LOCAL BINARY PATTERN ORIENTATION BASED FACE RECOGNITION

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ABSTRACT

Scale-invariant feature transform (SIFT) is a feature point based method using the orientation descriptor for pattern recognition. It is robust under the variation of scale and rotation changes, but the computation cost increases with its feature points. Local binary pattern (LBP) is a pixel based texture extraction method that achieves high face recognition rate with low computation time. We propose a new descriptor that combines the LBP texture and SIFT orientation information to improve the recognition rate using limited number of interest points. By adding the LBP texture information, we could reduce the SIFT orientation number in the descriptor by half. Therefore, we could reduce the computation time while keeping the recognition rate. In addition, we propose a matching method to reserve the effective matching pairs and calculate the similarity between two images. By combining these two methods, we can extract different face details effectively and further reduce computational cost. We also propose an approach using the region of interest (ROI) to remove the useless interest points for saving our computation time and maintaining the recognition rate. Experimental results demonstrate that our proposed LBP orientation descriptor can reduce around 30% computation time compared with the original SIFT descriptor while maintaing the recognition rate in FERET database. Adding the ROI at our proposed LBP orientation descriptor can reduce around 58% computation time compared with the original SIFT descriptor in FERET database. For extended YaleB database, our method has 1.2% higher recognition rate than original SIFT method and reduces 28.6% computational time. The experimental results with adding ROI reduces 61.9% computation time for YaleB database.

Index Terms— face recognition, scale-invariant feature transform, local binary pattern

1. INTRODUCTION

During the past decades, there is a huge improvement in face recognition. Many algorithms have been proposed,nevertheless, there are still many challenging problems in the face recognition, such as under the conditions of different facial expressions, pose variations, illumination variation, facial occlusion and facial rotation. Those issues make face recognition with a challenging problem in biometrics and computer vision applications.

Current face recognition methods can be divided into two main categories, the holistic and the local descriptor approach. Eigenface [1] [2] and Fisherface approaches [3] that are based on the principal component analysis (PCA) and the linear discriminant analysis (LDA), are the classic holistic face recognition methods. The holistic methods can measure the entire characteristic of an image, however, they are easily affected by the pose variance or facial expressions. The local descriptor methods are more effective to describe the detail and stable information of an image. The Local Binary Pattern (LBP) method [4] is proposed to extract the texture information of a pixel and its neighboring pixels. Many methods based on the LBP are proposed, such as Sobel LBP [5], statistical LBP [6], local directional pattern (LDP) [7], and local tenary pattern (LTP) [8]. The LBP methods represent the relationship between a pixel and its neighbors. In recent yeas, N.S. Vu *et al.* propose the patterns of orientation edge magnitudes (POEM) [9] to combine the LBP with other texture methods. It is a descriptor with the orientation and LBP, and it is discriminative, robust, and computationally inexpensive in terms of both time and storage requirement. D. Lowe *et al.* [10] propose the scale invariant feature transform (SIFT) that becomes popular in face recognition for its robustness under the scale and rotation variations. However, the computation time increases with the number of extracted feature points.

In this paper, we propose a new descriptor using the LBP texture and SIFT orientation information. By adding the LBP texture information, we could reduce the SIFT orientation number by half and the computation time while keeping the recognition rate.In addition, we propose a matching method to reduce the useless interest points to save the computation time, and reserves the high useful points to maintain the recognition rate.

The rest of the paper is organized as follows. Section II presents the LBP orientation descriptor and the matching method that eliminates the useless interest points. Section III presents the experimental results. Section IV gives a brief conclusion and future works.

2. LBP ORIENTATION BASED FACE RECOGNITION

In this section, we present our LBP Orientation based face recognition method as shown in Fig. 1. Our proposed method is composed of two major parts, the LBP orientation descriptor and the matching method. First, we perform contrast enhancement by histogram equalization on the probe image. Then we find the interest points by the SIFT method and describe the information for each interest point by the LBP orientation descriptor. The descriptor is composed of two parts, the histogram of gradient and the LBP orientation. We get magnitude and angle from the gradient and make a 8-bin orientation histogram. Finally, the matching method and matching score is applied to determine the similarity between gallery and probe images.

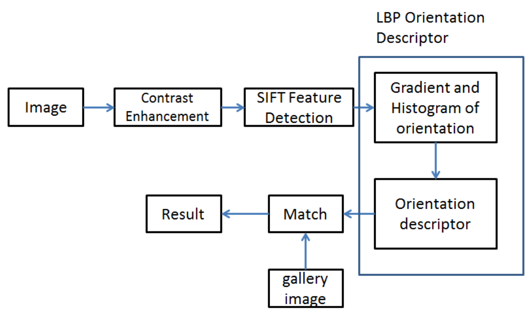

Fig. 1. The LBP Orientation Based Face Recognition flow.

2.1. LBP Oreintation Descriptor

After getting the invariable orientation for each interest point using SIFT, we make a descriptor to describe the interest points. First, the gradient magnitudes and orientations of the interest points are calculated. In contrast to the SIFT using 16×16 pixels to calculate the orientation histogram, we take more information from 20×20 pixels around the interest points. In Fig. 2, one block is composed of 4×4 pixels, and one cell is made of 5×5 blocks. We create a orientation histogram over the 4×4 pixels(one block). The orientation histogram has 8 bins covering the 360 degree ranges of orientation. Fig. 2 shows that there are eight bins for each orientation histogram in a block, with the length of each arrow corresponding to the magnitude of that histogram.

We obtain the orientation histogram of the cell. The orientation histogram computed them for eight individual orientation. As for each individual orientation in this cell, we use a 3×3 blocks LBP module to describe them. Traditionally, the LBP descriptor is calculated to produce the LBP histogram. To avoid the LBP histogram inaccuracy due to small range, we concatenate the LBP sequence for each individual orientation. There are $8 \times 9 = 72$ element feature vectors in the descriptor. Algorithm. 2 shows that flow of the LBP orientation descriptor.

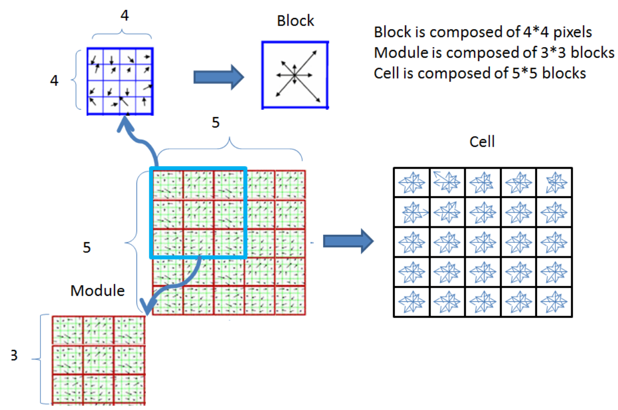

Fig. 2. The orientation histogram diagram. One block is composed of 4×4 pixels; one cell is made of 5×5 blocks.

Algorithm 1 LBP orientation descriptor algorithm

for orientation θ_i from 0° to 360° **do**
  for module j from 1 to 9 **do**
    for $a_{j,k}$ from 1 to 8 **do**
      $LBP_{\theta_i,j}(X) = s(m_{\theta_i,j,a_{j,k}}(X) - m_{\theta_i,j,c_j}(X))$
    end for
  end for
end for

The $m_{\theta_i,j,c_j}(X)$ is the histogram magnitude of the central block in module j with angle θ_i at the interest point X. The $m_{\theta_i,j,a_{j,k}}(X)$ is the histogram magnitude of the block around the central block at block k of module j with angle θ_i at the interest point X. The θ_i is the individual orientation from 0, 45, 90,..., to 360 degree.

Fig. 3 shows an example of the LBP orientation descriptor. The red arrow is individual orientation, which is at angle of 45 degree. The red square region is the LBP module, the blue square region is central block at this module. Fig. 4 shows 8×9 array of descriptor.

2.2. Matching Method

Traditionally, the LBP histogram descriptor uses chi-square, Euclidean distance or cosine similarity to measure the similarity between two histograms. However, the above methods may not find the best match due to the descriptor characteristics. We adopt three steps to improve the matching result. First, we use the xor distance to find the differences between zero and one of two histogram. Based on the xor distance, we select the best corresponding interest point in the reference image for each interest point in the test image. First, we discard the less discriminative interest points. A point is discriminative if its distance with the target interest point is much less

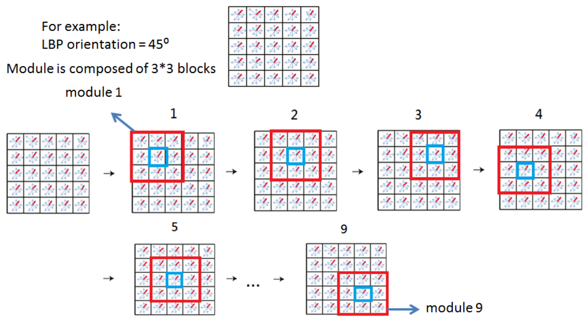

Fig. 3. The example for LBP orientation at angle 45 degree.

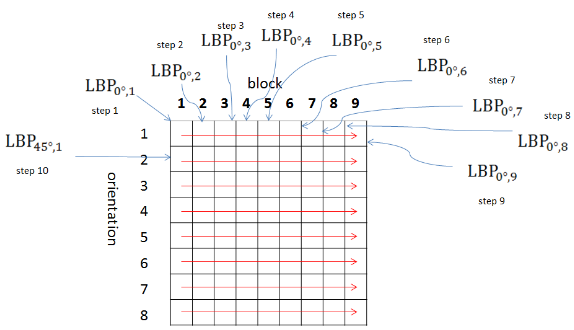

Fig. 4. LBP descriptor display by 2-D array.

than the others points. Next, we filter other incorrect matching pairs by the coordinate location. If the coordinate distance of a matching point is too far from the target point, it is removed. We obtain the final matching pairs through the above two selection steps. We combine the matching pairs number and the coordinate distances to calculate a score to represent the similarity of two images. The distances of all the final matching pairs are calculated and averaged. To reduce the error introduced by rotation, we use the median of all final matching pairs distance in the score calculation. It can be expressed as below.

$$distance_c = \sqrt{(X_p - X_q)^2 - (Y_p - Y_q)^2} - Median \quad (1)$$

$distance_c$ is the coordinate distance of a match pairs (X_p,Y_p) and (X_q,Y_q). The score equation is expressed as below.

$$Score = \alpha * distance_c + \beta * match_{num} \quad (2)$$

$match_n um$ is the matching pairs number. Our matching algorithm can be expressed as below. The computation cost in the SIFT method increase with the number of feature points. We propose a systems to eliminate the useless interest points and reserve the region of interest to reduce the computation time. We observe that most useful interest points are around the eyes and nose regions, especially the interest points on the edges.

Algorithm 2 Matching algorithm

for each probe image P **do**
  for each image Q in gallery data **do**
    for each interest point p_i in P **do**
      find an interest point q_k in Q such as the LBP xor distance p_i q_k is minimum, m1 is LBP xor distance p_i q_k
      find an interest point q_k1 in Q such as the LBP xor distance p_i q_k1 is second minimum, m2 is LBP xor distance p_i q_k1
      if if $\frac{m1}{m2} < T_r$ **then**
        p_i,q_k is a matching pair
        add p_i,q_k to the union U of matching pair
      end if
    end for
    for each pair U_i in union U **do**
      if $distance_c$ of $U_i < T_c$ **then**
        U_i is the final matching pair
        add U_I to the union FU of matching pair
      end if
    end for
  end for
  claculate the score
  Result
end for

Fig. 5 shows that the eyebrows, eyes, nose are the region of high correct matching.

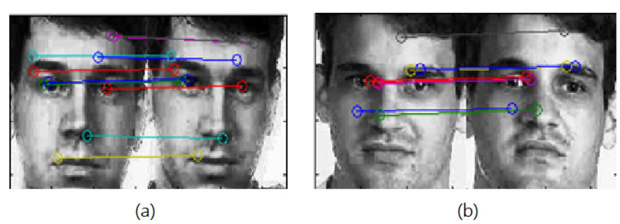

Fig. 5. The match pairs of (a) and (b) is collection in eyes, noses and on the edge.

3. EXPERIMENTAL RESULTS

The first experiment is to evaluate of the performance of the four subsets of the FERET database. The images contain variations in lighting, facial expression, and aging etc.. The subset Fa contain 1,196 frontal images of 1,196 subjects and it is used as the gallery set for other FERET datasets. The subset Fb contains 1,195 images with facial expression variations, and the subset Fc is under different lighting with 194 images. The DupI and DupII contain the aging images. There are 722 images taken between 0 and 1031 days for the corresponding gallery image in DupI, and 234 images taken at least one year after for the corresponding gallery images in DupII. The table 1 shows the recognition rate and processing time with SIFT, LBP, SIFT with our matching method, LBP orientation with our matching method and ROI/LBP orientation and our matching method. Our method saves about 30 percent computation time comparing with the original SIFT method, and has higher recognition rate than the original SIFT in the illumination condition for FERET fc database. Our proposed ROI LBP Orientation systems has 95.2% recognition rate and reduces 57.4% computational time in the FERET fb database.

Table 1. Recognition rate and Process Time with different method SIFT, LBP, SIFT+Match, SIFT+LBP+Match, SIFT+LBP+ROI+Match in feret fa with fb, fc, DupI, DupII.

database		SIFT	LBP	SIFT +Match	SIFT+LBP +Match	SIFT+LBP +ROI +Match
feret fb (1195)	recognition rate	95.9%	92.8%	96.4%	96.3%	95.2%
	execution time (s/frame)	0.817	0.151	0.838	0.580	0.349
	time ratio	1	0.184	1.025	0.710	0.426
feret fc (194)	recognition rate	66.1%	50.7%	66.3%	67.2%	64.7%
	execution time (s/fame)	0.086	0.150	0.089	0.061	0.036
	time ratio	1	1.741	1.036	0.714	0.422
feret dup1 (722)	recognition rate	65.2%	59.5%	66.1%	65.8%	61.8%
	execution time (s/frame)	0.947	0.151	1.005	0.696	0.417
	time ratio	1	0.160	1.061	0.734	0.440
feret dup2 (234)	recognition rate	55.4%	51.1%	55.9%	55.7%	54.1%
	execution time (s/frame)	0.981	0.151	0.989	0.695	0.410
	time ratio	1	0.154	1.008	0.708	0.418

The Extended Yale B database contains facial images from 38 subjects under 64 different illumination conditions and has 9 different poses. There are five subsets of this database according to the angle between lighting and camera position. The image with the frontal pose and illumination condition of P00A+000E+00 are used to be the gallery set images. In this experiment, all frontal face images are used to be the probe set images. Fig 6 shows the five different illumination condition of the Extended Yale B databases. Our method has the highest recognition rate in Extended Yale B and the lowest computation time. In this database, the ROI method has low recognition rate because the number of interest points is less.

(a) (b) (c) (d) (e)

Fig. 6. Extended Yale B database for different lighting condition: (a) yaleB01P00A+000E+00 (b) yaleB01P00A+010E+00 (c) yaleB01P00A+110E+40 (d) yaleB01P00A-25E+00 (e) yaleB01P00A-110E+00

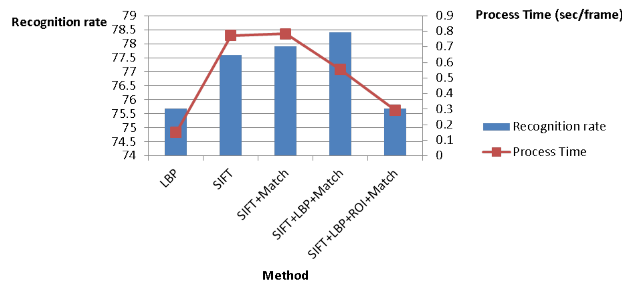

Fig. 7. Recognition rate and Process Time with different method SIFT, LBP, SIFT+Match, SIFT+LBP+Match, SIFT+LBP+ROI+Match in Extended Yale B.

4. CONCLUSION

In this paper, we propose a new descriptor and matching method for improving the SIFT algorithm in face recognition. The new descriptor combining the LBP texture and SIFT orientation information to improve the recognition rate using limited number of interest points. We also propose an approach using the region of interest (ROI) to remove the useless interest points for saving our computation time and maintaining the recognition rate. Experimental results demonstrate that our proposed LBP orientation descriptor can reduce around 30% computation time compared with the original SIFT descriptor while maintaing the recognition rate in FERET database. Adding the ROI at our proposed LBP orientation descriptor can reduce around 58% computation time compared with the original SIFT descriptor in FERET database. For extended YaleB database, our method has 1.2% higher recognition rate than original SIFT method and reduces 28.6% computational time. The experimental results with adding ROI reduces 61.9% computation time for YaleB database. In FERET database, our approach is comparable with original SIFT method with 30% computation reduction. In Extended Yale B database, our approach gains the higher recognition rate and the lower computation time. We extract feature in variant lighting conditions is better than the original SIFT method in Extended Yale B database.

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