A comparative study of Face Recognition Algorithms on R1 Face Database

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Abstract: This paper introduces the development process of face recognition and analyses representative algorithms for each period. Considering different races and numbers of samples in database, and a wide variety of pose, shelter, illumination, and expressions, different algorithms are tested based on the application requirement. It adopts CAS-PEAL-R1 face database, composed entirely by Asian faces, while the previous face recognition test are almost all based on Europe and America face database. The main work is to get two indices (recognition rate and recognition time) when applying different algorithms on R1 face database and then analysis the advantages as well as disadvantages of each algorithm. According to the comparison of the indices for each algorithm, it showed that LBP algorithm achieves state-of-the-art performance in both recognition rate and time, so it meets the requirements for real-time recognition. In addition, although the SFD (Improved SIFT Algorithm) obtained the highest recognition rate in the comparison, it doesn't satisfy the requirements in real-time recognition system for its long recognition time. Contrast previous face recognition algorithms utilized on R1 face database, some more comprehensive algorithms are introduced and tested on R1 in this paper and it sure can gives a more comprehensive reference for later researchers.

Key Words: face recognition; feature extraction; CAS-PEAL-R1; unconstrained condition

1 INTRODUCTION

Biometric identification has become a hot problem in pattern recognition in recent years, in which the face recognition is the most active areas in many counties. Contrast to other identification methods, face recognition has some advantages: direct and easy to get. It is precisely because of these advantages as well as the randomness of images make face recognition becomes even more challenging. Since the 1960s, although the accuracy and speed of face recognition is continuously increasing, it fails to achieve the desired effect.

Early recognition methods [1, 2] are mainly based on the geometric features. Local face features are often used as a key identified factor. E.g. by comparing differences of shape, size, structure and location of eyes, nose, mouth, chin, ears in each person's face and other organs as main identified features in face recognition. Five senses were positioned in order to represent one's face by a geometric feature vector. In 1970s, Kanda designed fully automated face recognition system based on geometric features for the first time. Poggio and Brunelli used improved integral projection method to extract the Euclidean distance of 35-dimensional characterization of facial feature vectors for pattern classification [3].

With continuously research, analysis method based on subspace is used for face recognition [4, 5]. The basic idea is to find a linear or non-linear space transformation to map the image to a subspace, which makes the same categories of data more compact for the convenience of classification. L.Wiskott, etc, proposed elastic graph matching algorithm (EGM) in 1999, and the theoretical basis is image matching. Its typical algorithms include DLA, which was proposed by Lades etc, [6] using dynamic link structure to indentify face. The face features is constituted by a set of linked nodes and the node corresponds to the particular facial feature points, called reference points. Edge is represented by the distance of nodes, the node is represented by the feature vector that contains information of the local gray distribution; The similarity between two tested images is measured by the similarity of elastic Figs.

A lot of emerging face recognition methods appeared in past decades, e.g., hidden Markov model (HMM) [7-10] use a sequence of training through space for more than one sample images to get a HMM model. This method allows a large angle rotation of image and with high recognition rate and good expansion, when adding new samples which do not need all of the samples to involve training [11]. The main idea of Neuro-based and SVM pattern recognition is using the best split hyper plane for face classification.

In recent years, with the development of stochastic machine learning and statistical theory, there are a lot of face recognition algorithm based on local feature description no longer on global characteristics, which are more concerned about extracting the local details, more consistent with the laws of the eye identify. Only that local feature information belonging to individual will be more conducive to face recognition. Wright J etc,[12] combining with compressed sensing method proposed sparse representation face recognition (SRC) method, the main idea of which is that the image was represented by a sparse linear combination of the training sample, through obtained sparse coefficient of determination of the sample to classify faces. It can effectively solve the problem of image with noise and shelter. The algorithms above have achieved good recognition results on a common face database, but have their own shortcomings.

Combined with evaluation of face recognition algorithm in previous articles [13-15], this paper adopt PCA, LDA

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and algorithms emerged in recent years and make statistical analysis on the CAS-PEAL-R1 face database, due to the past comparative study and analysis are mostly based on yale and orl alone. Firstly, evaluation points were not in uniform and lack of direct detailed comparison in the recognition test before; Secondly, since limited by the database size, the result can't fully explain the advantages and disadvantages of each method; Thirdly, the image of orl and yale is too standard which are tested only in constrained conditions and can't simulate in unconstrained environments. Fourthly, the recognition rate of each algorithm change with the increasing number of tested samples; its robustness must verify by being tested on a large face database.

This article focuses on the following questions: I: get recognition rate of different algorithms with the influence of illumination, expression, shelter, and gesture and research robustness of the various algorithms for different situations. II: Simulate the real world, since under normal circumstances; face images are limited, so the test uses single one image as the test samples. III: Real-time face recognition requires program quick enough to reach the level of real-time interactive applications. Meanwhile, searching large databases in a reasonable time (millisecond or second level, and ultimately relying on the application situation and the size of the database) to analyze the speed of recognition process for each algorithm.

Algorithm adopted in the paper can be divided into three types; the first one is based on the overall matching method, such as LDA, PCA, LPP, etc. These algorithms are mainly extracted face contour information. It is through modeling the training sample set to obtained the projection feature vector form the training samples and testing sample, finally realizing the face classification; the Second is based on a partial match, such as LBP, WLD, SIFT, these methods are primarily focused on the extraction of local image texture information, no training and modeling process. A single image can be used directly to get the desired feature descriptors. Considering the number of people face in actual situation and comparing with global matching algorithm, this method is more suitable for the product development, and the third class of algorithm is based on image sparse representation theory (also called multi-scale geometric analysis method). The sparse theory was first applied to the field of compressed sensing and signal reconstruction. It does not require modeling at first, but need to build ultra-complete dictionary, and using sparse matrix of coefficients characterize images features according to the dictionary.

2 RELATED ALGORITHMS

2.1 PCA (Principal Component Analysis) and LDA (Linear Discriminate Analysis)

Turk and other researchers applied PCA (Principal Component Analysis) into face recognition. The classic methods of face features are by getting a orthogonal basis to project onto a low-dimensional subspace for dimensionality reduction. Due to the feature-face method is relatively more suitable in the reconstruction, and doesn't emphasis the classification, so LDA (linear discriminate analysis) has been employed widely. Classification criteria are expressed to maximize the within-class classification and between-class classification and it receives good classified information. In order to achieve linear separability, Vapnik [16, 17] proposed Kernel-based algorithms, i.e., KPCA, KLDA, by mapping to a higher dimensional space; the nonlinear problem will be transformed into a linear problem to be solved.

2.2 LPP (Locality Preserving Projections)

He et al proposed algorithm of locality preserving projection (LPP) [18], which is through a certain performance target to find a linear transformation W and achieve the reduction of high-dimensional data. Many studies show that the image data can be expressed as a nonlinear manifold structure [19]. When the data is in sub manifold and nonlinear, LPP can well preserve local information. Instead of obtaining face feature by PCA, LPP can extract more discriminative characteristics for dimension reduction and better reflect the differences between classes, at the same time; it has a significant advantage in terms of local features retained. LPP is able to extract nonlinear and low-dimensional manifold features of high-dimensional samples in pattern recognition, which has been successful applied; however, in face recognition, LPP has size problem in the recognition. Test results show that although the LPP can achieve a higher recognition rate, it has less robustness. When randomly select five pictures as training set for each person on Yale, its highest recognition rate can reach 100%; however ,when the training using low-quality or low-light samples, the recognition rate decreased rapidly. It is greatly affected by the performance of the camera, external illumination conditions and angle of image acquisition.

2.3 LBP (local binary pattern)

LBP was first proposed by T. Ahonen et al [20]. Since then, it has been employed by a lot of the research teams. In its original method, three different feature levels are defined: the pixel level, regional level and global level. LBP defined one pixel as the center, and 3×3 neighboring pixel point bound condition to label tags. Then, the label tags of histogram can be used to describe the texture features. It has a high degree of discrimination as well as its unique advantages, i.e., monotonous and gray value progressive (recursive) of grayscale images has invariance characteristic, meanwhile, with the high computational efficiency. The first two levels is by dividing the face image into several numbers of smaller regions to extracting LBP feature and using histogram to express those useful texture information. Global information is composited by local information, e.g., connecting the whole local features makes up the global LBP face descriptors.

2.4 SIFT (Scale Invariant Feature Transform)

David G.Lowe summarized detection technique based on invariant feature in 2004 [21], and formally proposed local image characterization of operators - SIFT operator based on the invariance of the scale space, image scaling, rotation, and affine transformation. Firstly, SIFT detect and identify key points in the scale space and locate the key point on face image .Then using direction of the gradient of its neighborhood points act as its direction feature to proof the operator is independent on scale and direction. The process of SIFT is divided into four steps: (1) Scale-space extrema detection, in order to determine where the initial position and scales of the key points. (2) Accurately determine the location and scale of key points by fitting a three-dimensional quadratic function, at the same time, delete the low-contrast edges key points and unstable bordering response points to enhance the matching stability and improved noise immunity. Distribute the specified direction for each pixel by using surrounding gradient direction of the key point to make the operator has rotational invariance. (4) Generates SIFT feature vectors according to the gradient direction of its surrounding pixels. Original SIFT algorithm is more suitable for scene matching. Some boundaries of the key point are ignored when in the recognition process because of the large amount of calculation; it will impact the speed of face recognition in the matching process. Therefore Na, Jian et al proposed a simplified algorithm of the SIFT: FSD [22]. (1)When building the Gaussian pyramid (GOC), there need only one pyramid group and one set of feature extracted form pyramid for identifying; (2) Descriptors on the edge characteristic is retained in the FSD; (3) Remove SIFT calculation of the scale and rotation invariant, and complete to set the image size and position in the pretreatment; (4) Instead of one by one matching method, it take regional feature descriptors in the matching process.

2.5 WLD (Weber Local Descriptor)

Weber Local Descriptor is proposed based on Web's Law [23], theorem figures out that, under the same stimulus, the value of threshold is proportional to the strength of stimulus, and the ratio is a constant. Chen et al [24] did a lot of works in this aspect. WLD is mainly by calculating the gradient directions of the excitation and the pixel index to get one feature descriptor. The relative size of pixels and the center pixel is calculated by the ratio of the center pixel and the difference between its eight neighboring pixels and center pixel.

Two-dimensional histogram is established According to the difference excitation and gradient direction, and one-dimensional histogram is established based on difference excitation in each quantized component of the gradient direction to be as extracted features. WLD not only can well reflect the image texture features, but also has high recognition speed and robustness. In this paper, each image is divided into 4 * 4 and 4 *6 to extract the features. The gradient direction and the difference in the excitation directions are quantized to eight directions, so that each sub-image can extract a 64-dimensional feature vectors. Combining all sub-images of one face image builds up its whole extracted features.

2.6 Sparse Representation

In recent years, with the further development of compressed sensing theory, sparse representation is a better method especially in reconstruction and de-noising signal. John Wright, Michael Elad, and Yang have made a great contribution to this filed [25-27]. The main idea to represent the sparse representation of sparse signal is building a complete dictionary, generally using orthogonal basis to build complete dictionary in the process of representing image. This is because a complete orthogonal base is easier to represent and result is unique; however, the completely orthogonal base makes the image representation not sparse. In order to make the representation more sparse, face recognition often adopt over-complete dictionary. A more classical approach is called OMP (Orthogonal Matching Pursuit) [28, 29]. OMP obtained sparse representation of image by iterative and find the most relevant column vector image margin (iterative process obtained by the least squares residuals) of the ultra-complete dictionary in each iteration, save the updated sparse column vector and get the degree of the residual obtained by iteration. Due to the special of face recognition, it is easy to find out which type the test sample belongs to without iterating many times. The test result on ORL database shows that it can get high recognition rate after sixth or eighth iterations when using five samples.

SRC [30] is based on the OMP method, which integrates the location of nonzero elements in the sparse vector as well as size of the residual to determine which classes the test image belongs to. Compared with SRC, OMP algorithm has higher robustness. The main steps of the SRC is as following: (1) Structure a complete dictionary and set error margin; (2) Normalize each column of the dictionary by two-norm (each column corresponds to a sample image; (3) Find the sparsity of test images; (4) Calculate margin, and if the margin value is less than the set margin, then stop the iteration; (5) Determine which class the test images belong to according to the sparsity vector.

3 R1 FACE DATABASE

CAS-PEAL-R1 database contains a total of 30 863 face images, and the original format of the document is an RGB color image with 620x480 resolution .It requires 26.6GB storage space. To facilitate distribution, all of these files are converted to grayscale images, cropped to 360x480 and removed most of the background. Cropped image file using lossless LZW compression algorithm to compress and be stored as TIFF format. After the above processing, the entire contents of CAS-PEAL-R1 can be stored in one DVD disc. The image is divided into two major subsets. Table 1 summarizes the composition of AS-PEAL-R1 face image.

Table 1.The classification of CAS-PEAL-R1

Subset		Change numbers	Number of people	Number of image
Front	Criterion	1	1040	1040
	Expression changes	5	377	1884
	Accessories	6	438	2616

	changes			
	Illumination changes	>=9	233	2450
	Time changes	1	66	66
	Background changes	2-4	297	651
	Distance changes	1-2	296	324
	Total number	9031		
Non-front	Overhead view	7	1040	21832
	Look at the front horizontal	7		
	Look up	7		
	Total number	30863		

1) Frontal subset

All the images from the camera in the frontal face image subset, and captured object viewing camera in the front and horizontal way, in which 377 number of face images contain six facial expression, 438 number of images include six accessories changes, 233 images include at least nine changes in illumination, 297 number of images contain two to four kinds of background changes and 296 number of face images contain the distance changes. In addition, 66 people face images were captured with a time interval of half year

2) Non frontal subset

In the non-frontal face image subset, 1040 number of images contains 21 different posture changes, and contains only posture changed. 21 kinds of posture changes is composed of three pitching changes (overhead view, look at the front horizontal and look up) and seven kinds angle changes in left and right (selected nine images captured by camera). Use the algorithm of Haar face detection to extract facial feature on R1 face database. Figure 1 shows parts of obtained face by the detection algorithm.

Fig 1.A portion of the test results on R1 face database

4 ALGORITHM COMPARITIONS AND CONCLUSIONS

Since R1 is not standard database and each picture has background, so it needs detection and save by us own. The article will be tested in two aspects: incomplete training set and the complete training set according to the situation of obtained face image.

4.1 Test One

The test 1will be finished in face database which were consisting of 32 individuals whose images were influenced by illumination, gesture, facial expression and shelter .Randomly select five images with illumination change, three images with shelter change and two images with expression change as training set. Image with posture change is no longer used to train, because the posture changes affect identification process greatly. As a result, a training sample has total number of ten images for each person, the rest as the test sample to ensure that the training set and test set share no common image. Figure 2 shows the statistics of recognition rate.

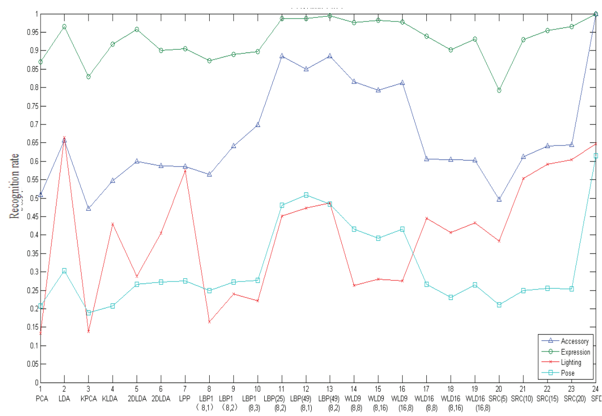

Fig 2.Recognition tests under complete training set

Figure 2 shows that when training image with these four influential factors mentioned above. Expression class has better results than others, especially algorithm like LBP, WLD, and SFD achieved a very high recognition rate; In the process of testing recognition rate under occlusion, the algorithm above appeared great volatility, the effect of traditional algorithm of PCA, LDA was significantly lower than LBP, WLD algorithm based on texture. SFD algorithm almost completely identifies people face with partial occlusion for its own merit of the key point matching method. Illumination has been the key factors influencing recognition rate, which can also be seen in previous studies. For illumination, the algorithm above appears greater volatility, LDA, LPP and SFD get a better recognition results than LBP, WLD, Sparse matrix representation and Kernel-based algorithm The posture test has the worst result on one hand, because the current face recognition algorithm has its defects; on the other hand, the inclination angle of the face is also a vital factor. Compared to some international standard face databases, such as ORL, FERET and Yale The rotation angle of sample in the test includes 45 degrees; some even 60 degrees, and it has a great advantage. Algorithms based on local texture have relatively better recognition effects as seen from the Figure 2, especially SFD, which has the highest recognition rate.

4.2 Test Two

Randomly select four, three and two images with illumination, expression, shelter and posture changes as the training samples. the number of face image is limited and it can not simultaneously have these four changes above in the reality. It needs special consideration in selecting the gesture- training samples which require rotation angle can not exceed 15 degrees, selecting No [1 8 9 15],And the rest images act as test samples. The posture tests are divided into three cases: No. [2 3 4 5 6 7] images act as the bottom angle test, No. [10 11 12 13 14] images as the left and right angle test, No. [161718192021] images as top angle test, where $Pose_p D$ stands for the recognition rate in bottom angle test , $Pose_p U$ stands for the recognition rate in the top angle test and $Pose_p M$ stands for the recognition rate in left and right angle test. The $Total$ Represents the average recognition rate of six cases. Statistical analysis is shown in Figure3.

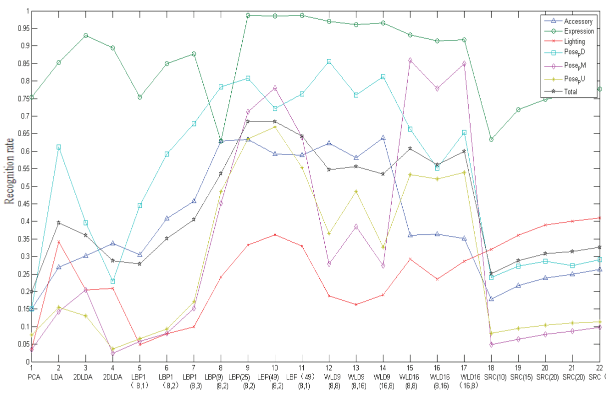

Fig 3 .Recognition test under incomplete training set

Select the incomplete images with only one or two influential factors in R1. It can be observed from the figure that the recognition rate has a significant decrease under different factors compared to that of the training set with illumination, posture, accessories and expression changes. In addition, different algorithm has a big difference recognition rate in expression test. Viewing from the average recognition rate of the four cases, LBP-25 (8, 2) has a relatively better recognition results. Algorithm based on sparse matrix performs poor in this case. The traditional identification methods based on the contour of face can not meet the case with deficient number of training set; on the contrary, algorithms based on texture have a better recognition performance.

The recognition accuracy is required to reach as high as possible in practical application, and its speed is a not negligible factor. Weather the algorithm can meet real-time face recognition is another an important index for practical application. The tests compared two indexes extraction time and identify time in feature extraction and recognition by using different algorithms on different databases and got the identify time on different face databases. Computer employed in the test is installed Windows XP3 operating system, and its processor model is Pentium (R) Dual-Core CPU E6700@3.20GHz (2.00GB RAM). As shown in the table 2, with the increasing number of images in database, there was big difference of identify time for the different algorithms. Recognition time of SFD is 32 times more than that of LBP-25 (8, 2) for a single face image. When the database include1000 samples, it does not meet the requirements of real-time recognition obviously. Among the algorithms above, LBP-25(8, 2) has the shortest recognition time and high recognition rate, which shows that LBP is a more suitable for real-time application.

Table2.Statistics of identification time

Algorith -ms	Feature Extraction (ms)	Image Matching (ms)	Total time of feature extraction and image matching				
			1	10	100	500	1000
PCA	4.1	<1	5.1	5.3	16.8	80.4	376.2
LDA	5.5	<1	6.5	7.5	18.5	96.3	553.6
LPP	4.3	<1	5.3	6.5	19.5	88.5	463.7
LBP-25(8,2)	2.3	<1	3.3	3.5	9.8	43.5	133.2
LBP-49(8,2)	3.3	<1	4.3	4.6	14.2	57.7	189.4
WLD-9(8,16)	4.1	<1	5.1	5.6	16.7	71.5	235.1
OMP -25	3.7	<1	4.7	5.2	16.8	75.5	228.3
SFD	150	9.2	240	468	1087	2087	4330

With comparison of reference [13], it is find that the conclusion of Gabriel Hermosilla et al, have some different points with this paper, Firstly, using different face database, Gabriel adopted infrared Equinox [31] and UCHhemalFace database in his test, while CAS-PEAL-R1 database were adopted in this paper. In addition, these two comparative studies have different recognition rate. Gabriel believed that WLD has the best practicality in both speed and accuracy, while comparing the results of this paper; it shows LBP is more practical considering both speed and accuracy. The main reason for the difference test result is maybe that different databases are selected. As to the recognition time, this paper and Gabriel have the same conclusion. Compare to the reference [14], as for the same algorithm, the conclusions of recognition rate in this paper is consistent with that of Wen Gao, et al, so as to demonstrate the correctness of this paper.

5 CONCLUSIONS

The paper mainly compared recognition rate and recognition time on the R1 face database by using some typical algorithms for the purpose of giving engineers and researchers some references. On the one hand, recognition rate is associated with algorithms itself, on the other hand, it related to face database adopted. Sometimes when using the same algorithm, there may be a different result on one face database. This article uses R1 face database established by the Institute of Computing Technology aiming to find suitable algorithm and method for Asian face recognition. By comparison, although the feature extraction algorithm of block LBP didn't achieve the highest recognition rate, it is conducive to identification speed. If each sample has sufficient images in a variety of environmental conditions in the face database, LBP can meet the requirements of both accuracy and real-time. SIFT has an advantage in recognition rate and rank first overall in the test; however, with the increase number of images in database, the recognition time is getting longer and longer, so it is not suitable in real-time recognition.

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