Selection of Distinctive SIFT Feature Based on its Distribution on Feature Space and Local Classifier for Face Recognition

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Abstract: *This paper investigates a face recognition system based on Scale Invariant Feature Transform (SIFT) feature and its distribution on feature space. The system takes advantage of SIFT which possess strong robustness to expression, accessory pose and illumination variations. Since we use each of SIFT keypoint as the feature of face and SIFT keypoints are very complicated in feature space, we apply the feature partition on Self Organizing Map (SOM) and adopt local Multilayer Perceptron (MLP) for each node on map to improve the classification performance. Moreover the distinctive features from all SIFT keypoints in each face class are defined and extracted based on feature distribution on SOM. Finally the face can be recognized through the proposed scoring method depending on the classification result of these distinctive features. In the experiments, the proposed method gave a higher face recognition rate than other methods including matching and holistic feature based methods in three famous databases.*

Keywords: *Face recognition, SIFT, distinctive features.*

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1. Introduction

Face recognition has been proved to be one of the most successful applications for image analysis and understanding. However there are still some factors including face size, view direction, illumination and facial expression whose variance affects the accuracy of face recognition. Many techniques have been proposed to reduce these influences [18]. General techniques can be broadly divided into the holistic and feature based methods. The holistic based methods such as principal component analysis [13] or linear discriminant analysis [2], is to project input faces onto a dimensional reduced space and recognize the face in this space by using linear transformed value. They are considered to be very popular for their simplicity and good performance. However they assume face can be reconstructed by linear combination of eigenface or fish face so that they are very sensitive to variance of illumination and facial expression. One of popular feature based methods recognize face using distinctive facial components like eyes, nose, mouth which is required to be robust to facial variance. But the accurate position of these features is difficult to be located due to various view position and scale of faces [14].

Recently scale invariant feature transform proposed by lowe [10] extracts distinctive local feature from images. Scale Invariant Feature Transform (SIFT) feature has been proved to achieve invariance to change of image scale, rotation and illumination. So after SIFT was invented, many researchers used it for object recognition including face recognition. Conventional SIFT feature based methods use keypoints matching approach. Bicego *et al.* [3], who first attempted to SIFT approach for face recognition subdivided images in sub-images using a regular grid with overlapping then performed a matching between two images by computing distance of pairs of sub-images. However faces are all, more or less, visually very similar so that keypoints matching between two faces yields many more matches than it would if the two subjects are clearly distinctive. Therefore this approach results in a poor recognition performance when it comes to faces. Instead of matching approach, we designed a more efficient classifier based method. In this approach, we use each of SIFT keypoints as input of classifier for the feature of face. Since whole SIFT features extracted from face images are very complicated and various in the feature space, the proposed method apply the feature space partition on Self Organizing Map (SOM) [7, 8], and adopt the local Multilayer Perceptron (MLP) classifier [4], for each node on the map. Thus the multiple classifiers realize classification in subspaces for improvement on classification performance. However the local classifier based method still cannot guarantee a good face recognition performance without considering of confusing features and noise features which can be misclassified very easily. The proposed method intends to categorize SIFT feature into distinctive and non-distinctive features for distinguishing faces based on their distribution on SOM. The distinctive features are the features of individual face class which are distinctive to ones in other face classes. The non-distinctive features include the common features in different face classes and noise features in all images. From the feature distribution on SOM, we define the dominant class in which much more patterns are contained than other classes in each node. The dominant classes in each node contain the patterns which are distinctive to other faces. According to the classification results, these distinctive patterns in each node respect to the dominant face class are on a higher classification rate. So the proposed method selects the distinctive patterns and uses the scoring method to calculate the score of each class according to the classification result of these distinctive patterns. Finally, the test image is recognized as the class ID which has the max scores.

The overall structure is as follows. In Section 2, we present the proposed approach including several main steps to achieve high performance of face recognition. Section 3 provides the detailed experimental results in three famous databases [5] comparing the proposed method to other existed methods. Section 5 summarizes the contribution of this paper.

2. Proposed Approach

The proposed face recognition system shown in Figure 1 contains five main steps including image preprocessing, SIFT feature extraction, SOM partition, Multiple MLPs classifier and Scoring method for face recognition. Firstly, the input image is cropped into the face image only with little background (face detection technology). Then the patterns are extracted by using SIFT as the features of face image. Each of features is described as a 128 dimensional vector. On the third step, the SIFT feature space are partitioned on SOM by mapping each 128 dimensional patterns into 2D map. After that we assign the local MLP to each node on map for patterns classification. As a result, output of the local classifier assigns the face ID to each of the patterns in the subspace. On the last step, we determine the face ID using the proposed scoring method from the feature distribution on SOM and the classification results of local MLPs. This method selects the distinctive features for each face class and recognizes face through the classification results of the distinctive features.

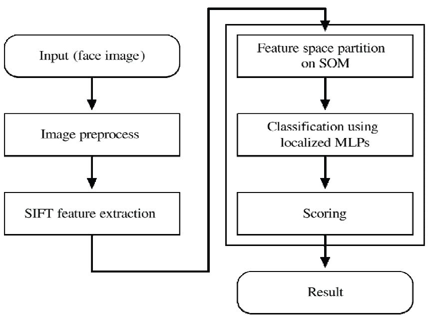

Figure 1. Outline of proposed face recognition system.

2.1. Feature Partition on SOM

There are several important motivations to use feature partition on SOM before classification. At first, the large variety of SIFT patterns extracted from face in feature space increases potential difficulty to give discriminate boundaries for classifying patterns into face classes by using only one classifier. SOM is applied to divide the feature space into subspaces by clustering similar patterns together and represent each subspace as node on a 2D map. Actually each node indicates each subspace and the location of the nodes on SOM give the platform to assign local MLPs as shown in Figure 2. The distance between each pair of neighbourhood nodes on the map are relatively shorter so that patterns located on the boundary of neighbour nodes are very similar. When adopt one MLP to each node, if only the patterns in the node are used for training corresponded MLP, the trained MLP may misclassify this kind of confusing patterns located on the boundary. To avoid this problem we utilize the neighbourhood relation to train each local MLP by using patterns inside its node and neighbour nodes together on 2D map. Last but most importantly, the SIFT feature distribution on SOM help find out the dominant class in each node. We proved that the dominant class contains the distinctive patterns for each face class. More details will be discussed later.

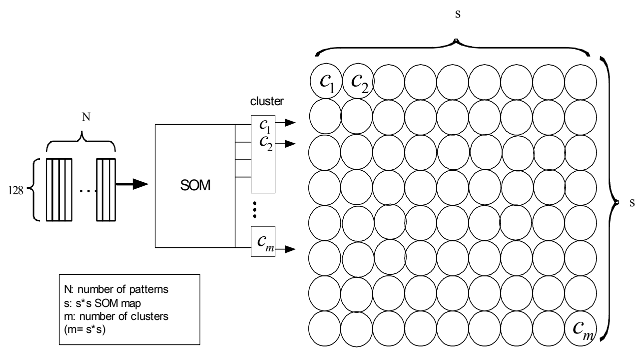

Figure 2. SOM clustering of SIFT features.

In the learning process, the training SIFT patterns extracted from training images are clustered by SOM. After learning process, the training patterns are distributed on each node on the 2D map and the weight of each node is saved for clustering new test patterns.

The SOM consists of neurons on a regular 20*20 two-dimensional grid map. The size of map is determined by the amount of patterns for training. Each neuron on the map is represented as a 128-dimensional weight vector. The neurons are connected to adjacent neurons related to a neighbourhood function which dictates the topology of the map. We define the neighbourhood function as the Gaussian function:

$$h_{ci}(t) = \eta(t) \cdot \exp\left(-\frac{\|r_c - r_i\|^2}{2 \cdot (\sigma(t))^2} \right) \quad (1)$$

The learning rate $\eta(t)$ which depends upon the iteration number t is chosen to decrease linearly as a function of time.

$$\eta(t) = a_0 \, (1 - t \,/\, t\,max) \tag{2}$$

Where a_0 is the initial learning rate and *t max* is the max number of iteration circles. In one circle of iteration, each input pattern x in training set is compared all W_n obtaining the node of the close match.

$$|x - W_c| = min\,|x - W_i| \tag{3}$$

Nodes in the SOM are updated according to:

$$W_i(t+1) = W_i(t) + h_{ci}(t)\left[x(t) - W_i(t)\right] \tag{4}$$

When all training patterns are mapped to the location of the SOM, one learning circle is finished then the second circle starts. The learning process is ended when it meets the stop condition iteration circles *t=t max*. After the learning of SOM, the final updated weight determines the sub feature space in which similar patterns are clustered together. This 2D map supplies the platform to assign multiple MLP classifiers on the nodes. Moreover the defined distinctive features are selected from the distribution of feature on the map.

When testing the unknown patterns from a test image, the input patterns are clustered into each node on SOM automatically according to the weight set produced in the training process. By this way, the test patterns in the feature space are distributed to their own belonged sub space on SOM. On the next step, we use the patterns in each node on SOM as input of local classifier and classify them into corresponded face class.

2.2. Classification Using Local MLPs

As discussed above, the sub space on SOM composes the input space of local classifier. We apply multiple MLPs for SIFT patterns classification based on the structure of one MLP corresponded to one node as shown in Figure 3. Thus each node is given by a specific MLP classifier. There are totally 400 local MLPs used for pattern classification in the case of 20*20 SOM.

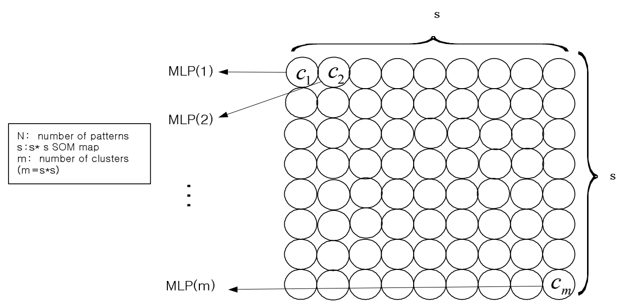

Figure 3. Structure of local MLPs based on SOM.

For training of local MLP, we use patterns not only in the corresponded node but also in neighborhood nodes as input of MLP. The objective of neighborhood training was discussed in the previous part. We define the relation of neighborhood by using one central node and its four adjacent nodes including the node on left, right, above and below. So the input patterns of local MLP are the patterns clustered in 5 nodes.

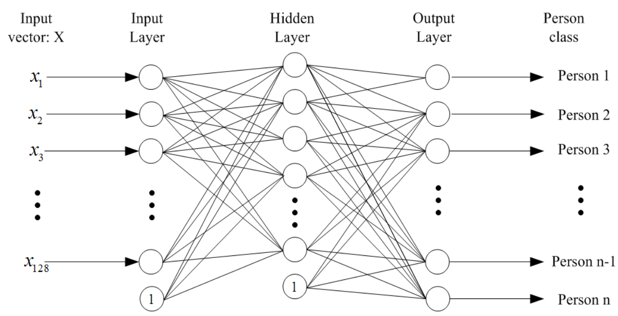

Figure 4. The architecture of local MLP for each node.

Next we introduce the basic architecture and parameters for local MLP used in this system. The architecture of deigned MLP is shown in Figure 4. Number of neurons in input layer is equal to 128 which is dimensional value of SIFT patterns. We use one hidden layer with 20 neurons which has been tested as the best performance. Number of output neurons is corresponded to number of face classes. The activation function is defined as bipolar sigmoid function:

$$f(x) = \frac{1}{1 + e^{-kx}} \tag{5}$$

The output value in each neuron varies from -1 to 1. The value in output neuron which corresponds to the key-point's class ID should be trained to approach 1 and value in the other neurons should be trained to approach -1. After the training process of all local MLPs on SOM, the weight set of each classifier is saved for testing new patterns.

The training process has been explained above. To test a new face image, the SIFT patterns extracted from the image are firstly clustered into sub space through the trained SOM. Then the trained local MLPs are applied to classify patterns distributed in the belonged nodes into face class. As mentioned before, output layer of MLP contains n neurons which indicate the number of face classes. From the output of MLP, the neuron of output layer which has the highest value is defined as the class ID of the input feature. By this way all the patterns in the node are processed through MLP and the output of MLP assign face ID to each of them.

The Multiple local MLPs based on feature distribution on SOM are proposed to achieve the improvement on the classification performance by partition classification. The classification rate of each MLP is calculated as number of correct classified patterns by the total number of input patterns. The whole performance of the multiple MLPs design is evaluated on the integration of all the classifiers. The classification result of the MLPs also helps us analyze the characteristic of the node and patterns distribution on SOM.

2.3. Feature Distribution on SOM

The SIFT patterns not only vary from value in the feature space but also vary from individual images. The extracted SIFT patterns include common patterns on different faces and noise patterns in individual image. These patterns from various faces can also lead to a low classification rate for classifying each pattern into face class. To overcome this problem, we categorize SIFT patterns into distinctive and non-distinctive features. The distinctive features are the own patterns of one face but distinctive to other faces. The non-distinctive features include common patterns on different faces and noise patterns in individual images. From the analysis of feature distribution on SOM for each face class, there are some nodes in which number of patterns clustered in this face class is much larger than other classes. We select index of these classes as the dominant class in the nodes. More importantly, we find out the classification rate of the patterns clustered in the dominant class of each node are relatively much higher than others from local MLPs classification result. It proves that the patterns clustered in the dominant class are the distinctive features to other classes. From the experiment result, some real sample of SIFT feature distribution are shown as follow: in Table 1, the shadowed class is the dominant class in the sample nodes and the value indicates the number of patterns in individual class of each node. Table 2 gives the corresponded classification rate of patterns from face class. We can see that the classification rate of patterns in dominant class of sample nodes is relative much higher. So we call the patterns in the dominant class the distinctive features of corresponded class.

The dominant class for each class is defined before selecting the distinctive features. From the SIFT features distribution on SOM, the number of patterns of individual class in each node can be obtained. If the number of class satisfies the conditions 6 and 7, we call this class the dominant class of this node.

$$\frac{N^{i}_{\max}}{N^{i}_{total}} > \frac{n}{P} \tag{6}$$

$$\frac{N^{i}_{c}}{N^{i}_{\max}} > T \tag{7}$$

where N^{i}_{total} is total mbenur of patterns in node i, N^{i}_{max} is the max number of patterns among P face classes in node i and n should be no less than 2. T is the threshold value. Some real data examples from experiment are shown in Table 1. The slight shadowed classes satisfy the condition 6 so they are dominant class in node. The darker shadowed classes satisfy condition 7, so they are also dominant classes in node.

Then we can make up the dominant class map of each class which is represented as node index on SOM. The simple example of 3 classes is shown in Figure 5. For each class, the patterns clustered in the selected nodes on its dominant class map are the distinctive features for this class.

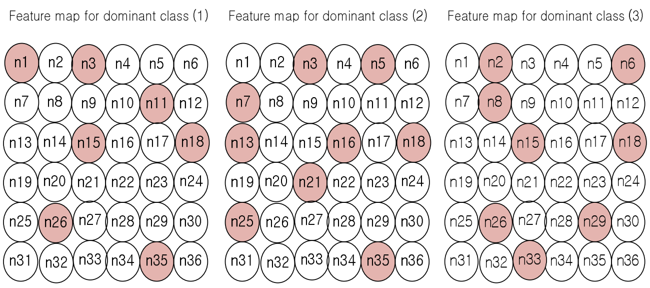

Figure 5. The dominant class map of 3 example classes.

Table 1. Dominant class in some sample nodes (test data from Markus Weber database).

Node \ Class	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	Total Num
305	1	17	2	2	4	0	1	0	3	4	0	2	4	1	0	2	43
207	1	3	0	2	3	2	26	3	6	6	1	9	3	3	1	1	70
329	2	6	3	0	0	21	0	4	0	0	0	0	0	5	1	0	42
87	3	2	0	0	0	0	2	15	2	5	0	1	2	2	0	0	34
282	8	4	5	6	11	2	4	4	36	14	6	9	8	2	5	0	124
9	0	0	0	0	0	0	8	1	19	4	1	2	2	0	0	0	37
101	3	3	0	3	4	1	11	3	14	4	7	3	4	2	4	3	69
254	0	4	12	0	0	0	0	1	0	0	2	0	0	12	1	20	52

Table 2. Classification rate of patterns in some sample nodes.

Node \ Class	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	Average
305	0	0.94	0	0.5	0	-1	0	-1	1	0.5	-1	0	0.75	0	-1	0	0.58
207	0	1	-1	0.5	0.67	0	0.96	0.67	1	0	1	0.11	0	0.67	1	1	0.64
329	0	1	0	-1	-1	1	-1	0	-1	-1	-1	-1	-1	1	1	-1	0.79
87	0.33	0.5	-1	-1	-1	-1	0	0.93	1	1	-1	1	0.5	0	-1	-1	0.74
282	0.12	0	0.2	0.33	0.64	0.5	0.5	0.5	0.86	0.43	0.33	0.44	0.25	0	0	-1	0.49
9	-1	-1	-1	-1	-1	-1	0.87	0	0.95	0.5	0	1	0.5	-1	-1	-1	0.81
101	0.33	0.67	-1	0.33	0.25	1	1	0.67	0.86	0.25	0.57	0	0	0.5	0.75	0.67	0.61
254	-1	0.25	0.92	-1	-1	-1	-1	0	-1	-1	0	-1	-1	1	0	1	0.85

2.4. Scoring for Face Recognition

The previous step has obtained the dominant class map for each face class. When the test face is input the system, the result of space partition can give the SIFT feature distribution on SOM. An example is shown in Figure 6. The classification result of local MLPs give the output face ID to each pattern. Next we can make up the distinctive feature map for each class by assigning the number of patterns which are classified into this class to the dominant class map as shown in Figure 7.

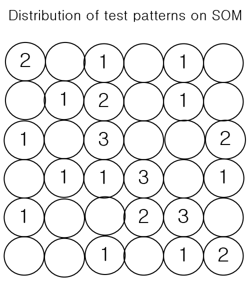

Figure 6. Test patterns' distribution on SOM.

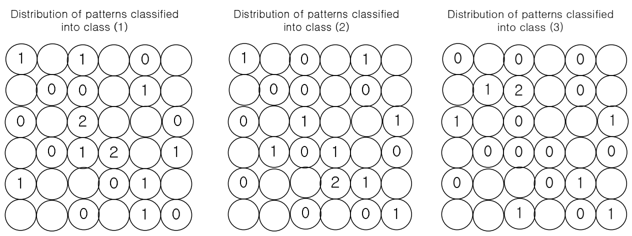

Figure 7. Distribution of patterns classified into 3 classes.

For each class, the distinctive feature map= dominant class map*distribution of patterns in the class. An example of distinctive feature map for class 1 is shown in Figure 8. Firstly, the patterns on the distinctive feature map are the distinctive patterns for class 1. Secondly, these patterns are classified into class 1. So the number of these patterns represents the similarity of test face image to class 1.

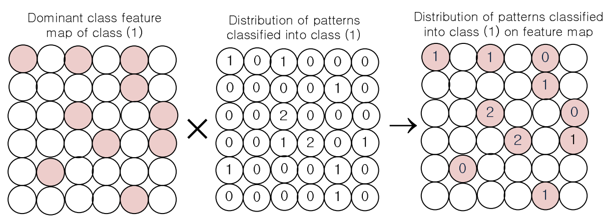

Figure 8. The obtaining of distinctive feature map for class 1.

For each class, we define a score which is the sum of number of patterns classified into class on the distinctive feature map. As mentioned before, the score represents the similarity of test image to each class. So the face ID of test image is selected as the class with the max score. In the example shown in Figure 9, the test image is determined as face class 1 because the score of class 1 is the highest. That means the SIFT keypoints extracted from test image.

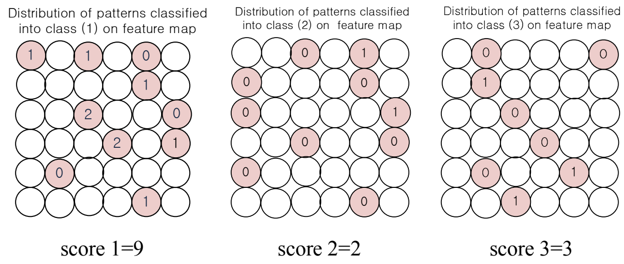

Figure 9. Scores of three example classes.

The proposed scoring method firstly selects the distinctive patterns from test image for each possible face class. Then count the total number of these distinctive patterns respectively. Finally, the class which has the max score is determined as the face ID of the test image.

3. Experimental Results and Discussion

In the experimental part, we evaluate our system from three important aspects:
Firstly, the performance of two methods are evaluated on classification rate and compared to each other. One is the proposed multiple local classifiers based and the other is one classifier based method. We select the frontal face dataset collected from Markus Weber at California Institute of Technology. Some of these images vary from large illumination and expressions. The experiment uses 20 images for each of 16 face classes. The images are resized and cropped into face areas. Some sample images of different conditions are shown in Figure 10. In each face class, the images are randomly selected for training and the remaining 15 images are used as the test images. So totally there are 80 training images and 240 test images.

As shown in Table 3, one MLP based method reached 89.6% face recognition rate. The proposed multiple local MLPs based on SOM achieved 97.9% recognition rate by using the scoring method. We prove the speculation that one classifier based method performs worse than the proposed multiple classifiers based on feature space partition on SOM due to its more complicated boundaries for separating various patterns.

Figure 10. Sample processed images in Markus Weber database.

Table 3. Comparison with one MLP based method.

Methods	Recognition Rate (%)
One MLP Based	89.6
SOM Multi-MLPs	97.9

Secondly, we evaluate the face recognition rate according to different number of dominant classes. The results show the best threshold value T to select the appropriate number of dominant classes for best recognition performance. The size of SOM is 20*20 which has been tested appropriate choice related to the size of training data. The number of dominant classes for each class is determined by T. So we test the proposed system by using different number of T. As shown in Table 4, the average number of dominant classes of each class decreases as T increases. The recognition rate remains lower while larger number of non-distinctive features are selected in dominant class in case of T<0.4. When T=0.4 the recognition rate reaches the highest when efficient distinctive features for each class are selected. But after the number of dominant classes decreases, the face recognition rate also decreases because the number of patterns in dominant classes become not enough for some special images. So the face recognition is failed by using little number of distinctive patterns.

Table 4. Recognition rate according to different number of patterns in dominant class.

T (n=2)	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Ave Num	230	188	138	103	86	50	42	34	30	0
Rec Rate	96.5	96.9	97.2	97.9	96.6	93.8	92.5	90.6	89.7	6.5

Finally, we have to compare the recognition rate of the proposed face recognition system to some other methods. Table 5 shows the comparative face recognition rate tested in ORL database. The training images are 5 images selected randomly in each face class and the remaining images are for test. Thus the total number of training samples and testing samples were both 200. The comparative methods include holistic image based methods such as the Fisherfaces, ICA, Kernel Eigenfaces and SIFT based methods such as direct matching approach, grid SIFT and cluster SIFT methods. From both sub tables, it is easily to see that our method gave the best classification rate 96.5%.

Table 5. Best recognition rate (%) of methods on ORL database.

Strategy	Method	Recognition Rate (%)
Select 5 images of each subject randomly as training images	Fisherfaces	94.5
	ICA [17]	85
	Kernel Eigenfaces [16]	94
	SIFT [1]	94.7
	SIFT GRID [3]	95.2
	SIFT CLUSTER [11]	95
	Proposed Method	96.5

The Yale database is more challenging than ORL database because it shows larger lighting variations due to non-uniform illumination source. We select 5 images of each class randomly as the training images. Table 6 shows the comparison of recognition rate on SIFT based methods. Some results in the table are from reference [15]. The proposed method gave a much more outstanding recognition rate than other matching based methods.

Table 6. Best recognition rate (%) of methods on Yale database.

Strategy	Method	Recognition Rate (%)
Select 5 images of each subject randomly as training images	SIFT [17]	86.7
	SIFT GRID [3]	89.6
	SIFT CLUSTER [11]	90.2
	Proposed Method	95.15

4. Conclusions

In this paper, we proposed a face recognition system based on extracting the distinctive features from SIFT through the multiple MLP classifiers on SOM. Firstly the system utilizes the robustness of SIFT feature on a design the classifier for each pattern extracted from image. This design is composed of the multiple local classifiers on feature space partition. To reduce the complexity of feature space for improving classification performance for classifier, we use SOM clustering to divide the space into subspaces then adopt local MLP to the corresponded node on the map. Moreover the common patterns and noise patterns in all SIFT keypoints are rejected by only selecting the distinctive features using a definition of dominant class for each face class. Then the distinctive SIFT features for each class are found in the distinctive feature maps. Finally the scoring method is invested to decide final face ID according to the score of each class. The score of each class indicates the number of recognized distinctive features. As a result, the face recognition rate of the proposed method is much higher than one MLP based classifier. Furthermore, the proposed face recognition system achieved a higher recognition rate than some other methods including holistic image feature based and SIFT matching based methods in the three famous databases.

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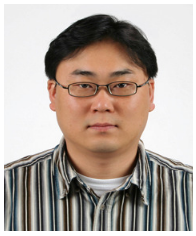

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