High-precision Immune Computation for Secure Face Recognition

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Abstract

The accuracy of face recognition is very important for its security in many applications, because wrong face recognition may cause such security problems as authorization. To increase the recognition rate in such face database as ORL, a face recognition algorithm should be good at minimizing the disturbances of facial pose, illumination and expression (PIE) to this recognition. In this paper, the improved clonal selection algorithm and diverse samples are designed. The improved clonal selection algorithm searches the most similar sample for unknown face image, according to the affinity between the unknown one and the most similar sample. The affinity is newly designed to improve the adaptive matching between the object and the samples. Compared with some state-of-the-art algorithms on the ORL face database, the proposed approach outperforms the other algorithms in the recognition rate, based on the experimental results.

Keywords: *Face recognition; PIE; high-precision immune computation; security; clonal selection.*

1. Introduction

The high-precision face recognition is of high recognition rate of faces, and this is important for many applications of security, management and service. To increase the recognition rate, face recognition algorithms have to minimize the disturbances of facial pose, illumination, and expression (PIE) [1]. He et al. proposed a Laplacianface method of locality preserving projection (LPP) to preserve the local structure of training samples [2]. This approach was improved by Cai et al. with an orthogonal locality preserving projection (OLPP) to use more local information [3]. Jiang et al. proposed a method to enhance maximum likelihood face recognition [4]. In this paper, a novel high-precision face recognition approach is proposed with an improved clonal selection algorithm of immune computation. It filters some disturbances of PIE and hence boosts the high accuracy of the face recognition approach.

2. Face Recognition Model based on High-precision Immune Computation

The face recognition model based on immunity is proposed and comprised of feature acquiring of the target face images, similarity searching in the feature space R^d of known face images, and classification of the target face images, as shown in Figure 1. Consider N d-dimensional samples $x_1, x_2, \ldots, x_N$, which constitute N_C classes of faces. Let x_j^i denote a sample in the feature space R^d representing the jth sample in the ith

class of size N_i. The known samples $x_1, x_2, \ldots, x_N$ are used to train the face recognition model based on immunity, and this model is built on the strategy for searching the most similar sample of the unknown objects $o_\alpha, \alpha = 1,2,\ldots,N_o$ in the feature space R^d of the samples. The antigens $Ag_\alpha, \alpha = 1,2,\ldots,N_o$ and the antibodies $Ab_m, m = 1,2,\ldots,N$ are the two repertories of face image matrixes in the improved clonal selection algorithm.

$$N = \sum_{i=1}^{N_c} N_i. \tag{1}$$

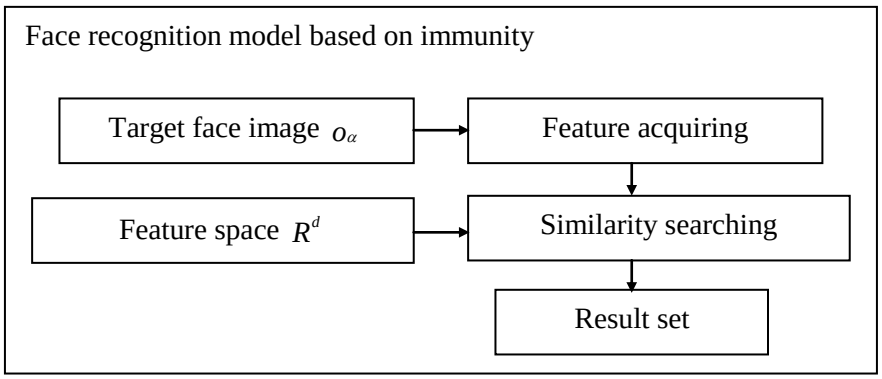

Figure 1. Face Recognition Model based on Immunity

In the pattern recognition cases of traditional clonal selection algorithms, the affinity measure was calculated with the Hamming distance between the antigen Ag_α and an antibody Ab_m [5]. Because the binary coding of the face images causes the loss of some image pixel data, the affinity measure is improved and calculated below.

$$M_m = \sum_{k=1}^{Ltp} (\delta_{mk} + \rho_{mk}),$$

$$\text{where } Ltp = Mtp \times Ntp, \delta_{mk} = \begin{cases} u, & \text{if } Ab_{mk} \pm \varepsilon \in Ag_\alpha \\ 0, & \text{otherwise} \end{cases},$$

$$\rho_{mk} = \begin{cases} v, & \text{if } Ab_{mk} \pm \varepsilon = Ag_{\alpha\omega},\ Ab_{m(k-1)} \pm \varepsilon = Ag_{\alpha(\omega-1)} \\ v, & \text{if } Ab_{mk} \pm \varepsilon = Ag_{\alpha\omega},\ Ab_{m(k+1)} \pm \varepsilon = Ag_{\alpha(\omega+1)} \\ v, & \text{if } Ab_{mk} \pm \varepsilon = Ag_{\alpha\omega},\ Ab_{m(k-Ntp)} \pm \varepsilon = Ag_{\alpha(\omega-Ntp)} \\ v, & \text{if } Ab_{mk} \pm \varepsilon = Ag_{\alpha\omega},\ Ab_{m(k+Ntp)} \pm \varepsilon = Ag_{\alpha(\omega+Ntp)} \\ v, & \text{if } Ab_{mk} \pm \varepsilon = Ag_{\alpha\omega},\ Ab_{m(k-Ntp-1)} \pm \varepsilon = Ag_{\alpha(\omega-Ntp-1)} \\ v, & \text{if } Ab_{mk} \pm \varepsilon = Ag_{\alpha\omega},\ Ab_{m(k-Ntp+1)} \pm \varepsilon = Ag_{\alpha(\omega-Ntp+1)} \\ v, & \text{if } Ab_{mk} \pm \varepsilon = Ag_{\alpha\omega},\ Ab_{m(k+Ntp-1)} \pm \varepsilon = Ag_{\alpha(\omega+Ntp-1)} \\ v, & \text{if } Ab_{mk} \pm \varepsilon = Ag_{\alpha\omega},\ Ab_{m(k+Ntp+1)} \pm \varepsilon = Ag_{\alpha(\omega+Ntp+1)} \\ 0, & \text{otherwise} \end{cases}, \tag{2}$$

$$1 \le \omega \le Ltp, u + v = 1.$$

Here, M_{tp} and N_{tp} represents the pixel lengths of the face images, Ab_{mk} represents the kth pixel value of the antibody Ab_m for matching the face image, $Ag_{\alpha\omega}$ represents the ωth pixel value of the antigen Ag_α for the face image, $Ag_{\alpha(\omega-1)}$, $Ag_{\alpha(\omega+1)}$, $Ag_{\alpha(\omega-Ntp)}$, $Ag_{\alpha(\omega+Ntp)}$,

$Ag_{\alpha(\omega-Ntp-1)}$, $Ag_{\alpha(\omega-Ntp+1)}$, $Ag_{\alpha(\omega+Ntp-1)}$, and $Ag_{\alpha(\omega+Ntp+1)}$ respectively represents the values of left-neighbor, right-neighbor, upper-neighbor, bottom-neighbor, left-upper-neighbor, right-upper-neighbor, left-bottom-neighbor, and right-bottom-neighbor for the ωth pixel value of the face image antigen Ag_α, and $Ag_{\alpha\omega}$ represents the ωth pixel value of the antigen Ag_α for the face image.

The neighbors of the kth pixel value of the antibody Ab_m for matching the face image use the same positioning value in Figure 2 as the ωth pixel value of the antigen Ag_α for the face image. Figure 2 shows the similarity matching between the antibodies and the antigens and their small differences are permitted for the similarity.

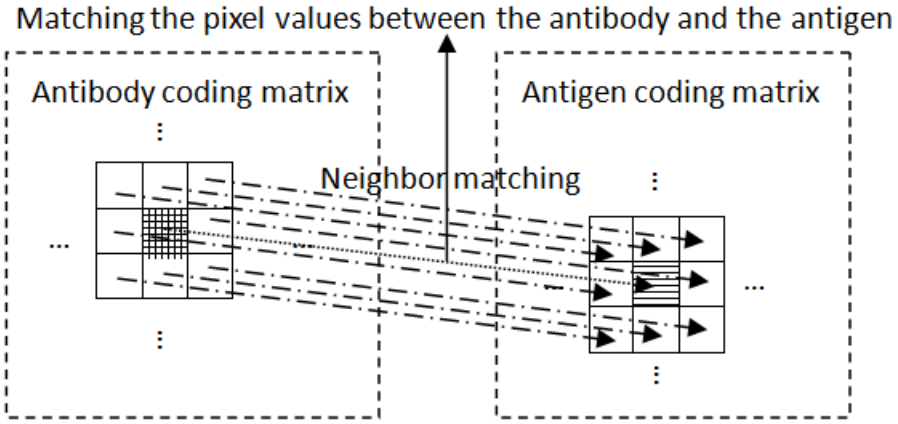

Figure 2. Affinity Measure on Matching between the Antibodies and the Antigens for Face Recognition

3. Improved Clonal Selection Algorithm for Face Recognition

Based on the characteristics of the faces with the disturbances of PIE and the improved affinity measure, the clonal selection algorithm is improved for better application in the face recognition below.

Input: N training samples $x_1, x_2, \ldots, x_N$, and the target face images $o_\alpha, \alpha = 1,2,\ldots, N_o$.

Output: The recognition type of the target face images $\{o_\alpha\}$.

Step 1: Initialize the parameters of the feature space, the feature-acquiring operator and the operator for searching the most similar sample.

Step 2: Build the feature space R^d with the feature vectors of the samples $x_1, x_2, \ldots, x_N$ and represent the vectors as the antibodies $Ab_m, m = 1,2,\ldots, N$.

Step 3: Acquire the feature information of the image o_α, and design the antigen Ag_α.

Step 4: Search the most similar sample of the object o_α with the improved clonal selection algorithm, by matching the antigen Ag_α with any of the antibodies $Ab_m, m = 1,2,\ldots, N$ according to the improved affinity measure.

Step 5: Output the recognition type of the target face image o_α.

4. Experimental Results

Some experiments were conducted to test the effectiveness of the proposed approach, and the benchmark ORL face database was used [6]. The ORL face data set is comprised of 400 images of size 92 by 112 and 40 individuals (10 images per person), with different PIE. All testing samples are matched with the training samples using some matching rules, and the sums of the training samples are respectively 4 and 5. The highest recognition rates of various training samples in the ORL face database for the comparing algorithms are listed in Table 1, and the standard derivations for these data sets are also compared in Table 1 to analyze the robustness of the proposed method.

Table 1. Recognition Rates on the ORL Databases (per cent)

Rate type	The highest		Average
Number of trains	4 Trains	5 Trains	4 Trains
PCA+LPPFace	91.25(41)	97.00(51)	89.95 ± 1.3
PCA+OLPPFace	94.17(37)	97.00(22)	92.37 ± 1.8
PCA+ONPDA	91.92(61)	95.25(27)	89.92 ± 2.0
PCA+MFA	89.16(69)	95.00(69)	87.16 ± 2.0
PCA+NFLE F_1	94.17(41)	95.00(22)	91.97 ± 2.2
PCA+NFLE F_2	94.58(39)	97.00(24)	92.38 ± 2.2
Novel approach	**100**	**100**	$\mathbf{99.17 \pm 0.9}$

Figure 3 shows that the affinity measures of recognizing the face images of No. 6 and No. 10 with failure are almost both the lowest ones in the 4 trains, and the affinity measure of recognizing the face image of No. 10 with failure is also the lowest one in the 5 train. From this table, the recognition rate of the proposed algorithm is maximal and the standard derivation of the proposed algorithm is minimal. Therefore, the performance of the novel face recognition approach is better than those of the other algorithms.

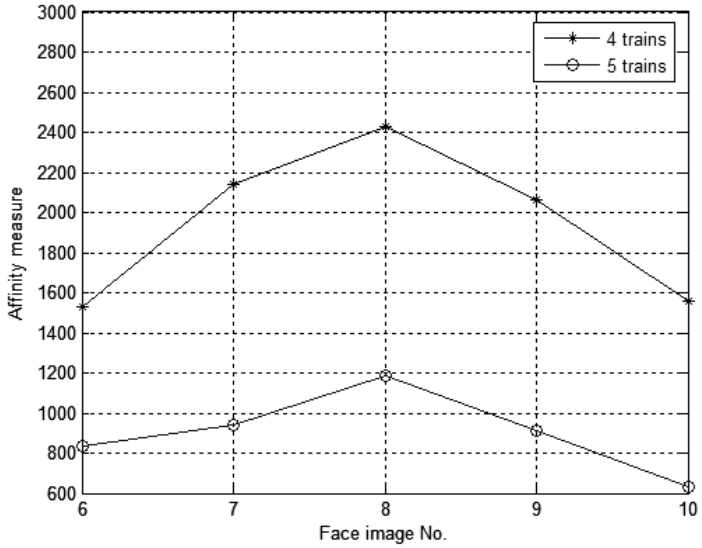

Figure 3. Affinity measures of recognizing the face images in the 4 trains and the 5 trains of the ORL face database

5. Conclusions

The improved clonal selection frame of immune computation [7-10] and the diverse samples are useful for recognize the face images with high recognition rates. The face recognition model based on the immunity can maximize the effectiveness of the feature search of the most similar samples to the target face images, and the affinity measure should be improved for matching the face feature with small differences due to the disturbances of PIE. The diversity and typicality are important to keep the high recognition rates [11], because the face recognition is sensitive to the unknown features of the face images. The high accuracy of the proposed approach is substantiated by the experiments on the ORL face database.

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References

[1] Y. N. Chen, C. C. Han, C. T. Wang and K. C. Fan, "Face Recognition Using Nearest Feature Space Embedding", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 33, No. 6, **(2011)**, pp. 1073-1086.
[2] X. He, S. Yan, Y. Hu, P. Niyogi and H. J. Zhang, "Face Recognition Using Laplacianfaces", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 27, No. 3, **(2005)**, pp. 328-340.
[3] D. Cai, X. He, J. Han and H. J. Zhang, "Orthogonal Laplacianfaces for Face Recognition", IEEE Transactions on Image Processing, Vol. 15, No. 11, **(2006)**, pp. 3608-3614.
[4] X. D. Jiang, B. Mandal and A. Kot, "Enhanced maximum likelihood face recognition", Electronics Letters, Vol. 42, No. 19, **(2006)**, pp. 1089-1090.
[5] L. N. De Castro and F. J. Von Zuben, "Learning and optimization using the clonal selection principle", IEEE Transactions on Evolutionary Computation, Vol. 6, No. 3, **(2002)**, pp. 239-251.
[6] F. Samaria and A. Harter, "Parameterisation of a stochastic model for human face identification", In Proceedings of 2nd IEEE Workshop on Applications of Computer Vision, Sarasota **(1994)**, pp. 138-142.
[7] T. Gong and B. Bhargava, "Immunizing mobile ad hoc networks against collaborative attacks using cooperative immune model", Security and Communication Networks **(2012)**, Published online in Wiley Online Library.
[8] T. Gong and Z. X. Cai, "Tri-tier Immune System in Anti-virus and Software Fault Diagnosis of Mobile Immune Robot Based on Normal Model", Journal of Intelligent and Robotic Systems, Vol. 51, No. 2, **(2008)**, pp. 187-201.
[9] T. Gong, Z. X. Cai and H. G. He, "Immune modelling and programming of a mobile root demo", J. Cent. South Univ. Technol., Vol. 13, No. 6, **(2006)**, pp. 694-698.
[10] T. Gong and Z. X. Cai, "Anti-Worm Immunization of Web System Based on Normal model and BP Neural Network", Lecture Notes in Computer Science, Vol. 3973, **(2006)**, pp. 267-272.
[11] T. Gong and Zixing Cai, "Parallel Evolutionary Computing & 3-Tier Load Balance of Remote Mining Robot", Transactions of Nonferrous Metals Society of China, Vol. 13, No.4, **(2003)**, pp. 948-952.

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Dr. Gong received the MS degree in Pattern Recognition and Intelligent Systems and PhD degree in Computer Science from the Central South University respectively in 2003 and 2007.He is an associate professor of computer sciences at Donghua University, China, and he was a visiting scholar at Department of Computer Science and CERIAS, Purdue University, USA. He is the General Editors-in-Chief of the first leading journal Immune Computation in its field, and an editorial board member of some international journals such as Journal of Computers in Mathematics and Science Teaching, International Journal of Security and Its Applications, and International Journal of Multimedia and Ubiquitous Engineering. He is a Technical Committee Chair of ISEEIP 2012, and a Publicity Chair of ISA 2012. He is also a program committee member of some international conferences such as IEEE ICNC 2011, IEEE BMEI 2011, WMSE 2011, ICARIS 2012, AITS 2012, CCA 2012, ASP 2012, IST 2012, ISA 2012 and SIS2013 etc. He is a Life Member of Sigma Xi, The Scientific Research Society, a Vice-Chair of IEEE Computer Society Task Force on Artificial Immune Systems, and Chen Guang Scholar of Shanghai. His research has been supported by National Natural Science Foundation of China, Shanghai Natural Science Foundation and Shanghai Educational Development Foundation etc. He has published over 70 papers in referred journals and international conferences, and over 20 books such as Artificial Immune System Based on Normal Model and Its Applications, and Advanced Expert Systems: Principles, Design and Applications etc. His current research interests include immune computation, evolutionary computation, pattern recognition, network security, security in mobile embedded systems, applications of artificial immune systems in information security and intelligent networks. He is also a committee member of intelligent robots committee and natural computing committee in the Association of Artificial Intelligence of China.