Remote Sensing of Environment 211 (2018) 248–260

Contents lists available at ScienceDirect

Remote Sensing of Environment

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

Adaptive neural network based on segmented particle swarm optimization for remote-sensing estimations of vegetation biomass

Yongnian Gao[a,*], Qin Li[a,b], Shuangshuang Wang[a,b], Junfeng Gao[a]

[a] Key Laboratory of Watershed Geographic Sciences, Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences, 73 East Beijing Road, Nanjing 210008, China

[b] University of Chinese Academy of Sciences, Beijing 100049, China

ARTICLE INFO

Keywords:
Vegetation biomass
Particle swarm optimization
Neural network
Remote sensing
Lake

ABSTRACT

In this study, the segmented particle swarm optimization (SPSO) algorithm and the concepts of the gradient boosting decision tree algorithm (GBDT) were combined to propose the SPSO adaptive neural network (SANN) method. The purpose of this method is to address the inadequacies of the traditional basis function (BP) and radial basis function (RBF) neural networks when solving problems that involve local optima and overfitting. Experimental results indicated that, overall, the SANN method is accurate in remote-sensing estimations of aquatic vegetation biomass. However, accuracies of estimations were unsatisfactory for certain indicators and sessions when data was taken. The estimations were analyzed using three sets of indicators: (i) root mean square error, average relative error, and total relative error; (ii) correlation coefficient and coefficient of determination, and their scatter plots; and (iii) relative error values and their distributions. The results clearly showed that the SANN method was superior to the BP neural network as well as the stepwise multiple linear regression analysis (SR). However, when the relative errors in biomass estimations by the other two methods were low, the advantages of the SANN method were less pronounced. This was particularly true when the relative errors were < 30%, in which case SANN was only marginally better than the other two methods.

1. Introduction

Above-ground biomass (AGB) is not only a major indicator of regional carbon cycling, but also serves as a critical indicator used in health assessment of vegetation ecosystems (Liang et al., 2016), including aquatic vegetation ecosystems. Thus, AGB monitoring of vegetation ecosystems is vital to ensure their ability to maintain necessary ecosystem services (Shoko et al., 2016). Currently, AGB monitoring is primarily accomplished by two means: field surveys or remote sensing estimations. Remote sensing estimations provide several advantages for AGB monitoring at a regional scale. These include increased speed as well as lower labor and economic costs. Biomass estimations through remote sensing are also more contiguous at the spatial scale and can be extended to the temporal scale (subject to the availability of remote sensing images). Therefore, remote-sensing estimations play an increasingly critical role in AGB monitoring of vegetation coverage (Costa, 2005; Silva et al., 2010; Goetz and Dubayah, 2011; Byrd et al., 2014), and an increasing number of researchers have focused their attention on this topic (e.g., Hall et al., 1997; Silva et al., 2010; Liao et al., 2013; Lu et al., 2014; Verrelst et al., 2015; Shen et al., 2015; Shoko et al., 2016; Liang et al., 2016; Gao et al., 2017).

Two main approaches are used to conduct remote-sensing estimations of biomass. The first approach is based on empirical models that are constructed using biomass data obtained from field surveys and spectrum characteristics of remote sensing images. The second approach involves substituting ecological parameters acquired from remote sensing images into models based on vegetation growth to estimate biomass (Hall et al., 1997; Fang et al., 2003). Regarding the second approach, relatively few studies have been conducted on the effects that the inherent complexities of the vegetation growth model (such as the model's need for numerous input parameters) have on remote-sensing estimations of vegetation biomass (Shoko et al., 2016). The first approach is simpler, leading to its widespread application for such estimations (Shoko et al., 2016). This is particularly the case with aquatic vegetation biomass, for which this approach predominates.

Currently, empirical models for remote-sensing estimations of aquatic vegetation biomass are built using two types of algorithms: parametric or non-parametric (Verrelst et al., 2015). The exact methods include linear regression using a single regressor (e.g., Zhang, 1998; Gao et al., 2017), multiple (stepwise) linear regression (e.g., Zhang,

* Corresponding author.
E-mail address: yngao@niglas.ac.cn (Y. Gao).

https://doi.org/10.1016/j.rse.2018.04.026
Received 22 July 2017; Received in revised form 10 April 2018; Accepted 11 April 2018
0034-4257/ © 2018 Elsevier Inc. All rights reserved.

1998; Silva et al., 2010), and back propagation artificial neural networks (e.g., Liao et al., 2013; Shen et al., 2015). Researchers have shown that parametric algorithms are not capable of capturing the complex relationships between remote sensing variables and AGB (Lu et al., 2014; Verrelst et al., 2015; Shoko et al., 2016). More advanced machine learning algorithms (e.g., artificial neural networks) have been shown to enhance the predictive accuracy of grass AGB (Shoko et al., 2016). Traditional neural networks use gradient descent for performance optimization. Gradient descent is a first-order iterative optimization algorithm used to find the values of the parameters of a function that minimize a cost function and is a popular method in the field of machine learning. However, the gradient descent method has limited ability to deal with complex high-dimensional spaces and is often trapped by local optima. Consequently, traditional neural networks cannot manage complex data effectively. This causes over- or underfitting, resulting in reduced model accuracies. Neural networks usually involve various parameters that require adjustments, and parameters such as network weights and offsets are adjusted through error back propagation. Therefore, high-dimensional spaces formed by multiple parameters are likely to contain many locally optimal solutions. For error back propagation, the parameter adjustment mode is also susceptible to the effects of gradient dispersion and saturation of activation functions. This delays adjustments to any underlying parameters, which hinders convergence of the neural networks (Glorot and Bengio, 2010).

Particle swarm optimization (PSO) is a stochastic population-based optimization method proposed by Kennedy and Eberhart (1995). It solves a problem by constructing a population of candidate solutions obtained by moving particles in the search-space according to simple mathematical formulae to set a particle's position and velocity. Each particle's movement is influenced by its local best known position, but is also guided toward the best known positions determined by other particles in the search-space. This process is expected to move the swarm toward the best (global) solution (Thamaraichelvi and Yamuna, 2016). Particle swarm optimization is a metaheuristic, as it makes few or no assumptions about the problem being optimized and can search very large spaces for candidate solutions. It has been successfully applied to many problems such as artificial neural network training, function optimization, fuzzy control, and pattern classification (Bonyadi and Michalewicz, 2017).

Based on these considerations, the main purposes of this study are as follows: (i) combine the segmented particle swarm optimization (SPSO) algorithm and the concepts of the gradient boosting decision tree (GBDT) algorithm to develop an SPSO adaptive neural network (SANN) model that addresses the inadequacies of traditional methods such as basis function (BP) and radial basis function (RBF) neural networks when solving problems that involve local optima and overfitting; (ii) apply the SANN method in experiments involving remote-sensing estimations of aquatic vegetation biomass (in this study, the term refers to the above-ground wet weight biomass of emergent vegetation) in Lake Tai, China and evaluate the method's accuracy; and (iii) compare the differences in accuracies among the remote-sensing estimations of aquatic vegetation biomass derived from the SANN method, BP neural network (hereafter “BP method”), and stepwise multiple linear regression analysis (hereafter “SR method”), as well as analyze the strengths and weaknesses of the SANN method for such estimations.

2. Methodology

2.1. Segmented particle swarm optimization

When a high-dimensional space is optimized, multiple optimal and locally optimal solutions are usually present. To avoid being trapped by local optimal solutions, maintaining the diversity of the particle swarm is critical. Assigning separate tasks to different particles is also necessary. The goal is then achieved by setting target milestones and timely adjustments of each particle's task. Thus, an SPSO algorithm was proposed (Li et al., 2017), where SPSO refines the population grouping and divides the iterative optimization process into multiple sub-processes. This is different from the original iteration, which is transient and irreversible. Thus, with SPSO, the trap of local optima is avoided. Example movements of SPSO particles are shown in Fig. 1.

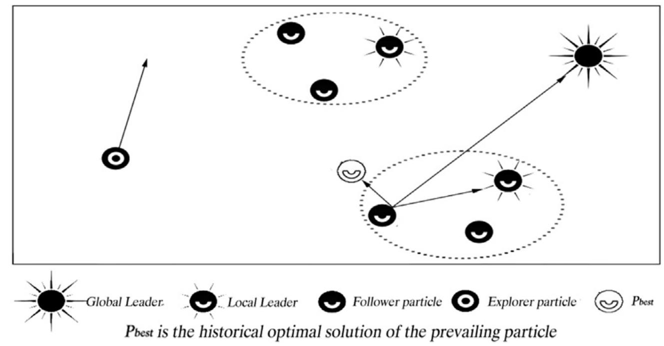

Fig. 1. Division and movement of particle swarm.

The population is first separated into three subgroups in descending order of adaptability: leaders, follower particles, and explorer particles. Among the leaders, the particle that is most adaptable is the global leader, and the rest are local leaders. During each iteration, the global leader remains stationary. This prevents any existing solutions from being omitted and preserves the current optimal solution. Each local leader maintains its proximity to the global leader and its own optimal solution. Each follower particle tracks three extrema: the global leader, its closest local leader, and its own optimal solution. In addition, random dithering is introduced among the local leaders and follower particles to improve their search capabilities. Finally, the explorer particles conduct random searches within the entire search space. After each iteration, the population is re-categorized by SPSO based on the respective particles' prevailing adaptability rankings.

Because SPSO does not have any inertial weight, the entire iterative process is implemented through multiple subprocesses. These subprocesses are divided into a divergent search phase t1 and a refined mining phase t2. During phase t1, the numbers of leaders and follower particles are reduced to their minimum. Most particles in the population are then explorer particles that conduct divergent searches for more optimal solutions within the search space. Once a new solution that is more optimal than the prevailing optimal solution is found, the entire population transitions immediately to phase t2. When this occurs, the number of explorer particles is reduced to its minimum. The vast majority of particles are then leaders and follower particles, which conduct refined searches on the optimal solution identified during the previous phase. If no solution that is more optimal is found after a specified period of refined searching, the algorithm is considered to be trapped by local optima. The process returns to phase t1 so that the population can diverge to the surrounding space, thereby expanding the search range and increasing its diversity.

The transition between phases t1 and t2 is regulated by a control factor m. When no solution that is more optimal is found after m successive iterations, the population begins an exploratory search. The upper limit of the algorithm's step size is one-tenth the search space. Based on this, the value of m is usually set to 10–20 to guarantee the algorithm's early exploratory capabilities, while its refined search capabilities are implemented at a later phase. In this study, we calculate m as follows:

$$m = 10 + 10 \times \left(\frac{1}{\pi} \times \arctan\left(1.5 \times \left(\frac{t \times 10}{T} - 5\right)\right) + 0.5\right) \tag{1}$$

where T and t are the upper limit and current number of the iteration, respectively.

The velocity function of the improved particle swarm algorithm is

Download English Version:

https://daneshyari.com/en/article/8866564

Download Persian Version:

https://daneshyari.com/article/8866564

Daneshyari.com