Face Recognition Based on Deep Belief Network Combined with Center-Symmetric Local Binary Pattern

Chen Li, Wei Wei, Jingzhong Wang, Wanbing Tang and Shuai Zhao

Abstract Human face recognition performances usually drops heavily due to pose variation and other factors. The representative deep learning method Deep Belief Network (DBN) has been proven to be an effective method to extract information-rich features of face image for recognition. However the DBN usually ignore the local features of image which are proven to be important for face recognition. Hence, this paper proposed a novel approach combined with local feature Center-Symmetric Local Binary Pattern (CS-LBP) and DBN. CS-LBP is applied to extract local texture features of face image. Then the extracted features are used as the input of Deep Belief Network instead of face image. The network structure and parameters are trained to obtain the final network model for recognition. A large amount of experiments are conducted on the ORL face database, and the experimental results show that compared with LBP, LBP combined with DBN and DBN, the proposed method has a significant improvement on recognition rates and can be a feasible way to combat with pose variation.

Keywords Face recognition · Pose variation · CS-LBP · DBN

1 Introduction

As a biometric technology, face has many distinct advantages compared with other biometric characteristics: it can be captured from a long distance which is friendly and convenience especially for the information security or access control application and it also has a wealthy structure and relatively larger area which is not easily

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to be occluded. Hence face recognition has becoming an indispensable biological authentication method and attracting many attentions.

During the last decades, many face recognition approaches have been proposed and can be roughly divided into two types: pixel-based approach and feature-based approach [1]. The Principle component analysis (PCA), Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA) methods are the most typical pixel-based methods and have been proved to be effective for recognition with large databases. The feature-based approach mainly include Local Binary Pattern (LBP), Gabor, SIFT and their modified approaches. Most the above methods can achieve satisfying recognition result upon frontal and high resolution face image. However the feature extraction methods usually rely on artificial selection. Besides, to extract more robust deep-level features in order to express face information more effectively is still difficult. Hence face recognition performances usually drops heavily due to pose variation and other factors under unconstrained environment, which is still a challenging task for researchers [2, 3].

Deep Learning [4] has become an important research area in computer vision. Deep Belief Network (DBN) is a typical Deep learning method with strong learning and expression ability. It can learn essential data feature from small samples and extract feature automatically without artificial selection. However, when pixel level image are import to DBN directly, the recognition performance normally decline since DBN ignores the local features of the images [5]. In order to make full use of the learning ability of DBN, proposed a novel approach combined with local feature and DBN is proposed. This paper is organized as follows: Sect. 2 describes the proposed technique, Experiment results are demonstrated in Sect. 3. Then we conclude the paper in Sect. 4.

2 Technical Approach

2.1 Center-Symmetric Local Binary Pattern (CS-LBP)

Local binary pattern (LBP) is an feature descriptor proposed by Heikkila which has been proven to be effective at texture feature description. And it can be seen as a standard approach for extract structural model of texture information. However texture features extracted by LBP is usually too nuanced to be robust for flat area of images [6]. To compensate the shortage, CS-LBP is proposed. It encode the change of the image from four different direction with center symmetric principle. The CS-LBP features can be described with Eqs. (1) and (2):

$$\mathrm{CS-LBP}_{R,N,T}(X,Y) = \sum_{i=0}^{\left(\frac{N}{2}\right)-1} S\left(n_i - n_{i+\left(\frac{N}{2}\right)}\right)2^i \tag{1}$$

$$s(x) = \begin{cases} 1, & x > T \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where n_i and $n_{i+(N/2)}$ correspond to the gray value of center-symmetric area pixels, N represents the pixel numbers on a circle of radius R. To enhance the robustness of CS-LBP feature on flat image regions, a threshold T is set for the change of image intensity. Compared with the traditional LBP, CS-LBP has lower dimension and lower computational complexity. Also it is more robust to noise interference. Hence CS-LBP is used for feature extraction to preserve more useful information of the image and reduce the impact of noises like pose variation.

2.2 *Deep Belief Network*

Since the deep learning architecture is proposed, it has drawn much interests. The deep learning architecture normally consist of feature detector units arranged in layers. Simple features are extracted by lower layers and put into higher layers to extract more complex features [7]. One of the most typical deep architectures DBN is proposed by Hinton in 2006 [8]. It is a multi-layer generative model composed of unsupervised Restricted Boltzmann Machine which consists of a visible layer as well as a hidden layer. It is build to detect more complex features which can reveal hidden information and higher-order correlations of the data.

To demonstrate its basic principle, a DBN model is shown in Fig. 1. As shown on the left part of Fig. 1, vi (i = 1, 2, …) represents the vector of visible layer; hi (i = 1, 2, …) represent the vector of the hidden layer. As shown on the right part of Fig. 2, a RBM [9] is composed of a visible layer and a hidden layer. The number of the visible units in the lower RBM equals to the number of the hidden units in next higher RBM. Pre-training the DBN model consists of learning the RBMs one by one, during which the learned features of one RBM are put into the next RBM as the input 'data'.

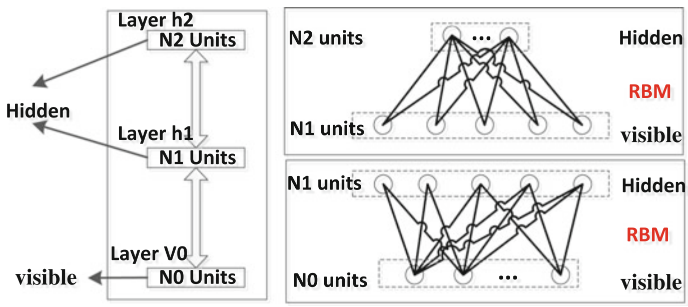

Fig. 1 DBN structure containing two RBMs

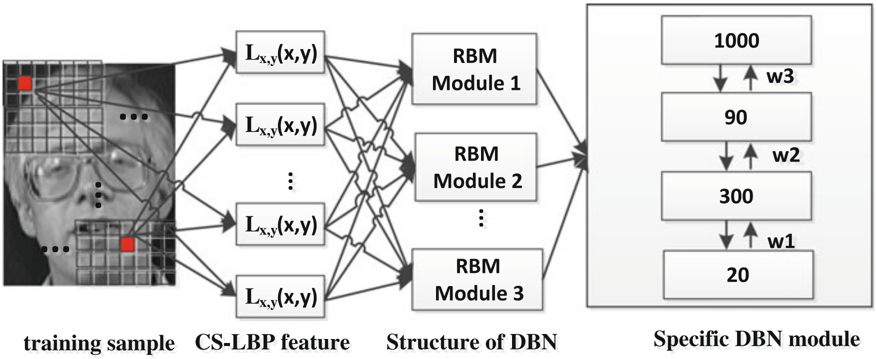

Fig. 2 Process of the proposed algorithm

2.3 DBN Combined with CS-LBP Based Face Recognition

Applying DBN to realistic-sized images is challenging because pixie-level face images are high-dimensional which will cause very high computationally complexity to the training algorithm. Besides DBN usually ignore the local features of images which is important for recognition. Hence the DBN Combined with CS-LBP algorithm is proposed in this part.

As shown in Fig. 2, firstly the local features of the input images are extracted by CS-LBP. Secondly, the obtained features are feed into the DBN instead of original face images as the input of the visible layer. Thirdly, pre-training the DBN from the bottom layer to the top layer. The main process is: training the first layer's network parameters and use its output as the second layer's input data and so on. To obtain the best net parameters, the Back Propagation (BP) algorithm is applied to fine tune the pre-trained DBN. In this paper, the final DBN model contains 3 layers and the number of iterations for each layer is 20. Finally, the Euclidean distance classifier is applied for classifying the face images accurately.

3 Experiment and Analysis

We conducted a number of experiments on the ORL face database [10] to evaluate the proposed face recognition algorithm. As shown in Fig. 3 ORL face databases consisted of 40 persons. Each person contained 10 different images with pose and expression variation.

Fig. 3 Images example of ORL database

3.1 Experiment 1

We selected the approximate frontal face image of each person to form the test dataset, and the remaining 9 images of the same person to form the training dataset. The training dataset consist of 360 images, and test dataset contains 40 images. The recognition results are shown in Fig. 4.

Figure 4 shows the comparison between the proposed method and other 3 methods including LBP combined with PCA, LBP combined with DBN and DBN. The experimental result shows that: the rank1 recognition rate of the proposed method is 97.5 %. It is at least 7.5 % higher than the rank1 recognition rate of the other 3 typical algorithm as shown in Fig. 4b–d. Hence, the proposed methods gains obvious performance improvement over the other three typical methods.

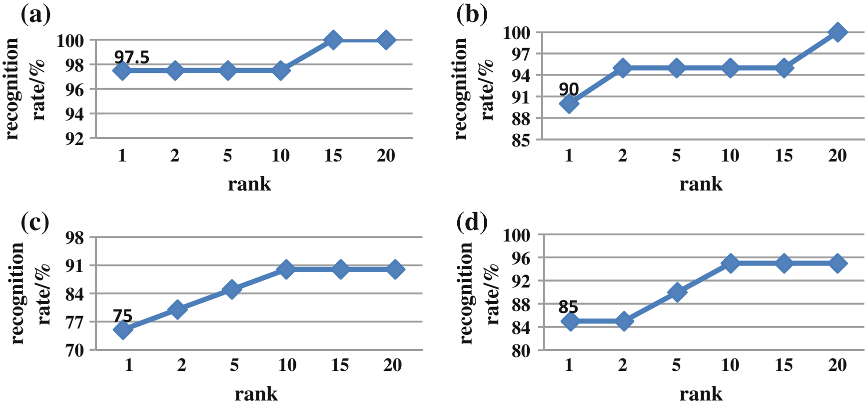

Fig. 4 Recognition rate comparison. **a** Proposed method. **b** LBP + DBN. **c** LBP + PAC. **d** DBN

Table 1 Comparison of different recognition method on multi-pose face image

Method	Multi-pose face recognition rate (%)	Approximate frontal face recognition rate (%)
Proposed method	92.78	97.5
LBP + DBN	87.89	90
LBP + PCA	65	75
DBN	81.5	85

3.2 Experiment 2

To further demonstrate the effectiveness of the proposed method on face images with pose variation, several other experiments are conducted. Since each person has 10 images with pose variation of different degree, each image of the same person is used to be the test image in turn, which means 10 group of test datasets and training datasets is formed. Then the proposed algorithm is performed on these 10 datasets. The final recognition rate is the average of these ten experiments, which demonstrate the recognition rate of the proposed method on multi-pose face images. Table 1 shows the result.

As shown in Table 1, when employing the face images with pose variation as the test set, the performance of the four algorithm all degrade to a certain extent. However, the proposed method still achieve the highest rank1 recognition rate 92.78 % which is at least 5 % higher than the other three methods. This verifies the proposed algorithm combining the local features and the advantage of DBN gains obvious performance improvement over the multi-pose face image.

4 Conclusion

A face recognition approach combining with CS-LBP and DBN is proposed in this paper. The CS-LBP is applied to extract local texture features of face image, which are imported to DBN instead of original face images. Then the network model is confirmed through pre-training and fine tuning layer by layer. A large amount of experiments are conducted on the ORL face database. By comparing with the LBP combined with DBN, LBP combined with PCA, and typical DBN, the proposed method is proven to be a significant improvement on recognition performance as well as a feasible way to combat the influence of pose variation.

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References

1. Klare B, Jain AK (2010) Heterogeneous face recognition: matching NIR to visible light images. In: Pattern recognition international conference on IEEE, pp 1513–1516
2. Shuicheng Y, Dong X, Benyu Z et al (2007) Graph embedding and extension: a general framework for dimensionality reduction. IEEE Trans Pattern Anal Mach Intell 29:40–51
3. Jian Y, David Z, Frangi AF et al (2004) Two-dimensional PCA: a new approach to appearance-based face representation and recognition. IEEE Trans Pattern Anal Mach Intell 26:131–137
4. Arel I, Rose DC, Karnowski TP (2010) Deep machine learning—a new frontier in artificial intelligence research [Research frontier]. IEEE Comput Intell Mag 5:13–18
5. Liang SF, Liu YH, Li-Chen LI (2014) Face recognition under unconstrained based on LBP and deep learning. J Commun 35:154–160
6. Coates A, Ng AY (2011) Selecting receptive fields in deep networks. Adv Neural Inf Process Syst, 2528–2536
7. Lee H, Grosse R, Ranganath R et al (2009) Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations. In: International conference on machine learning, pp 609–616
8. Hinton GE, Salakhutdinov RR (2006) Reducing the dimensionality of data with neural networks. Science 313:504–507
9. Schölkopf B, Platt J, Hofmann T (2007) Greedy layer-wise training of deep networks. Adv Neural Inf Process Syst 19:153–160
10. [Online] Available: http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html