Intelligent estimation of trees canopy size using ultrasonic sensors

Adel Hosainpour¹*, Mohammad Eskandari², Bahram Ghamary¹

¹. Department of Agricultural Machinery, College of Agriculture, University of Ilam, Ilam, Iran
². Ms.c studentDepartment of Agricultural Machinery, College of Agriculture, University of Ilam, Ilam, Iran

Corresponding Author: Adel Hosainpour

ABSTRACT: Site specific garden management requires accurate measurement of canopy size of trees. Measuring canopy size is a challenge due to the complicated growth structures and irregular shapes of trees. In this study, an ultrasonic and artificial neural network (ANN) based intelligent system was used for a precise estimation of canopy volume of trees. A special experimental system was built for measuring distance between sensors and trees canopy, and also for processing the collected data. The system had three ultrasonic sensors mounted vertically on a wooden mast with equal distances of 0.6 m. The system was composed of ultrasonic sensors, DC motors, an ultrasonic microcontroller board, the motor's microcontroller board and a laptop computer. The DC motors move the wooden mast of ultrasonic sensors with a constant speed and the ultrasonic sensors measure the thickness of tree canopy with a sampling rate of 4 Hz. Experiments were conducted for 5 samples of Benjamin trees. The real volume of trees was measured manually with rectangular elements method. After a full passing of ultrasonic sensors, potential features such as canopy diameter, average width of tree canopy and height of the tree canopy are considered as the input and the manually measured volume is considered as the output of ANN models. Different multi-layer perceptron neural network architectures were examined for an accurate estimation of tree canopy volume. Optimal ANN model was selected based on mean square error and correlation coefficient. The results show that 13-16-7-1 was the optimal ANN model structure for estimating canopy volume.

Keywords: artificial neural network, Precision agriculture, tree canopy, ultrasonic sensor.

INTRODUCTION

Plant canopy structure is the spatial arrangement of the above-ground organs of plants. Detailed information on canopy characteristics is needed for an adequate management of trees and crops (Llorens et al., 2011). Tree canopy geometric characteristics are directly related to tree growth and productivity, and hence can be indicators for tree biomass and growth estimations, yield prediction, water consumption estimation, health assessment, and long-term productivity monitoring (Lee & Ehsani, 2009). Thus, there is a whole range of key agricultural activities including pesticide treatments, irrigation, fertilization, and crop training which depend largely on the structural and geometric properties of the visible part of trees (Rosell & Sanz, 2012). Development of automated equipment with capability of variable agricultural inputs with consideration of canopy characteristics is considered as a suitable solution to reduce environmental pollutions and production costs.

Canopy characteristics such as canopy dimensions or canopy volume can be measured manually. Measuring canopy size is a challenging and time consuming task due to the complicated growth structures and irregular shapes of trees. Application of various remote sensing techniques such as image analysis techniques, digital stereoscopy photography, and analysis of the light penetration in the canopy have been investigated for the measurement of tree canopy structural characteristics (Meron et al., 2000). Satellite images have also been used to estimate canopy volume of trees in forest (Carreiras et al., 2006; le Maire et al., 2008; Mäkelä & Pekkarinen, 2004; Mõttus et al., 2006).

However, the scale of these remote sensing techniques is relatively large and consequently, the sensing resolution may be insufficient for a real-time variable rate application in a liner production field. In addition, remote sensing techniques typically have a chronological gap between detection and application, resulting in application errors. To reduce this problem, a LIDAR (Light Detection and Ranging) system or a laser scanner has been used to
measure canopy volume (Jeon et al., 2011). Promising results were reported for using this system in which measured canopy volume was close to the manually measured volume (Lee & Ehsani, 2008; Rosell et al., 2009; Wei & Salyani, 2005). LIDAR system is a relatively expensive sensor ($2000–6000) and increases the agriculture equipment cost and consequently production cost (Jeon et al., 2011). Thus, finding methods that are cheap and satisfactory and use software methods for increasing accuracy seem to be preferable alternatives.

Ultrasonic sensors that are affordable, relatively robust during outdoor conditions, and capable of estimating the canopy volumes of trees satisfactorily have been used by several researchers (Giles et al., 1988; Tumbo et al., 2002; Zaman & Salyani, 2004). However, due to the relative wide angle divergence of ultrasonic waves, the field of view becomes larger as the distance between the sensor and the canopy (target) increases, reducing the accuracy of the measurements and increasing the possible interference in the signal reception of two consecutive sensors (Wei & Salyani, 2004). Canopy characteristics such as small dimensions or orientation of leaves which present gaps in the outer layer of leaves and present zones with low density of leaves in surface of tree canopy have also been other sources of errors in estimation of tree canopy volume (Escola et al., 2011). However, a good correlation between ultrasonic volume and manual tree volume has been reported in some investigations. Zaman and Salyani (2004) reported that the difference between ultrasonic and manual volumes of individual trees ranged from −17.37% to 28.71%, at a 95% confidence level. They used correlation procedure to find the relationship between ultrasonic volume and manually measured tree volume, maximum height, and diameter of trees.

Tumbo, et al. (2002) reported a strong correlation between ultrasonic canopy volumes versus canopy volumes based on manual methods (R² = 0.90 and RMSE = 1.66 m³). The tree canopy volumes vary substantially depending on the dimensions of the tree canopy. Thus, a potential approach is to use artificial neural network (ANN) with trees dimensions as input for estimating tree canopy volume.

The main goal of this study is to investigate the feasibility of Software methods in order to decrease volume estimation error for tree canopies. An artificial neural network was used as software unit for this purpose.

**MATERIALS AND METHODS**

Five trees were selected for canopy volume measurement. The trees were two or three year old Ficus benjamina of the Moraceae family. The selected trees had approximately the same heights. The tree heights ranged from 2.3 to 2.45 m.

**Manual Tree Volume Measurement and Computation**

The measurement of the volume of a tree began firstly with the measurement of the maximum tree height and the height of the bare trunk in a plane perpendicular to the row containing the trunk axis. Secondly, the height of the foliated part of the tree was calculated by subtracting both previous heights. Next, the height of the foliated part was divided into three zones with equal heights. Each zone was divided to rectangular elements having the height of corresponding zone, 100 mm width and variable depths. The depth of the tree canopy corresponding to each width of rectangular elements was measured up to the perpendicular plane that passes through the middle of the trunk (Fig. 1).

**Experimental apparatus**

A test rig was built to measure dimensions of trees and for estimating the volume of trees. The schematic diagram of the experimental apparatus is shown in Fig. 2. The system consisted of ultrasonic sensors, DC motors, an ultrasonic microcontroller board, the motor’s microcontroller board, conveying platform and a laptop based data acquisition system.

The ultrasound sensors used in this research were SRF02. Specifications of the ultrasonic sensors are as follows: standard detection range 6000 mm, beam angle 45°, and carrier frequency 40 kHz. The SRF02 does not require any user calibration.
Figure 1. Rectangular elements for the manual measurement of the volume tree.

The volume of each rectangular element was calculated by multiplying its width by the corresponding height and mean value of the top and bottom depths. The volume of one half of the tree was obtained by summing the volumes of each rectangular element. The volume of other half of the tree was obtained in a similar way. Finally, the total volume of a tree was obtained by summing up the volume of front and back sides of the tree.

Figure 2. Schematics of experimental apparatus.

The conveying platform consists of an aluminum rail, a slider and a wooden mast. The wooden mast is vertical to the ground and is used to fix the three ultrasonic sensors with equal distances of 0.6 m. Transducer 1 was nominally 1.2 m above ground level, and transducer 3 was 2.4 m high. The wooden mast was mounted on the slider and a string was attached to the slider. DC motors were mounted on both ends of the aluminum rail and were used to pull the string that transports the slider. The ultrasonic sensors could move in two directions at a controlled...
speed. The speed was adjusted by changing the motor speed and duration of pulse signal. Motor's microcontroller board is used to control motor driver and to move slider precisely.

The trees were placed individually 2.7 m in front of the aluminum rail. The slider was moved at three travel speed groups: 0.76–0.93 m/s, 1.33–1.60 m/s, and 2.71–3.24 m/s with average speeds of 0.8, 1.5 and 3.0 m/s, respectively. The speed of the slider was computed by traveled distance divided by travel time. To prevent the signal interference between adjacent sensors the sequential firing method was designed. In this method only one sensor is on at any moment and the others are off.

When the slider moves along the aluminum rail, each transducer would measure the horizontal distance ($X_i$) between the mast and the nearest peripheral foliage of the tree canopy, and exports the data to the ultrasonic microcontroller board. The ultrasonic microcontroller board has a USB communication port and was mounted on the wooden mast between transducers 1 and 2 in order to transfer data to a laptop computer. Data were sent to communication port at 4 samples per second (each sample consisted of readings from 3 sensors). MATLAB software installed on a laptop was used for data acquisition and process support.

**Data processing and feature extraction**

After full passing of ultrasonic sensors, potential features such as maximum height of the tree canopy, average tree canopy width and canopy diameter are considered as the input of ANN and the manually volume as the output of ANN.

Maximum tree canopy heights were calculated by scanning all data arrays of three ultrasonic ranging measurements collected in 1 s time intervals. The scan was conducted in a program loop from the top transducer (3) downwards to lower transducer that detected half tree canopy. The tree canopy height for the each scan was number of ultrasonic transducer that detected the tree canopy, product in distance between two ultrasonic transducers (0.6 m) and the maximum of them represented the maximum tree canopy height. Average tree canopy widths corresponding to each ultrasonic sensor height were calculated by averaging the eight of maximums tree canopy width collected each ultrasonic sensor. Tree canopy widths corresponding to the three ultrasonic sensors height for each sampling point was calculated according to Equation (1), Fig. 3. (a).

$$C_{WU_i} = D - X_i$$

(1)

$C_{WU_i}=$ canopy width of the half tree canopy (m).

$D=$ distance between the center of tree trunk and sensor (m).

$X_i=$ measured distance from ultrasonic sensors to tree canopy when the sensor is at position i (m).

By averaging eight maximum tree canopy widths obtained using three ultrasonic sensors, a smoothed tree canopy width was calculated for each of ultrasonic sensors.

Tree canopy diameters corresponding to the three ultrasonic sensors height were calculated using sampling rate, slider speed and the number of points that ultrasonic sensor detected the tree canopy according to Equation (2), Fig. 3. (b).

$$CD_i = \frac{(n_i - 1) \times S_r}{(S_r - 1)}$$

(2)

$CD_i =$ tree canopy diameters for the $i$th ultrasonic sensor (m).

$S_r =$ ultrasonic sensor sampling rate (4 samples/s).

$n_i =$ number of points tree canopy detected for the $i$th ultrasonic sensor.

$i =$ number of ultrasonic sensor.

![Figure 3. (a) Distance to the external layout of the canopy; (b) Tree canopy diameters.](image)
Artificial neural network and back propagation algorithm

Artificial neural network (ANN) is a mathematical tool, which tries to represent low-level intelligence in natural organisms and it is a flexible structure, capable of making a non-linear mapping between input and output spaces (Rumelhart, McClelland, & Williams, 1986). The multilayer perceptron (MLP) is one of the most widely implemented neural network topologies that is very powerful in function optimization modeling (Lou & Nakai, 2001). A typical MLP neural network consists of an input layer (the first neuron layer), an output layer (the last neuron layer), and one or more hidden layer(s) between the input and output layers. MLPs are normally trained with the back propagation algorithm (BPA). BPA uses the supervised training technique where the network weights and biases are initialized randomly at the beginning of the training phase. For a given set of inputs to the network, the response to each neuron in the output layer is calculated and compared with the corresponding desired output response. Errors associated with the output neurons are propagated from output layer to the input layer through the hidden layers to update the weights and eventually reducing these errors. The error minimization process is achieved using gradient descent with momentum rule. Gradient descent with momentum (GDM) learning rule is an improvement to the straight GD rule in the sense that a momentum term is used to speed up learning and stabilizing convergence (Haykin, 1999). Therefore, the GDM method of learning was used throughout this study. After adequate training, the network weights are adapted and employed for cross validation in order to determine overall performance of the ANN model.

In this work, the ANN was first trained using a single hidden layer. However, the results of this configuration for volume prediction were not satisfactory; therefore, a neural network with two hidden layers was applied. The optimal number of neurons in the hidden layers was determined by trial and error. Several iterations were conducted with different numbers of neurons of hidden layers in order to determine the optimal artificial neural network structure. It was started with one neuron and increased the number of neurons up to forty. A hyperbolic tangent was used as the activation function in each hidden layer, and a linear activation function was used in the output layer. These activation functions help in nonlinearly transforming the inputs to the desired output. Learning rate was 0.2 throughout the momentum learning rule. Totally, 45 data points were experimentally collected and to avoid the potential problem of over-fitting, they were randomly divided into three groups: training (70%), validating (15%) and testing data (15%). The first part was used to perform the training of the network. The second one was applied to evaluate the quality of the network during the training and the last partition was used for estimating the performance of the trained network on new data. Weights were randomly assigned at the beginning of the training phase, according to the back-propagation algorithm. Training was finished when the mean square error (MSE) converged and was less than 0.001. If the MSE did not go below 0.001, training was completed after 1,000 epochs, where an epoch represents one complete sweep through all the data in the training set. Artificial neural networks were developed using the Neural Network Toolbox of Matlab software.

<table>
<thead>
<tr>
<th>Features</th>
<th>output</th>
<th>Topology</th>
<th>Cross validation (r)</th>
<th>Cross validation (MSE)</th>
<th>Epochs</th>
</tr>
</thead>
<tbody>
<tr>
<td>CD + CW + HS</td>
<td>HVRE</td>
<td>7-10-1</td>
<td>0.92315</td>
<td>0.004095</td>
<td>1000</td>
</tr>
<tr>
<td>CD + CW + HS</td>
<td>HVRE</td>
<td>7-8-3-1</td>
<td>0.5705</td>
<td>0.019735</td>
<td>1000</td>
</tr>
<tr>
<td>CD + CW + HS</td>
<td>VRE</td>
<td>7-4-1</td>
<td>0.039905</td>
<td>0.074554</td>
<td>1000</td>
</tr>
<tr>
<td>CD + CW + HS</td>
<td>VRE</td>
<td>7-15-1</td>
<td>0.027455</td>
<td>0.071481</td>
<td>1000</td>
</tr>
<tr>
<td>CD + CD + CW + HS</td>
<td>VRE</td>
<td>13-15-1</td>
<td>0.86222</td>
<td>0.0070764</td>
<td>1000</td>
</tr>
<tr>
<td>CD + CD + CW + HS</td>
<td>VRE</td>
<td>13-9-5-1</td>
<td>0.92855</td>
<td>0.012995</td>
<td>1000</td>
</tr>
<tr>
<td>CD + CD + CW + HS</td>
<td>VRE</td>
<td>13-16-7-1</td>
<td>0.98362</td>
<td>0.0027716</td>
<td>1000</td>
</tr>
</tbody>
</table>

CD: canopy diameter
CW: canopy width
HS: canopy height

HVRE: The half volume of the tree with rectangular element method
VRE: The volume of the tree with rectangular element method
i: indicates the number of ultrasonic sensors
f, b: represent front and back of the tree canopy
The best combination was tree diameter corresponding three ultrasonic sensors on the front and back sides of the tree, Average width corresponding three ultrasonic sensors on the front and back sides of the tree and maximum height of the tree canopy feature. The final structures of network were 13-16-7-1. Fig. 4 shows the neural network training procedure. It illustrates that in the first 100 epochs of the training and cross validation, MSE reaches to an acceptable magnitude.

After training the network, the selected model was evaluated with five data never used by the network during the training. The root mean square errors (RMSE) of the output of Neural Networks with actual tree canopy volume were determined. Results indicated that the difference between ANN estimation and manual volumes of trees canopy ranged from −4.37% to 7.78% and the RMSE was 0.039278 (m³) (Table 2). Error values of below 8% indicate that the predictive performance is sufficient for industrial applications.

results and discussion

To achieve the best combinations of potential features and optimal ANN configuration, different features were selected and tested by neural network. These features were fed to the ANN models and their performances were determined by evaluation of the mean square error (MSE) and correlation coefficient (r). Each combination of potential features with one or two hidden layers and neurons per hidden layer was trained for ten trial configurations, with each trial starting with a different set of randomized weights, and the best result saved. Table 1 shows the performance of some experiments.

conclusion

In the present study, an ultrasonic intelligent system was used for estimation of canopy volume of trees. Main advantages of this system are accuracy and low cost of equipments. In spite of the divergence angle of ultrasonic sensors and canopy characteristics, artificial neural networks are able to estimate tree canopy volume with suitable accuracy.

references


