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An Artificial Neural Network based expert system fitted with Genetic Algorithms for detecting the status of several rotary components in agro-industrial machines using a single vibration signal

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ABSTRACT

This article proposes (i) the estimation method of an expert system to predict the statuses of several agro-industrial machine rotary components by using a vibration signal acquired from a single point of the machine; and, (ii) a learning method to fit the estimation method. Both methods were evaluated in an agricultural harvester. Vibration signal data were acquired from a single point of the harvester under working conditions, by varying (1) the engine speed status (high speed/low speed), (2) the threshing operating status (on/off), (3) the threshing balance status (balanced/unbalanced), (4) the chopper operating status (on/off), and (5) the chopper balance status (balanced/unbalanced). Positive frequency spectrum coefficients of the vibration signal were used as the only inputs of an Artificial Neural Network (ANN) that predicts the five rotary component statuses. Four Genetic Algorithm (GA) based learning methods to fit the ANN weights and biases were implemented and its performance was compared to select the best one. The prediction system that is developed was able to estimate the rotary component status under consideration with a mean success rate of 92.96%. Moreover, the best GA-based learning method that was implemented reduced the number of generations by 70% in the best case, compared with a random learning method, allowing a similar reduction in the time needed to reach the expected success rate. The results obtained suggest that (i) an ANN-based expert system could estimate the status of the rotary components of an agro-industrial machine to a high degree of accuracy by processing a vibration signal acquired from a single point on its structure; and, (ii) by using the best implementation of the GA-based learning method proposed to fit the ANN weights and biases, it is possible to improve the success rate and by doing so to reduce the time needed to perform the adjustment. The main contribution of this work is the proposal of a classification method that estimates the status of several rotary elements placed each one far from the others employing the signal acquired from only one accelerometer and non-requiring a feature extraction stage.

1. Introduction

Vibration signals can reflect the status of rotary machinery (Li, Tse, Yang, & Yang, 2010). These signals sometimes propagate throughout the structure of the machine with low attenuation, which makes it possible to monitor rotating elements by positioning an accelerometer on the structure of the machine (Li et al., 2013). Nevertheless, this propagation capability has also the disadvantage of transmitting other vibration signals from other elements of the structure that can be added to the signal of interest, making it difficult to extract the relevant information (Albarbar, Gu, & Ball, 2010).

Vibration signals from rotary machinery are commonly analyzed in the frequency domain because of the relation between the rotation frequency of the element and their peaks in the spectrum signal. Some authors have used fast Fourier transform (Chwan-Lu, Shun-Yuan, Shou-Chuang, Jen-Hsiang, & Ke-Fan, 2014; Chwan-Lu et al., 2014; Taghizadeh-Alisaraei, Ghobadian, Tavakoli-Hashjin, & Mohtasebi, 2012), short-time Fourier transform (Vulli, Dunne, Potenza, Richardson, & King, 2009), wavelet transform (Bin, Gao, Li, & Dhillon, 2012; Chen, Tang, & Chen, 2013; Jayaswal, Verma, & Wadhwani, 2011; Lu, Xiao, & Malik, 2015; Rodriguez-Donate, Romero-Troncoso, Cabal-Yepez,

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Garcia-Perez, & Osornio-Rios, 2011; Wang, Makis, & Yang, 2010; Yan, Gao, & Chen, 2014), S-transform (McFadden, Cook, & Forster, 1999), and the Hilbert–Huang transform (Cheng, Cheng, Shen, Qiu, & Zhang, 2013; Lei, Lin, He, & Zuo, 2013; Li et al., 2010; Wang, Ma, Zhu, Liu, & Zhao, 2014) among others, to perform this analysis. Because of the relationship between the rotation frequencies of the machine elements and the peaks of the spectrum signal, experts can estimate the status of machine elements looking for patterns in the spectrum signal, when sufficient information is gathered on aspects such as the rotation frequency of the machine component. Nevertheless, to do so requires expert analysis of the vibration signals and a detailed knowledge of the working components of the machine, which are not always available. Automated systems have been proposed to estimate the status of machine elements using this strategy when no expert is available. These systems apply knowledge of the machine to extract characteristics from the spectrum signal and to estimate its status according to those characteristics.

Artificial Neural Networks (ANNs) are widely proposed in the literature as mathematical tools to implement the estimation methods needed in automated systems of this kind, because of its learning capability. There are some examples of ANNs implementing estimation methods in the literature (Bin et al., 2012; Cheng et al., 2013; Chwan-Lu et al., 2014; Chwan-Lu, Shun-Yuan, Shou-Chuang, et al., 2014; Jayaswal et al., 2011; Vulli et al., 2009; Yildirim, Erkaya, Eski, & Uzmay, 2009). Nevertheless, the authors have found no previous literature that applies to machine maintenance and vibration signal analysis in the context of ANN-based estimation systems that use previous knowledge to extract characteristics. In contrast, systems have been found with this feature for handwritten character recognition (Polat & Yıldırım, 2008a; Pradeep, Srinivasan, & Himavathi, 2011), hand geometry identification (Polat & Yıldırım, 2008b), sonar target classification (Erkmen & Yıldırım, 2008), and object recognition (Polat & Yıldırım, 2008a). The learning process of ANNs is typically called training, and it is a multivariable optimization problem which can involve hundreds or thousands of variables. To improve the performance of the ANN and to reduce the necessary training time, some authors propose the use of optimization heuristics such as Genetic Algorithms (GAs), particle swarm optimization, and evolutionary programming (Chia-Feng, 2004; Huang, Li, & Xiao, 2015; Leung, Lam, Ling, & Tam, 2003; Song, Hu, Xie, & Zhou, 2013; Xin & Yong, 1997).

Our objective here is to study the feasibility of estimating the status of the rotary machinery in agricultural and industrial machines by using a vibration signal acquired from a single point of the machine structure. To accomplish this general objective, three specific sub-objectives have been proposed. The first one is to design a prediction method to estimate the status of rotary machinery. This method must be able to perform the estimation using the vibration signal specified in the general objective. Moreover, this method must be generalizable to apply it to different rotary components and different agricultural or industrial machines. The second sub-objective is to design and implement four learning methods, to optimize the learning process for the prediction method that is designed for the first objective. The third sub-objective is to evaluate both the prediction method that is designed and the proposed learning methods by implementing an expert system which uses them in an agricultural harvester. To this end, five rotary component statuses of the agricultural harvester were considered: (1) the engine speed status (high speed/low speed), (2) the threshing operating status (on/off), (3) the threshing balance status (balanced/unbalanced), (4) the straw chopper operating status (on/off), and (5) the straw chopper balance status (balanced/unbalanced).

2. Background

This section introduces the theoretical basis of Artificial Neural Networks (ANNs) and Genetic Algorithms (GAs).

2.1. Artificial Neural Network

ANNs are massive parallel tools capable of relating a set of input and output variables. They are modeled on the animal nervous system, which is a highly complex, nonlinear, parallel processing system. They are composed of a set of neurons, commonly organized in layers, and by connections which connect the neurons.

An example of a perceptron, which is the most common neuron, is shown in Fig. 1(a), where $\{x_i\}_{i=1}^{N}$ are the input signals, $\{w_i\}_{i=1}^{N}$ the weights, b the bias and y the output signal. Perceptron applies a linear combination of its inputs, obtaining the signal $v = \sum_{i=1}^{N} x_i \cdot w_i + b$, and then applies a function f, which is called the transfer function, to this intermediate signal v to obtain the output signal. Sigmoid functions are commonly used as the transfer function to give the perceptron a nonlinear behavior.

One of the most commonly used ANN structures is the Multi-Layer Perceptron (MLP), because of its capability to solve non-linearly separable classification problems and to approximate continuous functions (Haykin, 1999). MLP topology comprises an input layer, one or more hidden layers, and an output layer, as shown in Fig. 1(b). The adjustment of its weights and biases is performed in a supervised way in the training stage, providing a set of pairs of input–output values, which allow the MLP to learn the relations between the input and the output variables. The training stage is usually done with the backpropagation (BP) method, in which the error of the MLP is calculated for each input–output pair and then this error is propagated from the output layer to the input layer, proportionally modifying the weights and biases of the MLP to the error committed by its neuron.

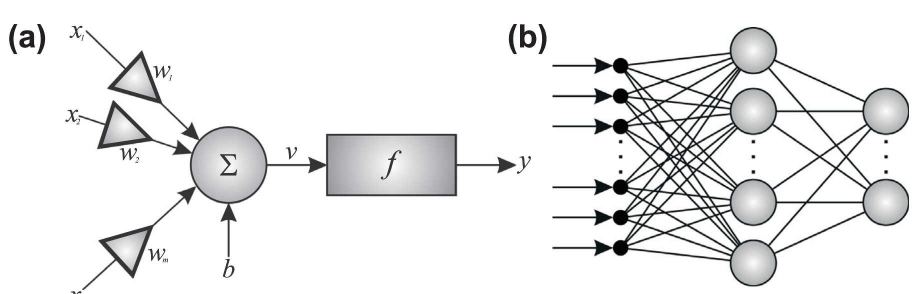

Fig. 1. (a) Example of a perceptron, where *x* are the input signals, *w* the weights, *b* the bias, *f* the transfer function and *y* the output signal. (b) Generic structure of a MLP with a single hidden layer.