summarized here. In our new algorithm, we perform logarithm transform to make dark regions brighter. We perform DTCWT transform to the normalized LOG images for several scales and set the approximation sub-band to zero values. If the noise standard deviation is greater than 5, then we threshold two highest frequency wavelet sub-bands by bivariate wavelet shrinkage. Otherwise, we set these two highest frequency wavelet sub-bands to zero values. An inverse DTCWT transform will generate the enhanced faces, which are approximately invariant to illumination changes and hence are good for face recognition. The combination of logarithm-DTCWT in this way is new to our best knowledge. In addition, our new algorithm is very robust to Gaussian white noise due to the introduction of bivariate wavelet shrinkage. Our method is easy to implement, and it yields higher recognition rates than several existing methods for both Extended Yale Face Database B [5] and CMU-PIE illumination face database [24] no matter there exist noise in the face images or not.

3 Two Face Databases

Our new algorithm was validated in experiments with the Extended Yale Face Database B [5] and the CMU-PIE illumination face database [29]. The Extended Yale B database contains face images of 38 subjects in 64 different lighting conditions: from normal to extremely badly illuminated. This database contains 2414 face images. We cropped and fixed the face images ending up with $192 x 168$ images. We take one well-lighted face image as the single reference and take all the rest available $2414 - 38 = 2376$ images as test samples. The faces can be divided into 5 subsets based on the angles between the light source direction and the camera axis. The degree of variation increases as we move from Subset 1 to Subset 5. Figure 4 presents samples of five subsets for one subject.

The second database used in experiments was the CMU Pose, Illumination and Expression (PIE) database with 41368 face images acquired from 68 subjects. The images for every subject are captured with 13 different poses and 43 illumination conditions. We only select images that focus on illumination variations of light intensity and of frontal view directions. There exist 68 subjects in each of 43 images producing a total of 2924 images. Figure 5 presents samples of face images from CMU-PIE under different lighting conditions
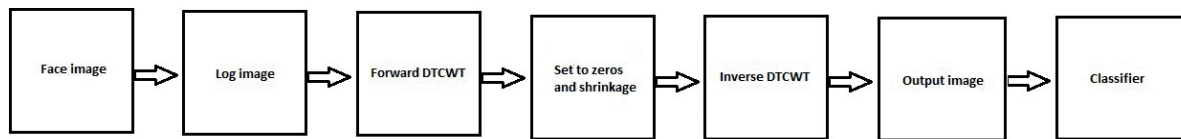
Figure 3. The different steps of our new face recognition algorithm LOG-DTCWT: (a) the input face image, (b) the logarithm of the input image, (c) the DTCWT transform on the logarithm image, (d) set the approximation sub-band to zeros and threshold/set to zero values for two highest frequency wavelet sub-bands by bivariate wavelet shrinkage, (e) the output illumination invariant face image generated by inverse DTCWT transform, (f) the CRC classifier.
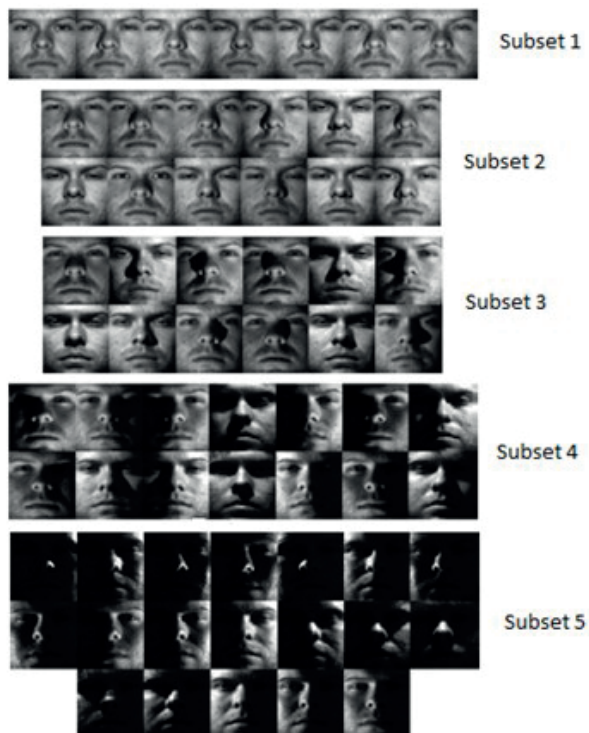

Figure 4. The five subsets of the Extended Yale-B face database.

For both Extended Yale face database B and CMU-PIE face database, we choose only one frontally lit face image in each class for training and the remaining face images for testing. We convert every face image to the logarithm domain and normalize the logarithm image to the range of $[0, 255]$. We then perform DTCWT transform to these normalized face images for several scales and set the approximation sub-band to zero values. If the noise standard deviation is greater than 5, then we threshold two highest frequency wavelet sub-bands by bivariate wavelet shrinkage. Otherwise, we set these two wavelet sub-bands to zero values. An inverse DTCWT transform will generate the enhanced faces, which are approximately invariant to illumination changes and robust to noise, and hence are good for face recognition.

4 Experimental Results

We conduct several experiments to test the effectiveness of the algorithm introduced in this paper. In Table 2 we compare the correct classification rates of our novel approach with a number of competing approaches obtained in experiments conducted on samples from the Extended Yale face database B and CMU-PIE face database. The correct classification rate is defined as the percentage of faces that are recognized correctly. In this paper, we only implement our proposed method in this paper, LOG-DTCWT [16] and LOG whereas all other classification results are copied from Xie et al. [14]. For subset 1 of the Yale-B face database B, our method yields classification rate of 94.67% whereas Large and Small-Scale features [14], LTV [11] and Local Binary Pattern [10] approaches yield perfect classification rate (100%). Xie et al. [14] obtained 91.2% average correct recognition rate for the Extended Yale database B. Our new algorithm proposed in this paper achieves 92.46% average classification rate which is the best rate for all the methods compared in this paper. This demonstrates the strength of our novel robust face recognition approach. We obtained the perfect 100% classification rate on the Extended Yale database B and on the CMU-PIE illumination face database. The same 100% rate was obtained by the competing algorithms on the former database, whereas on the latter one some competing algorithms obtained lower rate than 100%. Thus, we can conclude that the new algorithm proposed in this paper is very effective in illumination-invariant face recognition.

Figure 5. An example of the face images under different lighting condition of the CMU-PIE illumination face database.

Table 1. The five subsets of the Extended Yale Face Database, their corresponding angles, and the number of faces in each.

Subsets	Angles	Number of Faces
Subset 1	$1° \leq angle \leq 12°$	7×38
Subset 2	$13° \leq angle \leq 25°$	12×38
Subset 3	$26° \leq angle \leq 50°$	12×38
Subset 4	$51° \leq angle \leq 77°$	14×38
Subset 5	$78° \leq angle$	19×38

We also test the performance of our proposed algorithm for different noise levels. In our experiments, the noise standard deviation σ_n ranges from 5 to 40. The noisy face images are generated by adding Gaussian white noise to the noise-free face images ($B = A + \sigma_n I$, where I obeys Gaussian distribution N(0,1) with 0 mean and unit variance). Figure 6 shows the noise-added face images for σ_n ranging from 5 to 40. We compare our proposed algorithm with LOG-DTCWT [16], LOG-Discrete Wavelet Transform (LOG-DWT) and LOG-DCT for both extended Yale face database B and CMU-PIE face database. Table 3 shows the correct classification rates (%) of the proposed method, LOG-DTCWT [16], LOG-DWT, and LOG-DCT for face images corrupted by Gaussian white noise. For extended Yale face database B, our proposed algorithm outperforms LOG-DTCWT [16], LOG-DWT and LOG-DCT for all experiments. Nevertheless, for the CMU-PIE face database, all three algorithms

achieve perfect recognition results (100%). To sum up, our new algorithm proposed in this paper is very robust to Gaussian white noise for illumination invariant face recognition.

Conclusions

In this paper, we proposed a novel algorithm for face recognition by extracting DTCWT faces in the logarithm domain. We convert the face image to the logarithm domain and normalize the logarithm image to the range of [0, 255]. We perform DTCWT transform to the normalized logarithm face image for several scales and set the approximation subband to zero values. If the noise standard deviation is greater than 5, then we threshold two highest frequency wavelet sub-bands by bivariate wavelet shrinkage. Otherwise, we set these two wavelet sub-bands to zero values. An inverse DTCWT transform will generate the enhanced faces, which are approximately invariant to illumination changes and hence are good for face recognition. Our new algorithm with the CRC classifier is relatively invariant to illumination changes in the face images. Our algorithm beats several existing algorithms in terms of correct recognition rate for the Extended Yale Face Database B. Our algorithm outperforms every algorithm for the CMU-PIE illumination face database. The algorithm proposed in this paper is more suitable for recognizing face images with varying illumination. Also, our new algorithm is
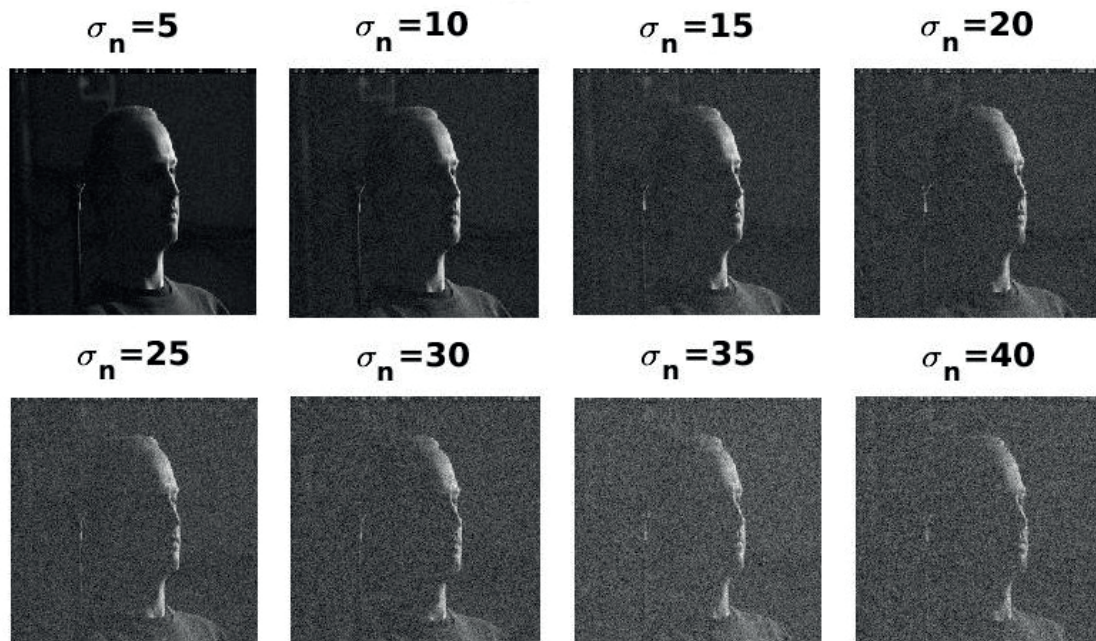
Table 2. The correct classification rates (%) of the proposed method, LOG-DTCWT [16], LOG alone, large and small scale [14], LOG-DCT [8], LTV [11], Local binary pattern [10], and no features extraction (None). In this table, we copied the classification rates from [14] for LOG-DCT, LTV, Local binary pattern, and no features extraction (None). The best results are highlighted in bold.

Methods	CMU-PIE	Extended Yale Face Database B					
		Subset 1	Subset 2	Subset 3	Subset 4	Subset 5	Average
Proposed	**100**	94.67	**100**	91.05	**88.63**	**87.96**	**92.46**
LOG-DTCWT	**100**	93.4	**100**	**91.1**	88.5	87.3	92.0
LOG	99.78	98.25	99.12	67.89	30.76	26.04	64.41
Large and Small-Scale features [14]	99.9	**100**	**100**	86.0	85.3	84.8	91.2
LOG-DCT [8]	**100**	92.5	**100**	89.2	87.0	82.8	90.3
LTV [11]	99.8	**100**	99.8	78.5	75.8	82.4	87.3
Local Binary Pattern [10]	75.4	**100**	**100**	62.3	10.3	6.6	55.8
None	35.1	99.6	96.7	41.1	7.4	3.2	49.6

Table 3. The correct classification rates (%) of the proposed method, LOG-DTCWT [16], LOG-DWT, and LOG-DCT [8] for face images corrupted by Gaussian white noise. The best results are highlighted in bold.

Databases	Methods	Noise Standard Deviation (σ_n)							
		5	10	15	20	25	30	35	40
Extended Yale Face Database B	Proposed	**87.87**	**82.82**	**79.91**	**77.85**	**76.98**	**75.96**	**75.22**	**74.77**
	LOG-DTCWT	87.32	82.39	79.61	77.32	76.54	75.70	74.47	73.71
	LOG-DWT	83.26	78.93	76.68	75.34	73.94	73.00	72.25	71.58
	LOG-DCT	87.28	82.28	78.85	77.17	75.85	74.59	73.94	73.53
CMU-PIE	Proposed	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**
	LOG-DTCWT	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**
	LOG-DWT	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**
	LOG-DCT	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

Figure 6. An example of the noisy face images with different noise levels.

very effective under the noisy environment for face recognition due to the bivariate wavelet shrinkage introduced in our algorithm.

Future research will be conducted in other areas of invariant face recognition including differences in shift, pose and expression, etc. We will also investigate new face recognition methods by using sparse representation, deep learning and low-rank approximation.

COMPLIANCE WITH ETHICAL STANDARDS

The authors declare that there are not conflict of interests for this paper. This paper does not involve animals either.

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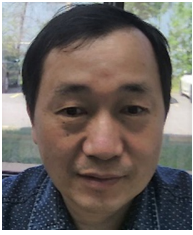
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