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Using an improved back propagation neural network to study spatial distribution of sunshine illumination from sensor network data

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ABSTRACT

The study of light distribution in orchards is very important for enhancing agricultural production. Nonlinear massive data, amounting to more than 190 MB, were collected over a 6-month period. Information such as the location, illumination, and time was obtained from wireless sensor networks, while that of canopy density and slope aspect was obtained through manual surveys. This paper proposes an improved back propagation (BP) neural network to study sunshine illumination distribution by exploiting these data. The basic BP neural network is divided into *Q* groups, each of which receives *R* samples and is trained individually using a gradient descent algorithm. Every grouped neural network records its error at the end of each training round. The new weights and thresholds, selected according to these error values, are employed in the next round of training, and the training process does not terminate until the error is within the desired goal. Finally, to verify the validity of the algorithm according to various criteria, the improved BP neural network is used to study sunshine illumination in an orchard. Our experiments show that the improved BP neural network algorithm performs better than traditional algorithms including the spline interpolation, Kriging, and basic neural network algorithms, and yields an accurate sunshine illumination distribution that can be used to improve agricultural production.

1. Introduction

Sunshine illumination, one of the most important factors for plant growth, directly affects plant photosynthesis (Iziomon and Mayer, 2001; Yang et al., 2006), material metabolism, structural morphology, and crop yields (Ramalho et al., 2002; Chazdon and Fetcher, 1984; Franklin and Whitelam, 2005). The study of sunshine illumination distribution not only increases crop yields by employing artificial light distribution according to light intensity, but also makes full use of land resources by planting proper crops that require corresponding illumination in orchards in terms of the illumination distribution(Avercheva et al., 2009; Tamulaitis et al., 2005; Lee,1987; Willey, 1979).

Many researchers have studied the distribution of sun irradiance in recent years to take full advantage of light. Typically, research on solar radiation distribution is roughly divided into four categories: (1) building regression equations (Romana et al., 2011; Ibrahimb et al., 2012; Duzen et al., 2012; Yang et al., 2006) using climatology methods (Akinoglu and Eceivit, 1990; Iziomon and Mayer, 2002) to calculate the solar radiation distribution; (2) simulating the solar radiation distribution by combining the digital elevation model (Dozier and Frew, 1990; Jun and Huang, 2006) and GIS technology (Romana et al., 2011); (3) retrieving parameters for solar radiation by utilizing satellite remote sensing data (Wild et al., 2005; Pinker et al., 2005); and (4) using a spatial interpolation fitting method, such as the least squares method, inverse distance squared method (Feng and Long, 2011), Kriging (Miao et al., 2011), and spline interpolation (Yang et al., 2010). While this research solves rough sun radiation distribution problems, in orchards the illumination distribution is uncertain and nonlinear owing to the slope aspect, water vapor, canopy density, and other factors. Therefore, it is necessary to find a new nonlinear fitting method to obtain an accurate illumination distribution.

Back-propagation (BP) neural networks have an advantage in terms of their nonlinear characteristic self-learning, self-organizing, and adaptive capacity, and are widely used in function approximation and data fitting. Since 1986, the use of BP neural networks has resulted in great achievements in the study of spatial distribution. These networks have achieved better performance than other methods in air quality distribution (Singh et al., 2012; Hu et al., 2011), water resource distribution (Chang et al., 2010; Singh et al., 2009; Singh and Gupta, 2012; Vesna et al., 2010), soil element distribution (Eriko et al., 2008; He et al., 2004; Jian-kang et al., 2010; Kim and Gilly, 2008), and other applications. Sunshine illumination distribution, with its nonlinearity and volatility caused by clouds, leaves, and hills, amongst others, can also be solved by employing a BP neural network. A number of scholars have carried out

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research on sunshine distribution using this method. Benghanem et al. (2009) used a BP neural network model to estimate and model daily global solar radiation using data from 1998 to 2002 at the National Renewable Energy Laboratory. Jiang (2009) employed BP neural network models to estimate monthly mean daily global solar radiation in eight typical cities in China, while Cao and Cao (2006) developed a new method combining an artificial neural network and wavelet analysis to forecast solar irradiance. Azadeh et al. (2009) proposed an integrated artificial neural network, which is trained and tested through multilayer perceptrons, and applied this approach to the prediction of solar global radiation using climatological variables. Furthermore, Ali, 2010 presented a BP neural network to estimate global solar radiation (GSR) as a function of air temperature data in a semi-arid environment. The models were then trained to estimate GSR as a function of the maximum and minimum air temperature and extraterrestrial radiation. Although the use of BP neural networks has resulted in many achievements in sunshine distribution, better performance can be achieved because more training data is now available as a result of advancements in data acquisition techniques.

Recently, with the rapid development of computer and communication technology, wireless sensor networks have been applied in agriculture to monitor environment variables automatically, in real-time, and over a long term, transmitting their data to a central computer through multi-hop technology (Wang et al., 2011a,b; Guo et al., 2011; Dong et al., 2011). Using wireless sensor networks, we can acquire more accurate basic data and thus provide strong technical support for precision agriculture. In this paper, a vast amount of data are collected in an orchard using wireless sensor networks with high-frequency acquisition rates, providing the basis for investigating sunshine distribution. If a basic neural network were used to study sunshine illumination, one of the following unfavorable situations would arise: (1) satisfactory results would not be obtained if training was carried out with a small number of samples; or (2) the time complexity would be too high, if a large number of samples were used for training. In this study, an improved BP neural network algorithm is proposed based on group training and combinatorial optimization to take full advantage of the data and improve the accuracy of the sunshine distribution model. Experiments in an orchard show that our model performs better than traditional models.

2. Materials and methods

2.1. Study area and data sources

2.1.1. Study area

The orchard, located in the city of Lin'an in the north-west of Jincheng county, Zhejiang Province, China, lies between longitude 119°43′15.24″ and 119°43′26.97″E and latitude 30°15′21.60″ and 30°15′33.27″N. The orchard covers an area of 59,500 m^2, bounded by a mountain in the north, a creek in the east, and a lake in the south. The average altitude is 50 m and the highest altitude is 170 m. The area receives average annual rainfall of 1613.9 mm over a total of about 158 days and has an average annual frost-free period of 237 days. The annual average temperature is 16.4 °C, with 1847.3 h of annual sunshine and a forest coverage rate of 76.5%. On the whole, this location, featuring a subtropical monsoon climate, is warm and humid and has sufficient illumination, abundant rainfall, and four distinct seasons.

2.1.2. Data sources

The orchard is divided into grids of size 25 m × 25 m, each of which is equipped with a sensor node, giving a total of 100 nodes. The wireless sensor networks comprise the 100 nodes working in a self-organizing manner in the orchard, with the data collected by the sensors being transmitted to a sink node using multi-hop technology. Each node is equipped with several sensors, including light sensors for collecting illumination and Zigbee sensors for data transmission. The wireless sensor networks, installed on 1st November, 2011, remained functioning for six months. The total data collected amounted to more than 190 MB. Data including location (such as longitude, latitude, and altitude), time, and sunshine illumination were collected every 10 min from each node and transmitted to the base station through the Zigbee communication module.

Two additional influential factors, forest canopy density and slope aspect, should also be measured. Canopy density, regarded as an indicator of the forest floor covered by the vertical projection of tree crowns, can be measured by forest inventory methods. The canopy density was measured twice a month in spring and autumn when the leaves of the trees changed dramatically, and once a month in other seasons when there was less change in the leaves of trees. The slope aspect in any one of eight directions, namely, east, southeast, south, southwest, west, northwest, north, and northeast, is constant. The data collected, as shown in Table 1, were stored in a database.

Additionally, all data were normalized. Let $x \in \{$longitude, latitude, altitude, canopy density, slope aspect, time, sunshine$\}$. If $x_{\max}$ and $x_{\min}$ denote the maximal and minimal values of x, respectively, x_i can be transformed into a value between [0,1) by $\frac{x_i - x_{\min}}{x_{\max} - x_{\min} + 1}$.

2.2. Improved BP neural network model design

2.2.1. The BP neural network

Artificial neural networks (ANNs), developed in the 1980s, have contributed to the advancement of science in the field of automatic control. An ANN is a large-scale parallel, complex nonlinear computing system with a parallel processing mechanism, variable topological structure, nonlinear mapping capability, and self-learning and self-organizing characteristics. The most popular algorithm for ANNs is the back-propagation neural network (BPNN), owing to its advantages in terms of a simple structure and ease of implementation for solving problems such as function approximation, time series forecasting, pattern recognition, and process control.

The BPNN training process is divided into two phases: Forward propagation of information and backward propagation of errors. Simple and mature, this is the most widely used neural network model. A BPNN contains three or more layers, including an input layer, several hidden layers, and an output layer. Each layer is composed of many simple neurons that can compute in parallel. Neurons in the same layer are not connected to each other, but are fully connected to other neurons in subsequent and previous layers. According to the Kolmogorov theorem, a BPNN consisting of an input layer, a hidden layer, and an output layer, can approximate any continuous function with arbitrary precision as long as the number of neurons in the hidden layer is flexible (Pan and Gu, 2008; Hornik et al., 1989). Thus, a three-layer BP neural network, the structure of which is illustrated in Fig. 1, is used in this paper.

Assume that the numbers of neurons in the input, hidden, and output layers are M, N, and L, respectively. Let $X = \{x_1, x_2, \ldots, x_M\}$ be an arbitrary input sample vector, $Z = \{z_1, z_2, \ldots, z_L\}$ be the actual output vector, $D = \{d_1, d_2, \ldots d_L\}$ be the desired output vector, w_{ij} $(1 \le i \le M, 1 \le j \le N)$ be the connection weight values between the input and hidden layers, v_{jk} $(1 \le j \le N, 1 \le k \le L)$ be the values between the hidden layer and the output layer, θ_j $(1 \le j \le N)$ be the output threshold of each neuron in the hidden layer, γ_k $(1 \le k \le L)$ be the threshold of each neuron in the output layer, and $f(x)$ be an