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ScienceDirect
Neurocomputing 70 (2007) 896–903
NEUROCOMPUTING
www.elsevier.com/locate/neucom

Shape recognition based on neural networks trained by differential evolution algorithm

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Available online 18 October 2006

Abstract

In this paper a new method for recognition of 2D occluded shapes based on neural networks using generalized differential evolution training algorithm is proposed. Firstly, a generalization strategy of differential evolution algorithm is introduced. And this global optimization algorithm is applied to train the multilayer perceptron neural networks. The proposed algorithms are evaluated through a plant species identification task involving 25 plant species. For this practical problem, a multiscale Fourier descriptors (MFDs) method is applied to the plant images to extract shape features. Finally, the experimental results show that our proposed GDE training method is feasible and efficient for large-scale shape recognition problem. Moreover, the experimental results illustrated that the GDE training algorithm combined with gradient-based training algorithms will achieve better convergence performance.

Keywords: Shape recognition; Generalization strategy; Differential evolution algorithm; Multiscale Fourier descriptors; Leaf image database

1. Introduction

The shape feature is one of the most important features for characterizing an object, which is commonly used in object recognition, matching and registration. In addition, the shape recognition is also an important part of machine intelligence that is useful for both decision-making and data processing. More importantly, the recognition-based on shape feature is also a central problem in those fields such as pattern recognition, image technology and computer vision, etc., which have received considerable attention recent years. Face recognition, image preprocessing, computer vision, fingerprint identification, handwriting analysis, and medical diagnosis, etc., are some of the common application areas of shape recognition. In particular, shape recognition has mutual effects with other research areas such as signal processing, neural networks, optimization theory, structural modeling and formal languages, etc. For shape recognition, there have been a wide range of methods proposed [1,2]: structural methods organizing local features into graphs, trees, or strings; Fuzzy methods; Statistical methods; Transform methods, such as Fourier transform [3] or Hough transforms; Neural networks methods [4,5], and so on. But most of approaches are confined to specific image types and require that all shapes must be preprocessed before recognition. However, an ever-increasing amount of image data in many application domains has generated additional requirements for real-time management and retrieval of images. Therefore, the emphasis on image recognition is not only on the accuracy, but also on the efficiency.

On the other hand, the neural network is widely used in pattern recognition kingdom as an effective classifier. Since the development of the back-propagation method, many algorithms have been proposed and used to train neural networks, such as modified back-propagation [6], back-propagation using the conjugate-gradient approach [7], scaled conjugate-gradient [8], the Levenberg–Marquadt algorithm [9]. The simulated annealing (SA) method and genetic algorithm (GA) method also have been proposed

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doi:10.1016/j.neucom.2006.10.026

for network with non-differentiable transfer functions where the gradient information is not available [10–12]. Many of the existing training algorithms are suitable to small or middle scale networks structures and have a rather fast convergence speed. For the small-scale problem or small network structure, the gradient information usually is available and the training methods based on gradient information are rather fast and can convergence to global minima by repeated training and using randomly initialized weight values. However, for some large-scale real world problems, such as the above-mentioned shape recognition problem, many of them have worse performances than small or middle scale problems on convergence accuracy and speed. There are seldom suitable and reasonable network training algorithms when the neural network structures or the number of network parameters grow rapidly. For such large-scale neural networks structure, many of the training methods need an unacceptable computation cost in time and space. And the local minima problem also must be considered. The global optimization algorithms, such as GA and SA, may be useful to avoid such a local minima problem. In fact, there is no single training algorithm can have the best performance compared with all other methods on all problem domains. One feasible solution method is that use the global optimization algorithms combined with gradient information methods to train the neural network to achieve acceptable solution.

For the global optimization methods, GAs have been studied and found to be promising stochastic optimization methods. A survey and overview of GAs in evolving neural networks can be found in [13,14]. Differential Evolution (DE) is one of the recent population-based global optimization techniques [15,16]. Some works have applied DE to train neural networks [11,12], in which the experimental data are small-scale problems. In this paper, a new generalization strategy of DE is applied to train feed-forward multi-layer perceptron neural networks (MLPNN) and compared with different type of training algorithms. Furthermore, this paper focuses on using the novel neural network-based method to perform shape recognition task through multiscale Fourier descriptors (MFDs) of shapes.

This paper is organized as follows: In Section 2, a generalization strategy of DE algorithm is described and discussed. In Section 3, a novel training method for neural network based on generalized DE algorithm is presented. In Section 4, the MFDs feature extraction method for shapes is presented. The experimental results are reported in Section 5, and Section 6 concludes the whole paper and gives related conclusions.

2. Generalization strategy of DE algorithm

DE is one of the recent population-based global optimization techniques [15,16], which is a heuristic method for minimizing nonlinear and non-differentiable continuous space functions. The DE scheme entirely corresponds to a typical GA. But the principle difference consists in the mutation operation. In GA mutation is caused by small alterations of genes, whereas in DE Mutation is provided by combinations of individuals. The core of this operation is the formation of a difference vector, which makes mutate an individual.

As all GAs, DE deals with a population of solutions. The population p^g of a generation g has NP vectors, i.e., individuals X^g. Each individual represents a potential optimal solution:

$$P^g = \{X_i^g\}, \quad i = 1, 2, \ldots, NP.$$

In turn, the individual X^g contains D variables (chromosomes):

$$X_i^g = x_{i,j}^g, \quad j = 1, 2, \ldots, D.$$

For each generation, the individuals are updated by means of a reproduction scheme. Thereto for each individual X_i^g, a set of other individuals is randomly extracted. To produce a new one, the operations of differentiation and recombination are applied to this set.

A set of individuals is firstly and randomly extracted for differentiation operation. Then a difference vector δ and a base vector β are designed based on these extracted individuals. Thus, the result of differentiation operation, i.e., trial individual, is

$$\omega = \beta + CF\,\delta, \tag{1}$$

where $CF > 0$ is the constant of differentiation.

Next recombination operation represents a typical case of exchange of chromosomes. The trial individual ω inherits chromosomes with some probability. Thus,

$$\omega_j = \begin{cases} \omega_j & \text{if} \quad \text{rand}() CR, \\ x_{i,j}^g & \quad \text{otherwise}, \end{cases} \tag{2}$$

where $j = 1, 2, \ldots, D$ and $CR \in [0, 1]$ is the constant of recombination.

In general, CF and CR affect the convergence speed and robustness of the search process. Their optimal values depend both on objective function characteristics and the population size NP, and thus, the selection of optimal parameter values is an application dependent task.

Selection is used to choose the best:

$$X_i^{g+1} = \begin{cases} \omega & \text{if} \quad f(\omega) < f(X_i^g), \\ X_i^g & \quad \text{otherwise}. \end{cases} \tag{3}$$

Differentiation operation plays a quite important role in the reproduction cycle. Geometrically, it consists in two simultaneous operations: the first one is the choice of a differentiation's direction and the second one is the step length. The principle of differentiation operation is based on a random extraction of individuals from the population. Possible directions entirely depend on the disposition of extracted individuals. Also, their disposition influences the step length. Furthermore, by increasing the number of extracted individuals, the diversity of possible directions and the variety of step lengths will be augmented. Thereby