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Design of face recognition algorithm using PCA -LDA combined for hybrid data pre-processing and polynomial-based RBF neural networks : Design and its application

Sung-Kwun Oh [a,*], Sung-Hoon Yoo [a], Witold Pedrycz [b,c]

[a] Department of Electrical Engineering, The University of Suwon, Hwaseong-si, Gyeonggi-do, South Korea
[b] Department of Electrical and Computer Engineering, University of Alberta, Edmonton, AB, Canada T6G 2G6
[c] Systems Research Institute, Polish Academy of Sciences, Warsaw, Poland

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ABSTRACT

In this study, polynomial-based radial basis function neural networks are proposed as one of the functional components of the overall face recognition system. The system consists of the preprocessing and recognition module. The design methodology and resulting procedure of the proposed P-RBF NNs are presented. The structure helps construct a solution to high-dimensional pattern recognition problems. In data preprocessing part, principal component analysis (PCA) is generally used in face recognition. It is useful in reducing the dimensionality of the feature space. However, because it is concerned with the overall face image, it cannot guarantee the same classification rate when changing viewpoints. To compensate for these limitations, linear discriminant analysis (LDA) is used to enhance the separation between different classes. In this paper, we elaborate on the PCA-LDA algorithm and design an optimal P-RBF NNs for the recognition module.

The proposed P-RBF NNs architecture consists of three functional modules such as the condition part, the conclusion part, and the inference part realized in terms of fuzzy "if–then" rules. In the condition part of fuzzy rules, the input space is partitioned with the use of fuzzy clustering realized by means of the Fuzzy C-Means (FCM) algorithm. In the conclusion part of rules, the connection weight is realized through three types of polynomials such as constant, linear, and quadratic. The coefficients of the P-RBF NNs model are obtained by fuzzy inference method forming the inference part of fuzzy rules. The essential design parameters (including learning rate, momentum, fuzzification coefficient, and the feature selection mechanism) of the networks are optimized by means of differential evolution (DE). The experimental results completed on benchmark face datasets – the AT&T, and Yale datasets demonstrate the effectiveness and efficiency of PCA-LDA combined algorithm compared with other algorithms such as PCA, LPP, 2D-PCA and 2D-LPP. A real time face recognition system realized in this way is also presented.

1. Introduction

In many pattern recognition systems, the paradigm of neural classifiers have been shown to demonstrate many tangible advantages with regard to their learning abilities, generalization aspects, and robustness, (cf. Lawrence, Giles, Tsoi, & Back, 1997; Lin, Kung, & Lin, 1997; Lippman, 1981; Song & Lee, 1998]). Neural networks have been employed and compared to conventional classifiers. The results have shown that the neural networks are effective constructs in comparison with some conventional methods (Lee & Landgrebe, 1997; Zhou, 1999). These properties make neural networks an attractive tool for many pattern classification problems. Among these classifiers, multilayer perceptrons (MLPs) have been in wide use. It is shown that the MLP can be trained to approximate complex discriminant functions (Lippman, 1981). However, the MLP classifier requires a large number of parameters to be determined especially in case of a multilayer topology of this network. The number of iterations required to train networks is often quite high (Patrikar & Provence, 1992). A central issue in neural networks is the problem of learning algorithm. The choice of learning algorithm, network topology, weight initialization and input signal presentations are important factors impacting the learning performance. In particular, the choice of the learning algorithm determines the rate of convergence and the suitability of the solution. Recently radial basis function neural networks (RBF NNs) have been found to be very attractive for many engineering problems. RBF NNs exhibit some advantages including global optimal approximation and classification capabilities, and a rapid conver-

* Corresponding author. Tel.: +82 31 229 8162; fax: +82 31 220 2667.
E-mail addresses: ohsk@suwon.ac.kr (S.-K. Oh), shyoo@suwon.ac.kr (S.-H. Yoo), wpedrycz@ualberta.ca (W. Pedrycz).

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gence of the learning procedures (see Balasubramanian, Palanivel, & Ramalingam, 2009; Cho & Wang, 1996; Er, Wu, Lu, & Toh, 2002; Mali & Mitra, 2005; Oh, Pderyz, & Park (2004); Park, Oh, & Kim, 2008). In spite of these advantages of RBF NNs, these networks are not free from limitations. In particular, discriminant functions generated by RBF NNs have a relatively simple geometry which is implied by the limited geometric variability of the underlying receptive fields (radial basis functions) located at the hidden layer of the RBF network. Those fields are then aggregated in a linear fashion by the neuron located at the output layer. To overcome limitation of architecture, we propose a concept of the polynomial-based radial basis function neural networks (P-RBF NNs). Given the functional (polynomial) character of their connections in the P-RBF NNs, these networks can generate far more complex nonlinear discriminant functions. Along with the enhanced architectural functionality we consider a comprehensive optimization environment using which this functionality could be fully exploited. With this regard, our intent is to consider using some of the biologically-inspired optimization techniques.

The main objective of this study is to develop an efficient learning algorithm for the P-RBF NNs and its applications in face recognition. The P-RBF NNs is proposed as one of the recognition part of overall face recognition system that consists of two parts such as the preprocessing part and recognition part. The design methodology and the procedure of the proposed P-RBF NNs are presented to construct a solution to high-dimensional pattern recognition problems.

In the data pre-processing part, principal component analysis (PCA) (Gumus, Kilic, Sertbas, & Ucan, 2010; Turk & Pentland, 1991), which is generally used in face recognition, provides high quality features such as a front face. It is useful to express some classes using reduction, since it is effective to maintain the rate of recognition and to reduce the amount of data at the same time. However, because of the use of the entire face image, it cannot retain the same classification rate when dealing with some the change of the viewpoints. It is too difficult to judge whether the changing face image comes from the change of illumination or various facial expression. Thus, to compensate for these limitations, linear discriminant analysis (LDA) (Belhumeur, Hespanha, & Kriegman, 1997; Zhao, Chellappa, & Krishnaswamy, 1998) is used to enhance the separation between classes. However, it still cannot separate the nonlinear data or the classes which have the same average values. In this pre-processing part, we introduce a combination mechanism aggregating PCA and LDA. Then we compare and analyze the performance of the PCA-LDA fusion algorithm.

In the recognition part, we design a P-RBF NNs based on the fuzzy inference mechanism. The essential design parameters of the system are optimized by means of differential evolution. The proposed P-RBF NNs dwell upon structural findings about training data that are expressed in terms of partition matrix resulting from fuzzy clustering in this case being Fuzzy C-Means (FCM). The network is of functional nature as the weights between the hidden layer and the output are treated as some polynomials. The use of the polynomial weights becomes essential in reflecting the nonlinear nature of data encountered in regression or classification problems. From the perspective of linguistic interpretation, the proposed network can be expressed as a collection of "if–then" fuzzy rules. The architecture of the networks discussed here embraces three functional modules reflecting the three phases of input–output mapping realized in rule-based architectures.

This paper is organized as follows: in Section 2, we introduce how to combine PCA-LDA algorithm for extraction the facial features. Section 3 we propose the general architecture of P-RBF NNs. Section 4 discusses the discriminant capabilities of P-RBF NNs and their learning procedure realized by means of the gradient descent method. In Section 5, we discuss the essentials of differential evolution and show its usage in the determination of learning rate, momentum coefficient, fuzzification coefficient and the realization of feature selection. Experimental results and implementation are presented in Section 6. Finally, conclusions are attained in Section 7.

2. Data pre-processing for extraction of facial features

One of the main issues in design of face recognition algorithm is to extract the face features. In this section, a method is proposed for extracting face features from face image. And we introduce how to combine PCA-LDA fusion algorithm.

2.1. Principal component analysis

Principal component analysis (Gumus et al., 2010; Turk & Pentland, 1991) is standard technique used in statistical pattern recognition and signal processing for data reduction and feature extraction (Haykin, 1999). As the pattern often contains redundant information, we map it to a feature space of lower dimensionality.

A face image of size $N \times N$ *pixels* can be considered as a one-dimensional vector of dimensionity N^2. For example, face image from the AT&T (formerly the AT&T database of faces) database of size 112×92 can be considered as a vector of dimension 10,304, or equivalently points in a 10,304 dimensional space. An ensemble of images maps to a collection of points in this highly-dimensional space. The main idea of the principal component is to find the vectors that best account for the distribution of face images within the entire image space. Because these vectors are the eigenvectors of the covariance matrix corresponding to the original face images, and because they are face like in appearance, we refer to them as 'eigenfaces' (see Figs. 1 and 2).

Let the training set of face images be $\Gamma_1, \Gamma_2, \ldots, \Gamma_M$, The average of the set is defined by

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n \tag{1}$$

Each face differs from the average by the vector

$$\Phi_i = \Gamma_i - \Psi \tag{2}$$

Fig. 1. Average face.

Fig. 2. Eigenface.