Neurocomputing 174 (2016) 749–755

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Face recognition algorithm based on discriminative dictionary learning and sparse representation

Zhenyu Lu [a,b,*], Linghua Zhang [a]

[a] College of Electronic & Information Engineering, Nanjing University of Information Science & Technology, Nanjing 210044, China
[b] Jiangsu Collaborative Innovation Center on Atmospheric Environment and Equipment Technology, Nanjing 210044, China

A R T I C L E   I N F O

Article history:
Received 12 May 2015
Received in revised form
17 July 2015
Accepted 26 September 2015
Communicated by Xiaofei He
Available online 21 October 2015

Keywords:
Face recognition
Regularized sparse representation
Uniform local binary pattern
Gabor filtering
Dictionary learning

A B S T R A C T

In order to overcome the defect that the face recognition (FR) rate is greatly reduced in the existing uncontrolled environments such as the change of illumination, occlusion, and posture, etc, Face recognition algorithm based on discriminative dictionary learning and regularized robust coding was proposed. In this proposed algorithm, the Gabor amplitude images of a face image are obtained via using Gabor filter at first, then we extract the uniform local binary histogram and use Fisher criterion to gain a new dictionary, finally the test image is classified as the existing class via sparse representation Coding. The experimental results obtained from Extended Yale B databases and AR databases show that the proposed algorithm has higher face recognition rate in the existing uncontrolled environments in comparison with K-SVD, LC-K-SVD, FDDL and so on.

1. Introduction

Face recognition is a hot research topic in the field of pattern recognition and multimedia technology [1–8], which analyzes the face image and extracts effective information to identify the face image via the computer. It is widely used in many fields such as security, authentication, digital surveillance, fusion and so on. Under normal circumstances, the classic face recognition algorithms such as principal component analysis [9], linear discriminate analysis method [10], independent component analysis [11], support vector machine [12], semi-supervised learning [13], Hypergraph based learning [14] etc. can get high recognition rate, but the performance and the robustness of the algorithms will greatly be reduced when the conditions of the illumination, the pose, and the expression etc. are uncontrolled. To solve these problems, Wright et al. [15] proposed a sparse representation algorithm based classifier which regards the identification problem as classification problem of multiple linear regression models. Such a method is widely used in image classification field [16–18]. Firstly, the image is represented according to the compacted sparse, then the reconstruction error of test samples is computed, finally the minimum residual error is classified and recognized. The robustness of the proposed algorithm is mainly decided by the sparse dictionary and the method of solving sparse solution, lots of scholars proposed many improved algorithms based on this method.

In terms of sparse dictionaries, Wright et al. [15] directly used the training samples' pixels of all classes as the dictionary to code the query face image; this so called sparse representation based classification (SRC) scheme shows interesting FR results. But the dictionary may not be effective enough to represent the query images when the training images are affected by noisy or many uncertain factors. Zhang et al. [19] proposed a sparse representation algorithm based on Gabor feature, which combines the Gabor features and the SRC algorithm, can reduce the computation complexity and improve the human face recognition rate. Ahonen et al. [20] proposed Face recognition with local binary patterns (LBP), the algorithm's robustness improved rapidly as the LBP histogram is not sensitive to light.

However, the number of atoms of such a dictionary is very big, which increases the coding complexity. Thus, lots of dictionary learning methods were proposed. For example, Aharon et al. [21] proposed K-SVD algorithm, which learns an over-complete dictionary from a training dataset of natural image patches. However, it is not suitable for classification tasks because it only requires that the learned dictionary could faithfully represent the training samples. Compared with the traditional dictionary, the discriminative dictionary contains not only the representational power but also the discriminative power which is good for object classification by adding a discriminative term into the objective function. Zheng et al. [22] proposed a discriminative dictionary learning method via Fisher discrimination K-SVD algorithm. Mairal et al. [23] proposed a discriminative DL method by training a classifier of the coding coefficients, and verified their method for digit recognition and texture classification. In [25], Pham et al. proposed a joint learning and

* Corresponding author.

http://dx.doi.org/10.1016/j.neucom.2015.09.091
0925-2312/

dictionary construction method with consideration of the linear classifier performance and applied their method to object categorization and FR. Based on [24], Zhang et al. [26] proposed an algorithm called discriminative K-SVD (D-KSVD) for FR, but the method does not enforce discriminative information into the sparse coding coefficients. Jiang et al. [27,28] introduced a label consistent regularization to enforce the discrimination of coding vectors. The so-called LC-KSVD algorithm exhibits good classification results. Yang et al. [29] proposed Fisher discrimination dictionary learning (FDDL) for sparse representation, it can not only improve face recognition rate but also reduce the computational complexity via applying the Fisher discrimination criterion into sparse representation. But the weights are simply determined by the number of samples of each class and the total number of training images.

In this paper, we propose an improved algorithm—face recognition algorithm based on discriminative dictionary learning and SRC, where the discrimination term is formulated as the weighted summation of the within-class error. The Gabor amplitude images of a face image are obtained via using Gabor filter at first. Then we extract the uniform local binary histogram and use Fisher criterion to gain a new dictionary. In this part, the logistic function [29] is used to make the weight assignment more adaptive and flexible and reflect the discrimination of the dictionary. Finally, the test image is classified as the existing class via sparse representation Coding. There are two advantages of the proposed algorithm: the first one is that it can make full use of LBP features of the Gabor filter images under different light conditions and the advantages of Fisher criterion to improve the robustness and FR recognition rate; the second advantage is that the dictionary obtained by our method is both representative and discriminative.

The rest of this paper is organized as follows. Section 2 briefly introduces the features extraction and the procedure of dictionary learning. Section 3 presents the SRC based classifier. Section 4 conducts experiments, and Section 5 concludes the paper.

2. Features extraction of uniform LBP (ULBP) based on Gabor wavelet

2.1. Gabor wavelet

Gabor wavelet kernel function has the same characteristics as 2D reflection region of the human brain's cortex simple cell. It can capture the information of different spatial frequency, spatial location, direction, and extract the local nuances effectively. Well, filtering process of face image can not only enhance some of the key characteristics but also has better robustness of local deformation.

The Gabor wavelet kernel function can be defined as

$$\Psi_{\mu,v}(z) = \frac{||k_{\mu,v}||}{\delta^2} e^{-(||k_{\mu,v}||^2||z||^2/2\delta^2)} [e^{ik_{\mu,v}z} - e^{-\delta^2/2}] \tag{1}$$

where μ and v denotes the orientation and scale of the Gabor filters, $z=(x,y)$. $||\cdot||$ denotes the norm operator, wave vector $k_{\mu,v} = k_v \exp(i\phi_\mu)$ $(k_v = k_{\max}/\lambda^v,\ \phi_\mu = \pi\mu/8)$, and $k_{\max}$ denotes the maximum sampling frequency. Parameter λ is the spacing factor

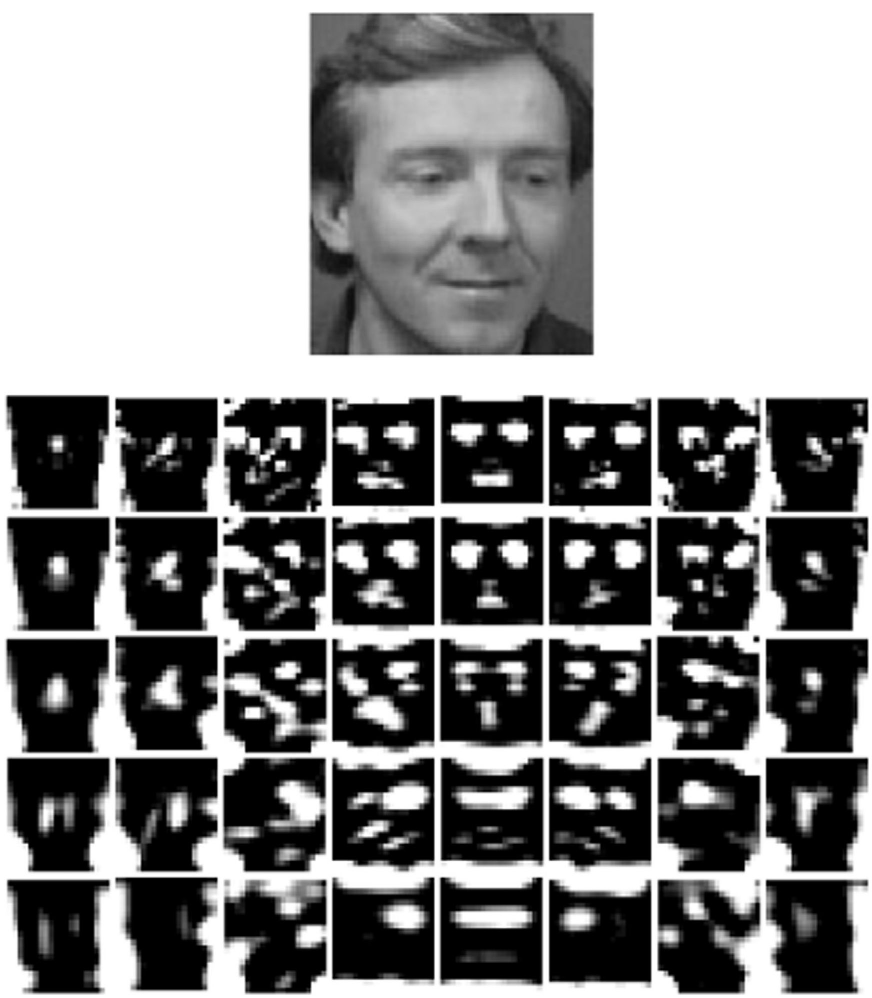

Fig. 1. Amplitude images based on Gabor wavelet.