DC MOTOR USING MULTI ACTIVATION WAVELET NETWORK (MAWN) AS AN ALTERNATIVE TO A PD CONTROLLER IN THE ROBOTICS CONTROL SYSTEM

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Abstract: In this paper, a robust MAWN is proposed. An application that constructs Wavelet Network as an alternative to a PD controller in the robotics control system with DC motor is fully investigated. Experimental results not only show that the target performance can be achieved by the proposed Wavelet Network, but also it outperforms the conventional PD controller. An literature survey was conducted to shed some light into this research field shows a sparsity of work addressing this concept, and this what stimulated the idea of this work.

1 INTRODUCTION

The design of intelligent, autonomous machines to perform tasks that are dull, repetitive, hazardous, or that require skill, strength, or dexterity beyond the capability of humans is the ultimate goal of robotics research. Examples of such tasks include manufacturing, excavation, construction, undersea, space, and planetary exploration, toxic waste cleanup, and robotic assisted surgery. Robotics research is highly interdisciplinary requiring the integration of control theory with mechanics, electronics, artificial intelligence and sensor technology (Xiao, 2001).

The ever increasing technological demands of today, call for very complex systems, which in turn require highly sophisticated controllers to ensure that high performance can be achieved and maintained under adverse conditions. There are needs in the control of these complex systems, which cannot be met by conventional approaches to control. For instance, there is a significant need to achieve higher degrees of autonomous operation for robotic systems, spacecraft, manufacturing systems, automotive systems, underwater and land vehicles, and others. To achieve such highly autonomous behavior for complex systems, one can enhance today's control methods using intelligent control systems and techniques (Feitosa et al., 2000).

Intelligent control methodologies are being applied to robotics and automation, communications, manufacturing, traffic control. To mention few application areas: neural networks, fuzzy control, genetic algorithms, planning systems, expert systems, and hybrid systems are all related areas. The term "intelligent control" has come to mean, particularly to those outside the control area, some form of control using fuzzy and/or neural network methodologies (Sgarbiy et al., 1997).

Neural networks have been applied very successfully in the identification and control of dynamic systems. The universal approximation capabilities of the multilayer perceptron (the backpropogation algorithm) make it a popular choice for modeling nonlinear systems and for implementing general-purpose nonlinear controllers (Calise and Rysdyk, 1996). The combination of soft computing and wavelet theory has lead to a number of new techniques: MAWN, wavenets, and fuzzy-wavelet (Yao, 1999).

It is difficult to model the environment to provide the controller with the relevant data and program actions for all possible situations. Hence, controllers with abilities to learn and to adapt are needed to solve this problem. Soft computing provides an attractive venue to deal with these situations. Soft computing methods are based on biological systems and can provide the following features: generalization, adaptation and learning. As more is realized about the use and properties of soft computing methods, the development of controller is

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shifting towards using soft computing (Gu and Hu, 2002).

In this paper a robust Multi Activation Function Wavelet Network Wavelet (MAFWN) is used as a controller analogous to a PD controller in the control of a robotic arm and a payload system with a DC motor that is required for conducting a pick and place operation to achieve the required performance.

2 THE MULTI MAFWN

An application of multi wavelet filters to neural networks is investigated in this paper. This new technique called MAFWN. It is an interesting alternative to wavelet networks that absorbs the advantage of high resolution of wavelets and the advantages of learning feed-forward neural networks.

The MAFWN is very similar to wavelet Network (WN) but, has some important differences, whereas wavelets have an associated scaling function $\phi(t)$ and wavelet function $\psi(t)$. MAWN has multi scaling $\phi1(t)$, $\phi2(t)$ … $\phi n(t)$, and multi wavelet functions $\psi1(t)$, $\psi2(t)$ … $\psi n(t)$. However, Two AFWN (TAFWN) has two scaling functions $\phi1(t)$, $\phi2(t)$ and two wavelet functions $\psi1(t)$, $\psi2(t)$. Subsequently, there are two scaling filters and two wavelet filters for the case of TAFWN, and this will be considered as a case study for this research.

3 WAVELET NETWORK ALGORITHM

The two activation function wavelet network (TAFWN) architecture approximates any desired signal $y(t)$ by generalizing a linear combination of two set of daughter wavelets $h_{1,a,b}(t)$ and $h_{2,a,b}(t)$, where the daughter wavelets $h_{1,a,b}(t)$ and $h_{2,a,b}(t)$ are generated by dilation, a, and translation, b, from two mother wavelets $h_1(\tau)$ and $h_2(\tau)$, where $\tau = \frac{t-b}{a}$.

$$h_{1,a,b}(t) = h_1\left(\frac{t-b}{a}\right) \qquad (1)$$

$$h_{2,a,b}(t) = h_2\left(\frac{t-b}{a}\right) \qquad (2)$$

Where:

a : Dilation factor, with $a > 0$.

b : Translation factor.

t : Signal time interval

The network architecture is shown in figure (1).

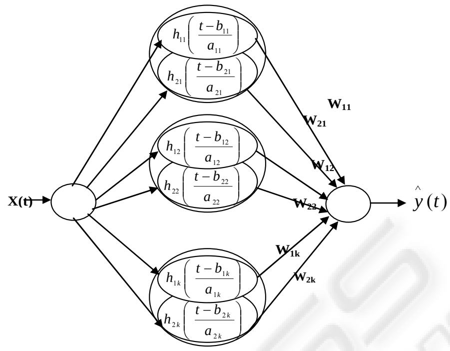


Figure 1: Structure of TAFWN.

A TAFWN is a 3-layers feed forward neural network. First the TAFWN parameters, dilation a's, translation b's, and weight w's should be initialized, and the desired sets of data, the input signal x(t), the desired output (target) y(t), the number of scaling functions p (p=2 in this work) and the number of wavelons k are given. The approximated signal of the network $\hat{y}(t)$ can be represented by equation:

TAFWN is trained by the gradient descent algorithms like least mean squares (LMS) to minimize the mean-squared error. During learning, the parameters of the network are optimized.

$$\hat{y}(t) = x(t) \times \sum_{j=1}^{p} \sum_{i=1}^{k} w_{j,i} h_{a_{j,i}, b_{j,i}}(t) \qquad (3)$$

Where: x(t) is the input signal.

$w_{j,i}$ is the weight coefficients between hidden and output layers.

j=1,2,…, p. p=2: a number of scaling functions.

i=1,2,…, k. k is a number of wavelons.

$h_{a_{j,i}, b_{j,i}}$ is a two set of daughter wavelets generated from two mother wavelets $h_1(t)$, $h_2(t)$ as in equations (1) and (2) respectively.

The TAFWN parameters $w_{j,i}$, $a_{j,i}$, and $b_{j,i}$ can be optimized in the LMS algorithm by minimizing a cost function or the energy function, E, over all function interval. The energy function is defined by equations (4) and (5), $y(t)$ is the desired output (target) and $\hat{y}(t)$ is the actual output signal of TAFWN.

$$E = \frac{1}{2} \sum_{t=1}^{T} e^2(t) \qquad (4)$$

$$E = \frac{1}{2} \sum_{t=1}^{T} (y(t) - \hat{y}(t))^2 \qquad (5)$$

Where, T is the total interval of function, $y(t)$ is the desired output (target) and $\hat{y}(t)$ is the actual output signal of WN.

To minimize E then the method of steepest descent is used, which requires the gradients

$$\frac{\partial E}{\partial w_{j,i}},\ \frac{\partial E}{\partial a_{j,i}},\ \text{and}\ \frac{\partial E}{\partial b_{j,i}}$$

for updating the incremental changes to each particular parameter $w_{j,i}$, $a_{j,i}$, and $b_{j,i}$, respectively. The gradients of E are given as follows:

$$\frac{\partial E}{\partial w_{j,i}} = -\sum_{t=1}^{T} e(t) h(\tau) x(t) \qquad (6)$$

$$\frac{\partial E}{\partial b_{j,i}} = -\sum_{t=1}^{T} e(t)\, x(t) w_{j,i} \frac{\partial h(\tau)}{\partial b_{j,i}} \qquad (7)$$

$$\frac{\partial E}{\partial a_{j,i}} = -\sum_{t=1}^{T} e(t) x(t) w_{j,i} \tau \frac{\partial h(\tau)}{\partial b_{j,i}} = \tau \frac{\partial E}{\partial b_{j,i}} \qquad (8)$$

$$\tau = \frac{t - b_{j,i}}{a_{j,i}} \qquad (9)$$

Derivatives of the various wavelet filters with respect to its translation $\frac{\partial h(\tau)}{\partial b_{j,i}}$, are given in (Oussar et al., 1996).

The incremental changes of each coefficient are simply the negative of their gradients.

$$\Delta w = -\frac{\partial E}{\partial w} \qquad (10)$$

$$\Delta b = -\frac{\partial E}{\partial b} \qquad (11)$$

$$\Delta a = -\frac{\partial E}{\partial a} \qquad (12)$$

Thus, each coefficient w, b and a of the network is updated in accordance with the rule given:

$$w(t+1) = w(t) + \mu_w \Delta w \qquad (13)$$

$$b(t+1) = b(t) + \mu_b \Delta b \qquad (14)$$

$$a(t+1) = a(t) + \mu_a \Delta a \qquad (15)$$

Where, μ is the fixed learning rate parameter (Oussar et al., 1996).

2. Set: the number of trainings, iter =0, the incremental changes of each coefficient, $(\Delta w, \Delta a, \Delta b) = 0$, and the initial square error, $E_{iter} = 0.5$

3. Calculate the approximated signal of the network $\hat{y}(t)$ using equation (3).

4. Calculate the gradients of each coefficient using equations (6), (7), (8) and calculate the coefficients incremental changes which are the negative of their gradients.

5. Choose a constant μ, such that $0.01 \le \mu \le 1$ and calculate the new coefficients w_{iter+1}, b_{iter+1}, and a_{iter+1} of the network in accordance with the rules given in equations (13), (14) and (15).

6. Calculate the square error E_{iter+1} using equation (5).

If E_{iter+1} is small enough, then the training is good and the run of the algorithm is stopped.

Otherwise, set iter = iter + 1 and go to (3) again.

At every iteration, the network parameters are modified using the gradient descent algorithm that will result in minimizing the parameter E.

The training algorithm of the proposed TAFWN consists of the following six steps:

1. Initialize TAFWN parameters, dilation a's, translation b's, and weight w's, p=2, two mother wavelets filters

$$\left[h_1\left(\frac{t - b_i}{a_i}\right), h_2\left(\frac{t - b_i}{a_i}\right) \right],$$

the desired sets of data, the input signal x(t), the desired output (target) y(t), and the number of wavelons k are given.

4 MAWN FOR CONTROLLING A ROBOTIC ARM

An example-control of a robotic arm and a payload system with a DC motor- is given in this paper to illustrate the use of the proposed MAWN as a PD controller and its performance.

4.1 Robotic Arm Properties

The Robotic arm is depicted in Figure (2). It is composed of a rigid beam which is connected to a motor shaft to create a robotic system conducting a pick and place operation. A solid disk is attached to the end of the beam through a magnetic device (e.g., a solenoid). If the magnet is on, the disk will stick to the beam, and when the magnet is turned off, the disk is released. The objective of the robotic arm is to drop the disk into a hole as fast as possible. The hole is 1 inch (25.4 mm) below the disk as shown in figure (3) (Oussar and Dreyfus, 1996). The robot arm is required to move in one direction only, from the initial position. Also, the hole location may be anywhere within an angular range of 20° to 180° from the initial position. It is in the angular position of 150° for the sake of this example. The idea of this control system is to move a metal object attached to a robot arm by an electromagnet from position 0° to the angular position 150° with a specified overshoot and minimum overall time.

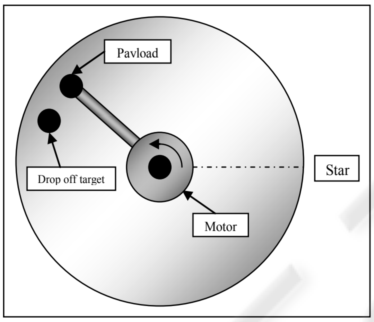


Figure 2: Control of a robotic arm and payload.

A system simulink model of the system is shown in figure (4) and the simulated DC Motor is portrayed in Figure (5). This figure represents a simple PD controller model with proportional gain of 15 and derivative gain of 2.1. In the Electromagnet Control block, drop-off payload location and the time delay (in seconds) to turn the magnet off after reaching the target parameters is adjusted to 150° and 0.8 sec, respectively. So, the "Drop position angle" is the angle where the electromagnets turn off, thereby, dropping the payload." However, start to wait for drop position at time" refers to the time where the position triggers starts to wait for the position specified by "Drop position angle." An overall time response for the system with PD controller is shown in Figure (6).

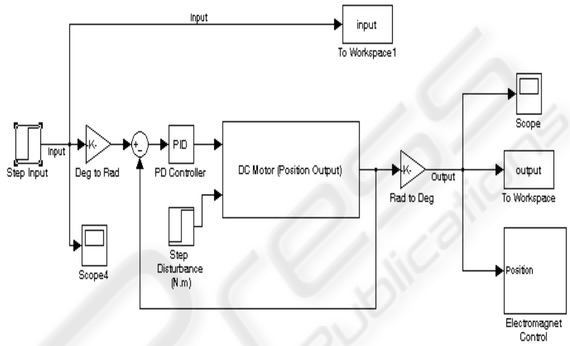


Figure 3: The robotic arm system simulink model.

4.2 TAFWN as PD Controller

Now, the PD controller shown in figure (5) is replaced with the proposed TAFWN structure. TAFWN of 40 [Morlet, Rasp2] filters and fixed learning rate of 0.1 is trained first with the desired input-output data set shown in figure (6- a and b). Figure (7) however, shows the training performance of the network.

After training to MSE value less than e-005, the trained TAFWN is employed to control the robotic arm system, the system simulink model with TAFWN controller is shown in figure (8). It is clear from the above results that the TAFWN is proved to be a PD controller, and its position response per time

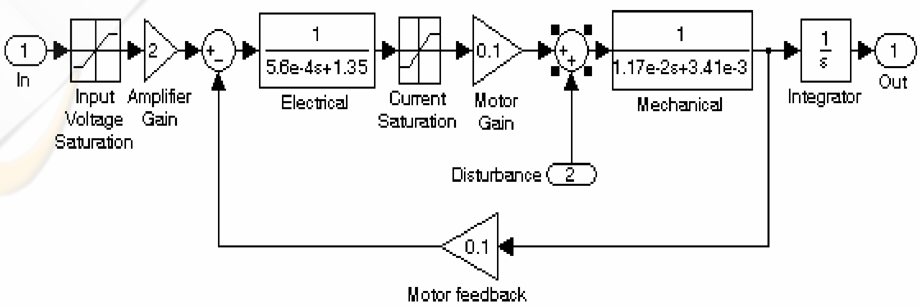


Figure 4: The simulated DC Motor.

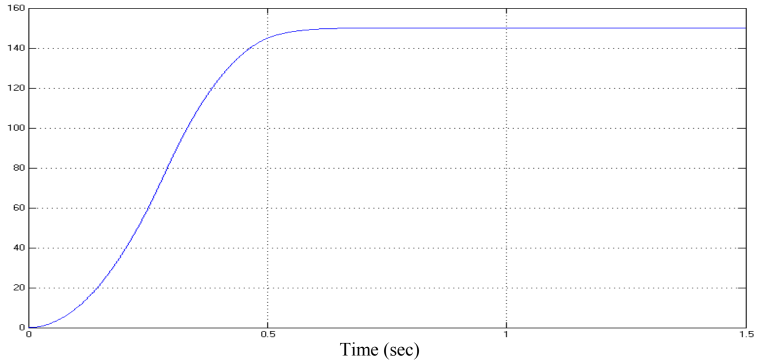
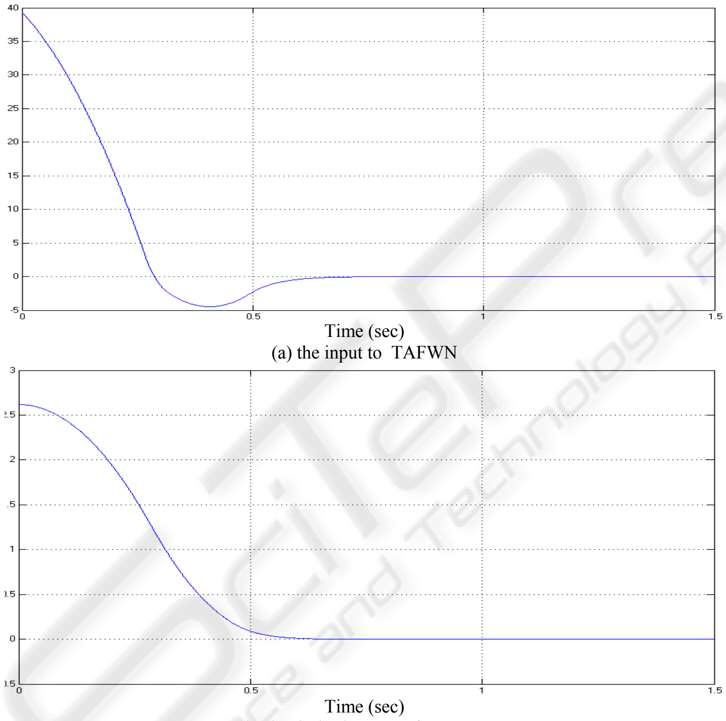


Figure 5: Position response (degree) per time (sec) with PD controller.



(a) the input to TAFWN

(b) the desired output of TAFWN

Figure 6: The desired input-output data set.

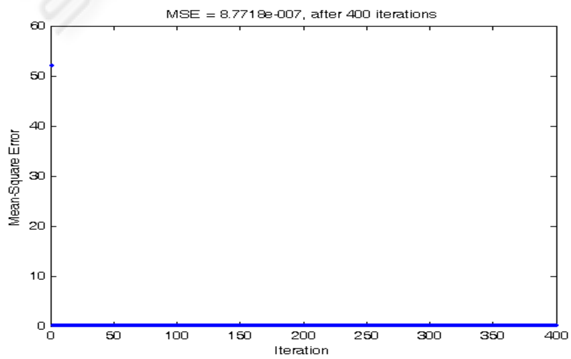


Figure 7: Mean-Square Error per learning iteration.

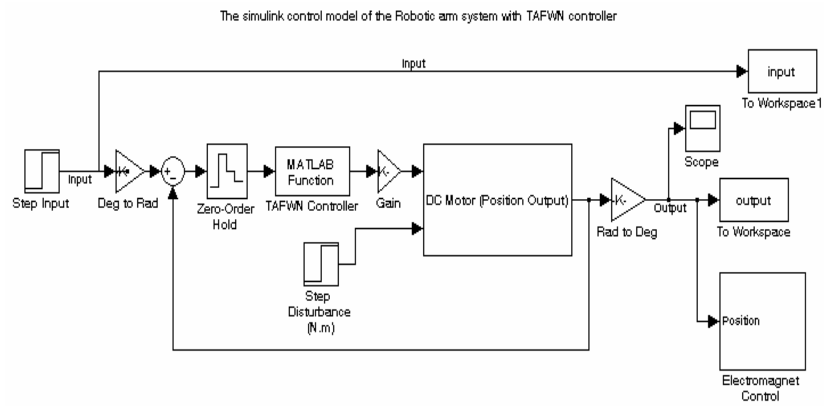


Figure 8: Robotic arm system simulink model with TAFWN controller.

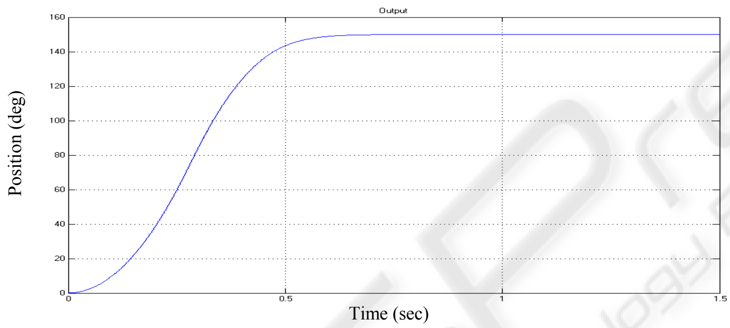


Figure 9: Position response (degree) per time (sec) with TAFWN controller.

is illustrated in figure (9). As it is shown at the specified time (0.8 sec), the angular position angle 150° and so the metal object attached to the robot arm is gotten to be in the "Drop position angle" (150°) at time (0.8 sec). Hence there is no significant difference between the position responses for both PD and TAFWN controllers.

5 CONCLUSIONS

In this paper, an advanced wavelet network, called Two Activation Function Wavelet Network is presented as an interesting alternative to wavelet networks. This technique absorbs the advantage of high resolution of wavelets and the advantages of learning and feed-forward of neural networks. The algorithm of function identification is designed and implemented using Matlab 6.5 tool.

The Two Activation Function Wavelet Network (TAFWN) structure is implemented and several examples are carried out to verify this implementation. It can be concluded that this structure achieves an approximation assuming reasonable choice of the number of wavelons and mother wavelet basis functions. The Two Activation Function Wavelet Network is proved to be a controller analogous to PD controller. After the off-line training of the TAFWN controller, it shows the ability to get the specified position response exactly at the specified time when it's embedded in the control system. No significant difference between the position responses for both PD and the proposed TAFWN controllers, indicating further the validity of the idea of this research.

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