Application of Neural Network Controller in the Seam Tracking of Arc-Welding Robot *

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Abstract: A neural network(NN) controller which improves the accuracy of seam tracking of an arc-welding robot is presented in this paper. The improvement of tracking accuracy can be achieved by applying the NN controller for compensating for model uncertainties of robot manipulator. Unlike the traditional NN compensation of model uncertainties which was carried through by modifying the joint/force of the robot, the proposed NN compensation is used to modify the reference Cartesian seam trajectory, which is easily applied in practice. The required internal signal level of proposed NN for the seam modification is much smaller. Simulations and experiments have been performed on an actual arc-welding robot manipulator to test the effectiveness of NN control scheme. It has been found that NN can generate better tracking performance than the traditional computed torque(CT) control method which is based on the manipulator dynamics only. One goal of this paper is to stimulate further discussion of application of NN in the arc-welding robot control.

Key words: arc-welding robot; seam tracking; neural network

弧焊机器人焊缝跟踪神经网络控制器

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摘要：介绍一种能提高弧焊机器人焊缝跟踪精度的神经网络控制器.通过神经网络的补偿作用,弥补了由于无法知道机器人精确模型所造成的控制上的误差.不同于机器人控制中传统的神经网络控制器,本文提出并应用了基于笛卡尔空间轨迹控制的机器人焊缝跟踪神经网络,大大简化了控制算法.计算机模拟及实验结果表明,该控制器非常适用于机器人的实际焊接,对于现有的机器人,无须改变其控制器内部结构,即可应用该技术.与常用的机器人关节力矩控制法相比,有效地提高了跟踪精度并具有较强的鲁棒性.

关键词：弧焊机器人；焊缝跟踪；神经网络

1 Introduction

Robot arc-welding represents a widespread technique in the field of metal manufacture. About 40% of all industrial robots are being used for welding tasks[1]. However, the increasing trend towards mechanization can not be easily extended towards arc-welding, because the welding process is subject to a great number of influencing factors such as heat radiation, arc flares, spatters, fumes, not to say the highly nonlinear and coupled characteristics of arc-welding robot. Though there are more and more advanced welding robots as well as control methods, the major problem appears to be the seam tracking and the control of welding parameters. The intelligent seam tracking ability is strongly required because the positional errors caused by thermal distortion of workpieces during welding and dimensional variations of fixtures prevent the formation of good welds.

When an industrial robot is used in arc-welding applications, the robot guides the welding torch along the welding seam. It is required that the welds are in the correct position, only small deviations being acceptable. This can normally be achieved with the help of not only a good vision sensor system but also an accurate robotic control.

During recent years many powerful robot control concepts and algorithms have been proposed. However, most robotic control methods are based on analytical robot models[2,3]. Based on these mathematical models

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servo controllers can be designed which are associated with different optimization criteria. It is well known that the practical efficiency of these model-based control concepts depends strongly on the accuracy in which the model represents the actual static and dynamic system behavior. Due to the strong kinematic nonlinearities, dynamic coupling of adjacent robot joints and the unavoidable elasticities of the mechanical structure, almost all methods of model identification are based on the simplified assumption of linear system response. In such cases control concepts based on such models can only provide insufficient performance and poor robustness.

Intelligent control has a strong impact on robotics, in that flexibility and heuristic characteristics of new control techniques, such as fuzzy logic and neural networks (NNs), have essentially changed the methodology of traditional controller design. The recent resurgence of research and applications of artificial neural networks to a diverse range of disciplines makes it possible to seekout solutions for robotic problems. An NN is a highly parallel dynamical system with the topology of a directed graph that can carry out information processing by means of its stable response. What makes a viable tool is the fact that autonomous system, such as robot manipulators, require a high degree of flexibility to deal with significant variations in the environment. These variations are often unpredictable and difficult to formulate with traditional mathematical approaches. The NNs are typically used to model the highly nonlinear structured and unstructured uncertainties of robot dynamics, and the NN model is used to generate a compensating torque[4].

While the analytical formulation of each control scheme is a major task, its application to an actual robot is another important task. Although many papers on NN control of robot manipulators have been published, experimantal work on an actual arc-welding robot reported is rare. In this paper, we present an NN compensator for arc-welding robotic seam tracking. Unlike the widespread compensation in joint space control problems[5], we studied the Cartesian space control problems which are more complex but appropriate to an actual arc-welding process. It is demonstrated via simulations and experiments that the accurate tracking improvement is obtained by applying the NN compensation at the reference seam trajectory level instead of that at the joint torque/force level. This approach is very attractive in practice welding because it can be incorporated in the seam trajectory planner of any existing arc-welding robot control system without having to alter the internal structure of the controller.

2 Configuration of the seam tracking system

The major functional blocks of the robotic arc-welding seam tracking system are illustrated in Fig. 1. The system consists of an articulated robot with five degrees of freedom, which carries the torch and the vision system. The vision sensor which consists of a charged coupled device (CCD) is used to view the weld seam ahead of the torch as the manipulator travels along the seam.

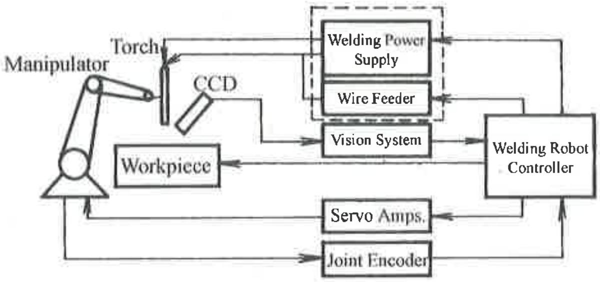

Fig. 1 Configuration of weld seam tracking system

The intelligent robot controller governs the overall operation of seam tracking in an uncertain environment. The functions of the control can be described as follows: 1) Recognizing the seam type associated with each visual scan (e.g. vee, groove, butt or fillet joint, end of seam condition, or an unknown seam condition); 2) Detecting the positions of both seam and torch, and generating a model of the seam environment; 3) Making real-time decisions to interact with the global seam environment and control the robot motion for seam tracking. The discussion is mainly focused on applications of the NN in the design of robot position control in this paper. It will be seen that the discrepancy between the torch and the seam is much reduced after using the NN compensation technique.

The paper is organized in the following way. First, the model of the manipulator used in the arc-welding is described. Then the proposed method of NN is discussed. Finally the salient effects of introducing the NN into the arc-welding seam tracking are illustrated by the computer simulations and actual welding experiments.

3 Model of the manipulator

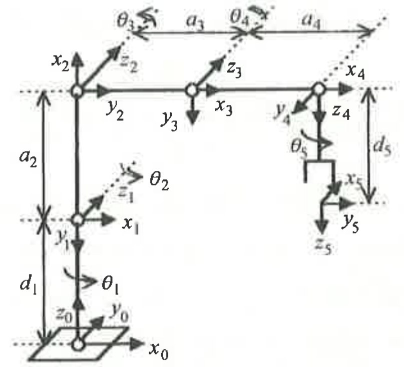

Fig. 2 The link coordinates of robot

The robot arm considered for seam tracking is a five degree of freedom electric-driven manipulator, as shown in Fig. 2. By using the Denavit-Hartenberg method the following kinematic parameters as shown in Table 1 can be obtained[6]. The transformation from coordinate frame of the torch to coordinate frame of the base can be realized by using the following matrix

$$T_{\text{base}}^{\text{torch}} = \begin{bmatrix} R(\theta) & P(\theta) \\ \gamma & 1 \end{bmatrix}, \ \gamma = [0 \ \ 0 \ \ 0] \quad (1)$$

where θ denotes the joint vector, the rotation matrix $R(\theta)_{3\times 3}$ specifies the orientation of the torch and the vector $P(\theta)_{3\times 1}$ indicates the torch tip position related to the base frame.

Table 1 Physical parameters of the links

i	Variables	a_i	d_i	α_i
1	θ_1	0	d_1	$-90°$
2	θ_2	a_2	0	0
3	θ_3	a_3	0	0
4	θ_4	a_4	0	$-90°$
5	θ_5	0	d_5	0

The dynamic equation of an n degree-of-freedom manipulator, in terms of the coordinates used to express the kinematic and potential energy, is expressed by

$$\Gamma = M(\theta)\ddot{\theta} + V(\theta,\dot{\theta})\dot{\theta} + G(\theta) + F(\theta,\dot{\theta}) \quad (2)$$

where $M(\theta)$ is the $n \times n$ coupling inertia matrix; $V(\theta,\dot{\theta})$ is the $n \times 1$ vector of centripetal and Coriolis forces; $G(\theta)$ is the $n \times 1$ vector of gravity loading; $F(\theta,\dot{\theta})$ is the $n \times 1$ vector of torque caused by coulomb, static and viscous friction; Γ is the $n \times 1$ vector of joint torques; $\theta, \dot{\theta}, \ddot{\theta}$ are the position, velocity, and acceleration vectors of joint variables.

Let $H(\theta,\dot{\theta}) = V(\theta,\dot{\theta})\dot{\theta} + G(\theta)$, then equation (2) can be simply rewritten as

$$\Gamma = M(\theta)\ddot{\theta} + H(\theta,\dot{\theta}) + F(\theta,\dot{\theta}). \quad (3)$$

The kinematic relationship between the joint space coordinates θ and the end effector (torch) Cartesian space coordinates X are

$$\dot{X} = J(\theta)\dot{\theta}, \quad \ddot{X} = J(\theta)\ddot{\theta} + \dot{J}(\theta)\dot{\theta} \quad (4)$$

where $J(\theta)$ is the $n \times n$ nonsingular Jacobian matrix. Thus equation (3) can be written as

$$\Gamma = M(\theta)J^{-1}(\theta)(\ddot{X} - \dot{J}(\theta)\dot{\theta}) + H(\theta,\dot{\theta}) + F(\theta,\dot{\theta}). \quad (5)$$

The relationship between the end point forces Γ^* and the joint torque Γ is depicted as

$$\Gamma = J^{\mathrm{T}}(\theta)\Gamma^*. \quad (6)$$

The Cartesian space robot dynamic equation is

$$\Gamma^* = M^*\ddot{X} + H^* + F^* \quad (7)$$

where $M^* = J^{-\mathrm{T}}(\theta)M(\theta)J^{-1}(\theta)$, $H^* = J^{-\mathrm{T}}(\theta)H(\theta,\dot{\theta}) - M^*\dot{J}(\theta)J^{-1}(\theta)\dot{X}$, and $F^* = J^{-\mathrm{T}}(\theta)F(\theta,\dot{\theta})$. It is well known that the equation (7) denotes a highly nonlinear and coupled system. It is difficult to know the exact values of $M(\theta)$, $H(\theta,\dot{\theta})$, and $F(\theta,\dot{\theta})$. Usually, the estimated models of them are available for controller design. Fig. 3 shows the well known computed torque control method of robot in Cartesian space. The control law is

$$\Gamma^* = \hat{M}^* u + \hat{H}^* + \hat{F}^*, \quad (8)$$

$$u = \ddot{X}_d + K_v\dot{X}_e + K_pX_e, \quad (9)$$

$$X_e = X_d - X \quad (10)$$

where $\hat{M}^*$, $\hat{H}^*$, and $\hat{F}^*$ are the estimated models of M^*, H^*, and F^*, respectively; X_d and X are the desired and actual trajectory; K_v and K_p are $n \times n$ symmetric positive definite gain matrices. According to equation (7), (8) and (9), the closed loop tracking error dynamic equation is described by

$$\ddot{X}_e + K_v\dot{X}_e + K_pX_e = \hat{M}^{*-1}(\Delta M^*\ddot{X} + \Delta H^* + \Delta F^*) \quad (11)$$

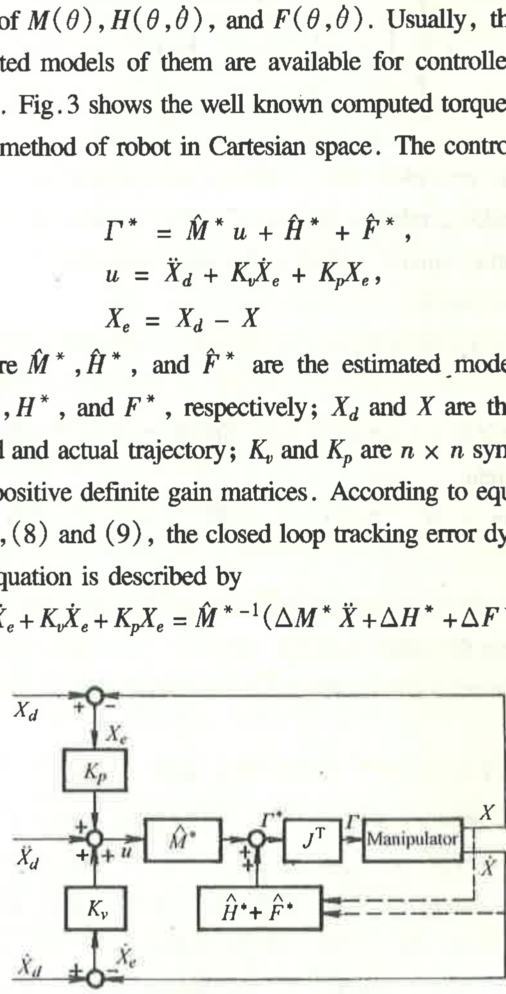

Fig. 3 Control configuration in Cartesian space

where $\Delta M^* = M^* - \hat{M}^*$, $\Delta H^* = H^* - \hat{H}^*$, and $\Delta F^* = F^* - \hat{F}^*$. For the ideal case when $M^* = \hat{M}^*$, $H^* = \hat{H}^*$, $F^* = \hat{F}^*$, equation (11) becomes

$$\ddot{X}_e + K_v\dot{X}_e + K_pX_e = 0. \tag{12}$$

Due to the unavoidable uncertainties in the robot dynamic model, the actual system performance is governed by equation (11) which is degraded and unpredictable. Obviously, the computed torque control method is not robust in practice. In ordor to control the manipulator to follow the seam accurately, NN controller is used to generate additional input for compensating for the disturbances caused by model uncertainties and arc-welding influencing factors.

4 Neural network controller

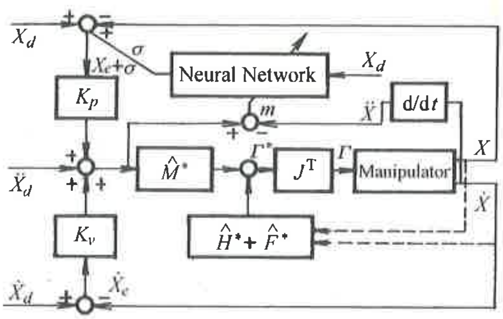

Fig. 4 Neural network control structure

The presented NN controller implemented on a real arc-welding robot is illustrated in Fig.4. The NN compensating input is placed at the input trajectory X_d. The control law is

$$\Gamma = J^T(\hat{M}^*(\ddot{X}_d + K_v\dot{X}_e + K_p(X_e+\sigma)) + \hat{H}^* + \hat{F}^*) \tag{13}$$

where σ is the output of NN. Substituting (13) into (3) can yield

$$m = \hat{M}^{*-1}(\Delta M^*\ddot{X} + \Delta H^* + \Delta F^*) - K_p\sigma \tag{14}$$

where signal m can be regarded as the error signal for training the neural network controller. The ideal value of NN output σ can be defined as that which $m = 0$. Therefore

$$\sigma = K_p^{-1}\hat{M}^{*-1}(\Delta M^*\ddot{X} + \Delta H^* + \Delta F^*). \tag{15}$$

The network consists of an input layer, a hidden layer and an output layer, as shown in Fig.5. Both input layer and output layer are made up of five nodes. In our experiment, the number of the hidden layer was set to 6. The output function for the hidden layer is sigmoid function. The summed signal at a hidden node activates the nonlinear sigmoid function. The output $\sigma_k(k = 1, \cdots, 5)$ at a linear output node is calculated as follows

$$\sigma_k = \sum_{j=1}^{n_h}\omega_{jk}^2\left(\frac{1}{1+\exp\left(-\left(\sum_{i=1}^{n_I}X_{d_i}\omega_{ij}^1 + b_j^1\right)\right)}\right) + b_k^2 \tag{16}$$

where n_I is the number of inputs, n_H is the number of hidden neurons, X_{d_i} is the ith element of input, ω_{ij}^1 is the first layer weight, ω_{jk}^2 is the second layer weight, b_j^1 is the biased weight for jth hidden neuron and b_k^2 is the biased weight for kth output neuron.

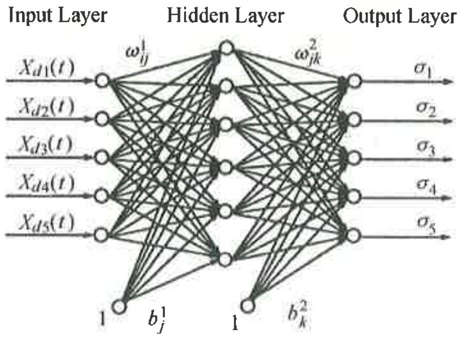

Fig. 5 Neural network controller

Usually, the quadratic function of the training signal m is used to define the objective function P which is given by

$$P = \frac{1}{2}m^Tm. \tag{17}$$

Differentiating (17) and considering (14) produces the gradient of m

$$\frac{\partial P}{\partial\omega} = \frac{\partial m^T}{\partial\omega}m = -\frac{\partial\sigma^T}{\partial\omega}K_p^Tm. \tag{18}$$

Therefore

$$\frac{\partial m^T}{\partial\omega} = -\frac{\partial\sigma^T}{\partial\omega}K_p^T \tag{19}$$

which shows that the gradient function is much less complex. The back propagation leaning rule for the weights with a momentum term is

$$\Delta\omega(t) = \eta\frac{\partial m^T}{\partial\omega}m + \alpha\Delta\omega(t-1) \tag{20}$$

where α is the momentum coefficient and η is the learning rate.

Making use of the above equations, the following results can be easily obtained

$$\Delta\omega_{ij}^1(t) = \eta d_j^1(1-d_j^1)X_i\left(\sum_{k=1}^{n}K_{p_{kk}}m_k\omega_{jk}^2\right) + \alpha\Delta\omega_{ij}^1(t-1), \tag{21}$$

$$\Delta\omega_{jk}^2(t) = \eta K_{p_{kk}}m_kd_j^1 + \alpha\Delta\omega_{jk}^2(t-1), \tag{22}$$

$$\Delta b_j^1(t) = \eta d_j^1(1 - d_j^1)(\sum_{k=1}^{n} K_{p_{kk}} m_k \omega_{jk}^2) + \alpha \Delta b_j^1(t-1), \qquad (23)$$

$$\Delta b_k^2(t) = \eta(K_{p_{kk}} m_k + \alpha \Delta b_k^2(t-1), \qquad (24)$$

$$d_j^1 = \frac{1}{1 + \exp(-(\sum_{i=1}^{n_I} X_{d_i} \omega_{ij}^1 + b_j^1))} \qquad (25)$$

where d_j^1 is the output of jth hidden neuron and $K_{p_{kk}}$ is the kk element of gain K_p.

5 Simulations and experiments

The above described NN control scheme and the computed torque method were implemented on an actual arc-welding robot. The same welding seam trajectory was chosen for both simulation and experiment. A curved welding seam in the Cartesian space was used as the commanded trajectory. The results of both simulation and experiment have shown the effectiveness of the proposed NN scheme.

5.1 Simulations

The proposed NN control and the CT control approaches have been demonstrated by numerous computer simulations in the case of moving the torch along the welding seam. The seam is a curved trajectory which is limited by

$$\begin{cases} (x-90)^2 + y^2 = 90^2, \\ 0 \leqslant x \leqslant 90\text{mm},\ 0 \leqslant y \leqslant 90\text{mm}, \\ z = 0. \end{cases} \qquad (26)$$

The parameter values of the robot dynamics are as follows: $a_2 = a_3 = 500$mm, $a_4 = 200$mm, $d_1 = 850$mm, $d_5 = 600$mm, $I_1 = I_2 = I_3 = I_4 = I_5 = 0.283\text{kgm}^2$, $m_1 = 9.7$kg, $m_2 = m_3 = 5.6$kg, $m_4 = 7.8$kg, $m_5 = 3.6$kg; gear-ratio: $r_1 = 230$, $r_2 = r_3 = r_4 = 532$, $r_5 = 372$, $g_0 = 9.80665\text{m/s}^2$.

The nominal system parameters are used to form the robot models $\hat{M}(\theta)$ and $\hat{H}(\theta,\dot{\theta})$ which are the estimates of $M(\theta)$ and $H(\theta,\dot{\theta})$. The back propogation algorithm parameters are: $\omega_{ij}^k(0) = 0$ and $\alpha = 0.9$. The NN weights are updated at each sampling time in online fashion. The controller gains are chosen as $K_v = \text{diag}[20,20,20,20,20]$, $K_p = \text{diag}[100,100,100,100,100]$ which give identical critically damped motions at the five axes. Here the welding speed is 14mm/s and sampling period is 33.4ms. In order to demonstrate the effectiveness and robustness of the NN, we added a disturbance signal whose form is $d(t) = 0.006\sin 2t$ in the control loop of every joint. This signal can be regarded as the interfering factor which is similar to the variations of the seam position due to the distortion of workpieces in the welding process. Seam tracking performance is measured by the following equation

$$E_L = \sum_{t=0}^{L} \| X_d - X \|^2 (m)^2 \qquad (27)$$

where L is the number of samplings. Through the simulations, we obtained the following values: $E_{L(NN)} = 0.021$, $E_{L(CT)} = 0.053$. Fig.6 shows the seam tracking error which the torch tip deviates from the weld seam while NN and CT are applied. It can be apparently seen that the deviation is still kept within about ± 0.25mm in case of disturbance when NN is applied, which shows much better robustness than CT method.

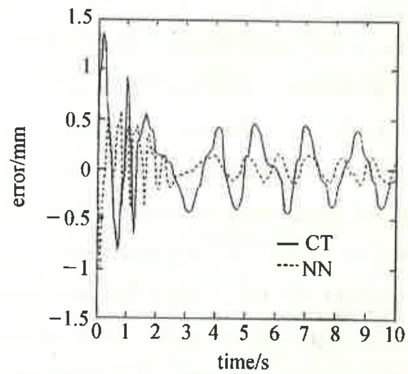

Fig. 6 Deviation between torch and weld seam

However, it was found difficult, if not impossible, to simulate realistically an actual arc-welding robot system with uncertainties. Experiments are always needed to test NN robust control scheme.

5.2 Experiment results

The NN controller was performed on a real arc-welding robot. The welding was carried out on a 0.3cm thick mild steel plate. The width of the seam gap is 0.3mm. Apart from the welding appendages for cooling, shield gas and spatter cleaning, there is water cooling circuit for the sensor and an air supply to reduce smoke disturbances. The welding speed is also 14mm/s. During the process of welding, the vision system was used to detect the seam location (X_d) and the torch position (X). The vision consists of a CCD image sensor and a compact optical projection system that generates a section of a conic light surface from a laser light beam. A narrow band optical interference filter centered on the He-Ne laser frequency blocks most of the ambient and welding arc light. The experiment results have shown that the average accuracy of seam tracking is 0.4mm and the maximum error of tracking is 0.9mm when CT is used. In case of applying NN, the average accuracy of tracking is 0.3mm and the maximum error of tracking is 0.6mm.

The experiment results did not completely match the simulation results. Generally, the experimental results are not so good as those obtained by simulation since there are always effects in the actual system which are not modelled in the simulation model. However, the experiment results have shown that the NN yields more superior performance than traditional CT method.

6 Conclusions

Within this paper the arc-welding seam tracking system by using NN has been investigated. The conventionl robot controllers are based upon a certain mathematical model of the robot manipulator. Inaccuracies in this model result in incorrect position and orientation of the weld torch tip relative to the seam trajectory. It has been found that NN is a very effective compensator for Cartesian space robot seam tracking control when compensation is applied to modify the reference seam trajectory. Since the proposed NN has a much smaller hidden layer signal level for seam modification, more accurate nonlinear mapping can be achieved. It is convenient to be incorporated in the seam planner of an existing arc-welding robot controller without modifying the controller internal structure. The results of simulations and experiments show that the robot seam tracking control system with NN compensator can yield salient performance.

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