Information Sciences 178 (2008) 3828–3839

Contents lists available at ScienceDirect

Information Sciences

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

Application of fuzzy *T*-norms towards a new Artificial Neural Networks' evaluation framework: A case from wood industry

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ARTICLE INFO

Article history:
Received 3 November 2007
Received in revised form 25 May 2008
Accepted 27 May 2008

Keywords:
Intelligent ANN evaluation algorithms
Fuzzy algebra
Fuzzy sets
T-norms

ABSTRACT

The development of an Artificial Neural Network requires proper learning and testing procedures that adopt error correction processes and algorithms. Monitoring of processing elements values and overall performance is one of the most critical issues of an Artificial Neural Network development process. This should happen as the network evolves and it is the actual task that enables the developer to make informed decisions about the proper network topology, math functions, training times and learning parameters. This manuscript presents an innovative and flexible error validation framework applying fuzzy logic. It offers an approach capable of viewing the task of performance improvement under several different perspectives. Then the developer has the capacity to decide which performance is most suitable according to his standards. The model has been tested for a specific industrial case study with actual data and a comparison to the existing methods is presented.

1. Introduction

The choice of an Artificial Neural Network's (ANN) optimal configuration is based on minimizing the differences between the ANN predicted values and the actual experimental data after a certain number of iterations. This is performed in both training and testing processes by using various diagnostic methods called instruments. The instruments provide the developer with diagnostic information that can be considered as indications of the ANN's good or poor performance.

During the iterative process of training, the error measurements between the desired output and the actual output (produced by the ANN) are very crucial. The adjustment of the synaptic weights is performed aiming in reducing these error values. In the training phase, usually the squared error values should drop and their comparison to a sufficiently low value determines the termination of the whole process. However, the choice of this termination value is more or less subjective and it depends on the designer. Also the production of crisp mean square error values in the output layer during testing, offers indications of the ANN's performance but it does not offer a representative overall in the case that the network has more than one output neuron.

This paper aims in proposing and describing a new fuzzy ANN evaluation model that has been incorporated by a prototype information system. The model is called NANNEF and it uses fuzzy sets and fuzzy aggregation operators in order to offer a flexible validation of an ANN's degree of convergence. NANNEF can operate as a tailored model according to the needs of the network's developer. For example if the developer requires an ANN with a high performance for all of the output parameters, existing evaluation methods may absorb the potential poor performance of one or more neurons. In this case the

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doi:10.1016/j.ins.2008.05.033

NANNEF can perform evaluation by using the drastic product T-norm which offers a low convergence index even if one neuron has an extremely wrong value. The drastic product is an aggregation operator between fuzzy sets.

In this way, the developed system can view the ANN evaluation process under different perspectives. From this point of view the model can be considered as quite innovative. After the description of the design principles and framework, this paper presents the application of NANNEF towards the validation of two ANN developed by Avramidis and Iliadis with actual data from wood industry [2,20].

More specifically the first ANN has been developed to estimate the loss factor of wood depending on its chemical composition and on the temperature and moisture of the environment. The second ANN estimates the modulus of elasticity (MOE) and the modulus of raptor (MOR) that determine the bending strength and stiffness of wood.

The determination of the input vector for the loss factor has been based in previous research efforts of wood scientists. In wood, radio frequency vacuum drying [18,19] and other high frequency electric field heating applications such as veneer and finger-joint gluing and parallam manufacturing [26], the knowledge of the fundamental dielectric properties of the material such as dielectric constant (ε'), loss tangent ($\tan\delta$) and loss factor (ε'') are imperative in process design, control, optimization and simulation.

The input vector for the estimation of bending strength and stiffness has been determined also by previous research efforts. Both MOE and MOR exhibit strong correlations with several inherent wood properties [27], including intrinsic density, moisture content, slope of grain, number and size of knots, internal/external checks, and forest type [27]. These cases from wood industry have been used only to demonstrate the performance of NANNEF.

1.1. Literature review

The most significant property of an ANN is its ability to learn from a subset of the universe of discourse and thus to improve its performance. In each development step, the network has to adopt a flexible error/cost function capable of determining its output error before the adjustment of the synaptic weights.

The literature proposes specific ways of measuring the error of an ANN's output, during training and testing processes. A typical error function is proposed by Callan [4]. According to this approach, if the m time step of an iterative process like learning or testing, and a neuron f in the output layer, then Eq. (1) can be considered as a prescribed way of measuring the error degree [4]:

$$E_f(m) = T_f(m) - Z_f(m). \tag{1}$$

It should be clarified that $T_f(m)$ is the target output value whereas $Z_f(m)$ is the actual output value of the network.

The overall error (OVER) using the classical approaches is estimated as the sum of all $E_f(m)$ [4]. However, in this way it is not possible to estimate deviations in the error degree between individual testing vectors in the output layer. The error signal $E_f(m)$ fires a control mechanism which aims in initiating a sequence of corrective operations. For this reason the effectiveness of an error validation algorithm can be considered crucial for the correct development of an ANN.

Two well known ANN evaluation instruments found in the literature are the root mean square error (RMS Error) and the confusion matrix (CM) that incorporates the common mean correlation. The RMS Error adds up the squares of the errors for each PE in the output layer, divides by the number of PEs in order to obtain an average and finally estimates the square root of that average. The squaring of the errors gets rid of the sign of the error but increases the magnitude. The square root is used in order to remove the magnitude. The RMS Error is a valuable and common measure of performance.

The CM provides an advanced way of measuring an ANN's performance during the "learn" and "recall" phases. It allows the correlation of the actual output of an ANN to the desired results in a two-dimensional visual graphical display [22,23]. This is achieved by providing the user with a graph consisting of numerous small cells called bins. The network with the optimal configuration must have the bins on the diagonal from the lower left to the upper right. In this way the CM can be considered as an instrument indicating how well the network is performing.

An important aspect of the CM is that the value of the vertical axis (in the produced histogram) is the common mean correlation (CMC) coefficient of the desired (d) and the actual (predicted) output (y) across the Epoch. The CMC is calculated by the following Eqs. (2) and (3) [22]:

$$\mathrm{CMC} = \frac{\sum (d_i - \bar{d})(y_i - \bar{y})}{\sqrt{\sum (d_i - \bar{d})^2 \sum (y_i - \bar{y})^2}}, \tag{2}$$

where

$$\bar{d} = \frac{1}{E}\sum_{1}^{n} d_i \quad \text{and} \quad \bar{y} = \frac{1}{E}\sum_{1}^{n} y_i. \tag{3}$$

It should be clarified that d stands for the desired values, y for the predicted values where i ranges from 1 to n (the number of cases in the data training set) and E for the Epoch size, which is the number of training data sets presented in the ANN learning cycles among weight updates.

Several research efforts combining fuzzy logic with ANN (like fuzzy polynomial neural networks) have been presented in the literature recently and they have offered powerful and advanced techniques [21,25]. Also fuzzy operators have been