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Investigate Model Reference Controller for Sun-Seeker Tracking System Based on Neural Network

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Abstract

Neural network are appropriate for the modeling and control of multifaceted physical systems because of their capability to manage multifaceted input-output charting without thorough mathematical model of the systems. Demonstrating a non-linear active charting, Model Reference Controller Neural Network (MRCNN) is appropriate to manage active non-linear complications. In this paper, a MRCNN have employed in a sun-seeker tracking system. First, the MRCNN will be used as identifier to recognize the opposite model of the system to be controlled through supervised, and then the MRCNN is used such as a feed forward controller, to create control voltage to power the sun-seeker to track pre-selected routes of location.

التحقق من النموذج المرجعي المسيطر لمنظومة تعقب الشمس مبنياً على اساس الشبكات العصبيه

الخلاصه

الشبكه العصبية هي مناسبة للنمذجة والتحكم في الانظمه المادية متعدد الأوجه وذلك بسبب القدرة على إدارة المدخلات والمخرجات المتعددة الأوجه دون رسم نموذج رياضي شامل للانظمه .لرسم الانشطه الغير الخطية ، النموذج المرجعي للتحكم الشبكات العصبية (MRCNN)هو الاداه المناسبة لإدارة مضاعفات الانشطه الغير خطية. في هذا البحث MRCNN وظف في نظام تتبع الشمس .أولا، سيتم استخدام MRCNN ليتعرف على النموذج المعاكس للنظام ليتم السيطره عليه من خلال المراقبه المباشره، ومن ثم يتم استخدام MRCNN كمسيطر تغذيه اماميه، لإنشاء جهد السيطرة على قدره متعقب الشمس إلى المسارات المحدده.

1. Introductions

For there are variation of parameters, such as load torque, inertia and mechanical friction, low speed sun seeker tracking system is a typical nonlinear system. It is difficult to get accurate system’s mathematical model due to unstructured uncertainties for the unmodelled dynamics like nonlinear friction. It is impossible to get high accuracy response by means of traditional control method based on system’s mathematical model, such as PID. The neural network area consists of a very promising direction to solve the problem relating to unknown nonlinear dynamic system. Hence, neural networks appear as a powerful tool for learning highly nonlinear dynamic systems. Their massive parallelism, very fast adaptation, and inherent approximation capability, have attracted extensively researchers in the field of system identification and control [1-4]. Many existing neural control laws for mechanical systems suffer from important shortcomings.

Such as intensive computation effort and high storage capacity [5-6], so it is impossible to apply neural control algorithm to system such as sampling time is very short. This is a main cause for neural network controllers have not been widely used so far. This paper presented a neural-network based control scheme for a low sun seeker tracking system. To reduce calculating time, a MRCNN is used to estimate the inverse model of plant to be controlled; parameters of neural network are updated on-line according to the dynamic back propagation algorithm (DBP). To ensure system's initial robustness and close-loop stability, a fixed gain feedback controller is used.

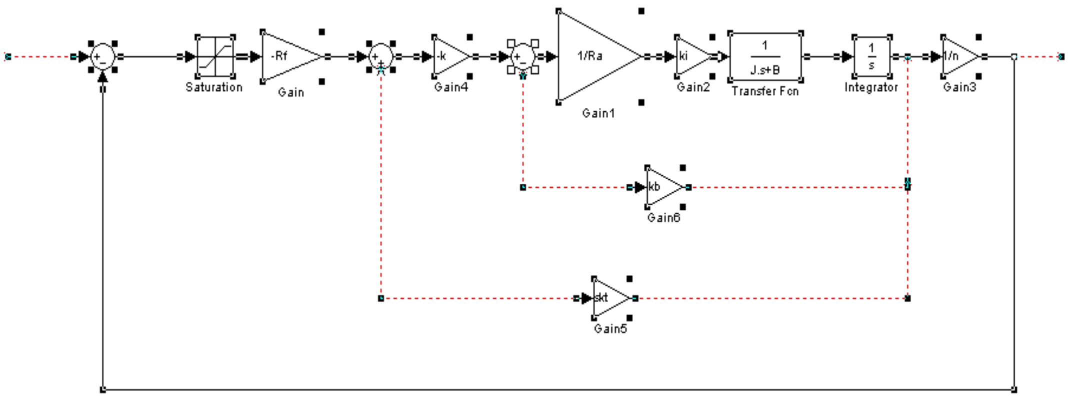

Fig. 1 the block diagram of the sun-seeker tracking system [5]

2. System Model

2.1 Error Discriminator

When the vehicle is aligned with the sun,

$$oa = \frac{W}{2} + L \tan \alpha(t)$$
$$ob = \frac{W}{2} - L \tan \alpha(t) \quad \text{..........................} \ \textbf{(1)}$$

Where *oa*- the width of the sun ray that shines on cell A, ob- is the same on cell B and α (t)- is the error angle between solar axis and vehicle axis.

Since the current $i_a(t)$ is proportional to oa, and $i_b(t)$ is proportional to ob, we have

$$i_a(t) = I + \frac{2LI}{W}\tan\alpha(t)$$
$$i_b(t) = I - \frac{2LI}{W}\tan\alpha(t) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{(2)}$$

2.2 Operational Amplifier

The relation between the output of the operational amplifier and the current $i_a(t)$ and $i_b(t)$ is

$$e_o(t) = -R_f[i_a(t) - i_b(t)] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{(3)}$$

2.3 Servo Amplifier

The gain of the servo amplifier –K. the output of the servo amplifier is expressed as

$$e_a(t) = -K[e_o(t) + e_t(t)] = -Ke_s(t) \quad \ldots\ldots\ldots \textbf{(4)}$$

The output voltage of the tachometer e_t is related to the angular velocity of the motor through the tachometer constant K_t.

2.4 Tachometers

The output voltage of tachometer e_t is related to the angular velocity of the motor through the tachometer constant K_t.

$$e_t(t) = K_t\omega_m(t) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{(5)}$$

The angular position of the output gear is related to the motor position through the gear ratio 1/n.

$$\theta_o = \frac{1}{n}\theta_m \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{(6)}$$

2.5 DC motor

The dc motor has been modeled as

$$\begin{aligned}
e_a(t) &= R_a i_a(t) + e_b(t) \\
e_b(t) &= K_b\omega_m(t) \\
T_m(t) &= K_i i_a(t) \qquad \ldots\ldots\ldots\ldots\ldots\ldots \textbf{(7)} \\
T_m(t) &= J\frac{d\omega_m(t)}{dt} + \beta\omega_m(t)
\end{aligned}$$

where J and β are the inertia and viscous-friction coefficient seen at the motor shaft.

3. MRCNN controller

As shown in figure 2, the basic control scheme consists of a feed forward MRCNN controller and a fixed gain feedback controller. The MRCNN is first used as an identifier to emulate the inverse dynamics of the dc servo system, and this network is called as MRNNI, it is trained off-line and on-line. When MRNNI is trained, it is used as a feed forward controller called as DRNNC. The system control voltage U is composed of the feed forward controller output voltage Un and the feedback controller U_P. If the MRNNI has learned the inverse model of the system, the MRCNN alone provides all the necessary voltage for the system to track the desired trajectory and output of the feedback controller will tend to zero.

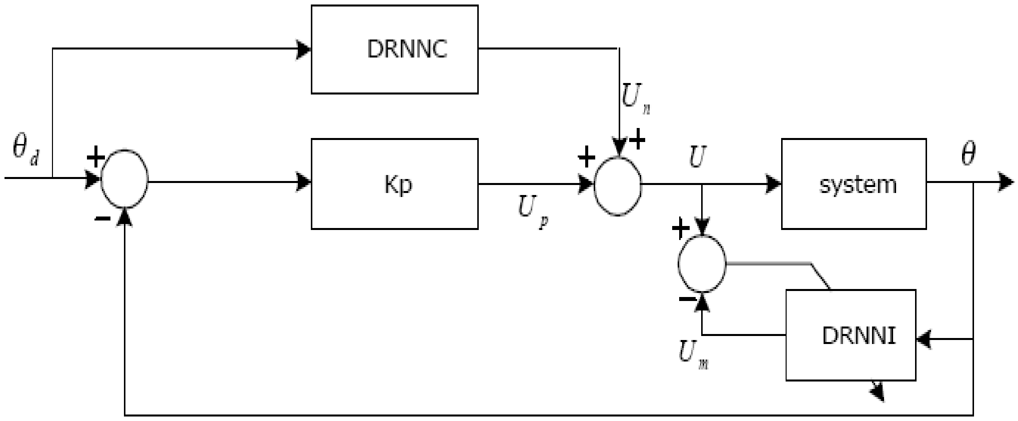

Fig.2. DRNNC control for the sun-seeker tracking system

4. Learning of MRNNI

In this paper we used a three-layered neural networks with 13^{th} hidden layer can approximate any nonlinear function to any desired accuracy [1]. MRCNN networks superior to multiplayer feed forward static neural networks to deal with dynamic problems [8]. The structure of three layers MRCNN is shown in figure 3. It Consists of an input layer, an output layer and one recursive hidden layer. Where $I(k)$, w, s_j and $O(k)$ are the ith input to the MRCNN, the connecting weight between jth recursive neuron and the output of networks, connecting weight between ith input to network and the jth hidden neuron, the output of jth hidden neuron and the output of the MRCNN. The mathematical model of MRCNN is shown below:

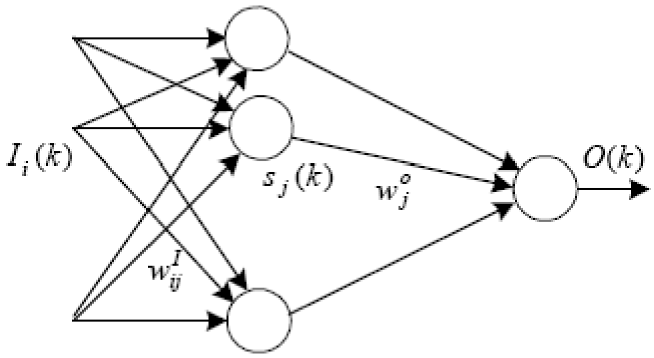

Fig. 3. DRNNC three layer Neural Network

Where $x_j(k)$ is the output of jth recursive neuron, $D_j w$ is the recursive weight of jth hidden neuron, $f(\,)$ is sigmoid function. When DRNN is used as MRNNI, output of networks $O(k)= U_m(k)$. When MRNN is used as MRCNN, $O(k)= U_n(k)$.

$$s_j(k) = w_j^D x_j(k-1) + \sum_i w_{ij}^I I_i(k) \quad \text{..........} \ \mathbf{(8)}$$

The cost function to train MRNNI is defined as:

$$J = \frac{1}{2}(U - U_m)^2 = \frac{1}{2} e_m^2 \quad \text{.....................} \ \mathbf{(9)}$$

The objective of the learning process is to adjust the network parameters (weights) so as to minimize the cost function J over the entire train set. The back propagation algorithm is given below [8].

$$\begin{aligned} \Delta w(k) &= -\eta \frac{\partial J}{\partial w} \\ &= \eta e_m(k) \frac{\partial U_m}{\partial w} \\ &= \eta e_m \frac{\partial O(k)}{\partial w} \end{aligned} \quad \text{..........} \mathbf{(10)}$$

Where $w(k)$ is any weight of MRNNI, h is the learning rate of this weight. Define the output gradients with respect to output, recurrent, and input weight, respectively as below

$$\frac{\partial O(k)}{\partial w_j^o} = x_j(k) \quad \text{...................} \ \mathbf{(11)}$$

$$\frac{\partial O(k)}{\partial w_j^D} = w_j^o P_j(k) \quad \text{...............} \ \mathbf{(12)}$$

$$\frac{\partial O(k)}{\partial w_{ij}^{I}} = w_j^{o} Qu(k) \quad \text{.............. (13)}$$

$$P_g(k) = \frac{\partial x_j(k)}{\partial w_j^{D}} = f'(s_j)x_j(k-1) \quad \text{......... (14)}$$

$$Q_{ij}(k) = \frac{\partial x_j(k)}{\partial w_{ij}^{I}} = f'(s_j)I_i(k) \quad \text{........... (15)}$$

From above equations, learning algorithm of weight w_{ij} , D_j w and O_{jw} can be got. The learning rate can be chosen properly [8].

5. Identification and Control

For the dc system position tracking, the MRNNI is used to identify the unknown system dynamics (dc motor, amplifier, and the mechanical friction) that mapping the control voltage U to the motor position. Because the MRNNI is used to identify the inverse model of the DC servo system, the inputs to feed forward controller MRCNN is a desired position trajectory and the output of DRNNC is control voltage for system to tack the desired trajectory. From function (7), the relation between control voltage and the motor position can be written as a difference equation below

$$U(k) = d_1\theta(k-3) + d_2\theta(k-2) + d_3\theta(k-1) \quad \text{........ (16)}$$

If the aim is to track the desired speed, similarly can get the difference relationship between control voltage and the speed of dc motor as below

$$U(k) = e_1 w(k) + e_2 w(k-1) + e_3 w(k-2) \quad \text{............ (17)}$$

Where d_1 , d_2 , d_3 and e_1 , e_2 , e_3 are system parameters . Function (16) and (17) can be written in this form

$$U(k) = h'(\theta'(k-1)', \theta'(k-2), \theta(k-3)) \quad \text{............. (18)}$$

$$U(k) = g(w(k), w(k-1), w(k-2)) \quad \text{.................... (19)}$$

The MRNNI is trained to emulate the unknown function $h(\theta')$ or $g(w)$. For position tracking, the inputs to the MRNNI are q (k -1),q (k -2) and q (k -3) .For speed tracking, the inputs to the MRNNI are $w(k)$,$w(k$ -1) and $w(k$ -2) . When the DRNNI is trained, it is used as a feed forward controller MRCNN. For position tracking, the inputs to MRCNN are desired trajectory dq (k -1),dq (k -2) and dq (k -3) . Control voltage U, is the sum of the MRCNN, U_n, and the feedback controller, U_p.

$$U = U_n + U_p \quad \text{...} \quad \textbf{(20)}$$

6- Experimental Results

The model reference model for sun seeker tracking is shown in Figure 4. The testing data fo NNMRC is illustrated in Figure 5, validation data of NNMRC as shown in Figure6. Figure 7 show the training data for NNMRC.

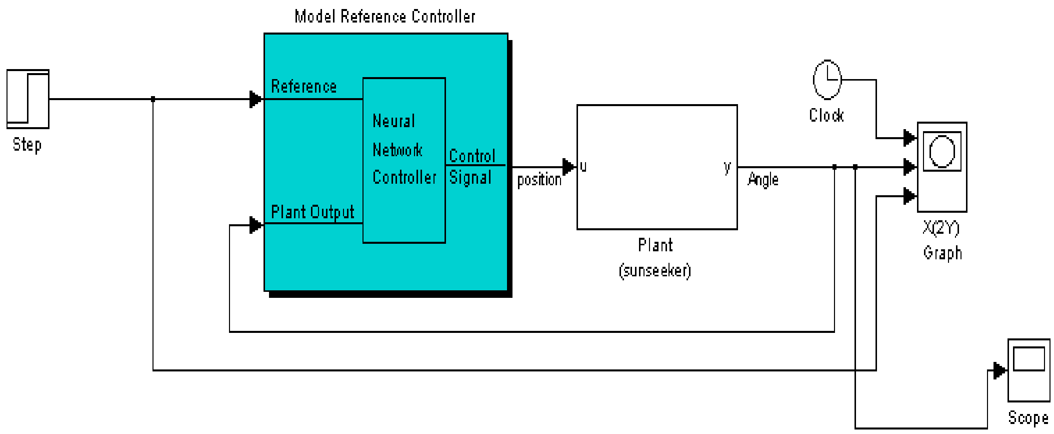

Fig.4. the model reference neural network model for sun seeker system

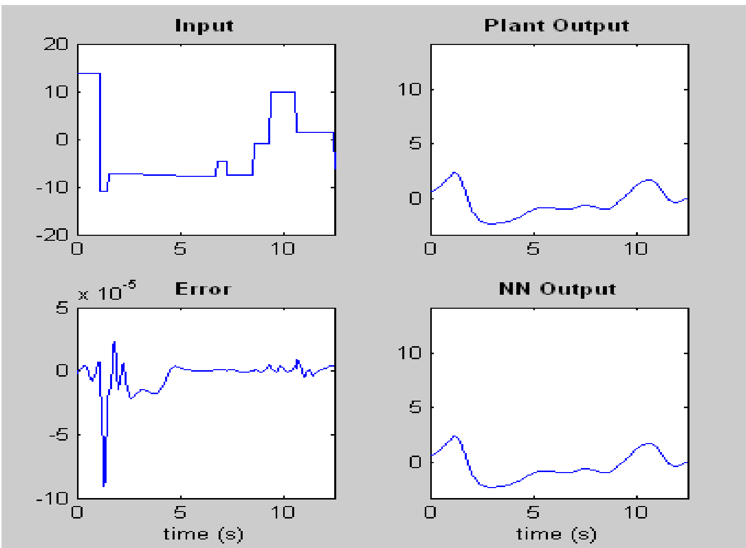

Fig.5. testing data for NNMRC

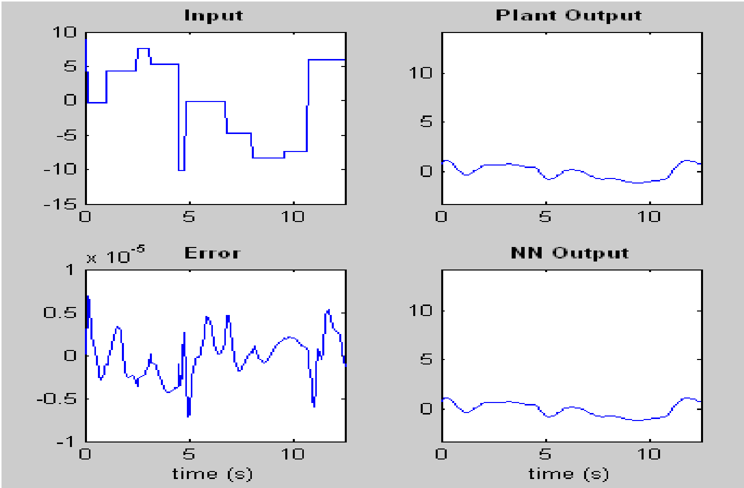

Fig.6. validation data of NNMRC

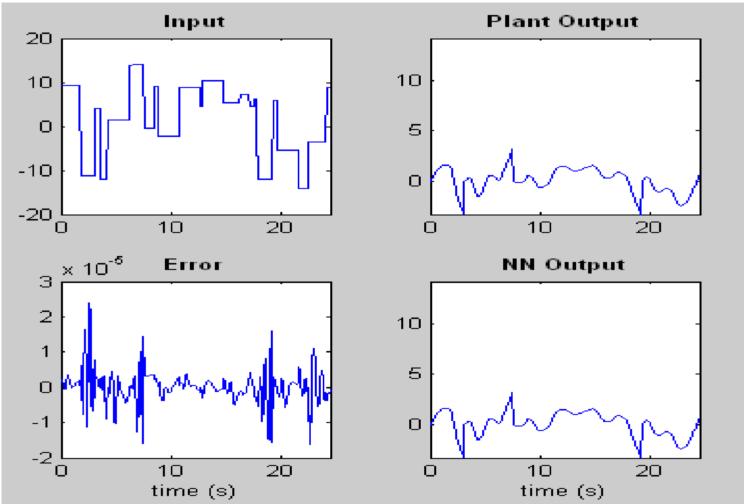

Fig.7. training data for NNMRC

7. Conclusions

This paper presents a real-time control of a low speed sun seeker tracking system. It is shown that, MRCNN is efficient for system identification and control, and this system. Through this proposed method, can tack any selected trajectories with high performance under strong mechanical friction and other nonlinear factors.

Also, it can be seen that with the higher system frequency of programming environment, the better control results will be got with this method proposed in this paper.

8. References

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