Neurocomputing 149 (2015) 151–157

Contents lists available at ScienceDirect

Neurocomputing

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

Deformation prediction of landslide based on functional network

Jiejie Chen [a,b,*], Zhigang Zeng [a,b], Ping Jiang [a,b], Huangming Tang [c]

[a] School of Automation, Huazhong University of Science and Technology, Wuhan 430074, China
[b] Key Laboratory of Image Processing and Intelligent Control of Education Ministry of China, Wuhan 430074, China
[c] Faculty of Engineering, China University of Geosciences, Wuhan 430074, China

ARTICLE INFO

Article history:
Received 25 June 2013
Received in revised form
20 August 2013
Accepted 28 October 2013
Available online 12 August 2014

Keywords:
Functional networks
Training data set
Landslide prediction
Separable
Associativity
Back-propagation neural network

ABSTRACT

This paper proposes functional networks as novel intelligence paradigm scheme for landslide displacement prediction. They evaluate unknown neuron functions from given functional families during the training process. General functional networks with two variables training data set (GFN), separable functional networks (SFN) and associativity functional networks (AFN) are applied to forecast a real-world example. In addition, we compare them with back-propagation neural network (BPNN) in terms of the same measurements. The results reveal that the landslide displacement prediction using functional networks is reasonable and effective, and GFN are consistently better than the other two types of functional networks and BPNN.

1. Introduction

Landslide hazards are geological phenomena and a seasonal problem in the Three Gorges Reservoir area, which is located at the upper reaches of the Yangtze River in China. Frequent landslides cause major socioeconomic disruptions, extensive property damage, and casualties, so it is essential to have a profound understanding as to what cause them and how people can either help hinder them from occurring or only avoid them when they do occur. Hence, early predictions and warnings are imperative for the reduction of property damage and loss of life. It is well known that landslides occur when the stability of a slope transforms from a stable to an unstable state. A transform in the stability of a slope can be caused by a lot of factors, acting together or alone. The rock–soil body of landslide is highly nonlinear process, and the complexity and uncertainty are its essence attributes. The evolution process of landslides can be considered as an open nonlinear dynamic system [1–4] with the complexity and uncertainty. The nonlinear theories and Artificial neural networks (ANNs) are effective in dealing with complex problems, which have been widely used in addressing the modeling and prediction problem of nonlinear time series [5–8].

At present, to solve such cutting-edge scientific issue like the landslide forecast and prediction has become a hot topic in landslide research [9–15]. Melchiorre et al. [9] demonstrate that the landslide susceptibility analysis is performed by means of ANNs and cluster analysis. The improved BPNN modeling to optimize the weights and biases of the network for landslide is investigated in [10]. Li et al. [11] present a methodology by an application of linear combination model with optimal weight in landslide displacement prediction. A data mining approach to predict landslide are adopted by de Souza and Ebecken [12]. Sezera et al. [13] present that the neuro-fuzzy model using remote sensing data and Geographic Information System (GIS) for landslide susceptibility analysis. The ensemble of extreme learning machine (E-ELM) and a modified ensemble empirical mode decomposition with E-ELM are proposed to predict landslide displacement in [14,15]. Inspired by significant and useful results, these theoretical and application views are benefit for the analysis and prediction of landslide hazards.

The reality which we should face that the landslide prediction as similar as the real effect is a difficult task to tackle, and it requires a thorough study of the past activities, which is still very challenging today due to many theoretical and technical difficulties. On the one hand, most ANNs based landslide forecasting methods used gradient-based learning algorithms such as BPNN, which are relatively slow in learning and may be easily limited by a local minimum [16,17]. On the other hand, the framework of functional networks models introduced by Castillo [18] as an extension of ANNs is able to solve a vast array of applications in statistics and engineering via learning and prediction.

Functional networks [18–32] estimate unknown neuron functions from given functional families during the training process.

* Corresponding author at: School of Automation, Huazhong University of Science and Technology China, Wuhan 430074, China.
E-mail address: chenjiejie118@gmail.com (J. Chen).

http://dx.doi.org/10.1016/j.neucom.2013.10.044
0925-2312/

They are very effective tools for the statistical pattern recognition problems and nonlinear complex prediction. Functional networks can be considered as a novel strategy for solving a wide range of problems, such as real-time flood forecasting [24], fishing catches [25,26], statistics and engineering [27], semi-parametric nonlinear regression and transformation [28], software reliability identification [29], software development efforts [30], predict permeability in a carbonate reservoir [31].

There are many different possible functional network forms, such as SFN [18], which make use of a functional expression that combines the separated efforts of input variables and AFN [18] which consider the intrinsic relationships of the input–output patterns. In this paper, considering that the broad application prospects of functional networks, both SFN and AFN may be used as the approximate models in landslide forecasting with the minimax method [32] for selecting the best model. Moreover, the new linear independent combination of a standard functional form for neuron function with two variables training data set in general functional networks is proposed. Take Baishuihe landslide in the Three Gorges reservoir of China as a real case to test and verify these new framework. The results show that these proposed methods can get over some of the common drawbacks of the existing models, and are proved to be reasonable and effective.

This paper is organized as follows. Section 2 introduces the framework of functional networks. Section 3 presents the analytical method about functional networks. Section 4 describes the application to landslide forecasting with four methods. Finally, Section 5 discusses future work and possible improvements.

2. Functional networks

ANNs are powerful tools for solving a wide range of practical problems. They have been applied to predict and forecast landslide [8–10]. Many researches are made to explore and develop the theory of ANNs. However, ANNs also suffered from some limitations. ANNs as data-driven (black-box) models use predefined activation functions without considering the properties of the phenomena being modeled. Furthermore, the number of hidden layers and hidden neurons of the network architecture is usually determined by experiment or by trial and error. But ANNs are very restrictive, and many scholars are pursuing improvements in several directions.

Functional networks are generalization of neural networks which combine both knowledge about the structure of the problem, to determine the architecture of the network, and to estimate the unknown functional neurons [27,28]. Fig. 1(a) shows a simply ANNs with a typical neuron that receives input from neurons $\{x_1, \ldots, x_k\}$ and calculates the output $O = f(\sum \omega_k x_k)$. The function f is assumed identical for all neurons, the differences between two neurons are owing to the number of input components, weights, or threshold values. Fig. 1(b) describes a simply functional network with k neuron that receives input from neurons $\{x_1, \ldots, x_k\}$ and calculates the output $\{O_1, \ldots, O_k\} = f(x_1, \ldots, x_k)$. The structure of the network is determined by the domain knowledge and the data determine the unknown functions which can be assumed to belong to a given family. Unlike ANNs to learn from the data, functional networks may be regarded as more problem-driven than as data-driven, so the initial architecture is designed based on a problem in hand.

As it is shown in Fig. 2, which represents a typical architecture of functional networks illustrating themselves principal components. Take it for an example, functional networks consist of several elements:

(a) One layer of input storing neurons of the data set $\{x_1, x_2, x_3, x_4\}$.
(b) None, one or several layers to store intermediate information, there one layer $\{x_5, x_6\}$.

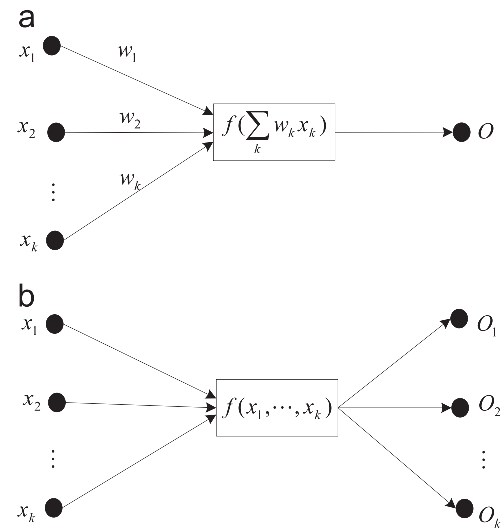

Fig. 1. (a) Artificial neural networks; (b) a functional network.

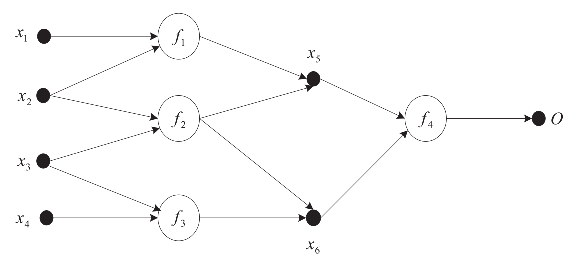

Fig. 2. Functional networks.

(c) One or several layers of processing neurons or computing units that evaluate a set of input values and deliver a set of output values f_i, there are two layers, the first layer of neurons contains neurons $\{f_1, f_2, f_3\}$ and the second layer of neurons contains neurons f_4.
(d) One layer of output storing neurons reduces to units O.
(e) A set of direct links between them.

All these elements together form the network architecture, which define the functional capabilities of the network. Functional networks allow neural functions f_i to be true multiargument and multivariate functions, which are different and learnable instead of fixed functions. Generally speaking, the neuron functions in functional networks are unknown functions from a given family, such as polynomial $\{1, x, \ldots, x^m\}$, exponential $\{1, e^x, e^{-x}, \ldots, e^{mx}, e^{-mx}\}$, and Fourier $\{1, \cos(x), \sin(x) \ldots, \cos^l(x), \sin^l(x), m = 2l\}$, which have to be emulated a given training data set.

2.1. Separable functional networks

SFN introduced by Castillo [18] are interesting family with many applications. SFN use a functional expression that combines the separated efforts of input variables. Fig. 3 depicts the topology of SFN, which have associated a functional expression which combines the separate effects of input variables. The topology of SFN contains two inputs and one output, where x_1, x_2 are the two input variables and O is the output of the functional networks, f_i and y_i are unknown neuron functions.

The relationship between O and $\{x_1, x_2\}$ can be designed mathematically:

$$O = F(x_1, x_2) = \sum_{i=1}^{n} f_i(x_1) y_i(x_2). \tag{1}$$