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Bee-inspired RBF network for volume estimation of individual trees

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ABSTRACT

The *Eucalyptus* is the most cultivated kind of tree in Brazil because it has adapted to the climate and has great importance for the industry. In cultivated forests, the wood volume is essential information to the forest management. Therefore, that information must be estimated as precisely as possible. There are several descriptive mathematical models which were developed for that purpose. However, Computational Intelligence techniques have been used in order to facilitate that process and substitute the volume models. Sundry works have proposed the use of Artificial Neural Networks for wood volume estimation, but there is a type of neural network, the Radial Basis Function – RBF, that can be designed automatically by clustering algorithms. This work presents the application of RBF networks automatically generated by the cOptBees clustering algorithm in the estimation of *Eucalyptus* volume and compares the results to the MLP networks and the classic models at the same dataset. The cOptBees is a clustering algorithm inspired by the behavior of bees which allows the number of clusters to be found automatically. To evaluate the various factors that can influence the quality of the results provided by RBF, the tests consider three training algorithms, three activation functions and three heuristics to define the spread. Besides the RBF generated by cOptBees, were evaluated another two types of RBF: randomly and k-means generated. In the volume estimation, the results indicate that neural networks and classical equations are equivalent to each other when there is high availability of data. However, when there are few training samples, the classical models performed better. Nevertheless, RBF networks are a viable alternative due to its ease of configuration and generalization capability.

1. Introduction

Because it was adapted well to the Brazil's climate and has great applicability as raw material for the industry, the *Eucalyptus* is the most cultivated tree genus in the Brazilian territory (IBA, 2017). In this activity, it is of fundamental importance to know the volume of wood produced.

It is common to select one of several existing equations to provide estimates of volume of wood. Most of these equations have as input the diameter at breast height and the total height of sample trees and have coefficients that are adjusted by means of the rigorous scaling of a certain number of trees. After adjusting some equations, the best equation, according to statistical criteria, is selected and applied to the problem.

Although the traditional estimation method has shown good results in most cases, recent works have demonstrated the interest of forest engineering in Computational Intelligence. Among the Computational Intelligence techniques, Artificial Neural Networks (or Neural Networks) can be perfectly adapted to the described problem. Artificial Neural Networks (ANN) are inspired by biological neural networks and have a massively parallel distributed structure and the capacity of learning with examples and generalizing. Generalization capacity refers to the fact that Neural Networks provide coherent result for input that was never presented in the training phase (Haykin, 1999).

Various works, like (Gorgens et al., 2009; Ozcelik et al., 2010; Binoti et al., 2014; Ozcelik et al., 2014; Sanquetta et al., 2018), use Neural Networks as a method to estimate the volume in cultivated forests. Another example is (Lacerda et al., 2018), that estimate volume in native trees. In the specialized literature the use Neural Networks to volume estimation is not a novelty. However, Computational Intelligence is in constant evolution and recently developed algorithms have not been yet used in this area. The theory suggests that MLP and RBF are equivalent in generalization capacity (Haykin, 1999) and RBF presents some advantages in terms of architecture. Some paper like (Zhang et al., 2016; Wang et al., 2018) explains more about MLP networks. The RBF network has an architecture with fewer parameters than MLP. According to Blanco et al. (2013), this kind of network requires fewer training samples and can be trained faster than MLP's.

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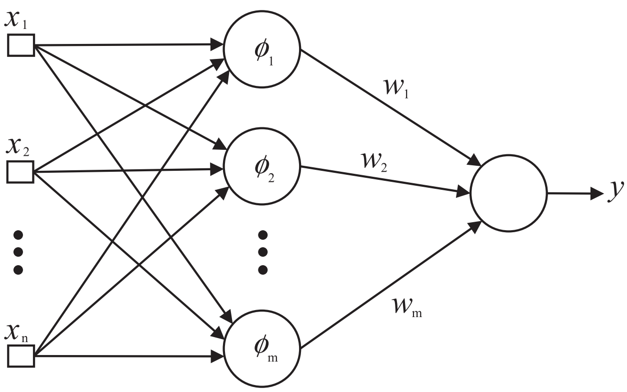

Fig. 1. Typical RBF architecture.

Moreover, the default architecture of RBF can be defined by clustering algorithms removing from the human operator this responsibility.

1.1. RBF networks

Differently to the MLP networks, that can have one or more hidden layers, RBF networks are often defined with only one hidden layer. Fig. 1 presents a typical architecture of a RBF network with n inputs and m neurons.

The neurons of the hidden layer implements a radial basis function. According to Haykin (1999), common functions applied in RBF are: gaussian (Eq. (1)), multiquadric (Eq. (2)) and thin-plate spline (Eq. (3))

$$\phi(u) = e^{-\frac{v^2}{2\sigma^2}} \tag{1}$$

$$\phi(u) = \sqrt{(v^2 + \sigma^2)} \tag{2}$$

$$\phi(u) = v^2 \log v \tag{3}$$

where $v = \|x-\mu\|$, which is usually defined as the Euclidean distance, x is the input vector and μ and σ are, respectively, the center and the spread (or radius) of the radial basis function. Fig. 2 shows two 2D gaussian functions with different spread values (Pazouki et al., 2015).

RBF networks can also be defined by matrix formulation to a better comprehension of how it works. Consider three matrices **G**, **W**, and **D** as, respectively, the result matrix of the hidden layer, the matrix of synaptic weights and the matrix of desired outputs. The goal of the training is find **W**, where:

$$\mathbf{G} \times \mathbf{W} = \mathbf{D} \tag{4}$$

$$\begin{bmatrix} \phi_{1,1} & \phi_{1,2} & \cdots & \phi_{1,m} \\ \phi_{2,1} & \phi_{2,2} & \cdots & \phi_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{n,1} & \phi_{n,2} & \cdots & \phi_{n,m} \end{bmatrix} \times \begin{bmatrix} w_{1,1} \\ w_{2,1} \\ \vdots \\ w_{m,1} \end{bmatrix} = \begin{bmatrix} d_{1,1} \\ d_{2,1} \\ \vdots \\ d_{m,1} \end{bmatrix} \tag{5}$$

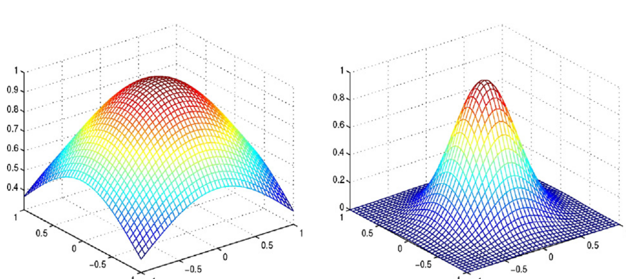

Fig. 2. Gaussian with $r = 1$ (left) and $r = 1/3$ (right) centered at the origin in $\mathbb{R}^2$.

1.1.1. RBF training

There are different learning strategies that we can follow in the design of an RBF network, depending on how the centers of the radial basis functions of the network are specified (Haykin, 1999).

The simplest approach is to assume fixed radial basis functions defining the activation functions of the hidden neurons. The locations of the centers may be chosen randomly from the training data set. In this approach, the only parameter that would need to be learned are the linear weights in the output layer (**W**). The main problem with the method of fixed centers is the fact that it may require a large training set for a satisfactory level of performance (Haykin, 1999).

The centers of the radial basis functions and all others parameter can be defined by supervised methods. Another approach suggests that the training can be separated in two different stages (hybrid learning). The first stage is the self-organized learning, where the purpose is to estimate appropriate locations of the centers (μ) and the spread (σ) of the radial basis functions in the hidden layer. At the second stage, supervised methods completes the design of the network by estimating the linear weights of the output layer (Haykin, 1999).

At the self-organized learning, is utilized a clustering algorithm that partitions the training set into subgroups which should be as homogeneous as possible. A well-know algorithm is the k-means, but any clustering algorithm can be applied at this phase. Algorithm 1 explains how to train a RBF network.

Algorithm 1. RBF Network training

Algorithm 1: RBF Network training

Input Parameters: *in*: input data samples; *out*: output data samples;
Output Parameters: *mse*: mean square error of training; *rbf*: trained network.
begin
  Select centers of radial basis functions using any clustering algorithm;
  for *i=0 to size(in)* **do**
    for *c=0 to size(centers)* **do**
      calculate the output of each input data in RBF function with center in $center_c$;
    end
    Use pseudo-inverse matrix to calculate weights;
    Calculate output of the network with weights adjusted previous;
    Calculate MSE (expected outputs - calculated outputs);
  end
end

There are several clustering algorithms and they can be used to train RBF networks. A recent work (Cruz et al., 2016) demonstrated the feasibility of applying a clustering algorithm inspired by bee behavior to automatically generate the optimal RBF network architecture for data classification. This algorithm has received some changes in order to become more efficient (Silva et al., 2016).

This paper presents RBF networks trained by the bee inspired algorithm as a method to obtain volume estimates of individual trees. The