ELSEVIER
Available online at www.sciencedirect.com
SciVerse ScienceDirect
Procedia Engineering 15 (2011) 1319 – 1323
Procedia Engineering
www.elsevier.com/locate/procedia

Advanced in Control Engineering and Information Science

Quantum Neural Networks for Face Recognition Classifier

Yan Xu, Xiaofeng Zhang, Huaicun Gai *

(School of Information Engineering, Nanchang Hangkong University, Nanchang 330063)

Abstract

In this paper, an approach to face recognition is presented, which based on multi-level transfer function quantum neural networks (QNN) and multi-layer classifiers. Firstly, image preprocessing is used to eliminate unrelated information in face images, which could help to locate eyes position. Secondly, feature extraction employs eigenface method based on Karhunen-Loeve transform to extract statistic feature and reduce dimensions. Finally, in the part of face recognition, quantum neural networks based on multi-level transform function are used. The QNN is trained and tested by the ORL faces digital database. At the same time with the classical BP neural network classifiers are compared, the results show that the identification method in more complex environments with a certain degree of robustness and effective and feasible.

Selection and/or peer-review under responsibility of [CEIS 2011]

Keywords: Quantum neural network; Qubit; Face Recognition; Multi-stage Classifier;

1. Introduction

Face Recognition Technology is a computer-assisted method. From a series of static or dynamic image sequences, it using existing face digital database to confirm, in the scene, whether the person is a particular one in the face digital database. Face recognition is a biological characteristic identification method without infringement, it research across the image processing, pattern recognition, computer vision, artificial neural network and neurophysiology, psychology research, make it become more challenging. At present, face recognition of mainstream research direction are [1, 2, 3]: Eigenface methods which based on principal component analysis [4], Fisher Face methods which based on FisherLDA [5], Elastic Graphite Matching and Local Feature Analysis. Eigenface methods as a relatively successful face recognition technology raised the second high tide in the research of face recognition. On the basis of Eigenface methods, Fisher Face methods introduced the category message of commons and differences in the classification, so that the cast shadow space applies to classified problem. Elastic Graphite Matching is a face recognition, which solved the varying changing problems of face and based on face recognition method of local informational face information. Local Feature Analysis considered the information of

* Corresponding author: Xiaofeng Zhang. Tel.: 15579138863; +86-791-3953432.
E-mail address: xfzhang1130@163.com

1877-7058 © 2011 Published by Elsevier Ltd. Open access under CC BY-NC-ND license.
doi:10.1016/j.proeng.2011.08.244

facial local feature and faces the topological relationship between them. Face analysis techniques have made great progress, but there are still many factors constraining its development.

2. Human Eye Positioning

Face positioning is required for almost all the face recognition techniques, especially the accurate positioning of eyes, and this is because the variation of light or facial expression has the slightest influence on the distance between eyes. So it often used as the standard of geometrical feature or image size normalization.

To determine the optimal thresholds and segregate eyes and face from complex backgrounds is the first step of eye positioning. Setting the initial threshold Ts as a fixed value (such as 10 greyscales), setting the maximum search threshold Te as 154 greyscales. Specific procedures are as follows: generated a binary image by the greyscale threshold T, determine whether black blocks in the image are human eyes according to the rules of geometric position of human eyes in the binary image .

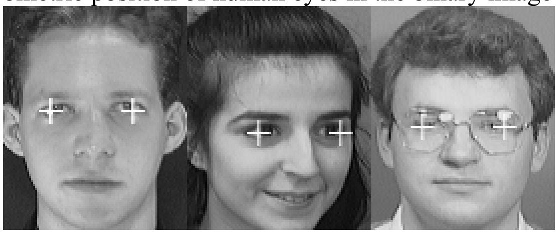

Fig. 1. experimental results

3. Face Feature Extractions

Face feature extraction is the core issue of pattern recognition. This extraction should be featuralized as representative ness, large amount in information, a small amount of redundancy, and the ability to maintain a certain degree of invariance and adaptability under some interference, it plays a crucial role for the classification results of classifiers to effectively reduce the feature vector dimension. In pattern recognition, it is the effect of classifier and it is the key to solve the problem successfully to know how to find out the features of both good performance and real-time extraction. Image feature extraction feature extraction is an important model component of model feature extraction.

Eigenfaces is refers to a high dimensionality vector, which formed by the unfolding of face image on ranks as a random vector and thus the KL (Karhunen-Loeve) can be obtained by the KL transform. In principle, a feature on face method is applied to KL transform to face model space. This method can effectively reduce data dimension, make store and identify more efficient and reliable. The total people of ORL face atlas the toll is 40, each one has 10 pictures. Take the first five face pictures of every person from here as training sets, and then the sum of training sets is 200 pictures.

4. The Design of Face Recognition Classifier

4.1. Learning algorithm of quantum neural networks

Multi-layer excitation function of hidden neurons in quantum neural networks：

$$b_r = \frac{1}{ns}\sum_{s=1}^{ns} f[\beta\left(W^T X - \theta_s\right)], \left(r = 1, 2, \cdots, u\right) \tag{1}$$

In this function: $f(x)=1/(1+\exp(-x))$ is activation function, W is the network weights, X is the network input vector, β s the slope factor, θ_s is the quantum interval(s=1, 2, ns).

The training algorithm of the neural network model of multi-layer excitation function adopts the gradient descent method. In each training cycle, the training algorithm both to revise the connection weight between the different level neuron. The revision algorithm connection weight between each layer's is achieved by the adoption of descend one phase-shift gate neon rotation angle, the algorithm of adjust hidden neurons quantum interval [6] is as follows:

The supposition regarding kind of C_m (m is pattern class number), the i implicit strata neuron output change is

$$\delta_{i,m}^2 = \sum_{x_k \in c_m} (\langle o_{i,m} - o_{i,k} \rangle)^2 \tag{2}$$

In the forum, $O_{i,k}$ is in the input of the i neuron in hidden layer when the input vector is x_k ; $< O_{i,m} >= \frac{1}{|C_m|} \sum_{x_k \in C_m} O_{i,k}$, $|C_m|$ is the cardinal number of Cm .We can see that $\delta_{i,m}^2$ is a function of quantum interval of θ_s , through its θ_s (s=1…ns) derivation, the minimum value of $\delta_{i,m}^2$ and then get change forum of $\theta_{i,s}$ (that is, the s layer of the i neuron hidden layer)

$\Delta \theta_{i,s} = \eta \frac{\beta}{ns} \sum_{m=1}^{n_0} \sum_{x_k \in C_m} (< O_{i,m} - O_{i,k} >) * (< V_{i,m,s} > - V_{i,k,s})$ In the forum, η the learning rate; n0 is the output layer nodes, namely the total class number; ns layers for quantum interval; $x_k \in x_m$ means that among all samples belong to the class Cm; $\langle V_{i,m,s} \rangle$ and $V_{i,k,s}$ obtained by the following two equations:

$$\langle V_{i,m,s} \rangle = \frac{1}{|C_m|} \sum_{x_k \in C_m} V_{i,k,s}, V_{i,k,s} = O_{i,k,s} * (1 - O_{i,k,s}) \tag{3}$$

In the forum $O_{i,k,s} = sig(\beta * (w^T x_k - \theta_s))$, when the input vector is x_k , it is the output of the s of the i neuron in hidden layer .

4.2. The design of quantum neural networks

This paper trains and discerns on the basis of ORL (Olivetti Research Laboratory) face image database, there are 40 people in all in the storehouse, 10 photos of each person. During the training, each one select 5 images from 200 face images as a training set. After image processing, the image shows as greyscale matrix of 48×48 , arrange it into a dimension vector x_i , according to row selection.

$$x_i = [x_{i1}, x_{i2}, ..., x_{im}]; m = 48 \times 48 = 2304 \tag{4}$$

As the training have 200 images, so you can get $[x_1, x_2, \cdots, x_{200}]$ .The number of input layer nodes depends on the number of dimensions of the data source, so we can propose the number of input nodes network N_{in} as vector dimension of facial feature. The number of output layer node is determined by the number of categories to be identified, if the number of category is s, then take $N_{out} = s$ the output node.

The number of output nodes N_{out} is the total number of corresponding identifies people, to the ORL face recognition database $N_{out} = 40$.

Hidden neurons, generally, the design of quantum state in quantum theory of phase line overlay, the selection of the number of hidden neurons is a very complex problem, often based on the designer's experience and experiments to determine. Generally, you can consider using the following method to determine the number of hidden units. $N_{hid} = \sqrt{N_{in} + N_{out}} + a$. Among it, N_{in} is the neuronal number of input layer, N_{out} is the neuronal number of output layer, a is a constant between [1, 10].

4.3. Test analysis

The hidden nodes are fixed in the trial, and network parameters of hidden layer to output layer is guaranteed by linear least squares method to get global optimal gradient descent method, then the search space can greatly reduce. The learning rate can also made great many relative to the standards adopted can BP algorithm. Here was adopted for learning rate $\eta = k\lambda^n$, $\lambda(0 < \lambda < 1)$, n is the times of circulation, k is the learning constants, after the experiment test，k for 10， λ for 0.986。

The relationship between characteristic matrix dimension and the recognition rate is shown in figure 2. The characteristic matrix dimension is around 50. It is suggests that best choice the more choice of characteristic vector is not better, the biggest vector of characteristic value contains the majority of features. Enrolling more vectors become no longer significant for improving recognition rate.

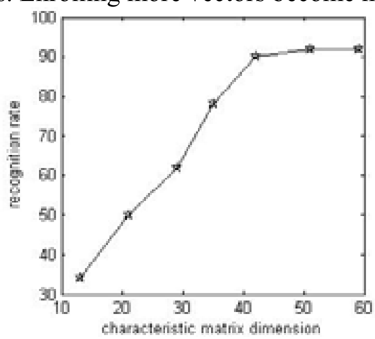

Fig. 2. characteristic matrix dimension and the recognition rate

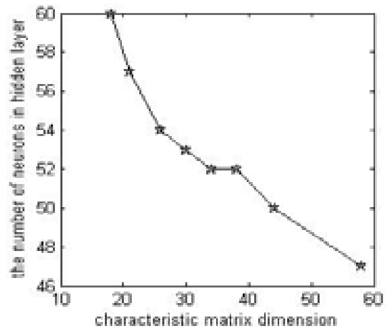

Fig. 3. the number of neurons in hidden layer with characteristic matrix dimension

The changes of the number of neurons in hidden layer with characteristic matrix dimension are shown in figure.3. Figure in each point, from left to right, correspond to 65,70,75,80,85,90,95,100 percent of energy characteristic vector. In figure 3, viewing from the X axis, every point in this figure shows a characteristic, from scatter to density, which reflects the advantage that the more determination of the transformation of transformative vector KL, the more concentrated to energy. Furthermore, from the change trend of the curve, we can see that the number of neurons in hidden layer is declining, with the increase of the characteristic matrix dimension, this is because become more complete with the increase of characteristic vector dimension, and then the cluster of hidden nodes is closer to the actual classification of faces. The experiment has separately carried on the training and the recognition with the same training set to the classics BP neural network and the quantum neural network. Test result as shown in Table 1:

Table 1. the results of tested neural network

Network type	Classic BP sorter	Quantum nerve network
Recognition rate（%）	90.6	97.8
Misrecognition rate（%）	6.8	0.7
Refuse recognition rate（%）	2.6	1.5
Creditability（%）	93.0	99.3

In the table, credibility = recognition rate/(recognition rate + misrecognition) ×100%.We can see from Table 1, compared with the classics BP neural network, the misrecognition and recognition rate of the quantum neural network have dropped, and its recognition rate has raised to a certain degree. This indicates that the method we put forward in this paper is feasible and effective.

5. Conclusions

Based on the quantum neural networks, the paper mainly studies and designs a face identifier. With the use of operation, such as, filtering, grey equalization and binary operation, realized the human eye location methods. Based on the KL transformation combining with singular value decomposition (SVD) through a normalized processing to those images after eye location; then puts forward the feature extraction. At last, the way of quantum neural networks which based on multi-level excitation function is put forward. This experiment shows that this method is applied in face recognition has good collective ability and adaptive learning ability, and the strong fault tolerance and good robustness, reflects the superiority and the huge potential of the quantum neural network for pattern recognition.

Acknowledgements

This Program is sponsored by the Natural Science Foundation of China (No.60973048), the Natural Foundation of Jiangxi Province of China (No.2009GZS0084), the Research Foundation of Nanchang Hangkong University (No.EA200906012), the Innovation Foundation of Postgraduate of Nanchang Hangkong University (No.YC2010025).

References

[1] Pentland A, Choudhury T. Face Recognition for Smart Environments*[J]*. *IEEE Computer*, 2000: 50-55.

[2] Zhang J, Yan Y, Lades M. Face Recognition: Eigenface, elastic matching, and neural nets*[C]*. *Proceedings of the IEEE*, 1997; 85(9): 1423-1435.

[3] Zhao W, Chellappa R, Rosenfeld A and Phillips P J. Face recognition: a literature survey. CS-Tech Report-4167, University of Maryland, 2000.

[4] Bai Z R,Zhang L,Ye Z F. A Method of Sky-subtraction Based on Principal Component Analysis*[J]*. *Chinese Astronomy and Astrophysics Analysis*,32(2008):109-177.

[5 Eremad K, Chellappa R. Discriminant analysis for recognition of human face images*[J]*. *Optical Society of American*, 1997; 8(14): 1724-1733.

[6] Gopathy P, Nicolaos B, Karayiannnis N B. Quantum neural network computes entanglement*[J]*. *IEEE Transactions on Neural Networks*, 1997; 8(3):679-693.