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A Novel Method of Gradient-Based Illumination Invariant Face Recognition

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Abstract:

The effect of illumination variation is one of challenging problems in a face recognition system, which can dramatically reduce the performance of face recognition. In order to solve this problem, this paper proposed a novel method for face recognition. First of all, illumination insensitive representation of image is extracted, which is based on the ratio of gradient amplitude to the original image intensity in the domain. Then, combined with the analysis of NS-LDA algorithm for feature extraction, and finally classified with the nearest distance classifier. Compared with the existed representative approaches, such as LBP (Local Binary Pattern, LBP), WF(Weber-face, WF),GF (Gradientfaces, GF) ,this method has better recognition rate on CAS-PEAL, Yalefaces, Extended Yale B face database.

Keywords — **Face recognition, gradient domain, illumination insensitive representation, null space LDA.**

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I. INTRODUCTION

Face recognition, as one of the primary biometric technologies, is used to many areas such as biometric authentication, surveillance, human-computer interaction and multimedia management. A face recognition system generally consists of four modules: face detection, image preprocessing, feature extraction and face classification. Feature extraction is one of the most important parts in face recognition, which can provide effective information for distinguishing different faces. However, the feature extraction is affected by many uncontrollable factors, such as illumination, expression, position and other factors, which makes it difficult to improve the ratio of face recognition.

Illumination variation is a significant factor affecting the performance of face recognition in some degree, and some preprocessing methods can effectively reduce the impact of illumination variation, combined with an effective feature extraction algorithm can further improve the accuracy of face recognition.

In recent years, a variety of algorithms with illumination invariant have been proposed，which are some certain degree of robustness to illumination variations. They can be divided into three main categories. The first category is to handle the illumination normalization problem with the traditional image processing methods, Including histogram equalization[1] and logarithmic transformation[2].However, this category only adjust the gray level distribution and ignore the physical illumination model，so it is difficult to account for different lighting conditions. The second category takes advantage of illumination samples to learn a face model of the illumination variations. For example, Batur and Hayes proposed a segmented linear subspace model for illumination variation face images[3].Georghiades made use of the spherical harmonics representation for face recognition under variable lightings[4].However, the main disadvantage of this category require a number of gallery samples and (it) is not practical for applications. The third category attempts to extract illumination invariant features or illumination insensitive measure, such as Local Binary Pattern(LBP)[5],Local Phase Quantisation (LPQ)[6],[7],Weber-face(WF)[8],[9],Gradientface

(GF)[10],Singal scale Retinex(SSR)[11], Self-quotient image(SQI)[12]. This algorithm can be directly applied to images without training and reconstructing the samples. However, the performance of most of exist methods against the illumination variation is not ideal.

As we all know, the pixel points are not completely independent of each other, there are some relationships between neighboring pixel points. However, many of face recognition methods only considers such relationships between neighboring pixel points and ignore the underlying relationships between neighboring pixel points, but it is exactly this underlying relationships in gradient domain reveal underlying inherent structure of image data. So, the features extracted from gradient domain are more effective than that extracted from pixel domain. Considered of this we adopt a new illumination insensitive representation of face image , which is obtained on the ratio of gradient amplitude to the original image intensity[13].The proposed algorithm not only suppresses the effect of illumination variations in face recognition, but also can extract the key feature of face image with higher resolution capability.

Linear Discriminant Analysis is one of the most effective approaches of feature extraction. Wilks et al.[14],[15] created the classical Fisher discriminant method. However, it usually generate the small sample size problem, owing to lack of face gallery samples in the practical application of face recognition. Some solutions are proposed by some researchers, such as Fisherfaces [16], but this approach abandoned the null space of matrix within samples, resulting in the loss of information about discrimination, so there is no guarantee that the extracted feature vector is optimal . Chen et al. proposed a null-space linear discriminant analysis [17], which improved the above problem and utilized the null space discarded by FisherFace to obtain more discriminant information.

In this paper, a new face recognition method proposed for the illumination variation image. First of all, illumination insensitive representation of image is extracted, which is based on the ratio of gradient amplitude to the original image intensity in the domain. Then, combined with the analysis of NS-LDA algorithm for feature extraction, and finally classified with the nearest distance classifier. Compared with the existed representative approaches, such as LBP (Local Binary Pattern, LBP), WF(Weber-face, WF),GF (Gradientfaces， GF) ,this method has better recognition rate on CAS-PEAL, Yalefaces, Extended Yale B face database than the other methods given in this paper. Method flowchart shown in Fig. 1.

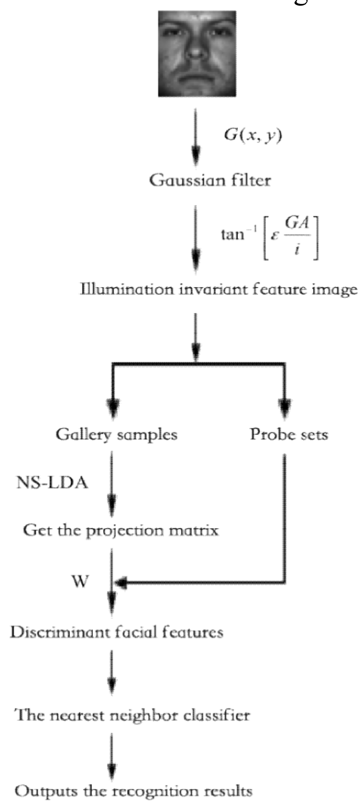

Fig.1 Flowchart of method proposed in this paper

The rest of paper is as follows. In Section II, illumination insensitive representation in gradient domain is introduced. Section III is about the null-space linear discriminant analysis algorithm. Section IV is related to the face databases and simulation results. The paper is concluded in Section V.

II. Illumination Insensitive Representation

In this part, we introduce the illumination insensitive feature of face image in gradient in details. We need to smooth the face image, using a Gaussian filter to make the gradient operation more stable against noise.

One hypothesis is that the input face image is $I(x,y)$, then

$$I'(x,y) = I(x,y) * G(x,y) \qquad (1)$$

in which, $G(x,y) = \frac{1}{\sigma\sqrt{2\pi}} \cdot \exp\left(-\frac{x^2+y^2}{2}\right)$,

the parameter, σ ,is chosen experimentally through an exhaustive search. Then we extract the illumination insensitive feature from the image. And the Lambertian reflection mode of image is as follows:

$$i(x,y) = R(x,y) \cdot L(x,y) \qquad (2)$$

where $i(x,y)$ is the image pixel value, $R(x,y)$ and $L(x,y)$ are the reflectance and luminance values. Due to the fact that $L(x,y)$ is the low-frequency component of the image and varies slowly, despite the abrupt changes in the reflection component, it is usually considered to be smooth, that means $L(x+\Delta x,y) \approx L(x,y)$, $L(x,y+\Delta y) \approx L(x,y)$,then we have

$$i(x+\Delta x,y) \approx R(x+\Delta x,y) \cdot L(x,y) \qquad (3)$$

$$i(x,y+\Delta y) \approx R(x,y+\Delta y) \cdot L(x,y) \qquad (4)$$

Some traditional illumination invariant operators such as Local Binary Pattern(LBP) and Weber-face are obtained by considering the gray value between pixels in the pixel domain. While, Gradientfaces is obtained in gradient domain because of the gradient domain contains more discriminative features than the pixel domain[18], which reveal the inherent relationship between the pixels.

In the gradient domain , according to the model (2) we get the partial derivatives of the image in the x and y directions is respectively:

$$\begin{aligned}\frac{\partial i(x,y)}{\partial x} &= \frac{i(x+\Delta x,y)-i(x,y)}{\Delta x} \\ &\approx \frac{[R(x+\Delta x,y)-R(x,y)]}{\Delta x} \cdot L(x,y) \\ &= \frac{\partial R(x,y)}{\partial x} \cdot L(x,y) \qquad (5)\end{aligned}$$

$$\begin{aligned}\frac{\partial i(x,y)}{\partial y} &= \frac{i(x,y+\Delta y)-i(x,y)}{\Delta y} \\ &\approx \frac{[R(x,y+\Delta y)-R(x,y)]}{\Delta y} \cdot L(x,y) \\ &= \frac{\partial R(x,y)}{\partial y} \cdot L(x,y) \qquad (6)\end{aligned}$$

The Gradientfaces approach, through dividing (5) and (6) to eliminate the illumination intensity value[18],and obtain the illumination insensitive representation. However, this approach neglects the image gradient amplitude information, which lead to the loss of some important features of face images. In the following, a new approach is acquired by considering the gradient amplitude.

The amplitude of image gradient is as follows：

$$\begin{aligned}GA &= \sqrt{\left(\frac{\partial i(x,y)}{\partial x}\right)^2 + \left(\frac{\partial i(x,y)}{\partial y}\right)^2} \\ &\approx \sqrt{\left(\frac{\partial i(x,y)}{\partial x} \cdot L(x,y)\right)^2 + \left(\frac{\partial R(x,y)}{\partial y} \cdot L(x,y)\right)^2} \\ &= L(x,y) \cdot \sqrt{\left(\frac{\partial R(x,y)}{\partial x}\right)^2 + \left(\frac{\partial R(x,y)}{\partial y}\right)^2} \qquad (7)\end{aligned}$$

The ratio of the gradient amplitude to the original image intensity value is:

$$\begin{aligned}\frac{GA}{i} &= \frac{L(x,y) \cdot \sqrt{\left(\partial R(x,y)/\partial x\right)^2 + \left(\partial R(x,y)/\partial y\right)^2}}{L(x,y) \cdot R(x,y)} \\ &= \frac{\sqrt{\left(\partial R(x,y)/\partial x\right)^2 + \left(\partial R(x,y)/\partial y\right)^2}}{R(x,y)} \qquad (8)\end{aligned}$$

Consequently, the ratio of the gradient amplitude to the original image intensity value is noting to do with the illumination intensity, which suppress the illumination effect significantly and leads to a robust illumination insensitive image representation with more discrimination power compared to the Gradientfaces.

In order to avoid the ambiguity because of the zero values of image intensity in the above ratio and reduce the noise , we use the tan-1 of the ratio, as follows:

$$\rho = \tan^{-1}\left[\frac{GA}{i}\right] \qquad \rho \in [-\frac{\pi}{2}, \frac{\pi}{2}) \qquad (9)$$

However, it will be found that the variation of the function value tends to be stable with the variable increasing. That means the change of ρ value is not obvious when the gray value of the original image is small, which makes texture features of image before and after the illumination processing can not keep synchronization. In order to solve this problem, we introduce parameter(negative number),and we can get the optimal illumination insensitive representation of image by adjusting the parameter values, which is expressed as follows:

$$\rho' = \tan^{-1}\left[\varepsilon \frac{GA}{i}\right] \quad \rho \in [-\frac{\pi}{2}, \frac{\pi}{2}) \qquad (10)$$

Finally, we obtain the illumination insensitive representation of the image. Figure 2 shows some sample images on the Extern Yale B face database and their illumination insensitive feature representations.

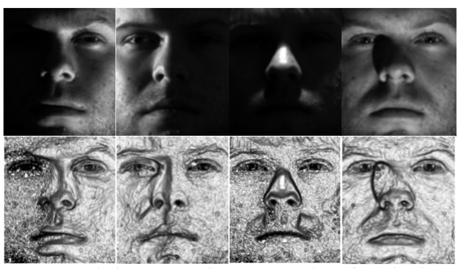

Fig.2 some sample images on the Extern Yale B face database and their illumination insensitive feature representations

III. The Null-space Linear Discriminant Analysis

In this part, we use the null-space linear discriminant analysis to extract the discriminative features of the image that is expressed by (10).

Let N be the gallery samples of face images, C is the number of face images category, N_i is the number of gallery samples of class i, then the within-class scatter matrix S_b, the between-class scatter matrix S_w and the total scatter matrix S_t is respectively:

$$S_b = \sum_{i=1}^{c} N_i (u_i - u)(u_i - u)^T \qquad (11)$$

$$S_w = \frac{1}{N}\sum_{i=1}^{c}\sum_{j=1}^{N_i}(x_{ij} - \mu_i)(x_{ij} - \mu_i)^T \qquad (12)$$

$$S_t = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)(x_i - \mu)^T = S_b + S_w \quad (13)$$

in which, $u_i = \frac{1}{N_i}\sum_{i=1}^{N_i} x_i$ is the mean value of the sample i, u is the mean value of all gallery samples , and x_{ij} is the sample j of the sample i.

The target of the linear discriminant analysis is to find a projection direction w that can maximize the within-class scatter matrix S_b and minimize the between-class scatter matrix S_w . For this, we need to refer to the Fisher criterion function:

$$J_F(w) = \frac{w^T S_b w}{w^T S_w w} \qquad (14)$$

In fact, the dimension of human face samples to be processed is usually very high. However, owing to the limitations of the practical conditions, the number of gallery samples we can get is insufficient that makes the between-class scatter matrix S_w is a singular matrix, which leads to a small sample problem.

In order to avoid the problem of small sample problem, the traditional Fisher-face LDA approach makes function (13) can be directly solved through discarding the null-space of the between-class scatter matrix.

But if $w^T S_w w = 0$ $w^T S_b w > 0$, then the objective function $J_F(w)$ of expression（14）reaches its maximum value, which means that some of the best projection direction w based on the Fisher criterion function are exactly in the null-space of S_w. We can see that the null-space of the between-class scatter matrix S_w contains many important discriminant information. The null-space linear discriminant analysis is one of the most effective approaches to solve this problem. The approach is to find the best projection direction in the null-space of the between-class scatter matrix S_w . The steps of the approach are as follows:

1) The PCA is used to reduce the dimension of the illumination insensitive feature image : The

within-class scatter matrix S_b ,the between-class scatter matrix S_w and the total scatter matrix S_t of gallery samples are calculated by using formulas (11),(12),(13) respectively. The eigendecomposition result of S_t is $S_t' = U^T S_t U$, where U is the eigenvector corresponding to the nonzero eigenvalue. Then the gallery samples are projected into the PCA space, and the between-class scatter matrix S_b' and the within-class scatter matrix S_w' are obtained as $S_b' = U^T S_b U$， $S_w' = U^T S_w U$.

2) Acquire the null-space of the within-class scatter matrix S_w'： The eigenvalues and the eigenvectors of S_w' are calculated, and Q is the matrix of eigenvectors corresponding to the non-positive eigenvalues of S_w' . The between-class scatter matrix S_b'' and the within-class scatter matrix S_w'' in the null-space are computed by using the formulas of (11) and (12) : $S_b'' = Q^T S_b' Q, S_w'' = Q^T S_w' Q$。

3) Elimination of null-space of the between-class scatter matrix S_b'' ： Calculating the eigenvalues and the eigenvectors of S_b'' ， and projection matrices V are composed of the eigenvectors corresponding to the nonzero eigenvalues。

4) The projection matrix of the discriminative feature extraction is $W = UQV$ for the inputted face illumination insensitive feature image. The gallery samples and the probe sets are projected on the matrix W to obtain their own discriminant features. Finally, the nearest neighbor classifier based on Euclidean Distance is used to classify and recognize.

IV. EXPERIMENTS

In this paper, firstly, reducing the noise by using a Gaussian filter after normalized the face image. Then through the formula of (10) extracting the illumination insensitive feature, and the discriminative feature is extracted by NS-LDA approach. Finally, we apply the nearest neighbour classifier based on Euclidean Distance for classify and recognize.

In order to test the stability of the proposed approach against image degradation caused by illumination variation, we proceed the experiments on three widely used databases, CAS-PEAL， Yalefaces and Extern Yale B. The CAS-PEAL database contains 40 individuals, each with 10 different illumination conditions and expressions . Yalefaces, there are 165 frontal images of 15 individuals with different illumination conditions and various facial expressions. Extended Yale B contains images of ten individuals with nine poses 64 illumination per pose. The experiment adopts 1280 frontal pose images of the top 20 individuals as samples, which is because the experiment studies illumination variation influence on the performance of face recognition.

The parameters in the approach will affect the performance of face recognition, which are chosen experimentally through an exhaustive search in this experiment.

The experiment is performed on the Intel(R) Core(TM) i50-4460 CPU @ 3.2GHz， storage is 4.00GB， VS2010+Opencv4.8.

A. Experiment one

The experiment adopts 1280 frontal pose images of the top 20 individuals as samples. They are divided into five subsets based on the angle of the light source directions. The five subsets are shown in Table 1.

TABLE1 SAMPLE CLASSIFICATION RESULTS

Subsets	Angle α	The number of samples
1	$0 < \alpha \le 12$	140
2	$12 < \alpha \le 25$	240
3	$25 < \alpha \le 50$	240
4	$50 < \alpha \le 77$	280
5	$77 < \alpha \le 90$	380

The experiment is devised to use the subset 1 as gallery images, the other images from subset 2 to 5 as probe set. Then the illumination insensitive features are extracted by using LBP[5],Weber-face[8], Gradientfaces, comparison results are shown in Fig.3.

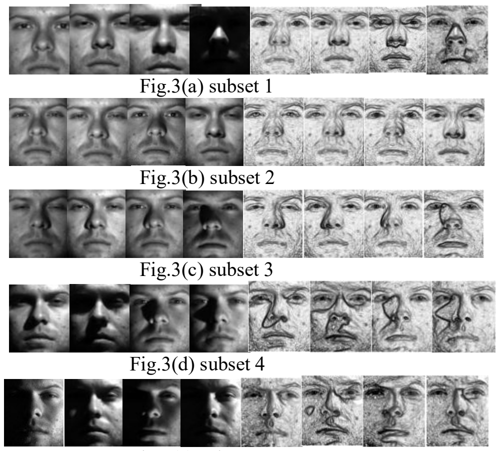

Fig.3(a) subset 1

Fig.3(b) subset 2

Fig.3(c) subset 3

Fig.3(d) subset 4

Fig.3(e) subset 5

Fig.3 Partial image and the illumination insensitive features of five subsets on Extended Yale B databases

The corresponding recognition rates of the each methods above for the five subsets on the Extended Yale B face database are illustrated in Table 2.

TABLE 2 EXTENDED YALE B DATABASES SUBSET 2-5 RECOGNITION RATE (%)

Methods	subset 2	subset 3	subset 4	subset 5
LBP	99.58	99.58	98.57	96.84
Weber-face	99.58	99.58	98.57	97.68
Gradientfaces	99.58	99.58	99.29	94.21
Proposed Method	100.00	100.00	100.00	98.42

Table 2 shows the performance of the proposed method under the various illumination conditions. We can see that the methods above achieve very high recognition rates on subsets 2-4, while the recognition accuracy drops significantly when probe sets come from subset 5 with extremely lighting conditions. In all cases ,the proposed method is better than other methods, indicating that the proposed method has a better robustness to illumination .

B. Experiment Two

We randomly selected five images from CAS-PEAL， Yalefaces，Extern Yale B face databases processed by illumination insensitive approach as the gallery, the other images as probe set. Owing to random selection of the gallery samples , we repeat the experiment 50 times independently to verify the effectiveness of the method. Finally, the average recognition rate is chosen as the index to evaluate the performance of different recognition methods. Table 3 shows the recognition results of the four methods on the above three face databases.

TABLE 3 RECOGNITION RATE OF DIFFERENT METHODS ON THREE FACE DATABASES (%)

Methods	CAS-PEAL	Yalefaces	Extended Yale B
LBP	95.23	98.00	96.62
Weber-face	71.04	80.60	92.74
Gradientfacees	96.14	98.67	98.26
Proposed method	96.39	99.01	99.29

As can be seen from Table 3, the recognition rate of the proposed method in CAS-PEAL, Yalefaces and Extern Yale B are 96.39%, 99.01%, 99.29% respectively. Since the CAS-PEAL database and the Yalefaces database is captured not only under variations in illumination but also under variations in expression, the recognition rate is lower than that of the Extended Yale B database. But on the whole, the recognition rate of the proposed method is better than the other three methods, which shows that the proposed method in the paper has good robustness against sever illumination.

The approaches of LBP and Weber-face only consider the relationship between the pixels and ignore the inherent relationship between them. Although he Gradientfaces approach considers that relationship, it neglects the gradient amplitude, resulting in the loss of texture information.

V. CONCLUSION

In this paper, we proposed a novel face recognition method for illumination variation. Firstly, an illumination insensitive image representation achieved in the gradient domain. Secondly, the null-space linear discriminant analysis is used to extract the discriminative features to the image. Finally, the nearest neighbor classifier based on Euclidean Distance is used to classify and recognize. Experiments were conducted on the three widely used face databases, CAS-PEAL， Yalefaces， Extern Yale B, and compared with LBP, Weber-face, Gradientfaces which demonstrates that the proposed method performed better than other illumination preprocessing, and had better robustness to the illumination of the face image and higher precision. That shows the proposed method is an effective method. But it also has the following shortcoming:

a． Gradient amplitude and the original image ration can capture the face illumination insensitive feature image, but lose the gradient direction information, while the gradient direction information is the important information in the face texture structure.

b．At the edge of the image , it can not avoid the appearance of halo that has some certain influence on the effective discriminating feature extraction.

Therefore， we will study above shortcomings to improve the performance of face recognition in the further work.

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