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Impedance Control of Exoskeleton Suit Based on RBF Adaptive network*

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Abstract—**Exoskeleton suit is a typical human-machine system. Control the exoskeleton suit to track the pilot's moving trajectory as well as to minimize the human-machine interaction force. The suit will help decrease the pilot's power consumption and assist the pilot to carry heavy load. Impedance control was introduced to the control of exoskeleton suit. As the control laws that based on the dynamic model without model uncertainty compensation will increase the human-machine force, a RBF neural network with adaptive learning algorithm was used to compensate the model uncertainty. The stability analysis of the control law was given and the simulation results show the feasibility and validity of the proposed control law.**

Keywords-exoskeleton suit; impedance control; RBF neural network; uncertainties; human-machine system

I. INTRODUCTION

Exoskeleton suit is also called exoskeleton robot which is a kind of special human-machine mechanical system combining the human's intelligence with the powerful mechanical system[1]. The primary function of exoskeleton suit is to enhance human's strength and endurance during locomotion with heavy load. The control of exoskeleton suit is very difficult. "HAL" used the myoelectrical sensors to measure the human's muscle biological information and to generate the actuators control instructions[2,3,4]. But myoelectrical sensors must be fitted on the pilot's muscle surface every time, which is inconvenient and troublesome. "BLEEX" use a control method named sensitivity amplification control (SAC), which can provide most of the assistant force but can't deal with the influence of the model uncertainties[7,8]. In this paper, a multi-axis force sensor was introduced installed between the exoskeleton suit and the pilot which can be mounted and dismounted easily. The human-machine force information was measured and utilized to generate the desired moving trajectory. An impedance control method was proposed which can minimize the human-machine interaction force by a proper selection of impedance parameters. A RBF neural network with adaptive learning algorithm was adopted to compensate the model uncertainties, and the human-machine interaction force was minimized, which means the pilot's power consumption was decreased.

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II. IMPEDANCE CONTROL OF EXOSKELETON SUIT

A multi-axis force sensor is mounted between the exoskeleton suit's body and the pilot's waistcoat. This sensor was used to control the exoskeleton suit in the support phase which is shown in Fig.1. The multi-axis force sensor mounted between the exoskeleton suit's foot and the pilot's shoes was used when the exoskeleton suit's leg is in swing phase.

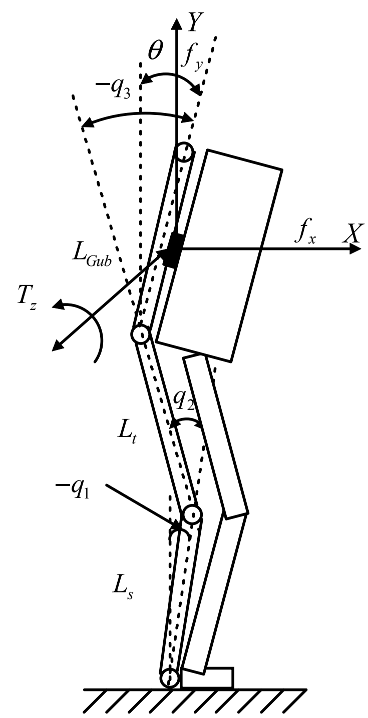

Fig 1 Support phase of exoskeleton suit

The dynamic equation of the exoskeleton suit in task space is[6,7]:

$$\boldsymbol{A}(\boldsymbol{q})\ddot{\boldsymbol{p}}+\boldsymbol{B}(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{p}}+\boldsymbol{D}(\boldsymbol{q})=\boldsymbol{u}+\boldsymbol{f} \tag{1}$$

Where $\boldsymbol{q},\dot{\boldsymbol{q}}$ denote the exoskeleton suit's joint angle and joint velocity in joint space respectively, $\boldsymbol{p},\dot{\boldsymbol{p}},\ddot{\boldsymbol{p}}$ denote the upper body gravity's position, velocity and acceleration in task space, $\boldsymbol{A}(\boldsymbol{q})$ is the inertial matrix, $\boldsymbol{B}(\boldsymbol{q},\dot{\boldsymbol{q}})$ is the coriolis and centrifugal items, $\boldsymbol{D}(\boldsymbol{q})$ is the gravity torque, $\boldsymbol{u}$ denotes the torque exerted by the actuator, $\boldsymbol{f}$ is

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the human-machine interaction force or denotes the force exerted to the exoskeleton suit by the pilot.

Design the control law based on inverse dynamic:

$$\boldsymbol{u} = \hat{\boldsymbol{A}}(\boldsymbol{q})\boldsymbol{\tau} + \hat{\boldsymbol{B}}(\boldsymbol{q})\dot{\boldsymbol{p}} + \hat{\boldsymbol{D}}(\boldsymbol{q}) - \boldsymbol{f} \tag{2}$$

$$\boldsymbol{\tau} = \ddot{\boldsymbol{p}}_c + \boldsymbol{K}_{Mp}{}^{-1}(\boldsymbol{K}_{Dp}\Delta\dot{\boldsymbol{p}} + \boldsymbol{K}_{Pp}\Delta\boldsymbol{p} + \boldsymbol{f}) \tag{3}$$

Where $\hat{\boldsymbol{A}}(\boldsymbol{q}), \hat{\boldsymbol{B}}(\boldsymbol{q},\dot{\boldsymbol{q}}), \hat{\boldsymbol{D}}(\boldsymbol{q})$ is the estimate value of $\boldsymbol{A}(\boldsymbol{q})$, $\boldsymbol{B}(\boldsymbol{q},\dot{\boldsymbol{q}})$ and $\boldsymbol{D}(\boldsymbol{q})$ respectively. $\boldsymbol{p}_{\mathrm{d}}, \dot{\boldsymbol{p}}_{\mathrm{d}}, \ddot{\boldsymbol{p}}_{\mathrm{d}}$ denote the position, velocity and acceleration of the desired trajectory in the task space, and $\Delta\boldsymbol{p} = \boldsymbol{p}_c - \boldsymbol{p}$, $\Delta\dot{\boldsymbol{p}} = \dot{\boldsymbol{p}}_c - \dot{\boldsymbol{p}}$, $\boldsymbol{K}_{Mp}, \boldsymbol{K}_{Dp}, \boldsymbol{K}_{Pp}$ denote the desired the inertial matrix, damping matrix and stiffness matrix.

Substituting equation (2) and (3) into (1), we get the close loop dynamic equation of the system:

$$\begin{aligned}&\Delta\ddot{\boldsymbol{p}} + \boldsymbol{K}_{Mp}{}^{-1}(\boldsymbol{K}_{Dp}\Delta\dot{\boldsymbol{p}} + \boldsymbol{K}_{Pp}\Delta\boldsymbol{p} + \boldsymbol{f}) = \\ &\quad \hat{\boldsymbol{A}}(\boldsymbol{q})^{-1}(\Delta\boldsymbol{A}(\boldsymbol{q})\ddot{\boldsymbol{p}} + \Delta\boldsymbol{B}(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{p}} + \Delta\boldsymbol{D}(\boldsymbol{q}))\end{aligned} \tag{4}$$

Where:

$$\Delta\boldsymbol{A}(\boldsymbol{q}) = \boldsymbol{A}(\boldsymbol{q}) - \hat{\boldsymbol{A}}(\boldsymbol{q}) \tag{5}$$

$$\Delta\boldsymbol{B}(\boldsymbol{q},\dot{\boldsymbol{q}}) = \boldsymbol{B}(\boldsymbol{q},\dot{\boldsymbol{q}}) - \hat{\boldsymbol{B}}(\boldsymbol{q},\dot{\boldsymbol{q}}) \tag{6}$$

$$\Delta\boldsymbol{D}(\boldsymbol{q}) = \boldsymbol{D}(\boldsymbol{q}) - \hat{\boldsymbol{D}}(\boldsymbol{q}) \tag{7}$$

In the ideal condition $\Delta\boldsymbol{A}(\boldsymbol{q}) = 0$, $\Delta\boldsymbol{B}(\boldsymbol{q},\dot{\boldsymbol{q}}) = 0$, $\Delta\boldsymbol{D}(\boldsymbol{q}) = 0$, then the behavior the exoskeleton suit fulfill the target impendence relation:

$$-\boldsymbol{f} = \boldsymbol{K}_{Mp}\Delta\ddot{\boldsymbol{p}} + \boldsymbol{K}_{Dp}\Delta\dot{\boldsymbol{p}} + \boldsymbol{K}_{Pp}\Delta\boldsymbol{p} \tag{8}$$

Then the human can control the exoskeleton suit move with the human easily by properly design the $\boldsymbol{K}_{Mp}, \boldsymbol{K}_{Dp}, \boldsymbol{K}_{Pp}$ though the load is very heavy.

III. Estimation of the Reference Trajectory

The desired trajectory of the exoskeleton suit is the pilot's moving trajectory. It's very difficult to measure the pilot's trajectory, because it needs to fit complex sensors on the pilot, which will decrease the comfort of the pilot and make the exoskeleton suit hard to pull on and off. To solve this question, a control method was proposed which uses the human-machine interaction force to estimate the human's moving trajectory. Some multi-axis force/torque sensors are installed between the pilot and the exoskeleton suit just as the backpack and the foot.

The human-machine interaction force model can be modeled as follows [11]:

$$\boldsymbol{f} = \boldsymbol{K}_{Pf}(\boldsymbol{p}_c - \boldsymbol{p}) \tag{9}$$

Where $\boldsymbol{K}_{Pf}$ denote the human's stiffness. So the reference trajectory can estimate as:

$$\hat{\boldsymbol{p}}_c = \boldsymbol{f} / \hat{\boldsymbol{K}}_{Pf} + \boldsymbol{p} \tag{10}$$

Where $\hat{\boldsymbol{K}}_{Pf}$ denote the estimation of human's stiffness, though the estimation of $\hat{\boldsymbol{K}}_{Pf}$ may be not accurate enough, but if $\hat{\boldsymbol{K}}_{Pf}$ fulfill some conditions，the system still be stable. Take the equation (10) into (8), we get:

$$\boldsymbol{K}_{Mp}\ddot{\boldsymbol{f}} + \boldsymbol{K}_{Dp}\dot{\boldsymbol{f}} + (\boldsymbol{K}_{Pp} + \hat{\boldsymbol{K}}_{Pf})\boldsymbol{f} = 0 \tag{11}$$

So the system can be stable as long as $\boldsymbol{K}_{Dp}$ and $\boldsymbol{K}_{Pp} + \boldsymbol{K}_{Pf}$ are positive and $\boldsymbol{f}$ will convergence to zero.

IV. Adaptive Neural Network Compensation of the Model Uncertainty

When $\Delta\boldsymbol{A}(\boldsymbol{q}) = \Delta\boldsymbol{B}(\boldsymbol{q},\dot{\boldsymbol{q}}) = \Delta\boldsymbol{D}(\boldsymbol{q}) \neq 0$ in equation (12), the control torque provided by the actuator can't guarantee the human-machine interaction force convergence to zero. The pilot needs to exert some extra torque to eliminate the influence of the model uncertainty and the power consumption of the pilot increases, so we must estimate the model uncertainties and compensate it.

Assume $\boldsymbol{x} = \begin{pmatrix}\Delta\boldsymbol{p} & \Delta\dot{\boldsymbol{p}}\end{pmatrix}^T$ and from equation (9), we can get $\boldsymbol{f}$ and state $\boldsymbol{x}$ has the relationship as follows:

$$\boldsymbol{f} = \begin{bmatrix}\boldsymbol{K}_{pf} & 0\end{bmatrix}\boldsymbol{x} \tag{12}$$

Let the model uncertainty as follows:

$$\boldsymbol{\Psi} = \hat{\boldsymbol{A}}(\boldsymbol{q})^{-1}[\Delta\boldsymbol{A}(\boldsymbol{q})\ddot{\boldsymbol{p}} + \Delta\boldsymbol{B}(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{p}} + \Delta\boldsymbol{D}(\boldsymbol{q})] \tag{13}$$

Then under the control laws (2) and (3), the system state space dynamic model can be written as:

$$\dot{\boldsymbol{x}} = \boldsymbol{M}\boldsymbol{x} + \boldsymbol{N}\boldsymbol{\Psi} \tag{14}$$

Where:

$$\boldsymbol{M} = \begin{bmatrix} 0 & \boldsymbol{I} \\ -\boldsymbol{K}_{Pp}/\boldsymbol{K}_{Mp} + \boldsymbol{K}_{pf} & -\boldsymbol{K}_{Dp}/\boldsymbol{K}_{Mp} \end{bmatrix}$$

$$\boldsymbol{N} = \begin{bmatrix} 0 \\ \boldsymbol{I} \end{bmatrix}$$

If the model uncertainties are known exactly and redesign the control laws (3) as follows:

$$\boldsymbol{\tau} = \ddot{\boldsymbol{p}}_c + \boldsymbol{K}_{Mp}{}^{-1}(\boldsymbol{K}_{Dp}\Delta\dot{\boldsymbol{p}} + \boldsymbol{K}_{Pp}\Delta\boldsymbol{p} + \boldsymbol{f}) + \boldsymbol{\Psi} \tag{15}$$

Then under the control of (2) and (15) the desired system impedance relation (8) can be realized.

But in practice the model uncertainties are not known exactly and the control law (15) can't be realized. So it needs to estimate the model uncertainty and compensate it in the control law. RBF neural network can approach arbitrary nonlinear function and it has a quick learning speed. So use RBF neural network to approach the model uncertainty is properly [13, 14]. The RBF neural network algorithm is:

$$h_i = f(\|\boldsymbol{x} - \boldsymbol{\varphi}_i\| / \sigma_i^2), i = 1, 2, \cdots, m \tag{16}$$

$$\boldsymbol{s} = \boldsymbol{\theta}^T\boldsymbol{h}(\boldsymbol{x}) \tag{17}$$

Where $\boldsymbol{x}$ is the input of the network, and $\boldsymbol{h}=[h_1,h_2,\cdots h_m]$ is the output of the Gauss base function, $\boldsymbol{\theta}$ is the weight of the network, m denote the number of the neuron.

Assume:

(1) The output of the neural network $\boldsymbol{s}(\boldsymbol{x},\boldsymbol{\theta})$ is continuous;

(2) The output of the neural network $\boldsymbol{s}(\boldsymbol{x},\boldsymbol{\theta}^*)$ approach continuous function $\boldsymbol{\Psi}$ and exist a small positive number ε and

$$\max\|\boldsymbol{s}(\boldsymbol{x},\boldsymbol{\theta}^*)-\boldsymbol{\Psi}\|\le\varepsilon \tag{18}$$

Where $\boldsymbol{\theta}^*$ is a $n\times n$ matrix and denote the optimal weight identify of $\boldsymbol{\Psi}$.

Let $\boldsymbol{\eta}=\boldsymbol{\Psi}-\boldsymbol{s}(\boldsymbol{x},\boldsymbol{\theta}^*)$ is the error of the neural network and the error has a bound $\boldsymbol{\eta}_0$ which is:

$$\boldsymbol{\eta}_0=\sup\|\boldsymbol{\Psi}-\boldsymbol{s}(\boldsymbol{x},\boldsymbol{\theta}^*)\| \tag{19}$$

Then the system equation (14) can be rewritten as:

$$\dot{\boldsymbol{x}}=\boldsymbol{M}\boldsymbol{x}+\boldsymbol{N}(\boldsymbol{s}(\boldsymbol{x},\boldsymbol{\theta}^*)+\boldsymbol{\eta}) \tag{20}$$

Let $\hat{\boldsymbol{\theta}}$ is the estimate value of $\boldsymbol{\theta}^*$ and using the RBF neural network to estimate the system model uncertainties based on equation (15), then the new control law is:

$$\begin{aligned}\boldsymbol{\tau}&=\ddot{\boldsymbol{p}}_c+\boldsymbol{K}_{Mp}{}^{-1}(\boldsymbol{K}_{Dp}\Delta\dot{\boldsymbol{p}}+\boldsymbol{K}_{Pp}\Delta\boldsymbol{p}+\boldsymbol{f})\\&+\boldsymbol{s}(\boldsymbol{x},\hat{\boldsymbol{\theta}})\end{aligned} \tag{21}$$

V. STABILITY ANALYSIS

Combining (2) and (21) with (1) yields:

$$\begin{aligned}\dot{\boldsymbol{x}}&=\boldsymbol{M}\boldsymbol{x}+\boldsymbol{N}(\boldsymbol{s}(\boldsymbol{x},\boldsymbol{\theta}^*)+\boldsymbol{\eta}-\boldsymbol{s}(\boldsymbol{x},\hat{\boldsymbol{\theta}}))\\&=\boldsymbol{M}\boldsymbol{x}+\boldsymbol{N}(-\tilde{\boldsymbol{\theta}}\boldsymbol{h}(\boldsymbol{x})+\boldsymbol{\eta})\end{aligned} \tag{22}$$

Where $\tilde{\boldsymbol{\theta}}=\hat{\boldsymbol{\theta}}-\boldsymbol{\theta}^*$.

Define the Lyapunov function is:

$$V=\frac{1}{2}\boldsymbol{x}^T\boldsymbol{P}\boldsymbol{x}+\frac{1}{2\gamma}\|\tilde{\boldsymbol{\theta}}\|^2 \tag{23}$$

Where $\gamma>0$, $\|\tilde{\boldsymbol{\theta}}\|^2=tr(\tilde{\boldsymbol{\theta}}^T\tilde{\boldsymbol{\theta}})$, $tr(\cdot)$ denote the matrix trace, $\boldsymbol{P}$ is symmetrical positive matrix and fulfill the Lyapunov equation as follows:

$$\boldsymbol{P}\boldsymbol{M}+\boldsymbol{M}^T\boldsymbol{P}=-\boldsymbol{Q} \tag{24}$$

Differential equation (23), we get:

$$\begin{aligned}\dot{V}&=\frac{1}{2}[\boldsymbol{x}^T\boldsymbol{P}\dot{\boldsymbol{x}}+\dot{\boldsymbol{x}}^T\boldsymbol{P}\boldsymbol{x}]+\frac{1}{\gamma}tr(\dot{\tilde{\boldsymbol{\theta}}}^T\tilde{\boldsymbol{\theta}})\\&=-\frac{1}{2}\boldsymbol{x}^TQ\boldsymbol{x}-\boldsymbol{h}^T(\boldsymbol{x})\tilde{\boldsymbol{\theta}}\boldsymbol{N}^T\boldsymbol{P}\boldsymbol{x}+\boldsymbol{\eta}^T\boldsymbol{N}^T\boldsymbol{P}\boldsymbol{x}\\&+\frac{1}{\gamma}tr(\dot{\tilde{\boldsymbol{\theta}}}^T\tilde{\boldsymbol{\theta}})\end{aligned} \tag{25}$$

Because

$$\boldsymbol{h}^T(\boldsymbol{x})\tilde{\boldsymbol{\theta}}\boldsymbol{N}^T\boldsymbol{P}\boldsymbol{x}=tr[\boldsymbol{N}^T\boldsymbol{P}\boldsymbol{x}\boldsymbol{h}^T(\boldsymbol{x})\tilde{\boldsymbol{\theta}}] \tag{26}$$

Then equation (25) can be written as:

$$\begin{aligned}\dot{V}&=-\frac{1}{2}\boldsymbol{x}^T\boldsymbol{Q}\boldsymbol{x}+\boldsymbol{\eta}^T\boldsymbol{N}^T\boldsymbol{P}\boldsymbol{x}\\&+\frac{1}{\gamma}tr(-\gamma\boldsymbol{N}^T\boldsymbol{P}\boldsymbol{x}\boldsymbol{h}^T(\boldsymbol{x})\tilde{\boldsymbol{\theta}}+\dot{\tilde{\boldsymbol{\theta}}}^T\tilde{\boldsymbol{\theta}})\end{aligned} \tag{27}$$

If we adopt the follows adaptive law as the learning algorithm of the weight:

$$\dot{\tilde{\boldsymbol{\theta}}}^T=\gamma\boldsymbol{N}^T\boldsymbol{P}\boldsymbol{x}\boldsymbol{h}^T(\boldsymbol{x}) \tag{28}$$

Which is:

$$\dot{\tilde{\boldsymbol{\theta}}}=\gamma\boldsymbol{h}(\boldsymbol{x})\boldsymbol{x}^T\boldsymbol{P}\boldsymbol{N} \tag{29}$$

Then

$$\dot{V}=-\frac{1}{2}\boldsymbol{x}^TQ\boldsymbol{x}+\boldsymbol{\eta}^T\boldsymbol{N}^T\boldsymbol{P}\boldsymbol{x} \tag{30}$$

We have known that

$$\|\boldsymbol{\eta}^T\|\le\|\boldsymbol{\eta}_0\|,\quad\|\boldsymbol{N}\|=1$$

And let $\lambda_{\min}(\boldsymbol{Q})$ is the minimal eigenvalue of matrix $\boldsymbol{Q}$, $\lambda_{\max}(\boldsymbol{P})$ is the maximal eigenvalue of matrix $\boldsymbol{P}$, then

$$\begin{aligned}\dot{V}&\le-\frac{1}{2}\lambda_{\min}(\boldsymbol{Q})\|\boldsymbol{x}\|^2+\|\boldsymbol{\eta}_0\|\lambda_{\max}(\boldsymbol{P})\|\boldsymbol{x}\|\\&=-\frac{1}{2}\|\boldsymbol{x}\|[\lambda_{\min}(\boldsymbol{Q})\|\boldsymbol{x}\|-2\|\boldsymbol{\eta}_0\|\lambda_{\max}(\boldsymbol{P})]\end{aligned} \tag{31}$$

So if we want $\dot{V}\le 0$, $\lambda_{\min}(\boldsymbol{Q})$ must fulfill the following inequality:

$$\lambda_{\min}(\boldsymbol{Q})\ge\frac{2\|\boldsymbol{\eta}_0\|\lambda_{\max}(\boldsymbol{P})}{\|\boldsymbol{x}\|} \tag{32}$$

VI. SIMULATION RESULTS

Assume only the hip joint of exoskeleton suit work and the knee joint is fixated. The leg is assumed to be in swing phase at the same time. So the exoskeleton leg can be regarded as a 1-dof system as shown in Fig 2. m,l are the mass and length of the exoskeleton leg. T_{a} denotes the hip joint actuator exerted torque, T_{he} denotes the human exerted torque. Assume the human's leg is fixed with the exoskeleton leg at the hip joint and joined together with a multi-axis force/torque sensor at the ankle joint. In this one degree case only one dimension of the sensor is used. The system's joint space overlapped with the task space because of it's a one dof system.

The dynamic function of the 1-dof system can be written as:

$$H_0\ddot{q}+C_0\dot{q}+G_0=T_a+T_{he} \tag{33}$$

Where $H_0 = \frac{1}{3}ml^2$, $G_0 = mgl\cos(q)$, C_0 is the friction coefficient, $T_{he} = K_{Pf}(q_c - q)$, q_c denote the human's moving trajectory and selected as $q_c = \sin 2\pi t$. Let m = 10, l = 1, C_0 = 0.02, K_{Pf} =500, the desired impedance parameter is: K_{Mp} =1, K_{Dp} =100, K_{Pp} =10. Design the adaptive parameter γ = 1000 and matrix $Q = [50 \quad 0; \quad 0 \quad 50]$.

The simulation results are shown in Fig.2 to Fig.7. Fig.2 shows the trajectory tracing curves. From Fig.2 we can see the estimated and the actual trajectory of the exoskeleton suit was coincide with the desired trajectory (the pilot's moving trajectory). In this paper, the exoskeleton suit was simulated under three conditions. The first is without model uncertainties. The second is the model parameters increased 20% and the third is the model parameters decreased 20%. When the model uncertainties exist, the trajectory tracing curve is similar to Fig.2 and was not show again. Fig.3 shows the human-machine interaction force of the exoskeleton suit without RBF neural network compensation under the three conditions. From Fig.3 we can see the human-machine interaction force increased very much when the model uncertainties exist.

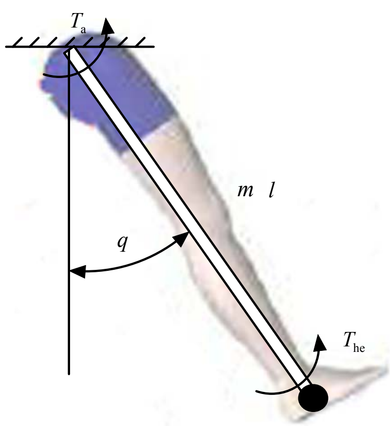

Fig 2 1-dof exoskeleton suit

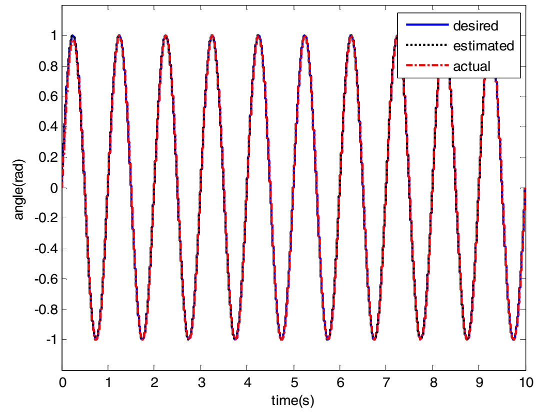

Fig 3 Trajectory tracing curves of exoskeleton suit

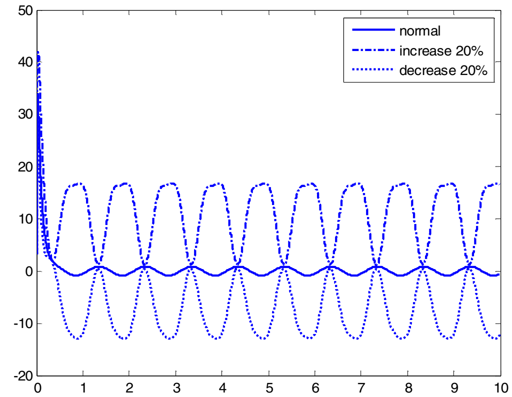

Fig 4 Human-machine interaction under three conditions force without adaptive RBF neural network compensation

Fig.5 shows the compensation torque estimated by the adaptive RBF neural network under the three conditions. Fig.6 shows the human-machine interaction force with adaptive RBF neural network compensation under the three conditions. From Fig.5 and Fig6 we can see that the human-machine interaction force is decreased when the adaptive RBF neural network was used, which means the human's power consumption was decreased. Fig.7 and Fig.8 shows the RBF neural network's estimation of the model uncertainties when the model parameters increased 20% and decreased 20%. From Fig.6 and Fig.7 we can see the RBF neural network estimated the model uncertainties very well.

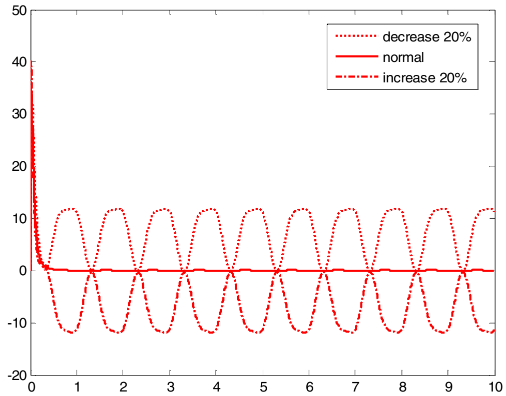

Fig 5 The RBF neural network compensation torque under three conditions

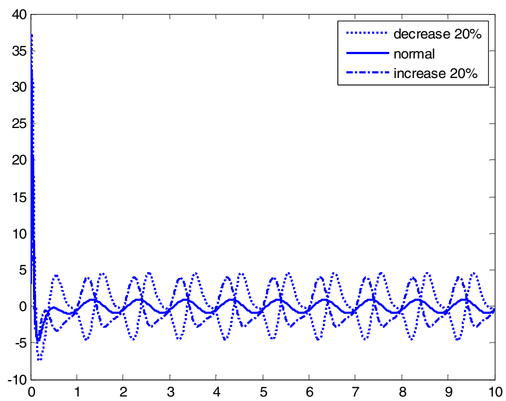

Fig 6 Human-machine interaction under three conditions force with adaptive RBF neural network compensation

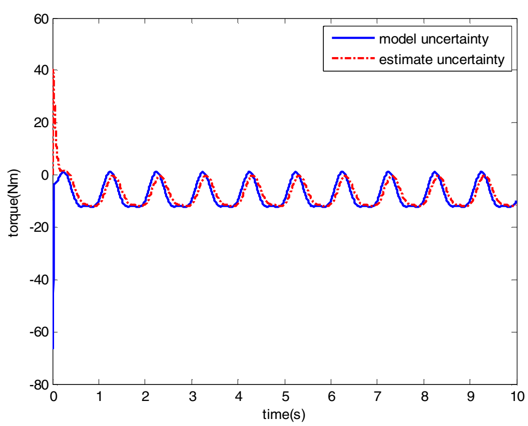

Fig 7 The RBF neural network estimation of the model uncertainties when the model parameters increased 20%

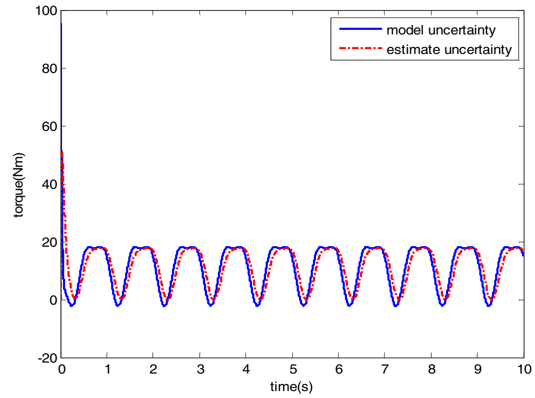

Fig 8 The RBF neural network estimation of the model uncertainties when the model parameters decreased 20%

VII. SIMULATION RESULTS

In this paper a multi-axis force sensor was introduced to measure the human-machine interaction force and an impedance control was proposed to control the exoskeleton suit to track the pilot's moving trajectory with certain impedance parameters. When the model uncertainties do not exist, the impedance control can control the exoskeleton follows the pilot with minimal pilot's effort. But when the exoskeleton suit have model uncertainties, the pilot need to exert more （extra） strength(or torque) to bring the exoskeleton suit along with him. A RBF neural network with adaptive learning algorithm was introduced to eliminate the model uncertainties and the simulation results shows the network can estimate the model uncertainties exactly and decrease the human-machine interaction force obviously.

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