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Local entropy-based adaptive-weight LBP for face recognition

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ABSTRACT

To increase the success rate of face recognition, a local entropy-based adaptive-weight Local Binary Patterns (LBP) for face recognition is proposed in this paper. The entropies of different facial regions are adopted to define the contributions of different facial regions for face recognition adaptively, and then, weight-based method is adopted for face recognition in this paper. Simulation results show that this method has a high success rate of face recognition.

KEYWORDS

Face recognition;
Local binary patterns (LBP);
Local entropy;
Adaptive-weight.

INTRODUCTION

Compared with other biometric identification technologies, face recognition has distinct advantages due to its non-invasiveness and user-friendliness. It has been one of the main targets of investigation for researchers in biometrics, pattern recognition, computer vision, and machine learning communities. Commercial applications of face recognition technologies include access control, automated crowd surveillance, face reconstruction, mugshot identification, human-computer interaction, multimedia communication[1]. For decades, many face recognition algorithms have been proposed, such as Principal Component Analysis (PCA)[2], Linear Discriminant Analysis (LDA)[3], Local Binary Pattern (LBP)[4-10] and so on. The LBP method was proposed by Ojala in 1992, and it has been considered high efficient and immune to illumination variations. The use of histograms as features also makes the LBP approach robust to face misalignment and pose variations[1]. In order to reduce the cost of calculation and improve the robustness of LBP, Ojala et al. proposed uniform LBP and Rotation Invariant LBP[6]. The original LBP face recognition method computes simple histogram similarities, however, it only considers the global information of the face and loses the spatial information of facial regions, and thus, Multi-Block LBP face recognition attracts people's attention. This method gives the same weight to each region, and ignores the factor that some facial features (such as eyes) play a more important role in human face recognition than other features[7]. Zhao et al. proposed an adaptive-weight LBP-based face recognition method[8]. This method considers the variance of training facial images as the weight and it increases the success rate of face recognition to a certain extent, however, this weighted method costs a lot of time in calculating the weight of each sub block, especially when the number of training facial images is huge.

In order to increase the success rate of face recognition under occlusion and variations in illumination and pose with small sample, an adaptive-weight LBP-based face recognition algorithm is proposed in this paper. In this algorithm, a face image is divided into several non-overlapping regions of the same size, and

Example			Threshold			Weights		
6	5	2	1	0	0	1	2	4
7	6	1	1		0	128		8
9	8	7	1	1	1	64	32	16

Pattern=11110001 LBP=1+16+32+64+128=241

Figur 1 : Original LBP operator

entropies of each region are assigned to each region of the face to weight different facial features. This algorithm takes both local information of face image and spatial information of facial organs into consideration. Simulation results show that the proposed method in this paper has increased the success rate of human face recognition.

LOCAL BINARY PATTERN DESCRIPTOR

The original LBP operator works in a 3*3-pixel block of an image. The pixels in this block are threshold by its center pixel value, multiplied by powers of two and then summed to obtain a label for the center pixel[1]. The specific calculation process is shown in Figure 1. By applying LBP operator to each pixel of an image, we can obtain a series of LBP codes. These LBP codes are used to make histogram for the image. This histogram contains texture features of the image.

However, for a facial image, this histogram only contains the global texture information of the face and loses spatial information of facial organs. To codify the texture information while retaining also their locations, the facial image is divided into several sub blocks and LBP descriptors are extracted from each sub block independently. These descriptors are then concatenated to form a global description of the face, as shown in Figure 2[1]. A spatially enhanced histogram is used to gather information about LBP codes in all sub-blocks.

Another reason for dividing the image into several sub blocks and extracting LBP descriptors from the sub blocks is that sub block-based face recognition method outperforms holistic method under occlusion, variation in illumination, pose, and expression.

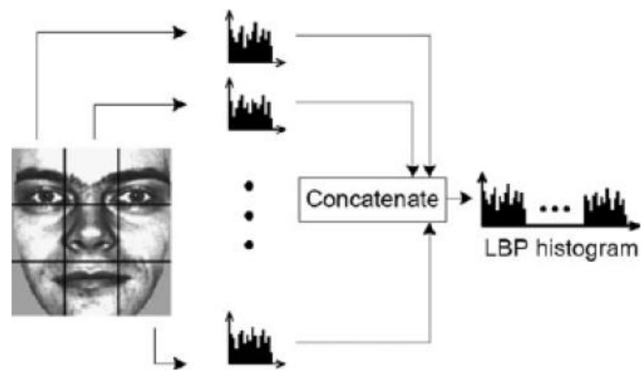


Figure 2 : LBP histogram

WEIGHT OF EACH SUB BLOCK

Although the results of the sub block-based method are better than the results of holistic method for face recognition under occlusion and variation in illumination, there are still effects caused by occlusion and variation in illumination on recognition result. Those occlusion and variations in illumination are not global and just appear in small parts of the facial images. To reduce the effect of the corrupted sub block caused by occlusion and variations in illumination on recognition result, an effective way is to give the corrupted sub block low weight for classification.

Weight based on variance

In[8], ZHAO et al. take the variance of sub blocks in the same position of all the training facial images as the weight of the corresponding sub blocks in probe image. Firstly, all the training facial images are divided into m*m non-overlapping equal-sized sub blocks. Then, the mean sub block of each position are calculated. Finally, the weight of sub block in each position is obtained by using the equation as follow:

$$Var^k = \frac{1}{N} \bullet \left[\sum_{i=1}^{N} d(S_i^k, S^k) \right]^2 \quad (1)$$

In which, N is the number of training facial images, S^k is the mean sub block of the k^{th} sub blocks of all training facial images, $d(S_i^k, S^k)$ denotes the distance between the k^{th} sub block of training facial image S_i and the mean sub block. As LBP method is used in this method, the distance is expressed by the chi-square distance between LBP histograms of the two sub blocks. The chi-square distance between the LBP histograms h^1 and h^2 is defined as follow:

$$\chi^2(h^1, h^2) = \sum_b \frac{(h_b^1 - h_b^2)^2}{h_b^1 + h_b^2} \quad (2)$$

In which, b denoted the bin in LBP histograms h^1 and h^2. In this situation, (1) is transformed to (3):

$$Var_k = \frac{1}{N} \bullet \left[\sum_{i=1}^{N} \chi^2 \left(h_i^k, h^k \right) \right]^2 \quad (3)$$

In which, h_i^k is the LBP histogram of the k^{th} sub block of training facial image S_i, and h^k is the LBP histogram of the k^{th} sub block of mean image.

This weighted method is based on the training facial image. The idea of this weighted method is that the changeful parts of human faces seem to be more discriminative than the changeless part of human faces. The variance is a measure to evaluate this variety. Therefore, the sub blocks whose variances are high should be given high weight and the sub blocks whose variances are low should be given low weight. This face recognition method increases the face recognition rate compared with original LBP face recognition method. However, it costs a lot of time in calculating the weight of each sub block, especially when the number of training facial images is huge. A weighted method based on the local entropies of sub blocks in probe image is proposed in this paper, which costs less time to calculate the weight of each sub block and outperform other LBP face recognition methods.

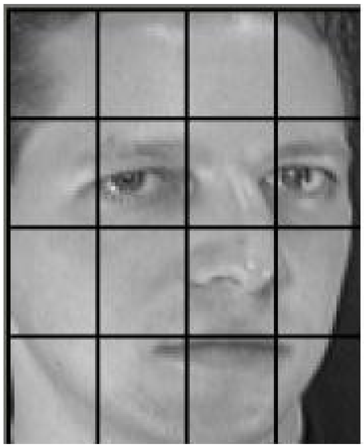
Weight based on local entropy

In information theory, entropy is a measure to evaluate the information content and it is defined by Claude E. Shannon in his paper "A Mathematical Theory of Communication" in 1948[12]. The information content is the average unpredictability in a random variable, in other words, the entropy is a measure to evaluate the average unpredictability in a random variable. For an image, information content contained in an image is decided by the intensities of the entire pixels in the image. The intensities of the entire pixels in an image are more variegated, and so the image will contain more information content. That is, the image entropy is a measure to evaluate the variegation of the pixel in an image. The image entropy of an image is defined as follow:

$$Entropy = \sum_{x=0}^{255} -p_x \log_2 p_x \quad (4)$$

In which p_x is the x^{th} gray value's probability in the image. Image entropy is an evaluation of the variegation of pixels in an image but does not contain spatial information. Compared with image entropy, local entropy is more meaningful to an image. Local entropy is calculated in a sub window of an image. It is more meaningful to an image because it contains the spatial information of an image. The definition of local entropy is similar to that of image entropy. The only difference is that p_x is the x^{th} gray value's probability in the sub block.

As the corrupted sub block caused by occlusion and variation in illumination usually present as a dark shadow, the local entropy of the corrupted sub block caused by occlusion and variation in illumination is usually low. Selecting the local entropies of each sub block as the weights of these sub blocks can reduce the effect of the corrupted sub block that will lead to bad recognition result. Another reason for selecting the local entropy as the weight of sub block is that some facial features (such as eyes) play a more important role in human face recognition than other features and the local entropies of human eyes are higher than the entropies of other features (such as nose and mouth). Therefore, selecting the local entropies of each sub block as the weight of these sub blocks can increase the face recognition rate. The entropies of different regions in



6.503	5.527	4.891	6.497
5.736	6.560	5.602	6.614
5.101	4.887	5.733	5.913
5.736	5.817	5.870	5.747

Figure 3 : Local entropies of each face regions

facial image are shown as in Figure 3.

As can be seen from Figure 3, local entropies of the upper facial regions are higher than local entropies of the lower facial regions in the image. This is because hair and eyes are on the upper part of the face. It also can be seen that local entropies of the regions on the right side are higher than those of the regions on the left side of the image. This is because the face in the picture turns to the left. What the most important fact is that the entropies of eyes (row 2, column 2 and 4 in the Figure) are higher than the entropies of other facial organs. Taking into account the factor that eyes contribute more in face recognition and local entropies of eyes are higher than other regions of facial image, local entropy of each sub block is selected to weight each sub block in this paper. Taking into account the physical meaning of the weights, these weights are normalized to values between 0 and 1[13].

CLASSIFICATION

For classification, the best way to classify histograms is to use a histogram similarity measure to compare model facial image and sample facial image. Histogram similarity measures include histogram intersection, log-likelihood, and chi-square distance, among which chi-square distance is adopted due to the excellent recognition rate by using chi-square distance in our experimental results. The chi-square distance is defined as follow:

$$\chi^2(\mathrm{S,M}) = \sum_{b=1}^{B} \frac{(\mathrm{S}_b - \mathrm{M}_b)^2}{S_b + M_b} \quad \textbf{(5)}$$

In which S and M denote (discrete) sample and model distributions, respectively. S_b and M_b correspond to the probability of bin b in the histograms of sample and model facial images.

Each sub block obtained in section 2 is fed into the classifier to get preliminary results, the final recognition result is based on these preliminary results. To get the final recognition result, a simple and effective way is to weight the preliminary results and sum all of them, which is shown as follow:

$$\chi_{\mathrm{w}}{}^2(\mathrm{S,M}) = \sum_{b,\mathrm{k}} W_k \frac{(\mathrm{S}_{b,\mathrm{k}} - \mathrm{M}_{b,\mathrm{k}})^2}{S_{b,\mathrm{k}} + M_{b,\mathrm{k}}} \quad \textbf{(6)}$$

In which, $S_{b,\mathrm{k}}$ and $M_{b,\mathrm{k}}$ correspond to the probability of bin b in the histograms of the k^{th} sub blocks of sample and model facial images, respectively. W_k is the weight of region k obtained in section 3.2, which is given by (4) and normalized.

1) To sum up, the specific algorithm in this paper is described as follows:
2) Divide the training facial image into regions, calculate LBP histogram of each region, and concatenate all of them in order to get a spatially enhanced histogram. Save the result in vector a_i.
3) Calculate the local entropy of each region, save the results in vector b_i.
4) Following step (1), calculate the spatially enhanced histograms of the sample image. Save

TABLE 1 : ORL face database (2 images for training, 8 images for recognition, regions n= 4*4)

	Original LBP	Weber's law based weighted LBP	Variance based weighted LBP	Method in this paper
Accurate recognition number	368	382	380	398
Failed recognition number	32	18	20	2
Recognition rate	92%	95.5%	95%	99%

TABLE 2 : ORL face database (4 images for training, 6 images for recognition, regions n= 4*4)

	Original LBP	Weber's law based weighted LBP	Variance based weighted LBP	Method in this paper
Accurate recognition number	373	384	381	400
Failed recognition number	27	16	19	0
Recognition rate Recognition rate Recognition rate Recognition rate	93.25%	96%	95.25%	100%

the results in vector c.

5) Calculate the chi-square distance between the sample image and each training face image according to equation (6). Use d_i to denote it.

6) Compare all the weighted chi-square distance. Choose the minimum chi-square distance $\chi_w^2(S, M_n)$, so the sample image belongs to class n. Then, display the recognition result.

EXPERIMENT RESULTS

In this paper, the process above is achieved on PC using OpenCV programming. The success rate of face recognition is obtained by simulating on the University of Cambridge's ORL face database. The PC system is Windows XP 2002, the programming environment is VC 6.0, CPU is INTEL I3, and the memory is 2G. The ORL face database includes 40 persons' face images and each person has 10 images which includes tiny facial expressions and post variants within the scale of 20%. In this experiment, the facial image is divided into 4*4 sub blocks. To assess the effect of different scales of model classes to recognition rate, the experiments based on different scales of model classes are conducted. To verify the effectiveness of the method proposed in this paper, it is compared with original LBP method and other weighted LBP methods (such as Weber's law based weighted LBP[14] and Variance based weighted LBP method). The simulation results are listed in TABLE 1 and TABLE 2.

As can be seen from TABLE 1 and TABLE 2, the number of training images influences the success rate of face recognition. The more the training images are, the higher the success rate of face recognition is. The success rate of face recognition of the three weighed LBP-based methods has been increased compared with the success rate of face recognition of original LBP-based method. Among these three weighted methods, the method based on Local Entropy-based Adaptive-Weight LBP outperforms the other two weighted LBP methods.

Simulation results show that the proposed method has a significant effect on increasing the success rate of face recognition. This is because the proposed method has the following three advantages. First, it takes into account the idea the idea in psychological theory that some facial features (such as eyes) play a more important role in human face recognition than other features. Second, it takes the meaning of entropy in information theory into consideration. Third, it considers the fact that the corrupted sub blocks are more probable to result in a wrong recognition.

CONLUSION

In order to further increase the success rate of face recognition under occlusion and variations in illumination and pose with small sample, a local entropy-based adaptive-weight LBP algorithm is proposed in this paper. The facial images are divided into several non-overlapping equal-sized sub blocks and match them all. In order to reduce the effect of the corrupted sub block caused by occlusion and variations in illumination on recognition result, all sub blocks are weighted. Taking into account the meaning of local entropy and the cost when the weight of each sub block is calculated, the local entropy of each sub block is selected to weight each sub block. Finally, the chi square distance is selected for classifying each sub block of the sample facial image to obtain the preliminary results. The final recognition result is obtained by weighting these preliminary results and summing all of them, in which the normalized entropy of each sub block is selected as the weight. The simulation results show that the proposed method in this paper has increased the success rate of human face recognition compared with other approaches without computational burden.

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