Evolvable Face Recognition Based on Evolutionary Algorithm and Gabor Wavelet Networks

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Abstract. Gabor Wavelet Networks (GWN) is a method for face recognition. Evolutionary Algorithms are proved to be efficient to deal with GWN optimization problems. Inver-over Evolutionary Algorithm (IOEA) mixed with GWN performs well in face recognition because of its considerable effects on complex functions optimizations, which is called IOEA-GWN put forward by us, and shows higher recognition rate than Simple Genetic Algorithm mixed with GWN (called SGA-GWN) in the same experiment conditions according to our practices.

Keywords: Face Recognition, Evolutionary Algorithm, Wavelet Networks.

1 Introduction

GWN for face recognition [1], [2], [3], [4]: Gabor wavelets functions and relative weight coefficients (multi-parameters) can be used to describe 2-Dimension faces. But optimizations of objective functions and relative parameters have a direct impact on the results of face recognition. However, in real-world applications of face recognition, it is impossible that efficient selections of initial values can be insured constantly considering robustness. Methods insensitive to initial values should be used to improve the effects of face images reconstruction and recognition.

Levenberg-Marquardt Algorithm (LMA) [3] is sensitive to initial values and relative results are easy to be made an impacted on by variant initial values [5]; SGA which is used to optimize GWN [5] (called SGA-GWN) can reduce the susceptibility to initial values. However, the results of SGA-GWN show slow convergence and easy to converge into local extreme values [5]. Inver-over Evolutionary Algorithm (IOEA) has considerable effects on functions and parameters optimizations [6], [7], [8], [9]. We respectively use IOEA and SGA to optimize GWN in the experiments.

2 Face Images Database

We select Yale face database as a tested object.

Fig. 1. Examples in Yale face database

Yale face database can be described here: 165 images (all are grayscale images), 15 subjects, 128×128 (image resolution), normal faces, different expressions, few covers, variant illuminant directions. One image of each subject is called sample-image (I) and the rest are called test-images (I').

3 Face Images Pre-processing

Face images pre-processing including lightness normalization is useful for following face recognition [10], [11].

We derive the whole expression of lightness normalization as follows during the pre-processing.

Gray value $f(x, y) \in [0, 255]$. We assume that the image-height is h , the image-width is w , and the default average lightness value $\bar{v}$ is 128.

$$\text{Average lightness value } v = \frac{1}{wh} \sum_{x=1}^w \sum_{y=1}^h f(x, y).$$

$f'(x, y)$ denote images (after we do lightness normalization).

$$f'(x, y) = g(\bar{v}f(x, y)/v), \quad g(x) = \begin{cases} 0, & x < 0 \\ x, & 0 \leq x \leq 255 \\ 255, & x > 255 \end{cases}$$

Therefore the whole expression is:

$$f'(x, y) = \begin{cases} 0, & f(x, y) < 0 \\ \frac{128hwf(x, y)}{\sum_{x=1}^w \sum_{y=1}^h f(x, y)}, & 0 \leq f(x, y) \leq \frac{255 \sum_{x=1}^w \sum_{y=1}^h f(x, y)}{128hw} \\ 255, & f(x, y) > \frac{255 \sum_{x=1}^w \sum_{y=1}^h f(x, y)}{128hw} \end{cases}$$

4 GWN Process Analysis

There are four steps in GWN process analysis.

4.1 Gabor Wavelets Optimizations

GWN is expressed by Gabor wavelets functions and relative weight coefficients. Gabor wavelets functions and multi-parameters optimizations' purpose is to describe face sample images and test images, and to search the effective reconstruction ($\hat{I}$) of image I . As to same subjects' different images, Gabor wavelets functions are close in values but relative weight coefficients are different. According to our experience, the number of Gabor wavelets funtions is selected 52 in each objective function ($i=1,2,3,4,...,52$):

$$\min g(G) = \min g(c_{x_i}, c_{y_i}, \theta_i, s_{x_i}, s_{y_i}) = \min \left[\left\| I - \sum_{i=1}^N w_i \psi_{n_i} \right\|_2^2 \right]$$

We expand the expression so that it is suitable for Matlab:

$$\begin{aligned} g(c_{x_i}, c_{y_i}, \theta_i, s_{x_i}, s_{y_i}) &= \left\| I - \sum_{i=1}^{52} [w_i \psi_{n_i}(c_{x_i}, c_{y_i}, \theta_i, s_{x_i}, s_{y_i})] \right\|_2^2 \\ &= \left\langle \left(I - \sum_{i=1}^N w_i \psi_{n_i} \right), \left(I - \sum_{i=1}^N w_i \psi_{n_i} \right) \right\rangle \\ &= \int_{-\infty}^{\infty} \left(I - \sum_{i=1}^N w_i \psi_{n_i} \right) \overline{\left(I - \sum_{i=1}^N w_i \psi_{n_i} \right)} dx \end{aligned}$$

Gabor wavelets functions are not orthogonal. Therefore the weight coefficient w_i can not be directly determined but can be derived from $\bar{\psi}$ (dual wavelet).

$$\langle \psi_{n_i}, \bar{\psi}_{n_j} \rangle = \delta_{i,j} = \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases},$$

$$\bar{\psi}_{n_i} = \frac{1}{\sqrt{2\pi}} \int e^{j\omega t} \psi_{n_i}(t) dt, \quad w_i = \langle I, \bar{\psi}_{n_i} \rangle.$$

$n_i = (c_{x_i}, c_{y_i}, \theta_i, s_{x_i}, s_{y_i})$ denote parameters of Gabor wavelets functions.

c_{x_i}, c_{y_i} denote translation factors. θ_i denote rotation factors. s_{x_i}, s_{y_i} denote scaling factors [5]. Odd Gabor wavelets functions reflect face structures:

$$\begin{aligned} \psi_{n_i}(x, y) &= \frac{2}{\pi^3} \exp \left\{ -\frac{1}{2\pi^2} [s_{x_i}((x - c_{x_i}) \cos \theta_i + (y - c_{y_i}) \sin \theta_i)]^2 \right. \\ &\quad \left. + [s_{y_i}(-(x - c_{x_i}) \sin \theta_i + (y - c_{y_i}) \cos \theta_i)]^2 \right\} \\ &\quad \cdot \sin [s_{x_i}((x - c_{x_i}) \cos \theta_i - (y - c_{y_i}) \sin \theta_i)] \end{aligned}$$

4.2 Super Gabor Wavelets Optimizations

Super Gabor wavelets are the results of Gabor wavelets translation, scaling, and rotation. The Super Gabor wavelets optimizations' purpose is to transform sample images to align with test images.

4.3 Gabor Wavelets Parameters Expressed in IOEA

T denotes transposition of a vector or a matrix.

$$G_i = (c_{x_i}, c_{y_i}, \theta_i, s_{x_i}, s_{y_i})^T \in R^n, \quad c_{x_i}, c_{y_i}, \theta_i, s_{x_i}, s_{y_i} \in D.$$

According to our experience, the range of parameters is:

$$D = \left\{ G_i \mid -64 \leq c_{x_i}, c_{y_i} \leq 63, 0 \leq \theta_i \leq 2\pi, 0 \leq s_{x_i}, s_{y_i} \leq 10 \right\}$$

M points in D are: $G'_j = (x_{j1}, x_{j2}, \dots, x_{jm})^T, j = 1, 2, \dots, m$.

They span a subspace S :

$$S = \left\{ G \in D \mid G = \sum_{i=1}^m a_i G'_i \right\}. \quad \sum_{i=1}^m a_i = 1, \quad -0.5 \leq a_i \leq 1.5$$

4.4 Contrasts of Various GWNs

We compare test-images' GWN with Super-GWN derived from results of Super Gabor wavelets optimizations. Various GWNs show distinctions between different subjects and same subjects under different conditions (illumination, expression, etc.). GWNs contrasts index are:

1) Euclidean distances [5] (V and W are weight coefficients vectors):

$$d_{\psi}^2(I, I') = \left\| \hat{I} - \hat{I}' \right\|_2 = (V - W)^T \langle \psi_i, \psi_j \rangle (V - W)$$

2) Cross-correlation factors [5]:

$$d_{\psi}^c(I, I') = \frac{V^T \langle \psi_i, \psi_j \rangle W}{\sqrt{V^T \langle \psi_i, \psi_j \rangle V} \sqrt{W^T \langle \psi_i, \psi_j \rangle W}}$$

Various GWNs tend to be more close when $d_{\psi}^c(I, I') \rightarrow 1$.

5 Algorithms and Experiments

We especially use IOEA to optimize GWN as follows (IOEA-GWN).

{ begin

- 1 Initialize Population $P = (G_1, G_2, \dots, G_{52})^T, G_i \in D$;
- 2 $t := 0$;
- 3 $G_{best} = \arg \min_{1 \leq i \leq 52} (g(G_i))$; ("arg" denotes relative parameters G when Gabor wavelets functions converge into overall optimum);
- 4 $G_{worst} = \arg \max_{1 \leq i \leq 52} (g(G_i))$;

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5 While ( $|g(G_{best}) - g(G_{worst})| > \varepsilon$ ) do
6 {Select M points  $G_1, G_2, \dots, G_m$  randomly from P to span subspace S;
7 Select one point  $G_{crossover}$  randomly from S;
8 If ( $g(G_{crossover}) < g(G_{worst})$ ) then  $G_{worst} = G_{crossover}$ ;
9  $t := t + 1$ ;
10  $G_{best} = \arg \min_{1 \leq i \leq 52} (g(G_i))$ ;
11  $G_{worst} = \arg \max_{1 \leq i \leq 52} (g(G_i))$ ;
12 end do}
13 output t, P;
14 end }
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We use IOEA-GWN and SGA-GWN respectively with 5×52 parameters by real number programming. Experiment Machine: CPU Celeron 1.7G, Memory 512M. Programming tool are both Matlab 6.5. Popular sizes are both 100 [12]. The Maximum numbers of generations are both 100. Selections are both roulette wheel selection.

- 1) In IOEA-GWN: According to our experience, the value of M is 10 and Multi-parent's crossover-probability is 0.6.
- 2) In SGA-GWN: Crossover-probability is 0.6. In our experiments, "multi-point crossover" destroys correct solutions, and "one-point crossover" shows low diversity of solutions. Therefore we use "two-point crossover" finally. Mutation-probability is 0.01.

Fig. 2. An original image

Fig. 3. Gabor wavelets optimizations

We select 55 images (including: 5 subjects and 11 images per subject) from Yale face database. Then we determine a sample image per subject and other 50 images (named test-images) for recognition.

The recognition rate of SGA-GWN is not same as the high rate 97.8% [5] because of different numbers of test-images and databases.

Fig. 4. Results of SGA-GWN (broken line) and IOEA-GWN (real line)

Fig. 5. Images marked 1-5 and 6-10 (The fifth is a sample image)

Fig. 6. $d_{\psi}^2(I, I')$

Fig. 7. $d_{\psi}^c(I, I')$

Table 1. Contrasts of Algorithms

Algorithm	SGA-GWN	IOEA-GWN
Test set	50	50
Recognition Images	41	46
Time(minutes)	22	16
Recognition rate	82%	92%

6 Conclusion and Future Work

Following methods can be used to improve convergent rate and continuous recognition rate.

- 1) Improved IOEA can be used to optimize GWN.
- 2) Gene Expression Programming (GEP) can be used to optimize GWN (called GEP-GWN). Because GEP has some features of dealing with high dimension parameters optimizations problems, and GEP can also be used for face modeling.
- 3) All these methods can be used in 2D/3D face recognition [13] and may be more useful for face tracking.

Therefore, the new branch “Evolvable Face Recognition, or Evolutionary Face Recognition” is considerable to research including “Evolutionary face modeling”, “Evolutionary face algorithms”, “Evolutionary automatic face programming”, and “Evolutionary face hardware”. All of these are considerable to be used to build “Evolvable Face Systems”.

Acknowledgments. acknowledge the financial support of the National Natural Science Foundation of China under Grant No.60473081.

References

1. Phillips, P., Moon, H., Rizvi, S., Rauss, P.: The feret evaluation methodology for face-recognition algorithms. *Pattern Analysis and Machine Intelligence, IEEE Transactions on.* **22** (2000) 1090–1104
2. Shan, S.: Study on Some Key Issues in Face Recognition. PhD thesis, Chinese Academy of Sciences (2004)
3. Krueger, V., Sommer, G.: Gabor wavelet networks for object representation. *Journal of the Optical Society of America.* **19**(6) (2002) 1112–1119
4. Lee, T.: Image representation using 2d gabor wavelets. *Pattern Analysis and Machine Intelligence, IEEE Transactions on.* **18** (1996) 959–971
5. Wang, B.: Global-Feature-based face recognition technology using genetic algorithms. PhD thesis, Beijing University of posts and telecommunications (2004)
6. Zhan, W., Dai, G., Gong, W.: A high-efficiency hybrid evolutionary algorithm for solving function optimization problem. *Computer Engineering and Applications.* (2006) 1–3

7. Li, Y., Kang, Z., Liu, P.: Guo's algorithm and its application. Journal of Wuhan automotive polytechnic university. (2000) 1–3
8. Wang, J., Chen, J., Wei, W., Li, Z.: Based on improved gt algorithm for tsp. Computer Engineering and Design. (2006) 1–3
9. Guo, T., Kang, L., Li, Y.: A new algorithm for solving function optimization problems with inequality constraints. Natural Science Edition, Journal of Wuhan University. (1999)
10. Qin, Z.: Research on face detection and face recognition technology (2005)
11. Wiskott, L., Fellous, J., Kfuger, N., Malsburg, C.: Face recognition by elastic bunch graph matching. Pattern Analysis and Machine Intelligence, IEEE Transactions on. **19** (1997) 775–779
12. Pan, Z., Kang, L., Chen, Y.: Evolutionary Computation. Tsinghua University Press (2000)
13. Hu, Y., Yin, B., Cheng, S., Gu, C., Liu, W.: Research on key technology in construction of a chinese 3d face database. Journal of Computer Research and Development. (2005) 1–3