ISSN 0146-4116, Automatic Control and Computer Sciences, 2016, Vol. 50, No. 5, pp. 318–323. © Allerton Press, Inc., 2016.

Face Recognition System Based on Block Gabor Feature Collaborative Representation[1]

Zhi Liu[a, b]

[a]*College of automation, Nanjing University of Aeronautics and Astronautics, Nanjing, Jiangsu, 210016 China*
[b]*Network and modern education technology center, Guangxi University of Science and Technology, Liuzhou, Guangxi, 545006 China*
e-mail: liuzh023@163.com

Received January 25, 2016; in final form, April 15, 2016

Abstract—Face recognition, one of the biological recognitions, has received extensive concern due to its secrecy and friendly cooperation. Gabor wavelet is an important tool in face feature description. In order to reduce the loss of useful information during down sampling, this work puts forward a Gabor feature representation method based on block statistics, which enhances the efficiency of Gabor feature representation. This study was designed to explore face recognition algorithms on the basis of highly recognizable and real-time collaborative representation. Experimental results indicated that, the face recognition based on block Gabor feature collaborative representation not only guaranteed the calculation speed, but also took full advantage of the robustness of Gabor feature. Besides, the block Gabor feature containing more details further improved the recognition rate.

Keywords: face recognition, robustness, collaborative representation, block Gabor feature

DOI: 10.3103/S0146411616050102

1. INTRODUCTION

In recent ten years, face recognition [1] has always been an active research hotspot in fields of pattern recognition, computer vision and machine learning. As an ideal biometric identification technology (biometrics), face recognition has a large potential market in various fields, such as military affairs, public security and civil affairs, etc. However, there is a big difference between the precision and practical requirements of face recognition at present.

Numerous representative algorithms in face recognition have been widely studied in recent twenty years [2, 3], including eigenface [4], Fisherface [5] and support vector machine (SVM) [6]. Traditional signal reconstruction approach is limited by the Nyquist sampling theorem, but the compressive sensing theory proposed by Donoho et al. [7] successfully solved this problem. Wright et al. [8] first applied sparse coding to pattern classification and also put forward a face recognition algorithm based on sparse coding representation classification. In 2015, Li Xiaonan et al. [9] carried out facial expression recognition based on Local Gabor Binary Pattern (LGBP) and sparse representation. Recently, some scholars started to question the function of sparseness in image classification, and a literature [10] indicates that the reason why sparse representation-based classification (SRC) algorithm is successful lies in collaboratively representing the test images, instead of restraining l_1 norm sparseness.

The classification algorithm based on block Gabor feature collaborative representation works fast in face recognition and obtains neck-and-neck recognition results to the SRC [11]. Considering the Gabor feature can not only reflect the changes in dimension and duration, but also show the characteristics of signal in frequency and time, it is believed that it is able to improve the robustness of face recognition and present the local details of image in blocking. Consequently, this work suggests applying block Gabor feature to face recognition on the basis of collaborative representation.

2. THEORETICAL BASIS

In theory, biological feature needs to be unique, safe, universal, stable and collectable [12]. Computer technology-based face recognition can be applied to verify identities of people by extracting facial features

[1] The article is published in the original.

from images. Abundant information can be acquired from human faces, such as age, gender, health condition, psychological state and career, etc. Advantages of face recognition technology are embodied in its friendly operation, good concealing and visual results. As more and more digital products begin to merge into people's daily life, there appear increasing relevant security and privacy problems. Many challenges existing in the face recognition greatly obstruct the development of the face recognition technology. A real-time, economic and accurate face recognition system is urgently needed to meet peoples' demand for daily life.

3. CONSTRUCTION OF FACE RECOGNITION SYSTEM BASED ON BLOCK GABOR FEATURE COLLABORATIVE REPRESENTATION

Sparse representation classification has achieved remarkable achievements in face recognition. The principles of SRC in face recognition are summarized as follows [13]. Assume there are k kinds of samples, each kind of sample is divided into test samples and training samples, and each 2-dimensional image is arranged into a 1-dimensional vector in column to constitute a training dictionary $X = [X_1, X_2, \ldots, X_k]$. When there is one test sample $y \in Rm$, SRC first expresses the test sample as a sparse linear combination of all training samples, i.e., $y \approx X_\alpha$, of which, $\alpha = [\alpha_1; \ldots; \alpha_i; \ldots; \alpha_k]$ and α_i is the coefficient of the i-th kind. Normally, only the element in α_i is not zero and other items should be zero if y belongs to the i-th kind; in practice, there is $y \approx X_i\alpha_i$ due to noise interference, α_i contains an obvious nonzero value and α_k $(k \neq i)$ has some nonzero values. As l_0 combination minimization is an issue about combinational explosion, l_1 is minimized to express y with X and solves the coefficient α, i.e.:

$$(\hat{a}) = \arg\min_a \|a\|_1 \, S.T. \|y - X\,a\|_2 < \varepsilon. \tag{3.1}$$

In (3.1), the constant ε is to balance y coding error and α sparseness. The following formula is used to calculate the reconstruction error after obtaining the sparse coefficient α:

$$e_i(y) = \|y - X_i\,\hat{a}_i\|_2. \tag{3.2}$$

In (3.2), $\hat{a}_i$ is the coding coefficient vector of the i-th kind. After the reconstruction error is acquired, the test sample is determined to be the kind with the minimum reconstruction error, that is to say:

$$\text{identity}(y) = \arg\min_t \{e_i\}. \tag{3.3}$$

We can see from the discussion above that the SRC algorithm has two key points: one is that the coding coefficient of the test sample y must be sparse; the other one is that y codes collaboratively by all of the training sample sets X, rather than a single subset X_i.

Another important fact in face recognition is that all face images are similar to some extent, which indicates that the dictionary X_i is very relevant to the dictionary X_j, and there is $X_j = X_i + \Delta$. The distance between e_i and e_j will be small if Δ is small, and the sparseness of y to X can be expressed as:

$$\min_a \|y - Xa\|_2 \, S.T. \|a\|_p \leq \varepsilon. \tag{3.4}$$

According to the analysis above, a conclusion can be drawn: one test sample is determined to be able to express its category using as less samples as possible. In order to minimize l_1, the formula of SRC in the form of Lagrangian is:

$$(a_i) = \arg\min_a \left\{\|y - X_i\,a\|_2^2 + \lambda\|a\|_1\right\}. \tag{3.5}$$

In (3.5), the reconstruction error $e_i = \|y - X_i\,a_i\|_2$ and the sparsity constraint $\|a_i\|_1$ are used for sample classification.

In the sparse representation theory, each kind is required to have enough training samples to ensure that the training dictionary subset X_i is complete. However, the face recognition has a typical problem of small sample size, so X_i is usually incomplete. The error may be very big if X_i is used to express y, so does when y belongs to the i-th kind. Therefore, the classification results will be unstable no matter whether the residual error e_i or sparseness $\|a_i\|_p$, or both of them are used. To handle this problem, there is an obvious method of expressing y with more i-th kind of samples. In face recognition, one crucial fact lies in that different kinds of face images have a lot in common, and the j-th kind of image is likely to be helpful to the presentation of the i-th kind test sample. The sparse representation based classification solves the problem of the lack of samples by taking all kinds of face images as each kind of possible sample, that is to say, collaboratively presenting the test sample y with the dictionary $X = [X_1, X_2, ..., X_k]$. In this way, the coding coefficient presents a natural sparse state, and l_2 norm with relatively weak sparseness can be used for constraint. To sum up, what really works in the SRC is collaborative representation, instead of sparse representation.

Collaborative representation is very important to the SRC. To collaboratively represent the test sample and reduce the computational cost, this work replaces l_1 sparse constraint with weak sparse l_2 norm constraint, so the formula (3.6) turns into:

$$(a_i) = \arg\min_a \left\{ \|y - X_i a\|_2^2 + \lambda \|a\|_1 \right\}, \tag{3.6}$$

$$\hat{a} = \arg\min_a \left\{ \left\| y - X^* a \right\|_2^2 + \lambda \, \|a\|_2^2 \right\}. \tag{3.7}$$

The solution of the formula above can be considered to be an issue on regularized least-squares, where λ is a regularization parameter. The regularization has dual functions: first of all, it stabilizes the solution of least squares; secondly, it introduces a certain number of "sparseness" into the solution $\hat{a}$. This sparseness is weaker than that brought by l_1 norm.

In the formula (3.7), the solution of normalized least-squares collaborative representation classification (CRC) can be deduced as:

$$\hat{a} = \left(X^T X + \lambda I\right)^{-1} X^T * y. \tag{3.8}$$

Suppose $P = \left(X^T X + \lambda I\right)^{-1} X^T$, thus P and y are mutually independent. Therefore, P as a projection matrix can be figured out in advance. Assume a test sample y, there is $\hat{a} = Py$, which makes the collaborative representation very quick. The classification of y is very similar to sparse representation's, $\|\hat{a}_i\|_2$ is added to one kind of peculiar reconstruction error $\left\|y - X_i^* \hat{a}_i\right\|_2$ of which, $\hat{a}$ referring to the coefficient vector of the i-th kind can distinguish the classification. Hence, both of them should be used in residual error calculation:

$$r_i = \|y - X_i \hat{a}_i\|_2 / \|\hat{a}_i\|_2 . \tag{3.9}$$

Finally, y is determined to be the kind with the minimum reconstruction error, i.e., $\mathrm{Identity}(y) = \arg\min_i \{r_i\}$.

Gabor feature can tolerate illumination and expression changes to some extent on account of its favorable scale and direction selectivity [14, 15]. In order to further highlight the characteristics of face's key parts such as eyes, nose and mouth, this work blocks Gabor features of the images.

4. SYSTEM TEST AND ANALYSIS

4.1. System Test

In a controlled environment, Extended YaleB and AR face database are used to test the performances of the face recognition method put forward in this study. The implement environment is set as system: Window XP; central processing unit (CPU): AMD; CPU series: Athlon(tm) II X_2 245 (2.91 GHz); random access memory (RAM): 1.75 GB; the software used: MATLAB7.10 R2010a. In the Extended YaleB, 10 targets are selected and half of their face images are randomly selected as the training images and the remaining face images are considered as test images (each target has 64 images in total). The size of images is normalized to be 192 × 168. The features extracted from each image are divided into 9 blocks (3*3) and each block constitutes a one-dimensional vector in column, thereby generating 9 one-dimensional vectors. Each image's Gabor feature dimension is 2240 (7 × 8 × 40). Afterwards, images are projected to different dimensions using principle component analysis (PCA) to compare the recognition rate. Gabor feature in different dimensions and directions can be obtained by wavelet transform. As adjacent pixels of Gabor feature are related, the dimension of Gabor feature can be reduced. The dimension reduction method used in this study is to perform PCA dimensionality reduction on Gabor transformation coefficient. Block Gabor feature is also effective in enhancing local features in addition to retaining the overall information of face images, which is beneficial to image classification. Therefore, this work suggests

Fig. 1. Part of the test samples in AR face database.

replacing face images with block Gabor feature to recognize faces. In view of the instantaneity of CRC, least square method is still adopted for classification after block Gabor feature vector is acquired.

First of all, Gabor features are extracted from all training samples and test samples and then divided into 9 blocks. Each block constitutes a one-dimensional vector in column, thereby generating 9 one-dimensional vectors. Those 9 vectors are normalized and formed into a one-dimensional vector, thus each image has one Gabor feature vector, of which, the block Gabor feature vector of the i-th kind of the j-th training sample image is denoted as X_{ij}.

Secondly, the dimension of the Gabor feature vector that the training samples and test samples correspond to is reduced using eigenface. Block Gabor feature vectors of all kinds of training samples collaboratively make up a training dictionary X, $X = [X_1, X_2, \dots, X_k]$, where $i = 1, 2, \dots$, and k is the training subset made up of Gabor feature vectors of all training sample images.

Finally, the test samples are collaboratively represented by the formula (3.6) and solved, then the coefficient α is collaboratively represented by the formula (3.7) and the residual error r_i is calculated using the formula (3.8) and the test sample is eventually classified as the kind of the minimum residual error. Block Gabor feature extraction can be learnt offline, so the running speed of the algorithm proposed in this study is not affected. Additionally, the block Gabor feature has many merits, which are about to be verified through the following experiment.

4.2. Test Results and Analysis

4.2.1. AR face database. The experimental results are compared with CRC – recurrence least square (CRC-RLS) in the literature so as to illustrate the advantages of the proposed algorithm. For the convenience of comparison, experimental database and parameters are consistent with the literature, a subset containing illumination and expression changes only of 50 males and 50 females in the AR face database is selected, 14 images for each one (60 * 43). The first 7 images of each one are taken as the training samples, and the rest of 7 images are the test samples. The dimension is set as 54, 120 and 300 respectively during dimensionality reduction using feature face. Part of the test samples in AR face database is shown in Fig. 1.

Table 1 displays the comparison between the recognition results of block Gabor CRC and CRC-RLS. Recognition accuracy and time of those two algorithms (CRC-RLS and block Gabor CRC) are mainly compared when the dimension is 54, 120 and 300 respectively.

As shown in Table 1, the recognition accuracy of block Gabor CRC is improved greatly, especially when the dimension is 120. From 54 to 120, both of the two algorithms' recognition accuracies are enhanced, which is because face image information is supplemented as the dimension rises. From 120 to 300, block Gabor CRC's recognition accuracy increases slightly due to information redundancy; while the recognition accuracy of CRC-RLS is improved to some extent by reason of information supplement. The above reflects that the block Gabor CRC is capable of taking full advantage of the given sample information in a moderate dimension. From the perspective of running time, the two algorithms are neck-and-neck, and the block Gabor CRC is superior to CRC-RLS in offline extracting test samples and training samples.

Table 1. Comparison on CRC-RLS and block Gabor CRC

	Dimension	54	120	300
Recognition accuracy	CRC-RLS	80.256%	90.130%	93.485%
	Block Gabor CRC	82.292%	94.711%	94.854%
Recognition time	CRC-RLS	3.7030s	3.7030s	5.7508s

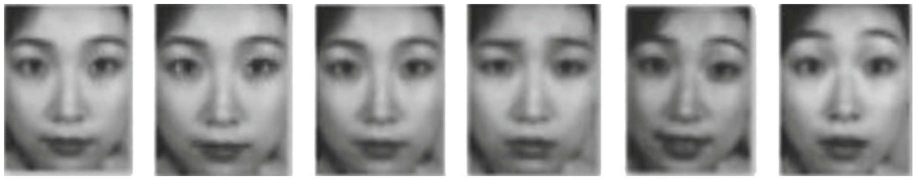

Fig. 2. Part of test samples in the Extended Yale B face database.

4.2.2. Extended Yale B face database. For the sake of verifying the range of application of the block Gabor CRC, this study is going to further compare in Extended Yale B face database. A total of 2280 images from 38 people in the face database (60 images for each one) are trimmed to 54 * 48. Those images contain obvious changes in illumination and sizes of open eyes. Half of each one's images are randomly selected as the training samples and the remaining images are the test samples. The dimension is considered to be 30, 54 and 75 in sequence for dimensionality reduction. Part of test samples in the Extended Yale B face database is shown in Fig. 2.

Table 2 displays the comparison on the improved algorithm and CRC-RLS [16].

It can be seen from Table 2 that, the block Gabor CRC algorithm runs faster than the CRC-RLS algorithm; besides, the images selected from the Extended Yale B face database have changes in illumination and eyes. Therefore, both of the two algorithms achieve good recognition results when the dimension increases to 54 from 30; at 30, the block Gabor CRC algorithm is inferior to the CRC-RLS algorithm, suggesting that block Gabor feature loses partial information; the block Gabor CRC algorithm is superior to the CRC-RLS algorithm with the increase of the dimension.

Table 2. Comparison on block Gabor CRC and CRC-RLS

	Dimension	30	54	75
Recognition accuracy	CRC-RLS	87.985%	97.803%	99.472%
	Block Gabor CRC	85.265%	98.156%	99.739%
Operation time	CRC-RLS	8.3426s	9.4332s	10.3039s
	Block Gabor CRC	7.5828s	8.0286s	8.6845s

5. CONCLUSION

To sum up, the face recognition based on block Gabor feature collaborative representation not only preserves the merits of CRC, but also takes full advantage of the robustness as well as abundant details of Gabor feature, thereby the recognition accuracy is further improved. In dimensionality reduction using eigenface, test samples can be reconstructed by the proposed algorithms in the study if appropriate dimension is selected. Considering that the fixed block may lose part of the image information, further researches will focus on face recognition based on multi-scale block collaborative classification, so as to make the best of various information reflected from different scales of blocks.

ACKNOWLEDGMENTS

(1) Team behavior recognition method based on multi feature fusion in video games, National Natural Science Foundation of China 61462008.

(2) Vehicle license plate recognition system based on Neural Network, University research project of the Education DepartmentLX2014187.

REFERENCES

1. Park, H., Ree, J.J., and Kim, K., Identification of promising patents for technology transfers using TRIZ evolution trends, *J. Expert Syst. Appl.,* 2013, vol. 40, no. 2, pp. 736–743.
2. Unruh, A., Bailey, J., and Ramamohanarao, K., Building more robust multi-agent systems using a log-based approach, *J. Web Intell. Agent Syst.,* 2009, vol. 7, no. 1, pp. 65–87.

3. Lim, M.H., Goi, B.M., and Lee, S.G., An analysis of group key agreement schemes based on the Bellare-Rogaway model in multi-party setting, *KSII Trans. Internet Inf. Syst.,* 2011, vol. 5, no. 4, pp. 822–839.
4. Abaza, A.A., Day, J.B., Reynolds, J.S., et al., Classification of voluntary cough sound and airflow patterns for detecting abnormal pulmonary function, *J. Cough,* 2009, vol. 5, no. 1, pp. 1–12.
5. Liao, P. and Shen, L., Unified probabilistic models for face recognition from a single example image per person, *J. Comput. Sci. Technol.,* 2004, vol. 19, no. 3, pp. 383–392.
6. Heisele, B., Ho, P., and Poggio, T., Face recognition with support vector machine: Global versus component-based approach, *IEEE International Conference on Computer Vision, Vancouver, BC,* 2001, pp. 688–694.
7. Balouchestani, M., Raahemifar, K., and Krishnan, S., Low sampling rate algorithm for wireless ECG systems based on compressed sensing theory, *J. PLOS One,* 2015, vol. 10, no. 1, pp. 1–7.
8. Wright, J., Yang, A., Ganesh, A., et al., Robust face recognition via sparse representation, *IEEE Trans. Pattern Anal. Mach. Intell.,* 2009, vol. 31, no. 2, pp. 210–227.
9. Ma, D., Li, M., Nian, F.Z., et al., Facial expression recognition based on characteristics of block LGBP and sparse representation, *J. Comput. Methods Sci. Eng.,* 2015, vol. 15, no. 3, pp. 537–547.
10. Zhang, L., Yang, M., and Feng, M., Sparse representation or collaborative representation: Which helps face recognition?, *International Conference on Computer Vision, Barcelona, Spain,* 2011, pp. 471–478.
11. Arjun, J.S. and Nair, M.S., Robust face recognition technique using Gabor phase pattern and phase only correlation, *CSI Trans. ICT,* 2014, vol. 2, no. 2, pp. 85–95.
12. Yu, D.H., Wang, B., Feng, Y., et al., Investigation of free volume, interfacial, and toughening behavior for cyanate ester/bentonite nanocomposites by positron annihilation, *J. Appl. Polym. Sci.,* 2006, vol. 102, no. 2, pp. 1509–1515.
13. Du, H.S., Hu, Q.P., Qiao, D.F., et al., Robust face recognition via low-rank sparse representation-based classification, *Int. J. Autom. Comput.,* 2015, vol. 6, pp. 1–9.
14. Chengjun, L., Gabor-based kernel PCA with fractional power polynomial models for face recognition, *IEEE Trans. Pattern Anal. Mach. Intell.,* 2004, vol. 26, no. 5, pp. 572–581.
15. Fan, W., Wang, Y., Liu, W., et al., Combining null space-based Gabor features for face recognition, *IEEE Computer Society International Conference on Pattern Recognition,* 2004, pp. 330–333.
16. Mooser, J., You, S., Neumann, U., et al., Computer vision – ACCV 2009, *Lect. Notes Comput. Sci.,* 2010, vol. 5995, no. 2, pp. 7–35.