Neural Networks 21 (2008) 1006–1019

Contents lists available at ScienceDirect

Neural Networks

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

dNSP: A biologically inspired dynamic Neural network approach to Signal Processing

José Manuel Cano-Izquierdo *, Julio Ibarrola, Miguel Pinzolas, Miguel Almonacid

Department of Systems Engineering and Automatic Control, School of Industrial Engineering, Technical University of Cartagena, Campus Muralla del Mar, 30202 Cartagena, Murcia, Spain

ARTICLE INFO

Article history:
Received 13 March 2006
Accepted 11 March 2008

Keywords:
Neural dynamic theory
Signal Processing
Correlation function
Power spectrum
Sigma-Pi units

ABSTRACT

The arriving order of data is one of the intrinsic properties of a signal. Therefore, techniques dealing with this temporal relation are required for identification and signal processing tasks. To perform a classification of the signal according with its temporal characteristics, it would be useful to find a feature vector in which the temporal attributes were embedded. The correlation and power density spectrum functions are suitable tools to manage this issue. These functions are usually defined with statistical formulation. On the other hand, in biology there can be found numerous processes in which signals are processed to give a feature vector; for example, the processing of sound by the auditory system.

In this work, the dNSP (dynamic Neural Signal Processing) architecture is proposed. This architecture allows representing a time-varying signal by a spatial (thus statical) vector. Inspired by the aforementioned biological processes, the dNSP performs frequency decomposition using an analogical parallel algorithm carried out by simple processing units. The architecture has been developed under the paradigm of a multilayer neural network, where the different layers are composed by units whose activation functions have been extracted from the theory of Neural Dynamic [Grossberg, S. (1988). Nonlinear neural networks principles, mechanisms and architectures. *Neural Networks*, *1*, 17–61]. A theoretical study of the behavior of the dynamic equations of the units and their relationship with some statistical functions allows establishing a parallelism between the unit activations and correlation and power density spectrum functions.

To test the capabilities of the proposed approach, several testbeds have been employed, i.e. the frequencial study of mathematical functions. As a possible application of the architecture, a highly interesting problem in the field of automatic control is addressed: the recognition of a controlled DC motor operating state.

1. Introduction

The temporal aspect must be taken into account to make a complete analysis of the information included in a signal. Biological (senses) or artificial sensors give a time sequence of data which is transmitted to the processing kernels (brain, computer). The order and time-delay of the data provide information as relevant as the magnitude value. So, in a biological or computational signal processing, a study of data timing must also be developed.

The auditory perception constitutes a clear example of the requirement of this time series processing. The auditory system's ability to discern sounds of different frequencies implies a temporal processing of the acoustic signal which involves aspects as correlation analysis and frequency decomposition of the signal energy. One approach to this problem based on a neural model which implements the autocorrelation function is developed in Licklider (1951). Although this model has been argued about (Kaernbach & Demany, 1998), the basic fundamentals are used on the new models developed in Patterson et al. (1992) and Patterson and Holdsworth (1996). In these papers, a transformation from the observed sound signal to a fixed pattern of neural activation is established. These models are described as a function of the signal frequency composition. For a first frequency analysis, an ARTSTREAM (Grossberg, Govindarajan, Wyse, & Cohen, 2004) architecture is proposed, where mathematical products must be carried out. Usually, the classic neural models work as a weighted sum of all excitatory and inhibitory synaptic inputs (point neuron hypothesis). Therefore, other neural models are needed to perform the multiplying interactions. This can be solved by the sigma-pi neurons (Rumelhart & McClelland, 1986), which offer a highly nonlinear processing and have been used for experimental purposes in Häusser and Mel (2003) and Mel (1994).

* Corresponding author.
E-mail addresses: JoseM.Cano@upct.es (J. Cano-Izquierdo), JulioJose.Ibarrola@upct.es (J. Ibarrola), Miguel.Pinzolas@upct.es (M. Pinzolas), Miguel.Almonacid@upct.es (M. Almonacid).

0893-6080/$ – see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.neunet.2008.03.015

The application fields of sigma-pi units are not only those with biological inspiration, but also other dynamic systems where the arriving order of data contains part of the information (e.g. to determine the dynamic system state).

Neuromorphic engineering was proposed for the design of Artificial Neural Networks whose architecture and design are based on those of biological nervous systems (Mead, 1990). Cochlear implants are a practical application of the advances achieved so far in the study of the auditory system. They work by transforming frequency patterns in sound into corresponding spatial patterns (Sarpeshkar, 2006). They constitute an example of how, by means of a biologically-inspired design, an engineering solution can be constructed, micmicking the biological process. Following this idea, we have studied the biological systems able to process the temporal information and to transform it into patterns that can be learned and recognized.

This work develops an architecture able to describe temporary signals by means of a spatial vector. To do this, a processing of the signal based on its frequency composition is proposed. Inspired by the human auditory system and the neural dynamic models, a neural-inspired approach to deal with on-line dynamic signal processing is studied. This processing is carried out through a multilayer neural architecture whose output is a neural activity pattern that captures the dynamic features of the input signal. The layers are composed of units with complex dynamics that mix additive and multiplicative behaviors. As a part of this work, a study of the relation between the information processing of the proposed architecture and some expressions in use in Digital Signal Processing is performed.

The paper is organized as follows: in Section 2, basic definitions of signal processing functions are stated. They allow a signal representation attending to several criteria; in this paper, a frequency domain description will be applied. Section 3 analyzes the dynamics of several neural models described by differential equations found in the literature. New models combining some of them are studied. In Section 4, an approximation to signal processing by means of dynamic neural models, named dNSP, is exposed. It is implemented into an architecture which allows the input signal processing in a dynamic and on-line way. The output of this structure is an activation vector representing the frequency composition of the input signal. The hidden layers of the network contain the processing stages. In Section 5 some experimental results obtained with the proposed architecture are shown. Sinusoidal signals are used to verify the system's ability to react to a unique frequency signal and to a linear combination of signals with different frequencies. An analysis of the processing stages and of the network behavior when confronted with frequency composition changes is performed. To test a possible real application, the structure is applied to determine the state of a simulated controlled DC motor. Finally, the main contributions of this paper are summarized in the last section.

2. Signal Processing

Usually, system analysis can only be developed from the numerical measurement of its variables. The results of these measurements come in the form of time series. It would be useful to develop a method to process the time series, offering a pattern-based description of the system state. Stochastic processes are those that can not be described by an explicit mathematical relationship. Dealing with these time series, the focus is placed on analysing the process by only using information about the signal values. In most cases it can be assumed that the studied process is ergodic. Therefore, it is possible to study its nature using a unique sampled function of it (Bendat & Piersol, 2000).

Most approaches use statistical methods for signal analysis (Bendat & Piersol, 2000; Childers, 1997; Stearns, 2002). These are usually based on an on-line analysis of the acquired signal. Some relevant functions to study the signal frequency composition are defined in the following sections.

2.1. Correlation function

The correlation function allows studying the temporal relations between the variable values, where periodicities, delays and other time-related characteristics arise.

Considering a stochastic process $\{z_k(t)\}$, the correlation function $R_{xx}(\tau)$ (Bendat & Piersol, 2000) can be defined as:

$$R_{zz}(\tau) = E[z_k(t)z_k(t+\tau)]. \tag{1}$$

If the stochastic process is weakly ergodic, the correlation function from a unique process realization (sampled function) can be formulated as:

$$R_{zz}(\tau) = \lim_{T\to\infty} \frac{1}{T}\int_0^T z(t)z(t+\tau)\mathrm{d}t. \tag{2}$$

2.2. Spectral Power Density Function

The Spectral Power Density Function offers a description of the energy frequency composition associated with the measured variable. It allows characterising the sampled function of the variable with a vectorial shape. The Spectral Power Density Function is a widely-used tool for system identification tasks. For a frequency f, it can de defined from the Fourier transform of the autocorrelation function as:

$$S_{zz}(f) = \int_{-\infty}^{\infty} R_{zz}(\tau)\mathrm{e}^{-j2\pi f\tau}\mathrm{d}\tau. \tag{3}$$

As the negative frequencies are not physically real, it is more appropriate to work with the one-sided autospectral density function $G_{zz}(f)$:

$$G_{zz}(f) = \begin{cases} 2S_{zz}(f) & \text{if } 0 < f < \infty \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

3. Neural dynamics

This term encloses a set of models obtained from differential equations, which follow to describe the internal processes taking place into neurons and their response to an external stimulus. These models allow to obtain the final result (neuron response) and to emulate the mechanism to generate the response. To obtain the time behavior of the neuron state, the well-known additive model (Nigrin, 1993; Kosko, 1992) is used, according to:

$$\frac{\mathrm{d}}{\mathrm{d}t}x_i = -Ax_i + \sum_{j=1}^{n} f(x_j)w_{ji} + I_i. \tag{5}$$

The x_i value corresponds with the activation state of the i-th unit. The constant $A > 0$ introduces a term named *passive decay* which, in the absence of external stimuli, drives the neuron activation to zero. It also can be considered as a *forgetting factor* because it causes past activity levels to gradually lose their influence on the present neural activity.

The second addend in Eq. (5) involves the interactions coming from other neurons. The channels connecting these neurons weigh their influence through the w_{ji} value. The external stimuli are reflected in I_i.