Lower Extreme Carrying Exoskeleton Robot Adaptive Control Using Wavelet Neural Networks

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Abstract

Using the wavelet neural networks, an adaptive control system, with two wavelet neural networks as controller and dynamics model identifier respectively, is developed for lower extreme carrying exoskeleton robot. Because the wavelet neural networks have the ability to approximate nonlinear functions and good advantage of time-frequency localization properties, this system can identify nonlinear system dynamic characters more precisely, and can map more complex control strategies. Results show that this control system is more effective than those based on normal controller, where the exoskeleton tracking precision is high and the operator feels very little torque.

1. Introduction

For the lower extreme carrying exoskeleton robot has the complex elements as nonlinear, uncertain and parameters time-varying, the accurate mathematics model is difficult to built, which bring difficult for the system design and affect the control results. BP neural network has the ability of approximating nonlinear functions, which has attracted people many attention and interest, but the BP network has some defects, such as the primary functions are not orthogonal, the convergence velocity is slow and difficult to determine the resolution scale. In this paper, the adaptive control using wavelet network is presented. The wavelet transform has the good advantage of time-frequency localization properties and can construct a set of orthogonal primary functions, which can make up for the defects of BP network[1-3].

Lower extremity exoskeleton intelligent carrying system is a new concept human-machine intelligent robot system. The exoskeleton should shadow the motions of the human and never interfere with these motions[4-7]. For the speciality of this system, the control method for the exoskeleton will be considered independently while not using the study method of the general robot. At present the mostly successful control method is virtual joint torque control, which needs no direct measurements from the pilot or the human-machine interface (e.g. no force or EMG sensors between the two); instead, the controller estimates, based on measurements from the exoskeleton suits only, how to move so the pilot feels very little force. This control scheme is an effective method of generating locomotion when the contact location between the pilot and the exoskeleton is unknown and unpredictable. The control method in paper[7] need the mathematic model of the exoskeleton dynamic equation, while the mass properties can not be gotten exactly. The control method is simple PD control, which is not applicable for the serious nonlinear lower extremity exoskeleton system.

To overcome the defaults of the virtual joint torque control, based on the analyze of the human behavior characteristics and the control mechanism of carrying system virtual joint torque control, the virtual prototyping technology is introduced to model the exoskeleton, which is used to the wavelet neural network dynamic model study. At the same time, the wavelet neural network controller is applied to motion control of lower extreme exoskeleton. Theoretical analyse and simulation results test the feasibility and validity of this control method.

2. Description of virtual joint torque control

Virtual joint torque control selects a generalized force vector such that the control law is constructed in the machine's joint space rather than a set of forces and torques applied at a point on the body. The block diagram of the virtual torque control law is shown in Fig.1. Where G_a represents the system transfer function. $G_a^{'}$ is an estimate of the machine forward dynamics. $K(s)$ is the controller.

T_{hm} denote the torque exerted on the plant by human. T_a denote the torque exerted by actuator. T denote all the external torque exerted on the exoskeleton. The human-machine torque can be modeled as:

$$T_{hm} = K_h(q_h - q) \tag{1}$$

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K_h is the impedance between the human and the machine, q_h is the human's position, q is the machine's position.

the system dynamics model can be built using Lagrange equation:

$$\vec{T} = \vec{J}(\vec{q})\ddot{\vec{q}} + \vec{B}(\vec{q},\dot{\vec{q}})\dot{\vec{q}} + \vec{G}(\vec{q}) \quad . \qquad (2)$$

$\vec{J}$ is the inertia matrix and is a function of $\vec{q}$, $\vec{B}$ is the centripetal and Coriolis matrix and is a function of $\vec{q}$ and $\dot{\vec{q}}$, $\vec{G}$ is a vector of gravitational torques, is a function of $\vec{q}$ only.

The tracking objective of $T_{hm} \to 0$ is identical to the tracking objective $q \to q_h$.

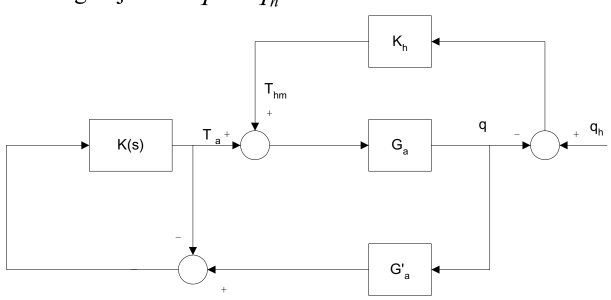

Figure 1. Block diagram of the virtual torque control law

3. Exoskeleton model building in SimMechanics of matlab

Using SimMechanics toolbox in Matlab, the virtual prototyping model of the control object is built. In figure 2 the swing leg model is shown. The inputs are three joint torque signals, the outputs are three joint angular signal, three joint angular velocity signals and three joint angular acceleration signals. The SmiMechanics toolbox has a set of visual tools, which can be used to display the simulation result dynamically, as presented in figure3.

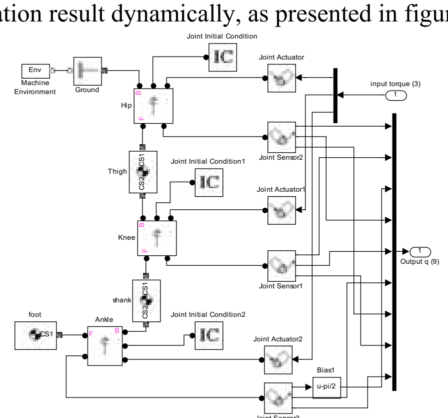

Figure 2 SimMechanics model of swing leg

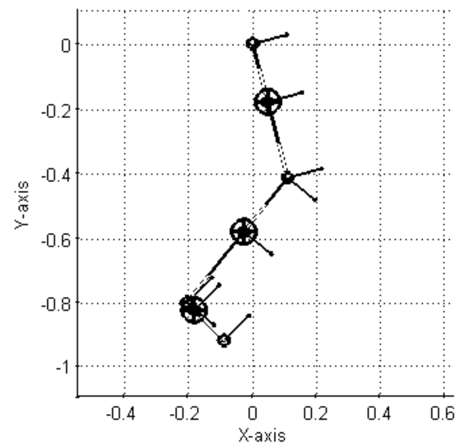

Figure 3 Demo model of swing leg

4. Exoskeleton dynamics model building using wavelet neural network study

For the dynamics mathematics model $G_a^{'}$ used in virtual torque controller can't be gotten accurately, such as $\vec{J}$, $\vec{B}$, $\vec{G}$, the wavelet neural network is used to approximate the dynamics mathematics model.

A Wavelet neural network structure

The wavelet series denote preset function by the summation of a series of function $\psi_{j,k}(x) = 2^{j/2}\psi(2^j x - k)$ gotten by binary system expand and integer translation, which is compact in $L^2(R)$. If $\psi(x)$ is a orthogonal wavelet, it is self dual and $\psi_{j,k}(x)$ is a orthogonal basis, which can denote any function $f(x) \in L^2(R)$. But for the actual system, infinity series summation is insignificant and is not necessary, the function can be signified approximately as followings:

$$f(x) \approx \sum_{j,k=-N}^{N} W_{j,k}\psi_{j,k}(x), \forall f(x) \in L^2(R) \qquad (3)$$

In this study, the Morlet wavelet $\psi(\mathrm{t})$ is chosen as the mother wavelet, which has good finity support both in time-domain and frequency-domain:

$$\psi(x) = -xe^{-\frac{1}{2}x^2} \qquad (4)$$

Transform equation (3) to equation (5), the wavelet neural network is constructed

$$f(x) \approx \sum_{j=1}^{N} W_j \psi\left(\frac{x-t_j}{s_j}\right) \tag{5}$$

$$\forall f(x) \in L^2(R)$$

Fig.4 show the wavelet network. The input vector is $\mathrm{x} = [\mathrm{x}_1, \mathrm{x}_2, \cdots, \mathrm{x}_n]$, the wavelet has N nodes, w_{ij} is coefficient of the jth wavelet node to the kth output variable, and the kth output variable is

$$y_k \approx \sum_{j=1}^{N} W_{jk} \psi\left(\frac{x-t_j}{s_j}\right) \tag{6}$$

The less s, that is, the higher frequency, the time precision is higher. On the other hand, the higher s, the less frequency, the frequency precision is higher. If the flex factor s_i and the translation factor t_i are not selected appropriately, the preset function can not be approximated exactly.

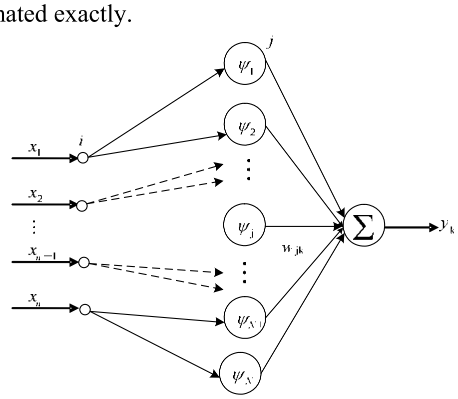

Figure 4 Schematic diagram of wavelet network

B Initialization of wavelet network parameter s and t

In general, the range of system output can be gotten. If the maximum of the output is $f_{\max}$, the minimum is $f_{\min}$, choose the first partition t_1 in the interval $[f_{\min}, f_{\max}]$, that is, $t_1 = f_{\min} + \xi(f_{\max} - f_{\min})$, s_1 is the interval contract, that is, $s_1 = \xi(f_{\max} - f_{\min})$, the typical value of ξ is 0.5. The interval $[f_{\min}, f_{\max}]$ is separated into two subinterval; In every subinterval, the separation is repeated and $s_2, t_2, s_3, t_3 \cdots$ are selected, similarly, all the wavelets are initiated. The number of wavelet cell used is $N = 2^0 + 2^1 + \cdots + 2^{m-1}$, where m is the number of interval separation.

C Exoskeleton dynamics mathematics model identification using wavelet neural network

Taking the wavelet neural network as the inverse model in virtual joint torque control, we must get the input and output data of the system to train the neural network so that the network has the same properties with the inverse model. The exoskeleton joint angular, joint angle velocity and joint angle acceleration are taken as wavelet network input, while the virtual prototyping model (shown in Fig.3) joint torque $\vec{T}$ is taken as output. Train the network using BP method, the adaptive law of the weight is selected according to the paper[1], the number of the wavelet cell is selected as 7.

In figure 5 and 6, the training and test results are given, where the error square summation of the network output and the train data is 0.005, which indicates the effectiveness of the wavelet network. On the same condition, the neural network training and test results are given in figure 7 and 8. From the simulation results we can draw a conclusion that the map ability of wavelet network is stronger than the neural network.

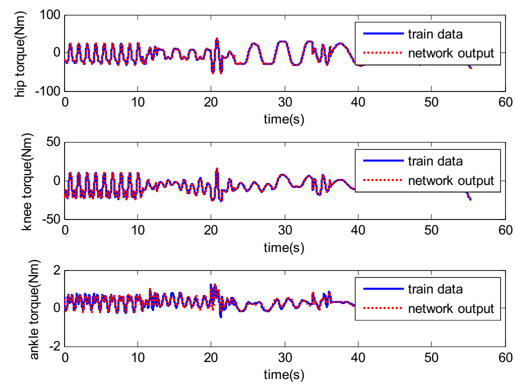

Figure 5 Train data and the wavelet network output data

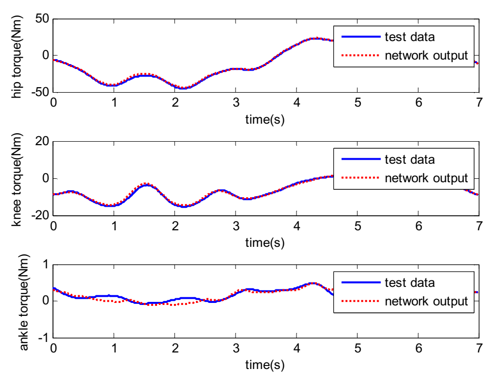

Figure6 Test data and the wavelet network output data

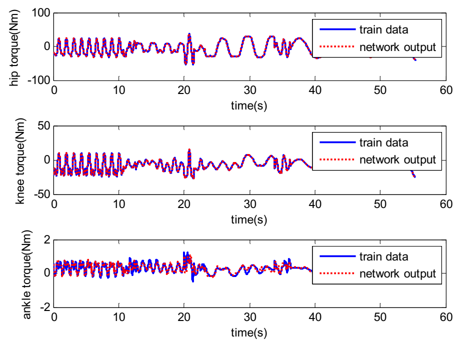

Figure 7 Train data and the neural network output data

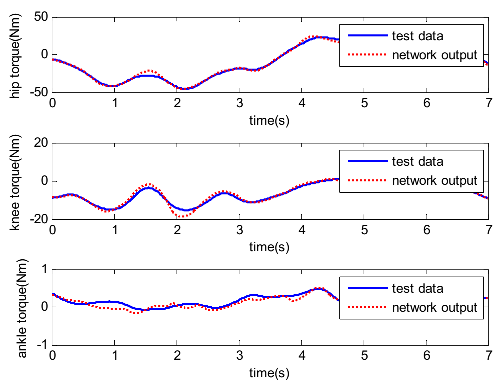

Figure8 Test data and the neural network output data

5. Wavelet network control of lower extreme exoskeleton

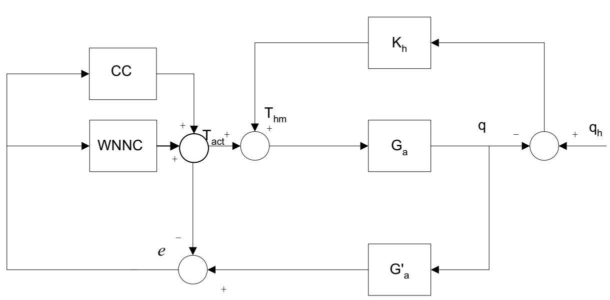

Figure 9 Virtual torque control law based on WNN

Based on the virtual torque control, the feedforward study controller is added, where the control signal is studied using wavelet neural network(WNN), and the compensation control(CC) is also added using PD controller. In movement control, the most concern is the track angle and the interaction force, so the interaction force between human and machine under initial controller is selected to act the teacher signal. The error signal e which is approximately equal to T_{hm} is taken as inputs in WNN. The control diagram is shown in Fig.9.

6. Simulation results

Using the anthropometric data computed from Winter D. A. as the parameters of the exoskeleton leg [8]and choosing the swing phase data from the Clinical Gait Analysis (CGA) data[9] as the desired motion of the human, assuming the pilot tied together with the exoskeleton at the hip joint and foot, making the SmiMechanics model of swing leg as G_a and the wavelet network identifier as $G_a^{'}$ as shown in figure 9, using the PD control, while not using the WNN controller, the simulation result of swing phase is shown in Fig.10, where the convergence is bad and the torque between human and machine is large. Adding the wavelet neural network controller, the simulation results are presented in Fig.11 and Fig. 12, which illustrate that the exoskeleton tracks the motion of the human very well and the torque exerted by the human is very small and the actuator exert the most which means the pilot (human) can swing the exoskeleton easily and only need to exert a little torque of the actuator.

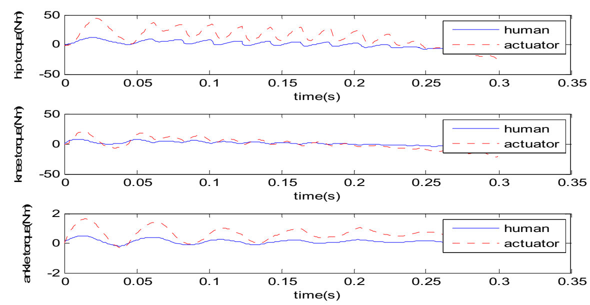

Figure 10 Torque exerted by human and actuator

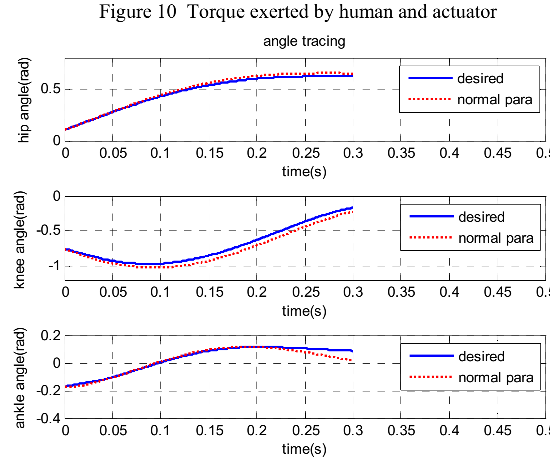

Figure 11 Trajectory of joint angle

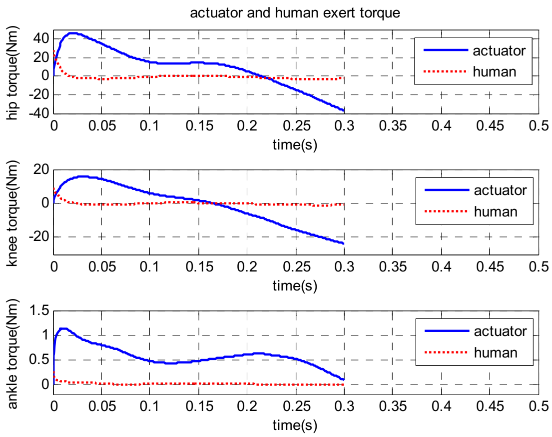

Figure 12 Torque exerted by human and actuator with WNN controller

7. Conclusion

Using the wavelet neural networks, an adaptive control system, with two wavelet neural networks as controller and dynamics model identifier respectively, is developed for lower extreme carrying exoskeleton robot. Simulation results show that this control system is more effective than those based on normal controller, where the exoskeleton tracking precision is high and the operator feels very little torque. Further study will focus on the robustness analyse.

8. References

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