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Multi-scale logarithmic difference face recognition based on local binary pattern

Lifang Lin[1], Chuanlin Zhang[2]
[1]*School of Information and Science Technology, Jinan University, Guangzhou, 510632, China, E-mail: 8202215932@qq.com.*
[2]*School of Information and Science Technology, Jinan University, Guangzhou, 510632, China, E-mail: tclzhang@jnu.edu.cn.*
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Abstract. In order to solve the problem that face recognition is sensitive to illumination variation and local binary pattern has small spatial support region. A novel face recognition approach which is multi-scale logarithmic difference face recognition based on local binary pattern is proposed. Firstly, LBP operator is used to extract the texture feature of the face. Secondly, the LBP feature is used to extract the light invariant based on the Lambertian reflection model. Then, the light invariant is used to obtain the multi-scale features according to the different distances, and the refined feature-map is obtained by the linear combination of multi-scale features. Finally, face recognition is performed using refined feature-map. Extension experiments on four data sets (Yale, FERET, ORL and MUI PIE) show that the proposed method which compares to LBP, MSLDE and Gradientface in different illumination conditions can improve the recognition performance.

Keywords: Local binary pattern (LBP); feature extract; face recognition; multiple scales; logarithm transform; difference.

1. Introduction

Face recognition is one of the most fundamental problems in computer vision and pattern recognition. In the past decades, it has been extensively studied because of its wide range of applications, such as automatic access control system, e-passport, criminal recognition, to name just a few [1]. In face recognition, a key problem is to find a valid description operator of face appearance. Some classical methods, such as principal component analysis and linear discriminant analysis, which are based on the whole face feature. Such methods are effective under controlled conditions. However, illumination variation is usually mixed with other complicated uncontrolled variations, such as expression, pose, occlusion, blurring, etc., which will lead to poor performance in face recognition.

In recent years, local feature descriptors attract much attention from researchers. Local binary patterns (LBP) [2-7] are considered among the most computationally efficient high-performance texture features and have made significant achievements in face recognition applications. LBP [8] has emerged as one of the most prominent texture descriptors, attracting significant attention in the field of computer vision and image analysis due to their outstanding advantages: 1) ease of implementation, 2) invariance to monotonic illumination changes, and 3) low computational complexity. Although the LBP method has achieved good results in earlier experiments, it can’t obtain the detailed scale and direction information, it is sensitive to the noise at the uniform region. Under the bad illumination condition, the classification performance will decrease sharply. In order to improve the performance of the LBP operator, extending LBP to local ternary mode (LTP) [9], which is more robust to illumination variation and noise. In reference [10], Center Symmetric LBP (CS-LBP) is proposed [10]. It has low dimension and strong anti-noise ability.

Although the LBP method has achieved good performance in earlier experiments, it can’t obtain the detailed scale and direction information. Under the influence of strong illumination, the classification performance will decrease sharply. Studies have shown that the effects of illumination are greater than those caused by individual differences [11-12]. Lambertian reflection model is used to extract the illumination invariant, there is no complex modeling process, which is easy to achieve in real-time processing requirements. The basic idea of the Lambertian reflection model is to separate out the light components of the image and obtain the illumination invariant.

The LBP [13-15] method is very sensitive to image noise and is unable to capture macrostructure information. To best address these disadvantages, in this paper, multi-scale logarithmic difference face

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recognition method based on local binary pattern is proposed. Firstly, LBP operator is used to extract the texture feature of the face. Secondly, we use logarithm difference to obtain the illumination invariant. Logarithm transform can expand the values of dark pixels and simulate the response of retina cells. In math, it can change a multiplication into an additive model, so that the difference between two neighboring pixels can eliminate light intensity. Thirdly, by dividing a neighborhood into sub-regions according to their distances to the current pixel, multiple feature-maps of different scales can be obtained. They can be modified and combined to form a robust holistic feature-map. A weight is assigned to each feature-map, controlling the importance and influence of this feature-map. A combination of all the weighted feature-maps forms the refined feature-map. Finally, the KNN classifier is used for face recognition of the refined feature map.

2. Related work

2.1. Local binary pattern

Local binary pattern (LBP) is a texture description method in gray scale. It uses the idea of structural method to analyze the characteristics of fixed window, and uses statistical method to extract the whole feature. It was proposed by Ojala et al originally. It is used to measure the local contrast of an image. The basic principle of the algorithm is to characterize the spatial structure of a local image patch by encoding the differences between the pixel value of the central point and those of its neighbors, considering only the signs to form a binary pattern. The resulting decimal value of the generated binary pattern is then used to label the given pixel. Formally, as illustrated in Fig.1.

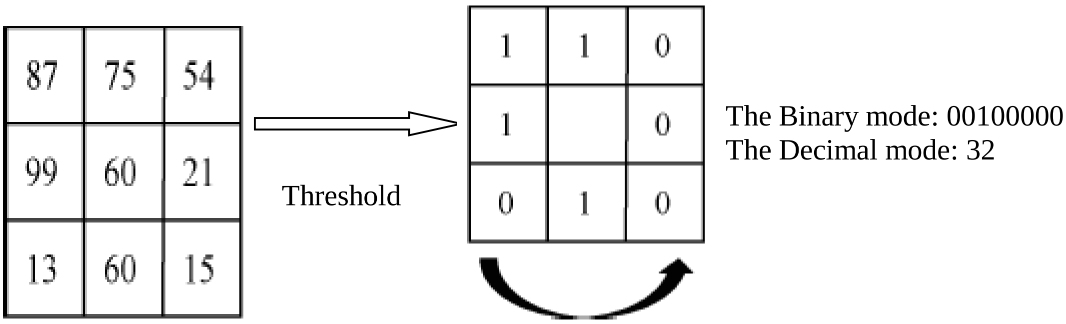

Fig.1. Examples of Raw LBP Operator Calculations

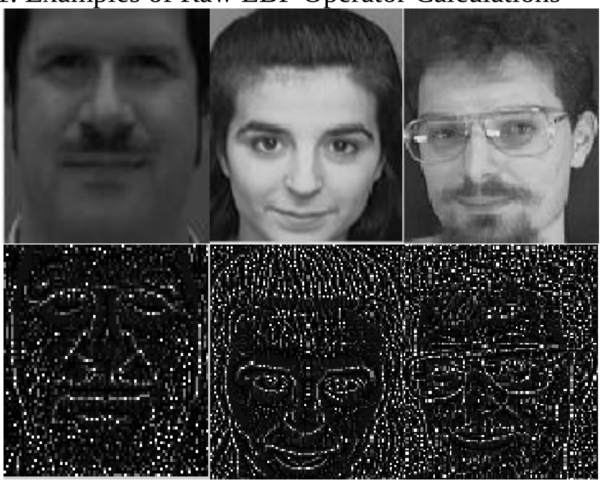

Fig.2. The first line is the original images,
the second line is LBP after transformation of the image

Consider a 3×3 window centering on point c, let the gray value of the corresponding center point is and the gray value of the neighborhood point are . Then the local binary pattern corresponding to the center on as:

$$\mathrm{LBP}(g_c) = \sum_{i=0}^{7} s(g_i - g_c)2^i. \quad (1)$$

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Where $(\cdot)$ is the sign function.

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}. \tag{2}$$

The sign function describes the two states of the neighborhood point and the center point, and reduces the range of the joint distribution of the gray value in the local area, so that the distribution can be represented by simple values. Formally, as illustrated in Fig.2.

2.2. Lambertian reflection model

Generally, an image refers to the external light source to the target object, then the target object surface reflects to the image pickup device sensor and forms a light intensity measurement. The illumination model describes the relationship between the light source, the target object, and the imaging. Commonly known experience light model includes Lambertian reflection model, Cook-Torrance illumination model, Phong illumination model and Bank BRDF illumination model.The Lambertian reflection model is used to extract illumination invariant which is based on illumination model in face recognition. Lambertian reflection model is a classic empirical illumination model, it assumes that the object surface has a Lambertian reflection characteristic, that is, when the light is irradiated to the object, the object surface in all directions have the same scattering, diffuse component only relate to the object surface and the incident angle of the light source.

$$f(x, y) = r(x, y)n(x, y)^T s. \tag{3}$$

Where $r(x, y)$ denotes the reflectivity of the target object surface, $n(x, y)^T$ denotes the normal vector of the target surface, s denotes the external light source, $f(x, y)$ denotes the imaging of the target object

On the basis of Lambertian reflection model, the reflectivity and normal vector of the object surface are regarded as the intrinsic characteristics of the object surface. Lambertian model (4) factorizes an image as a multiplication of a light intensity component and a surface albedo component.

$$f(x, y) = \rho(x, y)S(x, y), \quad \forall 1 \leq x \leq m, 1 \leq y \leq n. \tag{4}$$

Where $f(x, y)$ is an $m \times n$ gray-scale face image, $\rho(x, y)$ is the surface albedo component and $S(x, y)$ is the light intensity component. The objective is to retrieve ρ or eliminate S from f.

The Lambertian reflection model which extracts the illumination invariant to separate the illumination variable from the surface reflectance of the object surface. According to the characteristics of the external light source and target object, it can be assumed that the intrinsic characteristics of the target object change rapidly, while the external illumination changes slowly.

3. Model determination (LBPMSLDE)

3.1. Multi-scale logarithm difference

Illumination is one of the main factors that affect the appearance of face recognition. The change of illumination can lead to the change of image and the performance of various face recognition algorithms. In order to reduce the influence of illumination on the face recognition system, we hope to remove the illumination components in the face image, so as to reduce the influence of illumination on the subsequent processing algorithms and improve the illumination robustness and recognition rate. This paper uses logarithmic difference method. It has two advantages. First, Logarithm transform can expand the values of dark pixels and simulate the response of retina cells. Secondly, it can change a multiplication into an additive model, so that a difference between two neighboring pixels can eliminate light intensity.

$$i(x, y) = \log f(x, y) = \log \rho(x, y) + \log S(x, y). \tag{5}$$

The assumption of slow change of light intensity, so it can extend to a neighborhood whose size is not too large. That is, $S(x, y) \approx S(\tilde{x}, \tilde{y}), (\tilde{x}, \tilde{y}) \in N(x, y)$.Then we can eliminate light intensity by the difference of two neighboring pixels of a logarithm image i.

$$\begin{aligned} i(x, y) - i(\tilde{x}, \tilde{y}) &= \left(\log\rho(x, y) - \log\rho(\tilde{x}, \tilde{y})\right) + (\log S(x, y) - \log S(\tilde{x}, \tilde{y})) \\ &\approx \left(\log\rho(x, y) - \log\rho(\tilde{x}, \tilde{y})\right) \end{aligned} \tag{6}$$

Where $N(x, y) = \{(\check{x}, \tilde{y}): 1 \leq |\tilde{x} - x| \leq L, 1 \leq |\tilde{y} - y| \leq L$ is a $(2L + 1) \times (2L + 1)$ square neighborhood with the current position (x, y) in its center.

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Fig.3. The original image (left) the image after the logarithm (Right)

Simple logarithmic difference can only obtain the small scale features, and the face image includes not only the small scale feature but also the large scale features, so the simple logarithmic difference is extended to capture the large face Scale characteristics. The diagram shown in fig.4.

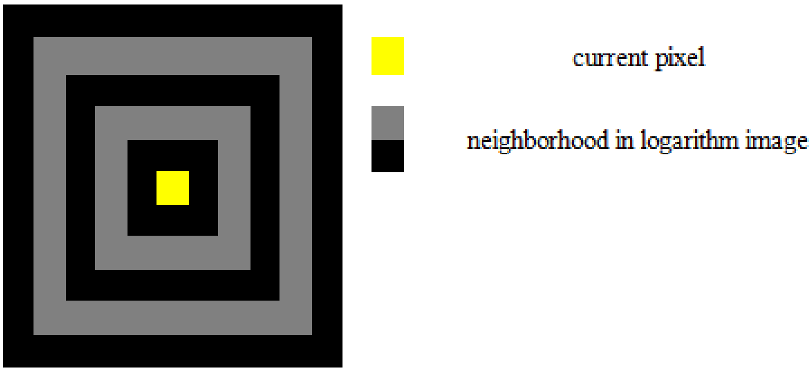

Fig.4. Dividing a neighborhood into sub-regions

To create a feature-map with all the logarithm differences, a feasible way is to take a sum:

$$I(x,y) = \sum_{(\tilde{x},\tilde{y}) \in N(x,y)} \big(i(x,y) - i(\tilde{x},\tilde{y})\big)\ , \qquad \forall x, \forall y. \tag{7}$$

The feature-map $I(x,y)$ is produced by local logarithmic difference, these local differences are different scales depending on the distance between $(\tilde{x},\tilde{y})$ and (x,y). To see this, we can further divide $N(x,y)$ into several sub-regions

$$N(x,y) = \bigcup_{l=1}^{L} N^{l}_{(x,y)}. \tag{8}$$

$$N^{l}_{(x,y)} = \{(\tilde{x},\tilde{y}): |\tilde{x}-x| = l\,, |\tilde{y}-y| \le l, \text{or } |\tilde{x}-x| \le l\,, |\tilde{y}-y| = l\,\}. \tag{9}$$

Hence the feature-map $I(x,y)$ in (9) can be decomposed into L difference edgemaps $\{I_l(x,y)\}$ of difference scales.

Different feature-maps contain different information that is beneficial or detrimental to face recognition. In order to refine the feature map, we assign a weight to each feature-map to adjust its importance. Hence we can adopt an independent training face dataset to determine a proper combination of these feature-maps.

$$I'(x,y) = \sum_{l=1}^{L} \mu_l I_l(x,y)\ \ , \ \forall \mu_l \ge 0,\ \sum_{l}^{L} \mu_l = L. \tag{10}$$

The refined holistic feature-map can be defined as (11). arctan function can suppress some sharp noise

$$I^{LBPMSLDE}(x,y) = \arctan\big(beta * I'(x,y)\big) \tag{11}$$

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3.2. Parameter tuning

In order to ensure the validity of the parameters in the model, we need to analyze the sensitivity of the parameters. The main adjusted parameters are beta, weight μ and the size of the neighborhood L.

3.2.1. Beta tuning

In (11) beta is used to adjust the difference edgemaps. A plot of recognition rates with respect to beta on Extended Yale B is shown as Figure 4. It shows that beta = 4 achieves good recognition performance with other parameters set.

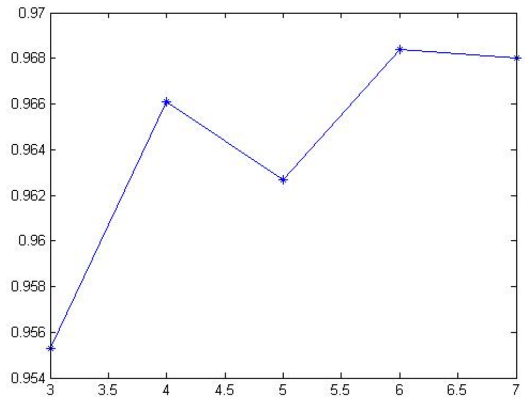

Fig.5. Different beta and Their Recognition Performances on Extended Yale B.

3.2.2. Weight tuning

It can be seen from (11) that different scales L need to assign different weights to adjust its influence, we use an independent training set to determine the weights. Suppose we have p people and $f(f \geq 2)$ face images per person in the independent training set. Denote $I_l^{m,n}$ as the l-th edgemap of the n-th image of the m-th person$(1 \leq l \leq L, 1 \leq n \leq f, 1 \leq m \leq p)$.Then we can calculate the class-wise mean edgemaps and the overall mean edgemap of the l-th scale as follows:

$$\overline{I_l^m} = \frac{1}{f}\sum_{n=1}^{f} I_l^{m,n} \quad , \quad \overline{I_l} = \sum_{m=1}^{p}\sum_{n=1}^{f} I_l^{m,n} \, . \tag{12}$$

Then we define within-class error $D_w(l)$ and between-class error $D_b(l)$ of the l-th scale as follows:

$$D_w(l) = \sum_{m=1}^{p}\sum_{n=1}^{f}\left\|I_l^{m,n} - \overline{I_l^m}\right\|_F^2, \tag{13}$$

$$D_b(l) = t\sum_{m=1}^{p}\left\|\overline{I_l^m} - \overline{I_l}\right\|_F^2, \tag{14}$$

Where $\|\cdot\|_F$ denotes the Frobenius Norm.

If the feature-maps of the l-th scale have a high discriminating ability, then according to the Fisher criterion, we will maximize the between-class error and minimize the within-class error. Hence, the discriminating ratios $\{\widetilde{\mu_l}\}$ in (15) are good indicators for the weights of feature-maps (16) normalizes $\{\widetilde{\mu_l}\}$ into weights μ_l.

$$\widetilde{\mu_l} = \frac{D_b(l)}{D_w(l)}, \qquad \forall 1 \leq l \leq L \, . \tag{15}$$

$$\mu_l = \frac{L\widetilde{\mu_l}}{\sum_{l=1}^{L}\widetilde{\mu_l}}, \qquad \forall 1 \leq l \leq L \, . \tag{16}$$

The weights are determined according to the independent training set are selected in each face data set .The independent training set used in this paper is a subset of the Extended Yale B, containing images of 10 people and 640 images, each image is cropped to 48 * 42 pixels in the face area. The experience result is shown in table 1.

3.2.3. Neighborhood Size Tuning

It can be seen from Table 1 that the weights are not the same for different neighborhoods, we need to determine the neighborhood size and effectiveness. If the neighborhood size L is too small, the extendibility

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and adaptivity of LBPMSLDE will be limited. If the neighborhood size L is too large, the neighborhood will be too large that light intensity cannot be effectively eliminated and calculation will be too much. Considering these, we go through the procedure to determine 4 sets(Extended Yale B、ORL、FERET、CMUPIE) of recognition performances for L =3,4, 5, 6, 7, 8, shown as fig.7. It can be seen that the recognition rate of different L is not much different. Considering the generalization ability of the model and the stability of the result, Hence L=6 is a suitable neighborhood size for LBPMSLDE. Now, we investigate the determined weights of L=6:

$$[\mu_1, \mu_2, \mu_3, \mu_4, \mu_5, \mu_6] = [0.4147，0.6829，0.9390，1.1561，1.3333，1.4739] \quad (17)$$

Table 1. Different neighborhood sizes L and their determined weights

L	Weight
3	1.7118, 2.1622, 2.1259
4	0.1031, 0.4190, 2.7876, 2.6903
5	0.0230, 0.2430, 0.8807, 1.9036, 2.9498
6	0.4147,0.6829,0.9390,1.1561,1.3333,1.4739
7	0.0071,0.0843, 0.2616, 0.5793, 1.0837, 1.7376, 2.2465
8	0.0051, 0.0366, 0.2298, 0.3485, 0.9106, 1.0079, 1.7425, 1.7189

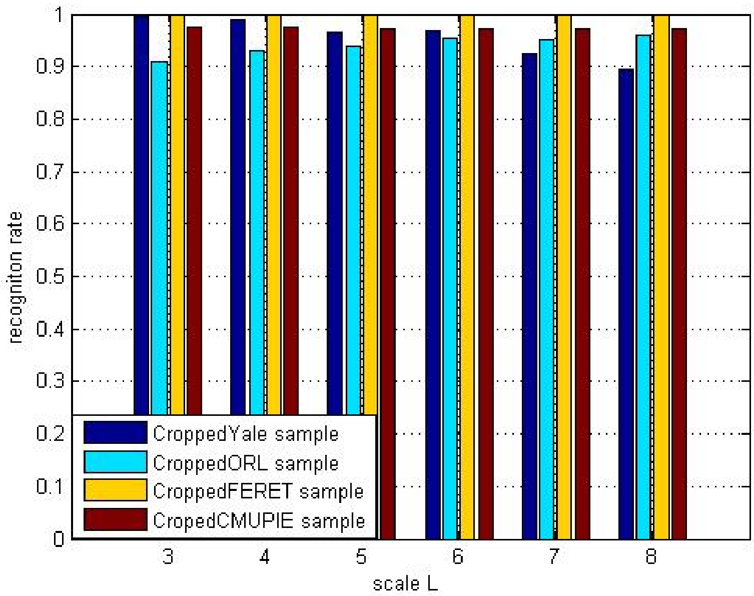

Fig.6. The difference recognition performance correspond to the different scale L

To show the effectiveness of the determined weights, we compare (17) with 5 sets of weights on recognition performance in Extended Yale B data set shown as in table II. No.1 is the set of determined weights (17). The mean recognition rate is 0.9685. Hence the weight determination is necessary and effective, and the small-scale features are also importance and cannot be discarded.

Table 2. 6 sets of weights and their recognition performances on Extended Yale B

No	intention	weights	mean±std
1	Discarding the Last weights	0.4147,0.6829, 0.9390,1.1561,1.3333,0	0.9506±0.0137
2	Discarding the First weights	0,0.6829,0.9390,1.1561,1.3333,1.4739	0.9561±0.0117
3	retaining the Last weights	0,0,0,0,0,1.4739	0.9251±0.0044
4	retaining the First weights	0.4147,0,0,0, 0,0	0.9030±0.0139
5	Determined in (17)	0.4147,0.6829,0.9390,1.1561,1.3333,1.4739	0.9685±0.0140
6	Trivial weights	1,1,1,1,1,1	0.9569±0.0116

3.3. Overview of the proposed LBPMSLDE

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The whole LBPMSLDE algorithm can be referred to in Fig.7.

4. Experimental results

In order to show the effectiveness of LBPMSLDE in face recognition, FERET、ORL、CMU PIE、Extended Yale B are taken in the experiments.

- FERET: FERET face data set, created by FERET project, contains more than 14051 face grayscale images which includes multi-gesture, different illumination conditions, and more than 1000 volunteers face images are strictly divided training set, Gallery set, test sets, etc., it is one of the most widely used face databases in face recognition. The image was aligned, cropped and resized to 80 * 80 pixels which only include the face.
- CMU PIE: The CMU PIE face data set, created by Carnegie Mellon University in the United States, contains 41368 face grayscale images which includes multi-gesture, different illumination, different expression and 68 volunteers face images captured under tightly controlled conditions, and it is mainly used for posture and light research. The image was aligned, cropped and resized to 64 * 64 pixels which only include the face.
- ORL: The ORL face data set, created by the AT & T Lab of the Cambridge University, contains 400 face grayscale images which includes multi-gestures, different expressions, and different occlusion and 40 volunteers face images captured under scale changes of less than 20%, it is mainly used for facial expression recognition. The image was aligned, cropped and resized to 112* 92 pixels which only include the face.
- Extended Yale B: The Extended Yale B Face Data Set, created by the Computing Visual and Control Center of the Yale University, contains 2414 face grayscale images which includes multi-pose, different illumination images and 38 volunteers face images captured under strictly controlled conditions, it is mainly used for the modeling and analysis of light and pose problems. The image was aligned, cropped and resized to 48 * 42 pixels which only include the face.

In this section, we will perform extensive experiments to validate the recognition performance of LBPMSLDE in different conditions. LBPMSLDE will be compared with other effective illumination-treating methods: LBP, Gradientface, MSLDE. The nearest neighbor classifier is used. We evaluate the performances of different methods in different data sets, shown as in Table 3, Figure 7 (ORL Face Data Set), Figure 8 (Extended Yale B Face Data Set), Figure 9 (FERET Face Data Set), Figure 10 (CMU PIE Face Data Set).

It can be seen from Table 3 that the proposed method has the highest average recognition rate compared with the other three methods, which are 0.9685, 0.9996, 0.9723 and 0.9700 on the four data sets respectively. The Fig (7-10) show that the gradientface uses the quotient model and uses only two neighboring pixels to eliminate the light intensity, so it has the lowest recognition rate. LBP method has a small spatial support area, can only capture the small scale features of face images and it is sensitive to noise, so although it gets a higher recognition rate in some points than LBPMSLDE, its variance is relatively large. Most of the illumination methods are based on Lambertian model, thus they can deal with in controlled illumination variations to some extent. However, uncontrolled lighting conditions may not be well described by Lambertian model. So MSLDE method can do well in ORL、FERET, but not do well in Extended Yale B and CMUPIE. Since the LBP is a feature extraction method, the texture features of the face will not change much under the influence of illumination, pose, expression and occlusion and the multiscale logarithmic difference method is adopted to obtain small scale features and large scale features, so LBPMSLDE achieves effective, robust and applicable results.

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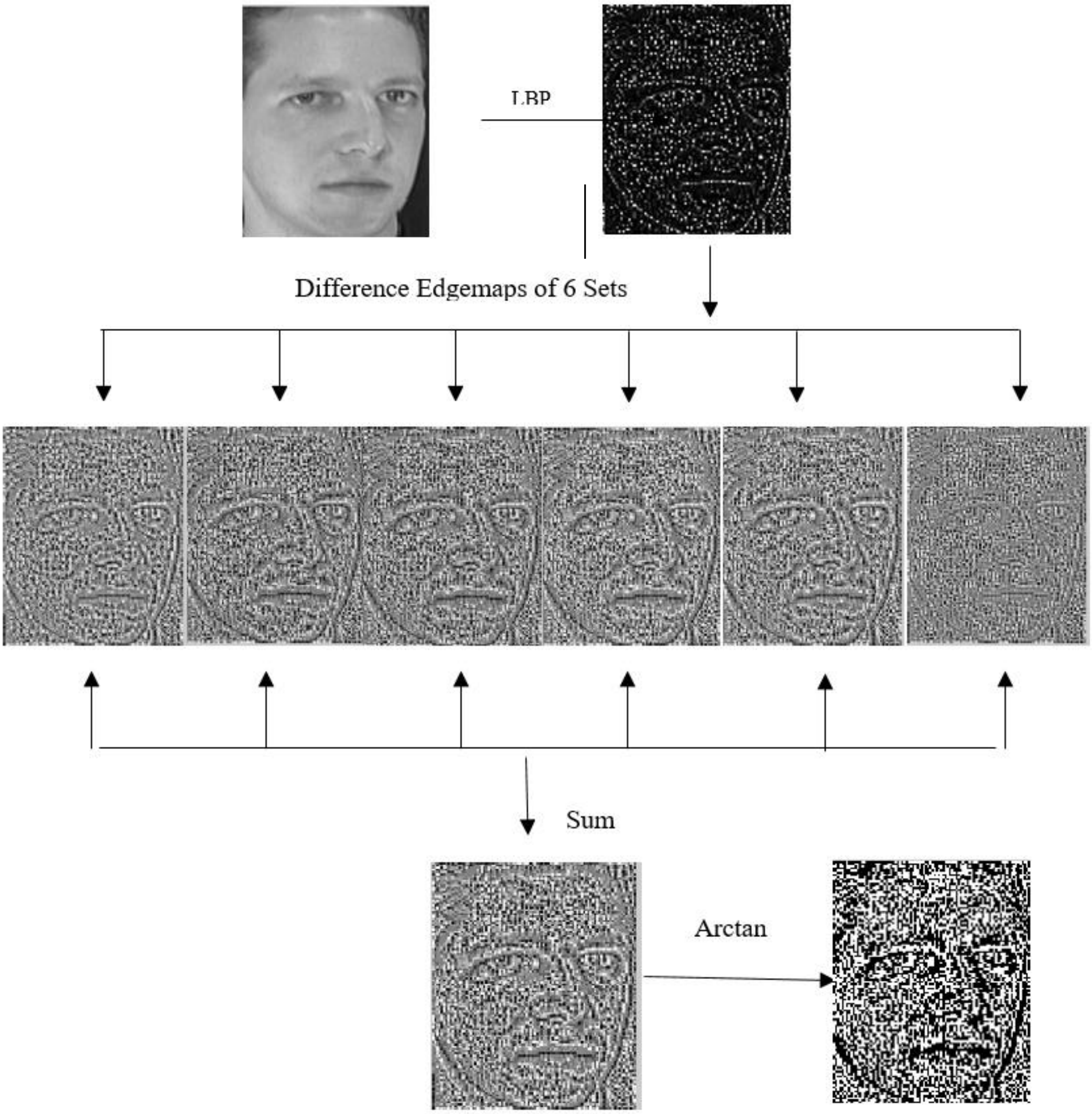

Fig.7. Diagram of the whole LBPMSLDE algorithm

Table 3. Recognition rates for different methods on Extended Yale B, ORL, FERET, CMU PIE

Dataset	Extended Yale B	FERET	CMU PIE	ORL
method	Mean±std	Mean±std	Mean±std	Mean±std
LBPMSLDE	0.9685±0.0140	0.9996±0.0011	0.9723±0.0068	0.9700±0.0232
LBP	0.9553±0.0187	0.9442±0.0604	0.9295±0.024	0.8935±0.0300
MSLDE	0.9244±0.0137	0.9500±0.0478	0.9320±0.0435	0.9533±0.0358
Gradientface	0.9021±0.0145	0.2851±0.0471	0.9278±0.0080	0.5500±0.0764

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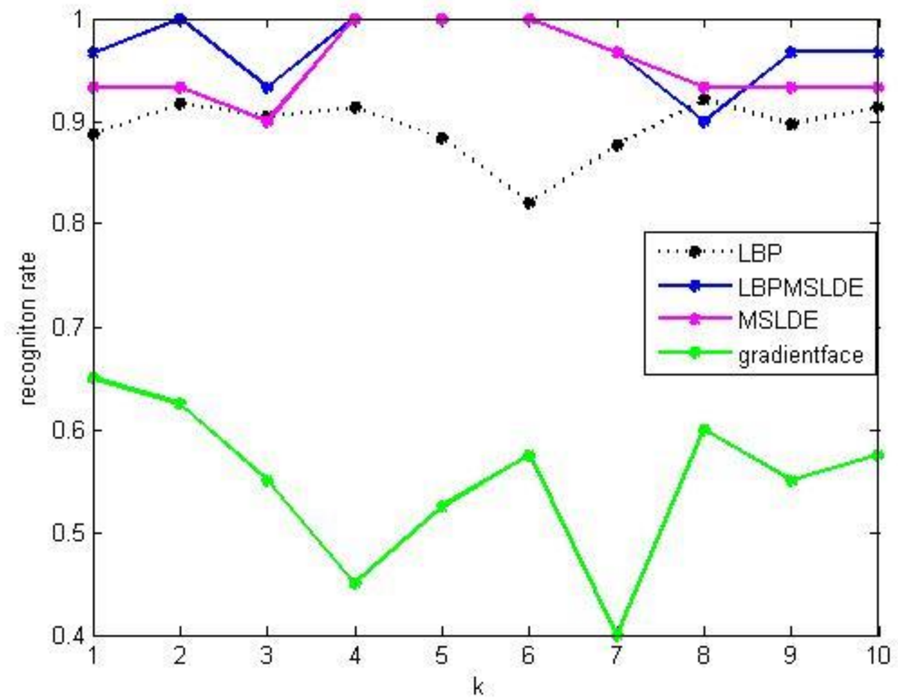

Fig.8. Plots of 10 Recognition Rates for Different Methods on Extended Yale B.

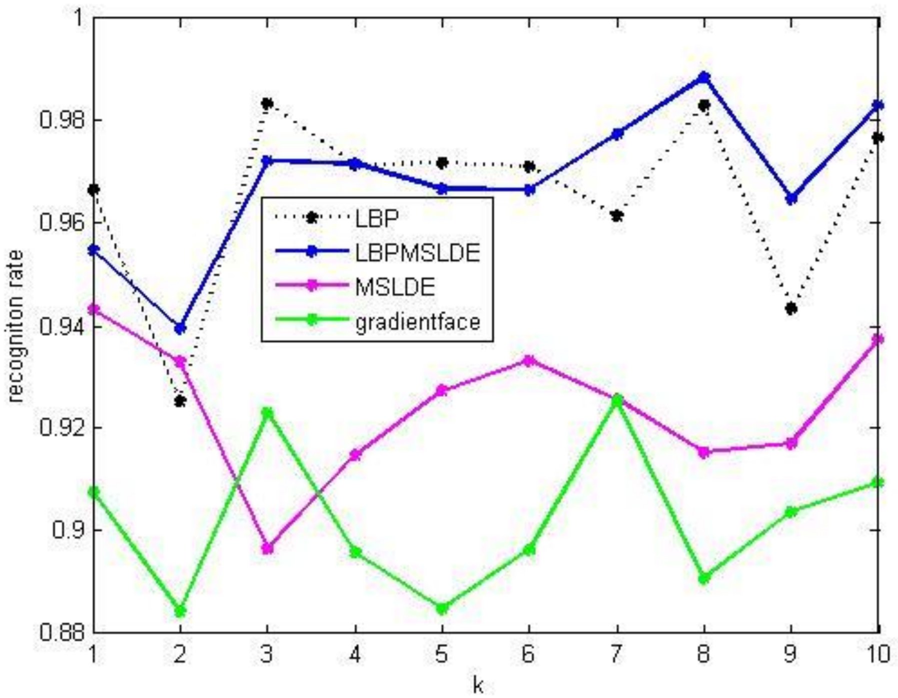

Fig.9. Plots of 10 Recognition Rates for Different Methods on ORL

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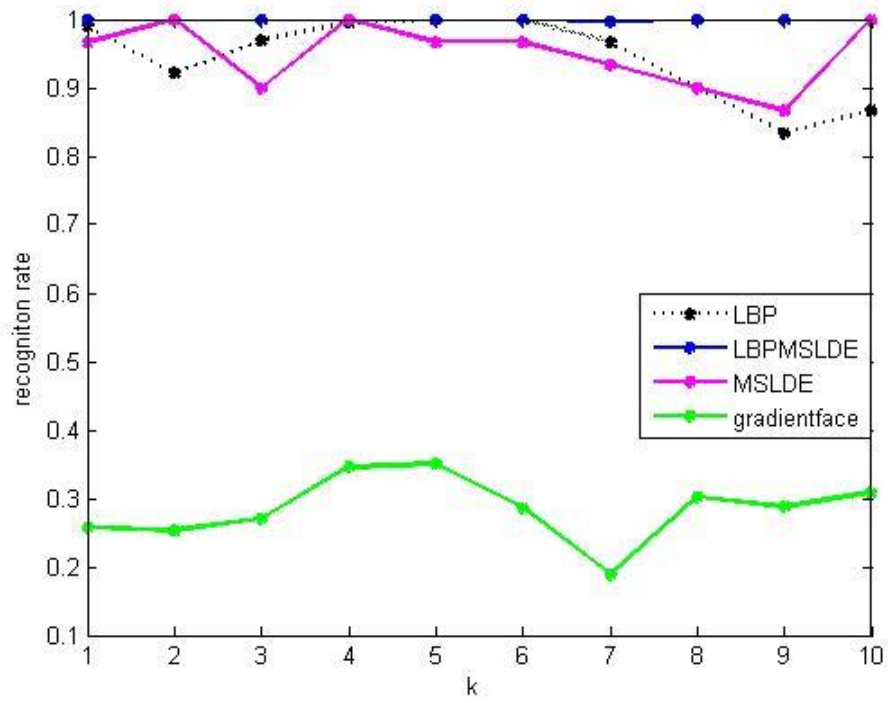

Fig.10. Plots of 10 Recognition Rates for Different Methods on FERET

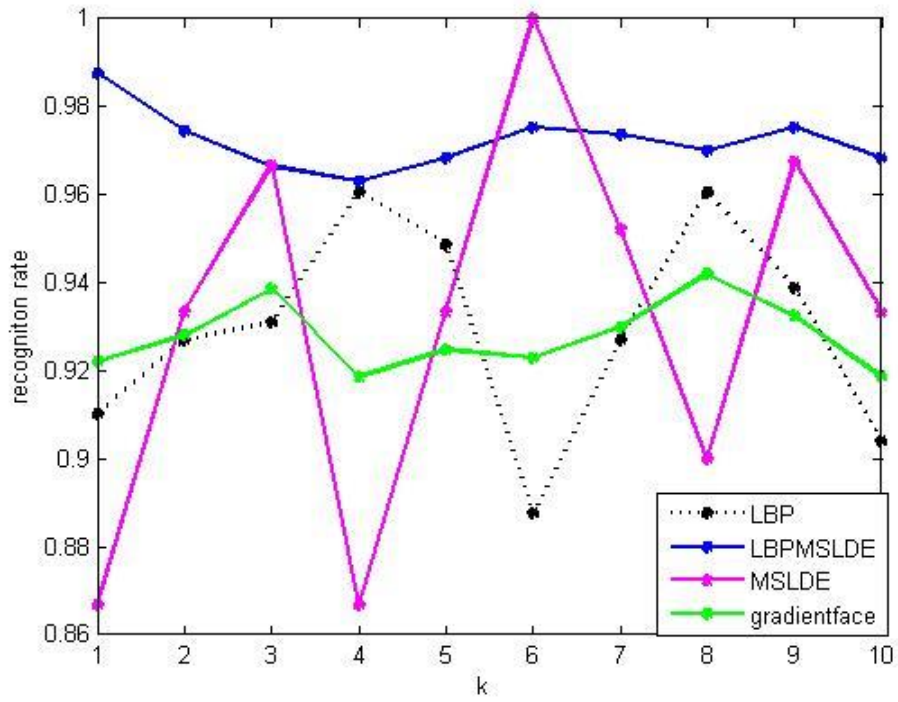

Fig.11. Plots of 10 Recognition Rates for Different Methods on CMUPIE

5. Conclusion

This paper proposes a novel image processing method LBPMSLDE to deal with illumination variations, pose variations and occlusion variations, so that the proposed method can be applied in real-world scenarios. It employs a logarithm difference model that can eliminate light intensity. Each logarithm difference feature-map is multiplied by a weight to adjust its influence in the final holistic feature-map, to further filter out light intensity, which is better than ill-posed quotient models and Gradientfaces which only involve a neighboring pixel that are not sufficient for multi-scale treatments. Experimental results show that the proposed method has the best mean recognition rate among all the compared methods. LBPMSLDE performs very effectively

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and is much better than other methods in different illumination and pose conditions. In summary, LBPMSLDE is effective, robust and applicable to many different scenarios, thus it has a promising prospect and is worth further investigations.

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