Expert Systems with Applications 37 (2010) 1522–1527

Contents lists available at ScienceDirect

Expert Systems with Applications

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

Wavelet network-based motion control of DC motors

Hasan A. Yousef [a,*], Mohamed E. Elkhatib [b], Omar A. Sebakhy [a]

[a] Department of Electrical Engineering, Alexandria University, Alexandria 21544, Egypt
[b] Department of Electrical and Computer Engineering, University of Waterloo, Waterloo, ON, Canada N2L 3G1

ARTICLE INFO

Keywords:
Wavelet networks
DC motors
Inverse control
Least square methods
Multi-resolution analysis

ABSTRACT

In this paper, a wavelet network is presented to design different controllers for DC motors based on the multi-resolution analysis and the wavelet transform. One of the basic advantages of wavelet network is that training is done using the recursive least square method which is suitable for online training usually required for adaptive control. The wavelet network is used to design adaptive speed controllers for a DC motor to achieve high performance speed control even if the motor model is unknown, the load characteristics are also unknown function of speed and the load torque changes online. Simulation and experimental results are presented to validate the effectiveness of the proposed controllers.

1. Introduction

Wavelet transform is a signal processing tool based on representing any signal as a weighted summation of wavelet basis functions. Wavelet basis functions are dilated and translated versions of certain function called the *mother wavelet*. For certain function to be a valid mother wavelet, it must satisfy certain admissibility conditions (Rao & Bopardikar, 1998). Since its introduction as a specialized field in the mid 1980, wavelet transform has found many applications in many different fields. Combining both the wavelet transform and the basic ideas of neural networks results in a new network called wavelet network (WN) (Zhang & Benveniste, 1992). The objective of such network was to use the wavelet transform to overcome the problems arising in feed-forward neural network especially the computationally heavy training and the application dependent structure. Actually, the network proposed in Zhang and Benveniste (1992) was essentially an ordinary radial basis function network with wavelet functions used in the hidden units. In Zhang, Walter, Miao, and Lee (1995), a wavelet network which depends on multi-resolution analysis and wavelet transform is proposed. The wavelet networks can be classified into orthogonal and non-orthogonal networks depending on the properties of the wavelet function used to construct the network. Orthogonal wavelet networks depend on generating orthonormal basis using the wavelet function. However, in order to generate an orthonormal basis, the wavelet function has to satisfy some restrictions (Zhang, 1997). The training of the orthonormal wavelet network is fast and the construction is easier. On the other hand, the non-orthogonal wavelet network uses the so-called wavelet frame (Daubechies, 1990). The orthogonal wavelet network has received more interest especially in control applications where the emphasis is on the fast training required in online training. Sureshbabu and Farrell (1999) have proposed a general method for the use of orthogonal wavelet networks in nonlinear system identification. In Xu and Tan (2007) an adaptive wavelet network-based control approach is proposed for highly nonlinear uncertain dynamical systems. The adaptive learning control approach with wavelet approximation is applied to two general classes of plants (Xu, Yan, & Wang, 2007). In Kulkarni and Purwar (2009), a wavelet-based adaptive backstepping controller for a class of nonlinear, nonregular systems is proposed to provide the desired performance in presence of actuator constraints. The integration of fuzzy set theory and wavelet neural network is considered in Abiyev (2005) to design control system for uncertain dynamic processes.

High performance electric drive systems are increasingly used in modern applications. Conventional controllers usually have poor performance due to their inability to capture the unknown load characteristics over wide operating region. The adaptive control could have better performance. The motor could be identified using a linear parametric model; for instance an ARMA model. However, the characteristics of the load are usually nonlinear. Hence, it is required to identify the motor based on nonlinear model. Neural networks have been used to control DC motors (Weerasooriya & El-Sharkawi, 1991) with good results. However, the main disadvantage of using neural networks is the back-propagation training algorithm which requires a heavy computation load and thus not suitable for online training. In Rubaai and Kotaru (2000) the dynamic back-propagation algorithm was used to improve the identification, however, the computational load is still heavy.

In this paper, an orthogonal wavelet network is used to achieve high performance motion control for a DC motor with unknown

* Corresponding author. Tel.: +20 112 3338717; fax: +20 03 3812017.
E-mail addresses: hyousef456@yahoo.com, hyousef56@hotmail.com (H.A. Yousef), m2elkhat@engmail.uwaterloo.ca (M.E. Elkhatib), omarsebakhy@hotmail.com (O.A. Sebakhy).

0957-4174/$ - see front matter © 2009 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2009.06.069

parameters and unknown load characteristics. Three different speed controllers are designed and implemented. Moreover, the paper investigates the use of forgetting factor in the least square algorithm for the online training of the wavelet network. The paper is organized as follows: Section 1, presents an introduction and brief literature survey. Wavelet transform and the capability of multi-resolution analysis to approximate nonlinear functions are outlined in Section 2. System identification and adaptive speed control of DC motors using wavelet network are given in Sections 3 and 4 respectively. To validate the effectiveness of the proposed controllers, both simulation and experimental results are shown in Sections 5 and 6 respectively. Conclusions are drawn in Section 7.

2. Wavelet transform and multi-resolution analysis

Essentially the multi-resolution analysis (MRA) represents the successive approximation of a function in a sequence of nested subspaces of linear vector space (Rao & Bopardikar, 1998). Wavelet transform appears naturally in the context of the MRA which is based on orthogonal wavelet function. This is done by defining two functions, namely scaling and wavelet functions. Scaling function $\{\varphi_{j,\ n}\}$ forms an orthonormal basis for a sequence of nested spaces such that:

$$\cdots \subset V_{-1} \subset V_0 \subset V_1 \subset \cdots \tag{1}$$

$$\bigcap_{j\in Z} V_j = \{0\} \tag{2}$$

$$\bigcup_{j\in Z} V_j = L^2(R) \tag{3}$$

where $L^2(R)$ is the space of square integrable functions and $j \in Z$ where Z is the set of integers, and $\varphi_{j,n} \in L^2\ (R)$, $\varphi_{j,n} = \varphi\ (2^{-j}t - n)$, n is the translation parameter and j is the resolution (dilation) parameter. In particular, the above representation means that a function $f(t)$ in the $L^2(R)$ space could be approximated with different accuracies depending on the resolution of the space at which the function is approximated. That is:

$$f_j(t) = \sum_{l=-\infty}^{\infty} \mu(j,l)\varphi(2^{-j}t - l) \tag{4}$$

where the function $f_j(t)$ denotes the approximation of the function $f(t)$ at resolution j and $\mu(j,l)$ are the coordinates of the scaling function at this sub-space. The details added at each approximation are located in other subspaces. These new subspaces W_i – which contains the details – are orthonormal and have the so-called wavelet orthonormal basis defined by $\psi_{j,n} = \psi(2^{-j}t - n)$ where $j,n \in Z$. The function ψ is the wavelet function which must have the orthonormal properties. In this paper, Meyer scaling and wavelet functions are used. It could also be proved that (Rao & Bopardikar, 1998)

$$V_{j-1} = V_j \oplus W_j \tag{5}$$

where $\oplus$ denotes the direct sum of the two spaces. Repeating this equation successively we reach the following equation:

$$L^2(R) = \cdots \oplus W_{-1} \oplus W_0 \oplus W_1 \oplus \cdots \tag{6}$$

That is, the orthonormal wavelet basis generates an orthogonal decomposition of the L^2 space. It is noted in (4) that, as the resolution parameter j decreases, the approximation gets finer. Thus for a given constant $\varepsilon > 0$ there exists an integer j_0 and a function

$$\hat{f}(t,j_0) = \sum_{l=-\infty}^{\infty} \mu(j_0,l)\varphi(2^{-j_0}t - l) \tag{7}$$

where $\|f(t) - \hat{f}(t,j_0)\| < \varepsilon$ and $\varphi(2^{-j_0}t - l)$ denotes the scaling function with certain resolution j_0 (Sureshbabu & Farrell, 1999) and the functional $\|.\|$ is the L^2 norm. Moreover if the function $f(t)$ is defined over a small region, then we can truncate the above summation and write (7) as

$$\hat{f}(t,j_0) = \sum_{l=L}^{U} \mu(j_0,l)\varphi(2^{-j_0}t - l) \tag{8}$$

for some $U,L \in Z$. The choice of the parameters U,L depends on the region over which the function is defined. In other words, noting that the distance between two successive functions in the above series equals 2^{j_0} and denoting the period over which we try to approximate the function f as $[X_1,X_2]$ then,

$$L \approx \frac{X_1}{2^{j_0}} \text{ and } U \approx \frac{X_2}{2^{j_0}} \tag{9}$$

Eq. (8) represents a wavelet network which provides an approximation of a given function in single resolution j_0. A structural representation of (8) is shown in Fig. 1. Therefore, the problem of approximating a single dimension function at certain predetermined resolution is reduced to the problem of finding the parameters $\mu(j_0,l)$ appearing in (8) by iterative method using the input and output data only. Note that the parameters $\mu(j_0,l)$ appear linearly in Eq. (8), thus the problem of finding the best parameters constants $\mu(j_0,l)$ – which corresponds to the training of the network – could be solved easily using recursive least square algorithms.

The extension of the wavelet network to the multi-dimensional case is straight forward. This is achieved by defining multi-dimensional scaling functions as follows

$$\Phi(x_1,x_2,\ldots,x_n) = \varphi(\|X\|) \tag{10}$$

where $\varphi(\cdot)$ is the scaling function in one dimension and $\|X\|$ denotes the Euclidean norm. Thus, after defining the multi-dimensional scaling or wavelet functions, the process of approximating a multi-dimensional function is typical to the case of single dimension function as discussed previously. However, the approximation of multi-dimensional functions is more difficult due to the curse of dimensionality problem (Zhang, 1997).

3. System identification using wavelet network

For certain dynamical system, let $y(t)$ and $u(t)$ denote the output and input of a given system respectively at time t. Collecting the values of input and output at discrete instances, one should have the following data

$$\phi(t) = [y(t-1),\ldots,y(t-a),u(t-1),\ldots,u(t-b)] \tag{11}$$

where a,b are positive integers. In the identification setup, one is looking for a model which would map the past data vector set $\phi(t)$ to the next output of the form

$$\hat{y} = f(\phi(t)) \tag{12}$$

The non-linear mapping $f(t)$ is a function from R^d to R, where $d = a + b$, represents the number of elements of the $\phi(t)$ vector.

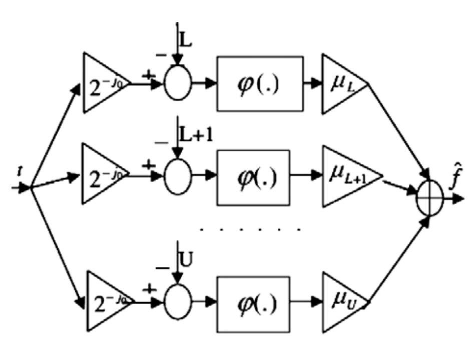

Fig. 1. Structure of wavelet network.