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# Face Recognition under Varying Illumination Conditions: Improving the Recognition Accuracy for Local Ternary Patterns based on Illumination Normalization Methods and Singular Value Decomposition

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Abstract. *Local ternary patterns (LTP) descriptor is a discriminative and effective yet very simple local texture descriptor. Nevertheless, it is not robust against illumination changes. This study introduces a new approach based on the illumination preprocessing and singular value decomposition (SVD) methods to improve the recognition accuracy for a face recognition system using LTP in an illumination variation environment. The training images are first preprocessed light by an illumination preprocessing method. Secondly, SVD is applied to the encoded images. Next, the encoded images are extracted features based on LTP. In the classification phase, the test images are also preprocessed illumination by an illumination normalization method. Then, the singular value matrix of a lighting pretreated image is combined with that of a training encoded image to adjust the illumination of this before the features are extracted and classified. The recognition is performed using a nearest neighbor classifier with Chi–square as a dissimilarity measure. Experimental results on the extended Yale B database demonstrated the efficiency of our proposed method. Thus, the proposed approach is expected to contribute to the face recognition problem under varying illumination conditions.*
**Keywords:** Face recognition, Illumination pretreatment, Singular value decomposition, Local ternary patterns.

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1. **Introduction.** In a face recognition system, illumination variation is considered as one of the biggest challenges. It reduces the performance of the system. To overcome this problem, numerous methods have been proposed. These methods can be fallen into three strategies: illumination normalization [1], illumination compensation [2, 3, 4], and feature extraction [5, 6, 7, 8]. The first type normalizes the illumination of face images by extracting illumination–invariant components. For this type, the visual appearance of an obtained image can be dissimilar that of the input image. The second category adjusts the lighting of face images by compensating brightness for low lighting parts of the input images. It can directly apply on the input images or follows an illumination

normalization method. The third category is designed to extract features that are robust against illumination changes.

According to previous studies, illumination normalization methods are very effective to the illumination–variation problem in face recognition [1, 9, 10, 11, 12]. They are used to normalize face images before extracting the features. Despite the achievements made, however, the output images of them have a slight difference of brightness.

In local descriptors, local ternary patterns (LTP) descriptor [8] has proven to be discriminative and robust to noise in the near–uniform image regions yet very simple local texture descriptors. Nevertheless, it is not robust against illumination changes. In this case, the illumination preprocessing methods will help to significantly improve the recognition rate of LTP [8, 13].

In this study, based on the illumination preprocessing methods and singular value decomposition (SVD), we introduce a new approach in order to improve the accuracy of face recognition systems using LTP under illumination variation conditions. In the training phase, the training images are first extracted lighting components by an illumination normalization method. Next, SVD is applied to the encoded images. Finally, the training encoded images are extracted features based on LTP. In the classification phase, the test images are also preprocessed illumination by an illumination preprocessing method. Then, the singular value matrix of a lighting preprocessed image is combined with that of a training encoded image to adjust the brightness of this before the LTP based features are extracted and classified. Experiments that were conducted on the Extended Yale B face database [14] indicated that the proposed method improved recognition accuracy under varying illumination conditions. It is expected to contribute a solution for accuracy improvement of the face recognition problem using illumination normalization method and local descriptors under varying illumination conditions [15].

The remaining part of the paper is organized as follows. Section 2 briefly introduces related works. LTP based feature extraction is introduced in Section 3. Section 4 presents proposed method. The information of database and experiment settings is described in Section 5. The experimental results and discussion are presented in Section 6. Finally, Section 7 draws the conclusion remarks.

## 2. **Related works.** 
In this section, a brief review of the self–quotient images, Weber–face, SVD, and LTP methods is provided.

### 2.1. **Self–quotient images.** 
Self–quotient images (SQI) is an illumination normalization method based on the Lambertian model. It is proposed by Wang et al. [16] for illumination invariant face recognition. For a given image $I$, the implementation of SQI as follows:

$$SQI(x,y) = \frac{I(x,y)}{LF * I(x,y)}, \tag{1}$$

in which * is the convolution operator and $LF$ is a low–pass filter such as Gaussian filter. The Gaussian kernel function with standard deviation $\sigma$ can be defined as follows:

$$G(x,y,\sigma) = \frac{1}{2\pi\sigma^2}\exp(-\frac{x^2+y^2}{2\sigma^2}). \tag{2}$$

### 2.2. **Weber–face.** 
In [9], an illumination normalization method based on Webers law was proposed, called Weber–face. For a given image $I$, the implementation of Weber–face (WF) is performed in two steps as follows:

**Step 1**. Smoothen $I$ with a Gaussian filter:

$$I^{'} = I * G(x,y,\sigma), \tag{3}$$

where * is the convolution operator and $G$ is the Gaussian kernel function with standard deviation $\sigma$.

**Step 2**. Process $I$ with a Weber local descriptor:

$$WF(x,y) = \arctan(\alpha \sum_{i\in A}\sum_{j\in A} \frac{I'(x,y) - I'(x - i\Delta x, y - j\Delta y)}{I'(x,y)}), \tag{4}$$

in which A=(-1,0,or 1) and *f(x,y)* is the intensity value of the pixel at location *(x,y)*. The arctangent function is a normalization function and the parameter is a weight coefficient for adjusting the relativity between the intensity difference and the current center pixel.

2.3. **Singular value decomposition.** Singular value decomposition (SVD) [17] is a factorization of a real or complex matrix. In computer vision, it has many useful applications such as image hiding [18], image compression [19], image equalization [20], and so on.

For a given image matrix $I$ with size $N \times N$, it can be factorized into three matrices:

$$I = U_I \Sigma_I V_I^T = [u_1, u_2, ..., u_N] \begin{bmatrix} s_1 & & & \\ & s_2 & & \\ & & \ddots & \\ & & & s_N \end{bmatrix} \times [v_1, v_2, ..., v_N]^T, \tag{5}$$

where $U_I$ and $V_I$ are orthogonal square matrices known as the hanger and aligner, respectively, and $\Sigma_I$ is an $N \times N$ diagonal matrix with entry $s'_i s$ (singular values) satisfying: $s_1 \geq s_2 \geq \ldots \geq s_N$.

2.4. **Local ternary patterns.** Local ternary patterns (LTP) was first proposed by Tan and Triggs [8]. They modified the sign function of LBP from a binary function to a ternary function:

$$LTP_{R,P,\tau} = \sum_{i=0}^{P} s(g_i - g_c) \times 3^i, \tag{6}$$

$$s(x) = \begin{cases} 1 & x \geq \tau \\ 0 & |x| < \tau \\ -1 & x < \tau \end{cases}, \tag{7}$$

where $g_c$ is the gray value of the central pixel, $g_i$ is the value of its neighbors, $R$ is the radius of the neighborhood, $P$ is the total number of involved neighbors, and $\tau$ denotes the user threshold.

The dimensionality of the LTP histogram is very large. $LTP_{1,8}$ will result in a histogram of $3^8 = 6561$ bins. Thus, [8] splits the LTP code into a positive LBP code and a negative code as:

$$s'_p(x,\tau) = \begin{cases} 1 & x \geq \tau \\ 0 & x < \tau \end{cases}, \tag{8}$$

$$s'_n(x,\tau) = \begin{cases} 1 & x \leq -\tau \\ 0 & x > -\tau \end{cases}. \tag{9}$$

3. **LTP based feature extraction.** After the LTP pattern of each pixel is identified, an encoded image is divided into a set of small sub–regions from which LTP histograms are extracted and concatenated into a single feature histogram. Suppose a sub–region of the given image is of size I*J. A histogram is built to represent a sub–region of an encoded image as follows:

$$H(k) = \sum_{i=1}^{I}\sum_{j=1}^{J} f(LTP_{R,P}(i,j), k), k \in [0,K], f(x,y) = \begin{cases} 1, & x = y \\ 0, & otherwise \end{cases}. \tag{10}$$

where $K$ is the maximum LTP pattern value and $R$=1 and $P$=8 are used for this study.

For further details of this approach, see [21, 22, 23].

4. **Proposed method.** Illumination normalization methods are robust to obtain ratio images from input images. However, in the case two different varying lighting images of a person, output images still have a slight difference about brightness. In fact, training face images are often captured in good, stable lighting environments, while testing face images are captured in varying lighting environments. From these characteristics, we propose an approach, which uses the lighting of training images as the standard reference from which using the SVD method to adjust the illumination of the test images following the training images.

In phase training, the training image, $I$, is initially extracted as illumination-invariant components by an illumination pretreatment method

$$I' = ill\_norm(I), \tag{11}$$

where $ill\_norm$ is an illumination method.

Next, SVD is applied to the obtained images.

$$[U_{tr}, S_{tr}, V_{tr}] = svd(I'). \tag{12}$$

Then, the illumination pretreated images are encoded by the LTP descriptor.

$$E_{tr} = LTP_{\tau}(I'). \tag{13}$$

Finally, the encoded images are used to extract histogram–based feature using Equation 10.

$$H_{tr} = get\_hist\_feature(E_{tr}). \tag{14}$$

In phase classification, the test image, $T$, is first performed as step 1 of phase training.

$$T' = ill\_norm(T). \tag{15}$$

Secondly, SVD is applied to the obtained images.

$$[U_{ts}, S_{ts}, V_{ts}] = svd(T'). \tag{16}$$

Thirdly, before implementing classification, singular value matrix of the training and test illumination pretreated images are utilized to adjust the illumination of the test illumination pretreated image.

$$S_{ts} = \frac{(S_{tr} + S_{ts})}{2}. \tag{17}$$

Fourthly, we update the test illumination pretreated image:

$$T' = U_{ts} \times S_{ts} \times V_{ts}^{T}. \tag{18}$$

Fifthly, the image obtained from the previous step are encoded by the LTP descriptor.

$$E_{ts} = LTP_{\tau}(T'). \tag{19}$$

Sixthly, the encoded images are used to extract histogram–based feature using Equation 10.

$$H_{ts} = get\_hist\_feature(E_{ts}). \tag{20}$$

Seventhly, compute distance between $H_{ts}$ and $H_{tr}$ using a nearest neighbor classifier with Chi–square as a dissimilarity measure.

$$D_i = dist(H_{tr}^{i}, H_{ts}). \tag{21}$$

Finally, find a label $L$ that has minimum distance:

$$L = get\_label(D), \tag{22}$$

where *get_label* is a function return a label which has corresponding minimum distance.

The implementation of proposed methods performing a training image, a test image, and classification are summarized in Algorithms 1, 2, and 3, respectively.

Algorithm 1 shows the steps which are used to perform the histogram based feature and singular value matrix of a training image.

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**Algorithm 1**: Performing the feature of a training image (PFTr)
**Input**: Training image *I*.
**Output**: Histogram based feature $H_{tr}$ of *I*, singular value matrix $S_{tr}$ of *I*.

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Apply an illumination normalization method to *I*: $I' = ill\_norm(I)$.
Apply SVD to *I′*: $[U_{tr}, S_{tr}, V_{tr}] = svd(I')$.
Encode *I′* by LTP descriptor: $E_{tr} = LTP_{\tau}(I')$.
Extract histogram-based feature: $H_{tr} = get\_hist\_feature(E_{tr})$.

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Algorithm 2 summarizes the steps which use the singular value matrix of a training image to generate the histogram based feature of a test image.

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**Algorithm 2**: Performing the feature of a test image (PFTs)
**Input**: Test image *T*, singular value matrix $S_{tr}$ of a training image.
**Output**: Histogram based feature $H_{ts}$ of *T*.

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Apply an illumination normalization method to *T*: $T' = ill\_norm(T)$.
Apply SVD to *T′*: $[U_{ts}, S_{ts}, V_{ts}] = svd(T')$.
Adjust the singular value matrix of the test image: $S_{ts} = \dfrac{(S_{tr} + S_{ts})}{2}$.
Update the test illumination preprocessing image: $T' = U_{ts} \times S_{ts} \times V_{ts}^T$.
Encode *T′* by LTP descriptor: $E_{ts} = LTP_{\tau}(T')$
Generate histogram-based feature: $H_{ts} = get\_hist\_feature(E_{ts})$.

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As above mentioned, before computing the distance between the training and test images, the illumination of test image is adjusted based on the illumination of the training image via SVD. The implementation of the classification method is displayed in Algorithm 3 below.

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**Algorithm 3**: classification method
**Input**: Training feature set *TR*, test image *T*.
**Output**: Label *L* of *T*.

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For each *X* in *TR*
  Apply PFTs to *T* and the singular value matrix $S_{tr}$ of X: $H_{ts} = PETs(T, S_{tr})$.
  Compute distance between $H_{tr}$ of X and $H_{ts}$ of *T*: $D_i = dist(H_{tr}^i, H_{ts})$.
End For
Find a label *L* that has minimum distance: $L = get\_label(D)$.

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## 5. Database and experiment settings.

**5.1. Data input.** The extended Yale B database [14] consists of gray–scale frontal face images of 38 individuals under nine poses. Each subject has 64 images (2414 images out of 2432 images are used, since 18 images are either missing or named bad by the respective owners). In this experiment, the images are cropped with a resolution of $192 \times 168$ pixels and categorized into six subsets, based on the angle between the direction of the light source and the central camera axis, as follows: Subset 0 (0°, 228 images), Subset 1 (1–12°, 301 images), Subset 2 (13–25°, 380 images), Subset 3 (26–50°, 449 images), Subset 4

(51–77°, 380 images), and Subset 5 (≥ 78°, 676 images). We used Subset 0 (A+000E+00), which has six images per subject, for training. Figures 1 and 2 list the original sample images and the corresponding images.

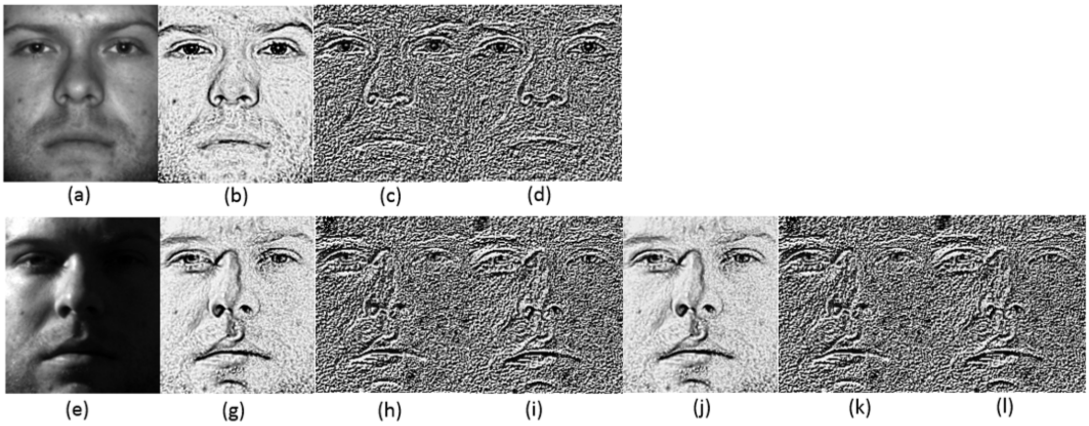


Figure 1. Illumination preprocessing of proposed approach on a face image in Extended Yale B database. The images in the first row are illumination preprocessing of a training image: (a) original image, (b) SQI–face image, (c) Upper LTP representation of a SQI image, (d) Lower LTP representation of a SQI image. The images in the second row are illumination preprocessing of a test image: (e) original image, (g) SQI image, (h) Upper LTP representation of a SQI image, (i) Lower LTP representation of a SQI image, (j) SQI image after processing by proposed method, (k) Upper LTP image of SQI image processed by proposed method, (k) Lower LTP image of SQI image processed by proposed method.

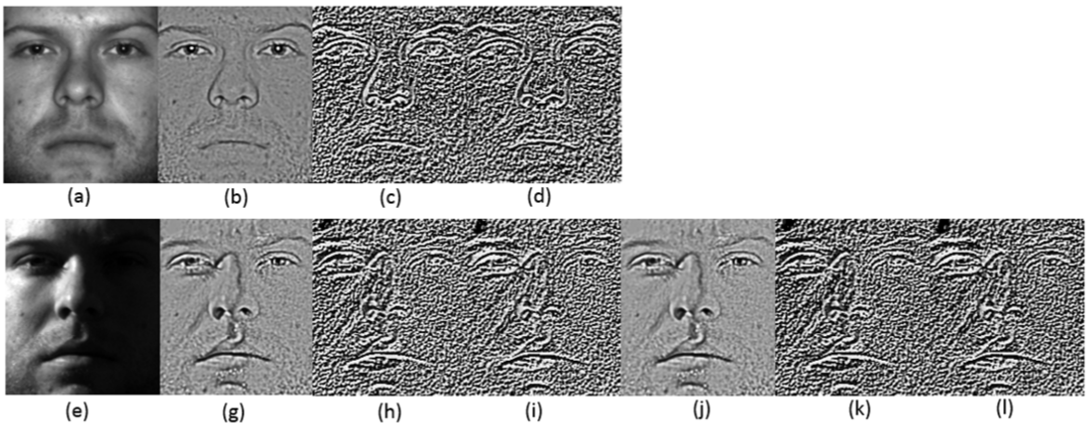


Figure 2. Illumination preprocessing of proposed approach on a face image in Extended Yale B database. The images in the first row are illumination preprocessing of a training image: (a) original image, (b) WF image, (c) Upper LTP representation of a WF image, (d) Lower LTP representation of a WF image. The images in the second row are illumination preprocessing of a test image: (e) original image, (g) WF image, (h) Upper LTP representation of a WF image, (i) Lower LTP representation of a WF image, (j) WF image after processing by proposed method, (k) Upper LTP image of WF image processed by proposed method, (k) Lower LTP image of WF image processed by proposed method.

5.2. **Experiment settings.** Numerous classifiers using distance measures have been introduced [24, 25]. In order to compare the efficiency of the methods in this study, the Chi–square [23] distance is used for the nearest neighbor classifier. The accuracy of the methods is calculated as a percentage of correct classifications as follows:

$$\text{Accuracy}(\%) = \frac{\#\text{of correct classifications}}{\#\text{of total testing images}} \times 100. \tag{23}$$

In the experiments, each image was divided into $10 \times 10$ blocks. For the SQI method, the parameter $\sigma$ was set to 1. For the WF method, the standard deviation of the Gaussian filter as 1 ($\sigma$), the size of the neighborhood as $3{\times}3$, and the parameter balancing the range of the input values of the actan function as 2 ($\alpha = 2$). For the SQI and WF methods, the output result is normalized to the 8–bit interval.

## 6. Experimental results and discussion.

6.1. **Visual comparision for preprocessed face images.** In this sub–section, we will compare the visualization effects of the normalized images to understand the principle behind each method. Figures 1 and 2 list some original face images and preprocessed face images using different illumination normalization methods. A comparison of Figures 1(b), 1(g) and 2(b), 2(g) show that the brightness of them has still a slight difference. Therefore, LTP representation of them has also a slight difference about illumination (see Figures 1(c, d), 1(h, j) and 2(c, d), 2(h, j)). Figures 1(j) and 2(j) are resulting images of the proposed method. Comparing Figure 1(j) with Figure 1(g), it can be seen that Figure 1(j) is darker than Figure 1(g) and Figure 1(j) is similar to Figure 1(b) about illumination. This is also similar to Figure 2(j) and Figure 2(g). Due to these, LTP representation of test images, which were preprocessed illumination by the proposed method, will be closer to LTP representation of SQI/WF training images. This explains why the proposed method is the most effective.

6.2. **Results on the extended Yale B database.** The extended Yale B database is a well–known and suitable database evaluating the effectiveness of proposed method. Figure 3 displays the relation between threshold $\tau$ of LTP and the average recognition rates of methods. As can be seen, $\tau = 2$, the proposed method reached the highest recognition rate. The recognition rate with $\tau = 2$ are summarized in Table 1, which shows the advantage of our methods. The obtained results of the proposed method

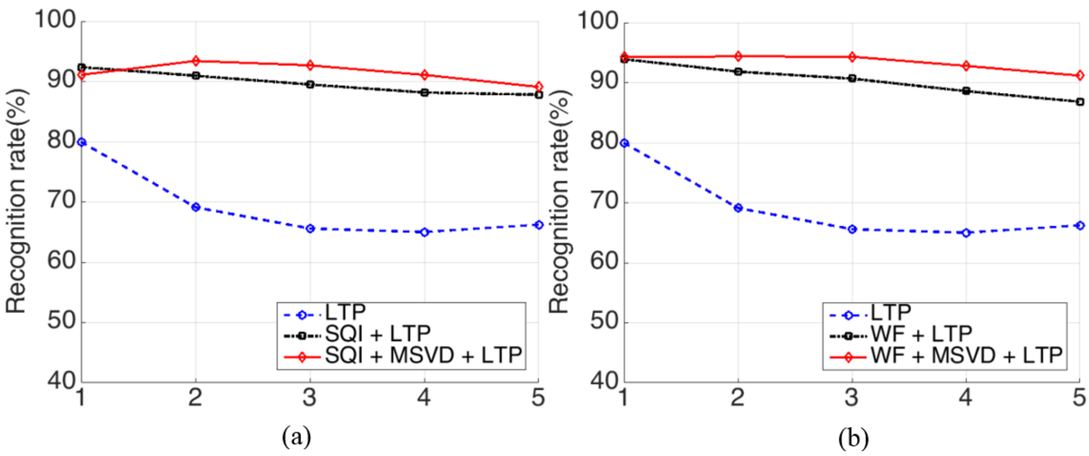


FIGURE 3. The relation between threshold of LTP and the average recognition rates of methods. (a) The results of methods combined with SQI. (b) The results of methods combined with WF.

Table 1. Recognition accuracy (%) of proposed method and related methods

| Subset | LTP | SQI + LTP | SQI + MSVD + LTP | WF + LTP | WF + MSVD + LTP |
|---|---|---|---|---|---|
| 1 | 100 | 100 | 100 | 100 | 100 |
| 2 | 99.47 | 99.47 | 99.47 | 99.73 | 99.47 |
| 3 | 89.08 | 97.55 | 97.99 | 98.21 | 98.44 |
| 4 | 27.89 | 86.31 | 93.68 | 92.63 | 95.26 |
| 5 | 29.14 | 71.44 | 75.88 | 68.63 | 78.69 |
| **Average** | 69.11 | 90.95 | 93.40 | 91.84 | 94.372 |

*Abbreviations*: SQI + MSVD + LTP means the proposed method using SQI; WF + MSVD + LTP means the proposed method using WF.

and related methods are given in Table 1. It can be found that the proposed method (SQI + MSVD + LTP) reached the best average accuracy compared to other methods, obtaining an accuracy improvement of 2.45% and 24.28% over SQI + LTP and LTP methods, respectively. For WF–related methods, the proposed method also reached the best average accuracy compared to other methods, obtaining an accuracy improvement of 2.53% and 25.25% over WF + LTP and LTP methods, respectively.

The experimental results indicated that the improved methods, SQI + LTP, WF + LTP and the proposed method obtained better results than the LTP method; however, the proposed method is the best out of the three methods. It can be seen that the introduced method is very efficient for face images captured under strong lateral light (Subsets 4 and 5). Despite the achievements made, the proposed method still has a limitation that it is only efficient for face training images taken under good lighting conditions because these are used as reference illumination to adjust the brightness of the test images.

7. **Conclusion.** This study has addressed a new approach for the illumination variation problem of a face recognition system using basic LTP operator. In the training phase, the training images are the first extracted illumination components by an illumination normalization method. Next, SVD is applied to the encoded images. Finally, the training encoded images are extracted features based on LTP. In the classification phase, the test images are also preprocessed illumination by an illumination preprocessing method. Then, the singular value matrix of a lighting preprocessed image is combined with that of a training encoded image to adjust the brightness of this before the LTP based features are extracted and classified. Experiments indicated that the proposed method can achieve competitive results compared to the LTP, SQI/WFLTP methods. It is expected to contribute a solution for accuracy improvement of the face recognition problem using illumination normalization method and local descriptors under varying illumination conditions.

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## REFERENCES

[1] H. Han, S. Shan, X. Chen, and W. Gao, A comparative study on illumination preprocessing in face recognition,*Pattern Recognition*, vol. 46, pp. 1691–1699, 2013.

[2] J.W. Wang, N.T. Le, J.S. Lee, and C.C. Wang, Recognition based on two separated singular value decomposition–enriched faces,*Journal of electronic imaging*, vol. 23, p. 15, 2014.

[3] Y.S. Huang and C.Y. Li, An Effective Illumination Compensation Method for Face Recognition,*in Advances in Multimedia Modeling: 17th International Multimedia Modeling Conference, MMM 2011, Taipei, Taiwan*, 2011, pp. 525–535.

[4] Y. Adini, Y. Moses, and S. Ullman, Face Recognition: The Problem of Compensating for Changes in Illumination Direction,*IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 19, pp. 721–732, 1997.

[5] T. Ahonen, A. Hadid, and M. Pietikäinen, Face Recognition with Local Binary Patterns,*in Computer Vision - ECCV 2004. vol. 3021, T. Pajdla and J. Matas, Eds., ed: Springer Berlin Heidelberg*, 2004, pp. 469–481.

[6] J. Chen, S. Shan, C. He, G. Zhao, M. Pietikainen, X. Chen, et al., WLD: a robust local image descriptor,*IEEE Trans Pattern Anal Mach Intell*, vol. 32, pp. 1705–1720, 2010.

[7] O. Dniz, G. Bueno, J. Salido, and F. D. l. Torre, Face recognition using Histograms of Oriented Gradients,*Pattern Recognition Letters*, vol. 32, pp. 1598–1603, 2011.

[8] T. Xiaoyang and B. Triggs, Enhanced Local Texture Feature Sets for Face Recognition Under Difficult Lighting Conditions,*Image Processing, IEEE Transactions on*, vol. 19, pp. 1635–1650, 2010.

[9] B. Wang, W. Li, W. Yang, and Q. Liao, Illumination Normalization Based on Weber's Law With Application to Face Recognition,*IEEE Signal Processing Letters*, vol. 18, pp. 462–465, 2011.

[10] Y. Wu, Y. Jiang, Y. Zhou, W. Li, Z. Lu, and Q. Liao, Generalized Weber–face for illumination-robust face recognition,*Neurocomputing*, vol. 136, pp. 262–267, 2014.

[11] T. Zhang, Y. Y. Tang, B. Fang, Z. Shang, and X. Liu, Face Recognition Under Varying Illumination Using Gradientfaces,*IEEE Transactions on Image Processing*, vol. 18, pp. 2599–2606, 2009.

[12] G. Chen and W. Xie, A Comparative Study for the Effects of Noise on Illumination Invariant Face Recognition Algorithms,*in Intelligent Computing Theories and Application: 12th International Conference, ICIC 2016, Lanzhou, China, August 2–5, 2016, Proceedings, Part II, D.S. Huang and K.H. Jo, Eds., ed Cham: Springer International Publishing*, 2016, pp. 257–267.

[13] T. K. Marks, R. Kumar, and M. Jones, Morphable Reflectance Fields for enhancing face recognition,*presented at the 2010 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2010.

[14] K.C. Lee, J. Ho, and D. Kriegman, Acquiring Linear Subspaces for Face Recognition under Variable Lighting,*IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, pp. 684–698, 2005.

[15] C.K. Tran, C.D. Tseng, and T.F. Lee, Improving the Face Recognition Accuracy under Varying Illumination Conditions for Local Binary Patterns and Local Ternary Patterns Based on Weber-Face and Singular Value Decomposition,*in 2016 3rd International Conference on Green Technology and Sustainable Development (GTSD)*, 2016, pp. 5–9.

[16] H. Wang, S. Z. Li, Y. Wang, and J. Zhang, Self quotient image for face recognition,*in Proceedings of the International Conference on Pattern Recognition*, 2004, pp. 1397–1400.

[17] S. J. Leon, Linear Algebra with Applications,*Pearson; 8 edition*, 2009.

[18] K.L. Chung, C.H. Shen, and L.C. Chang, A novel SVD– and VQ–based image hiding scheme,*Pattern Recognition Letters*, vol. 22, pp. 1051–1058, 2001.

[19] A. M. Rufai, G. Anbarjafari, and H. Demirel, Lossy image compression using singular value decomposition and wavelet difference reduction,*Digital Signal Processing*, vol. 24, pp. 117–123, 2014.

[20] P. Sivakumar, K. Maguesway, and M. Rajaram, Image contrast enhancement using singular value decomposition for gray level images,*in Signal Processing, Communication, Computing and Networking Technologies (ICSCCN), 2011 International Conference on*, 2011, pp. 1–5.

[21] C.K. Tran, T.F. Lee, l. Chang, and P.J. Chao, Face Description with Local Binary Patterns and Local Ternary Patterns: Improving Face Recognition Performance Using Similarity Feature-Based Selection and Classification Algorithm,*in Computer, Consumer and Control (IS3C), 2014 International Symposium on*, 2014, pp. 520–524.

[22] M. Pietikäinen, A. Hadid, G. Zhao, and T. Ahonen, Computer Vision Using Local Binary Patterns,*Springer Verlag*, 2011.

[23] C.K. Tran, C.D. Tseng, P.J. Chao, H.M. Ting, L. Chang, Y.J. Huang, et al., Local intensity area descriptor for facial recognition in ideal and noise conditions,*Journal of Electronic Imaging*, vol. 26, pp. 023011–023011, 2017.

[24] J.S. Pan, Q. Feng, L. Yan, and J.F. Yang, Neighborhood Feature Line Segment for Image Classification,*IEEE Transactions on Circuits and Systems for Video Technology*, vol. 25, pp. 387–398, 2015.

[25] Q. Feng, C. Yuan, J.S. Pan, J.F. Yang, Y.T. Chou, Y. Zhou, et al., Superimposed Sparse Parameter Classifiers for Face Recognition,*IEEE Trans. On Cybernetics*, vol. 47, pp. 378–390, 2017.