LOCAL CORRELATION CLASSIFICATION AND ITS APPLICATION TO FACE RECOGNITION ACROSS ILLUMINATION

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Abstract:

In this paper, a real face image is regarded as the result of adding the so-called "standard" face image under an ideal illumination condition to the corresponding "error image", which reflects the imaging difference between the real illumination and the ideal illumination. Furthermore, based on two propositions, we infer that for two images of the same face the correlation between two corresponding areas of the two images will be great enough, while the one between two corresponding areas of two face images of two different individuals will be low. From the viewpoint, a classification algorithm, which is based on a specific definition of correlation between two image areas, is developed. It is computationally tractable and may be regarded as one normalization method. Differing from other normalization methods, this algorithm need not explicitly normalize one face image. The experiment shows that the algorithm is efficient and very excellent for categorizing frontal faces with varying illuminations.

Keywords:

Face recognition; varying illuminations; PCA; local correlation classification

1. Introduction

Face recognition is one of the most challenging tasks in the area of pattern recognition. Obviously a varying illumination will make face recognition based on face images more difficult [1]. If the illumination condition varies severely, it will be possible that the difference between two face images of one person is greater than that between two images of two different individuals [1]. Many researches focus on developing some methods, which can perform well in classifying face images obtained under varying illumination conditions [2-8]. The existing methods devoted to the subject may be classified into three categories. The first kind of method aims at extracting invariant features across illumination, and then implements face recognition based on these features. For example, the quotient image [4] appears to be independent of illuminations and suitable for face recognition under various lighting conditions to some extent. The second kind of method tries to model face images with varying illuminations and then recognize the faces. The third kind of method may be called normalization methods, which attempt to transform face images into normalized ones and classify faces based on them. Note that these methods usually correspond to high computational costs.

In addition, classification methods associated with definitions of the correlations between two images have been widely applied in face recognition. Generally it computes the correlations between test face images and training face images and classifies faces using them. The cosine classifier is one typical example. When applied to face recognition across illumination, in some cases it may achieve acceptable classification accuracies. In some sense, the method is suitable for illumination invariant face recognition, because the correlation between two images is less related to illuminations, compared to the distance measurement between them. However, under the condition of complicated illuminations, it is possible that real face images of one person may be weakly correlative to each other, which may make the methods based on correlations unfavorable.

On the other hand, we may consider that one face image is composite of some areas, and in a certain area the pixel points correspond to similar gray values, while for two pixel points respectively from two different areas, the corresponding two gray values may be quite dissimilar. If there is a great variation of the illumination, the gray value difference between two pixel points respectively from two areas in a certain face image may be strong. However, it seems that within most of local areas with suitable sizes the intensity of the pixel point varies slowly within a small scope. As a result, for two images of the same face with different illuminations, the correlation of the corresponding two local areas may be high, even if the correlation of the two whole images may be not. In addition, it is noticeable

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that the modular PCA has recently achieved encouraging performance in face classification [5]. Its basic idea is also dividing one face image into some areas(sub-images) and performing PCA for all the areas respectively. However, this method is very time-consuming. In this paper we mainly focus on face recognition across illumination for frontal faces with fixed poses, based on the correlation between the corresponding sub-images from two different images. The proposed classification algorithm is feasible and computationally tractable, while it performs well in face recognition under varying lighting conditions.

2. The model of the "error image"

Assume that every face image may be regarded as the combination of the "standard" image, which may or may not be known and may be obtained under the condition of an imaginary ideal illumination, and the corresponding "error image". One error image is directly related to the difference between the real illumination and the ideal illumination and the corresponding face. Suppose that the error image is associated with the corresponding "standard" image as follows:

$$I_1(x,y) = k_1(x,y)I_o(x,y) + k_2(x,y)I_o^2(x,y) + \cdots,$$

where $I_1(x,y)$ is the intensity(gray value) of the point (x,y) in the error image, and $I_o(x,y)$ is the intensity(gray value) of the point (x,y) in the "standard" image. Hence, the real intensity(gray value) of this pixel point under the condition of the real illumination will be $I_r(x,y) = I_o(x,y) + I_1(x,y)$. In this model, I_o is the imaging of the face under the condition of the ideal illumination and reflects the ideal illumination and the character of the corresponding face, while the coefficients $k_1, k_2, \cdots$ show the effects on the imaging of the difference between the real illumination and the ideal illumination. We propose the following propositions.

Proposition 1. In an error image, the scales of the high-order terms $k_2(x,y)I_o^2(x,y)$, $k_3(x,y)I_o^3(x,y), \cdots$ are all much smaller than the one-order term $k_1(x,y)I_o(x,y)$, i.e. the following formula is almost satisfied for all the pixel points in one real image:

$$I_r(x,y) = I_o(x,y) + k_1(x,y)I_o(x,y).$$

Besides proposition 1, we propose another proposition on the error image as follows.

Proposition 2. For a point (x,y), there exists a neighbor $\Omega(x,y)$, in which the k_1 of all the pixel points are identical. In other words, the ratio of the error in gray value, mainly reflecting the difference between the real illumination and the so-called ideal illumination, to the corresponding "standard" gray-value is a constant within the neighbor.

For a suitable "neighbors", it can be expected that proposition 2 is almost satisfied. In two images, corresponding to two different illuminations, of one individual, suppose the areas corresponding to a certain Ω are Ω_1 and Ω_2 respectively. A correlation coefficient between the two image areas can be defined by the two corresponding vectors, i.e. the coefficient can be expressed as $corr(\alpha_1, \alpha_2) = |\alpha_1 \cdot \alpha_2| / \|\alpha_1\| / \|\alpha_2\|$, where α_1, α_2 are obtained by concatenating the pixel points in all the rows of the corresponding areas, the two areas own the same number of pixel points, and neither of α_1 and α_2 is zero-vector. In this paper $\{\Omega_1, \Omega_2\}$ is called an area couple, and Ω_1, Ω_2 are called two elements in the area couple. Based on the above two propositions, the following property can be derived.

Property 1. If Ω_1 and Ω_2 are two elements corresponding to a certain area couple derived from two face images of one individual under the condition of different illuminations, and neither of the corresponding vectors is a zero-vector, the correlation coefficient between Ω_1 and Ω_2 will be 1.

Proof. If the above two propositions are sure, the vectors α_1, α_2 corresponding to Ω_1, Ω_2 can be written as

$$\alpha_1 = [(1+k)I_{o1} \quad (1+k)I_{o2} \quad (1+k)I_{o3} \cdot \cdot \cdot]^T$$

$$\alpha_2 = [(1+k')I_{o1} \quad (1+k')I_{o2} \quad (1+k')I_{o3} \cdot \cdot \cdot]^T$$

Obviously, if both α_1 and α_2 are not zero-vectors, then $corr(\alpha_1, \alpha_2) = 1$. In a perfect case, an error image consists of a finite number of areas, in which property 1 is satisfied; consequently, the two images of the same face consist of different elements of area couples respectively. On the other hand, for two face images of two different individuals, there will be hardly any area couple owning property 1.

However, in most of real cases, proposition 1 and proposition 2 are not strictly satisfied. We may assume that two images of the same face respectively consist of different elements of area couples almost owning property 1, and for two face images of two different individuals, there are no area couples in which property 1 is approximately satisfied. Based on this supposition, an experiment scheme can be developed. Note that if a shadow area is included in one face image, the vector corresponding to the shadow area may be a zero-vector. Thus, for two areas, one of which corresponds to a zero-vector, it is defined that the correlation coefficient between them is zero.

3. Area partition and face classification

As presented above, we can suppose that two real face images of the same face respectively consist of elements in area couples approximately owning property 1 in section 2. But how to find these area couples is still a problem. In this paper the following simple scheme is adopted. An image is divided into some rectangles, and all the images are portioned using the same scheme. Let it be supposed that for every rectangular area the two propositions in section 2 are almost satisfied. In one image, all the rectangles are assigned different numbers in succession. In addition, the rectangular areas of every image are numbered by the same approach. If two rectangular areas respectively from two images are assigned an identical number, they are called two elements in one rectangle area couple. Then, for every rectangle area couple corresponding to one test image and each training image, the correlation coefficient between the two elements is computed. The summation of these correlation coefficients is called "image correlation coefficient" between the test image and the corresponding training image. If the "image correlation coefficient" between the test image and a certain training image is the maximum of all the "image correlation coefficients", then the test image is classified into the category of the test image. The above method is called local correlation classification.

Figure 1 shows two face images, corresponding to two different illuminations, of one identical individual.

0.65	0.94	0.95	0.95	0.96	0.89	0.77	0.81
0.84	0.94	0.90	0.98	0.98	0.98	0.95	0.87
0.87	0.87	0.85	0.92	0.85	0.87	0.79	0.88
0.89	0.98	0.97	0.81	0.87	0.89	0.97	0.97
0.87	0.98	0.74	0.90	0.81	0.73	0.96	0.99
0.95	0.95	0.92	0.81	0.82	0.88	0.95	0.97
0.99	0.93	0.79	0.85	0.90	0.91	0.97	0.98
0.98	0.96	0.95	0.95	0.96	1.00	0.99	0.97

Figure 1. The correlation coefficient between two elements of rectangle area couples derived from two face images of a certain individual(each face image is divided into 64 rectangular areas).

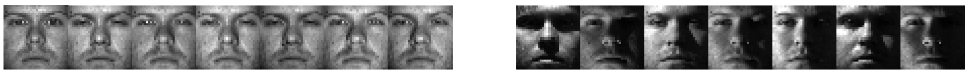
If the correlation is computed directly based on the two image vectors, the correlation coefficient is only 0.69. On the other hand, while the image is divided into 64 rectangular areas(each rectangular area consists of 4×4 pixel points), the average of the correlations of these rectangle area couples is 0.90. This means that with the definition of the local correlation, the images of the same face may become more similar, which can help us classify faces easier. It is noticeable that one rectangular area should contain enough pixel points. If the number of pixel points in one rectangular area is lower than some level, the correlation between two areas from two different individuals' images will be also large enough and the task of recognizinging faces may be difficult. For example, if each vector only corresponds to one point, the correlation coefficient between the two vectors must be 1 (except for the case that either of the vectors is a zero-vector).

4. Experiment

An experiment is performed based on the Yale B face image database. The images in the database are obtained with varying illuminations and unfixed poses. To focus on face recognition with varying illuminations, we select 45 face images with pose 00 for every person. Each of these images is cut as 32×32, and they are sorted to form a novel database, called new Yale B database. The new database is divided into 4 subsets(some images shown in Figure 2) according to the azimuth angle and the elevation angle of the light source with respective to the camera axis. Subset 1 includes the images in which the azimuth angle and the elevation angle are smaller than 12^0. Subset 2 includes the images in which both the azimuth angle and the elevation angle don't exceed 25^0 and either of them is between 20^0 and 25^0. Subset 3 includes the images in which the azimuth angle and the elevation angle don't exceed 50^0 and either of them is between 35^0 and 50^0. Subset 4 includes the images in which the azimuth angle and the elevation angle don't exceed 77^0 and either of them is between 60^0 and 77^0. The samples in subset 1 is regarded as training samples, and the others are taken as test samples.

For the new Yale B database, two classification approaches, respectively based on the cosine classifier associated with whole images and the local correlation classification, are performed first. Experimental results are showed in Table 1. Based on the cosine classifier for images, error classification rates for subset 2, subset 3 and subset 4 are 0%,8%,50% respectively. On the other hand, the local correlation classification achieves obvious improvement in right classification rates, especially for subset 4 in which the illumination is the most different from the training set. Note that, based on the divided 64 rectangular areas of each image, error classification rates for the three subsets are only 0%,0%,5% respectively. It appears suitable to divide each of these face images into 64 rectangular areas. In other words, the optimal size of the rectangular area is 4×4.

Moreover, an experiment on PCA and the modular PCA is performed. Error classification rates of PCA and the modular PCA are listed as table 2. Obviously PCA and the modular PCA do not perform well based on the distance classifier of ref.[5], and the local correlation classification(see the classification result in Table 1) is quite superior to them. Meanwhile, with the above the local correlation classifier, the performance of the modular PCA can be partially improved. It seems that in the transformation space derived from the PCA technique, the classification based on the local correlation is still workable and promising.



a) Several images in Subset 1 b) Several images in Subset 4

Figure 2. Some face images, obtained under different illumination conditions, of the same face

Table 1 Error classification rates on the new Yale B database

	Number of rectangular areas in each image	Error classification rates		
		Subset 2	Subset 3	Subset 4
The cosine classifier for the holistic images		0%	8%	50%
The local correlation classification	4(each with 16×16 pixels)	0%	8%	31%
	16(each with 8×8 pixels)	0%	8%	21%
	64(each with 4×4 pixels)	0%	0%	5%

Table 2. Error classification rates of PCA and the modular PCA on the new Yale B database

Algorithm	Number of rectangular areas in each image	Error classification rates based on ref.[5]			Error classification rates based on the local correlation classifier		
		Subset 2	Subset 3	Subset 4	Subset 2	Subset 3	Subset 4
PCA		6%	50%	79%	5%	44%	79%
The modular PCA	4(each with 16 × 16 pixels)	5%	36%	81%	2%	12%	70%
	16(each with 8 × 8 pixels)	28%	66%	85%	2%	13%	71%
	64(each with 4 × 4 pixels)	71%	77%	90%	3%	4%	60%

5. Conclusions

In this paper one face image is taken as the summation of one "error image" and the corresponding "standard" face image obtained under the condition of the so-called ideal illumination. It is assumed that within a certain suitable area, the ratio of the real gray value of the pixel point and the corresponding "standard" gray value in the "standard" face image is almost fixed. Then, for two face images, associated with two different illuminations, of one individual, the correlation coefficient between two corresponding local areas of them will be great enough, while for two images respectively corresponding to two different individuals, the correlation between two corresponding local areas respectively from the two images will be not high. From this view, a local correlation classification method is developed. It may be taken as one of normalization methods; however, unlike other normalization methods, the method can work well though the normalization face images need not be worked out.

The experiment on Yale B shows that the error classification rate of the local correlation classification is lower than that of the cosine classifier for holistic images. Compared to the cosine classifier, the severe the variation of the illumination is, the better the local correlation classification is. In addition, the local correlation classification can be also applied for face recognition based on the features extracted by PCA and the modular PCA, and encouraging classification accuracies are also achieved. Thus, it seems that the proposed model for the error image is reasonable and quite suitable for face images with varying illuminations and fixed poses. Moreover, the classification algorithm based on the model is computationally tractable, by contrast with other algorithms that aim to recognize face images with varying illuminations.

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