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RESEARCH ARTICLE

Research on Adaptive Fuzzy Impedance Control of Human-Massage Robot Interaction Based on Kelvin-Voigt Modeling

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ABSTRACT Due to the deformable surface and unknown biomechanical properties of human skin tissue, it brings a large impact on the contact position and force control of robotic massage. In this paper, an adaptive hybrid impedance control method is proposed. To adapt the massage robot to the environmental changes of muscle tissues in the human massage area, a human muscle tissue model was established, and a recursive least squares algorithm was optimized to identify the model parameters online. To determine the parameters of the impedance controller, a fuzzy system between the parameters of the skin tissue model and the robot contact dynamics model was developed. To keep the robot with proper end-effector orientation and stable contact force during the massage process, an adaptive force-position hybrid control strategy is proposed. On the one hand, a position controller for adaptive attitude adjustment is used to control the move position and the normal direction of the robot. On the other hand, a force controller based on impedance control is used to ensure a stable contact force during dynamic interaction with human. Furthermore, since massage is a human contact task, the adaptive impedance control strategy also improves the interaction safety performance and contact detection. The effectiveness and feasibility of the massage system using adaptive fuzzy impedance control adapted to the variation of human muscle tissue is verified through experiments on the robot massage movement.

INDEX TERMS Massage robot, human skin tissue model, fuzzy control, adaptive impedance control.

I. INTRODUCTION

Massage is the behavior of rubbing, kneading or tapping the surface of the body back and forth with hands or instruments, and is an effective means used for healing and maintenance. In addition, massage has many benefits for the human body. For example, it relaxes the meridian system, improves blood circulation, enhances the function of internal organs and promotes human health [1]. Healthcare has become a hot issue in today's aging world. Due to the shortage of massager, the long training period and the poor work decency, the massage is time-consuming and laborious, and also easy to cause muscle fatigue and injury to healthcare workers, non-invasive treatment automation has become one of the focuses of the development of many organizations.

Many massage devices such as automatic massage chairs, foot massagers, and eye massagers have been developed over the decades. However, this massage equipment is limited in that one massage device is needed for each part of the body and not all of them are universal because patients have different body types and needs, which results in less versatility and more expensive equipment. The above problems can be largely avoided by combining collaborative robots with end-effector with different massage functions, which on the one hand ensures enough freedom and working range, and on the other hand can be adapted to the majority of

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patients with a wide range of application scenarios. Many researchers have already carried out studies in this area. Wang et al. [2] designed a foot massage robot that trajectory planning for acupoint path points to accomplish foot massage. Huang [3] designed a 4-degree-of-freedom robot arm and massage end-effector to realize pressing and kneading, and proposed a passive-based control strategy for massage robots. However, the motion space of the robot is small and cannot cover most parts of the human body for massage. Hu et al. [4] designed a robot that can realize a variety of key massage techniques such as kneading, pressing, rolling and pinching, which uses vision to track acupoints, summarizes and analyzes the expert massage process, proposes a pain threshold-based force-position control method, and preliminarily verifies the therapeutic effect of the massage robot. Luo et al. [5], [6] developed a humanoid double arm tapping robot, which designs an online trajectory generator to control the frequency of tapping, and its effect has a strong positive correlation with the tapping motion of a professional massager. Khoramshahi et al. [7] implemented a kneading massage method on a human arm using manipulator, employing a dynamical systems approach and support vector machines to learn a skin surface model. Most of the existing massage robots such as the tapping massage robots, foot massage robots and kneading massage robots are mainly focused on the research of realizing individual massage techniques. The cost of using manipulators would be significantly higher, and the force provided by manipulators is not sufficient for massage tasks and is not suitable for large-scale people.

To establish a positive massage effect, the first step is to establish a mathematical model of human skin muscle, and to obtain the environmental characteristics of human skin tissues by establishing the model to realize a reasonable control design. Many studies on human skin modeling have been widely conducted, such as the Kelvin-Voigt model, Maxwell model and nonlinear Hunt-Crossley model. Erickson et al. [8] reviewed and compared four algorithms for the identification of contact stiffness and damping during robot constrained motion, accurately calculated contact stiffness and damping for a contact dynamics model, and gave the conditions of applicability and applications of the four estimation methods. Diolaiti et al. [9] and Haddadi and Hashtrudi-Zaad [10], among others, argued that the H-C model is more than a classical linear model. It is more consistent with the contact physics model and is particularly suitable for describing the behavior of soft materials, such as human tissues, where the viscoelastic effect is significant. Mouri et al. [11] established a model of human skin muscle through the perception of impedance by the robot, and proposed a control strategy adapted to the change of human skin muscle. Hajimiri et al. [12] used the Hunt-Crossley nonlinear model as soft tissue model and a virtual reference trajectory is generated by online estimate of tissue parameter using smooth projection. During the robot's interaction with the human and the environment, the basic attributes of the environment (positional and material characteristics) can be made known [13], [14], [15], [16] by modeling the unknown environment. However, most of the researches are on environment modeling alone, and there are fewer researches on combining with the robot control strategy. In this paper, we adjust the corresponding control strategy by updating the soft and hard state of the contact tissue in real time, so that it can cope with the variable environment.

Another key to the realization of massage robots is interaction control, a massage robot control strategy that adaptively adjusts to the impedance of human skin muscles. Minyong et al. [17] proposed a hybrid position-based and force-based impedance control method using a manipulator with sensors to recognize human muscle impedance to determine the parameters of the impedance controller. Huang et al. [18] described the contact dynamics of a massage robot using a port- hamiltonian modeling approach, used a nonlinear Hunt-Crossley model to capture the intrinsic features of human tissues, and theoretically analyzed the coupled stability between the flexible robotic arm and the impedance control from an energy perspective. Duan et al. [19] formulated the adaptive impedance control framework as a secondary planning problem, where each objective is weighted by its task priority, and variable impedance gain is obtained by learning from the demonstrations of medical experts. Zhai et al. [20] integrating graph-based knowledge transfer learning into particle swarm optimization identification algorithm, and designing an adaptive impedance control algorithm to ensure accurate position and force control of massage robot. Xiao et al. [21] et al combined neural networks with the cross-entropy method to construct a reinforcement learning algorithm for impedance control parameter search. Amanhoud et al. [22] used dynamical system (DS) for real-time planning of the force and position of the manipulator while massaging the human arm. The above methods usually do not consider the influence of the shape of the curved surface of the human massage site on the massage motion process and the change of the human muscle tissue environment on the robot's contact force [23], [24], [25], which makes it difficult to realize the stable contact between the robot's massage end and the human tissues and the attitude adjustment. During massage, impedance control with adjustable impedance parameters allows the robot to be as compliant as a human arm when touching human bones or other disturbances, avoiding a greater threat to the people.

There are a variety of existing massage methods, considering the current patient's acceptance of massage robots, this paper focuses on the study of the push method, the reason is that the push method has a high frequency of use in many massage techniques; the push method requires more force and tends to cause muscle fatigue and joint abrasion for the massager; it has a high degree of repeatability and is highly replaceable. Push method of massage parts selected in the human back, because the back muscle tissue changes are more rich, contains a large gap between the thickness of the skin tissue layer, more massage acupoints, and the different distribution of bone. After studying the back push method, it is extended to other massage methods and other parts of the body by modifying the robot's movement path and force, with greater specific practicality and applicability. The main contributions of this paper are:

1) A massage robot scheme is proposed with a combination of a 7-DOF flexible robotic arm and an end tool, a human skin muscle model is established, and an online estimation method of the model parameters is designed, which is combined with a robot impedance control strategy.

2) To solve the problems of contact force and attitude adjustment of the massage robot, and to ensure that the force is stable and direction is vertical to the human body shape during the massage process, an adaptive force-position hybrid control strategy is proposed.

3) To adapt to the changes of human muscle tissue, fuzzy variable impedance control is proposed to adaptively adjust the impedance parameters according to the contact environment, and this control strategy greatly ensures the safety and stability of the massage robot system.

II. SYSTEM SETUP AND DEFINITION OF PUSH MASSAGE

A. SYSTEM SETUP

The massage robot system consists of three main components: the robot (Agile-7, Agile Robotics Co., Ltd., China), the back massage end-effector (self-designed), and the six-dimensional force/torque (F/T) sensors (KUNWEI, KUNWEI Technology Co., Ltd., China), as shown in Fig. 1. The robot control algorithm and data processing algorithms are implemented using C++ in linux Ubuntu environment on an Intel Core i7-12750H 2.60 GHz PC with 16GB RAM. The massage head is attached to the end of the robot via a customized adapter flange and the force sensor is installed between them to measure the contact force.

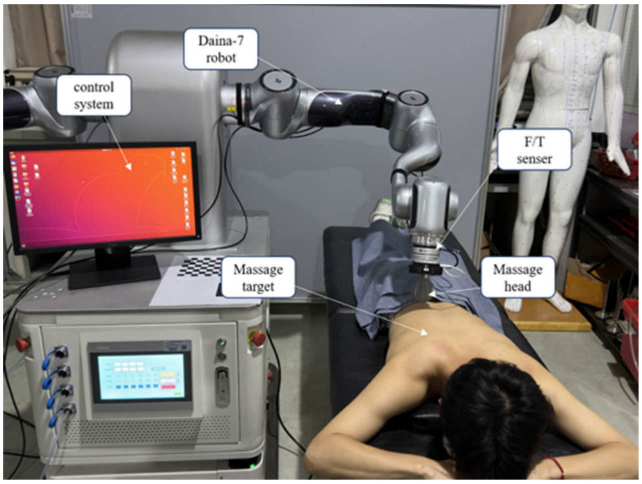

FIGURE 1. Massage robot system building.

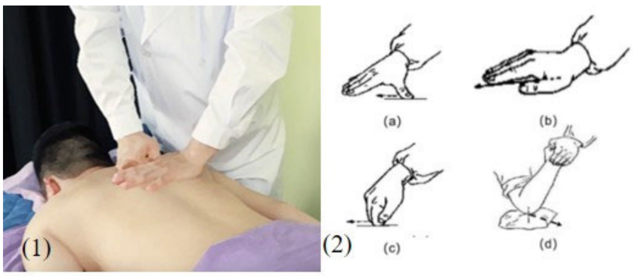

FIGURE 2. (1) Massage movements by massage therapists; (2) Massage methods: (a) thumb-push, (b) palm-push, (c) fist-push, and (d) elbow-push.

B. DEFINITION OF PUSH MASSAGE

There are several main methods in massage therapy: stroking, pushing, pressing and tapping. Each method has its own definition and purpose. For the purposes of this article, we will focus primarily on the push method. Pushing consists of thumb pushes, palm pushes, fist pushes and elbow pushes. Fig. 2 illustrates several different massage methods. Fig. 2(1) shows the massager making a fist with one hand and pushing slowly in the direction of the muscle fibers with the interphalangeal joints of the second, third, fourth, and fifth fingers, which is the more stimulating method of pushing massage. Its massage effect has the effect of relaxing tendons and activating collaterals, relieving stagnation, enhancing muscle excitability, promoting blood circulation and eliminating fatigue. At the same time, this method treats symptoms caused by meridian obstruction, such as nausea, vomiting and abdominal distension. When used on the chest, back and abdomen, it should be used in conjunction with breathing, with orderly intervals.

Therefore, summarizing the specific issues that need to be addressed in robotic massage: Perceiving the soft and hard state of the tissue in contact with the skin, which in turn adjusts the robot's control strategy; Adapts to changes in the softness and hardness of body tissues to maintain a constant massage force; Adjust the robot attitude so that the press force is vertical to the contact skin.

III. HUMAN MUSCLE TISSUE MODEL AND PARAMETER IDENTIFICATION

The working parts of the massage robot are the back, abdomen and legs, the skin muscle tissue of different persons or even the same person in different parts is significantly different, like athletes' muscle tissue will be harder than non-athletes', which will bring about two problems. First, massaging targets with different muscle tissue strengths requires different robot control strategies; second, human skin tissue is a more complex system with a high of uncertainty. In response to the differences of muscle and skin tissue, there is a need to ensure the versatility and adaptability of massage robots. Therefore, to improve the effectiveness of massage therapy and to satisfy the key points of the massage, real-time recognition of the human skin muscle tissue is necessary, and of course, good precision is required.

A. MODELING OF HUMAN MUSCLE TISSUE

A literature review [26] mentions that the Hunt-Crossley model has a more realistic behavior than other contact models. Hunt and Crossley also showed that location-dependent environmental damping models are more physically intuitive [27]. A detailed explanation of the Hunt-Crossley (HC) model consistent with the concept of the coefficient of recovery describes the energy loss during impact [8]. Thus, this nonlinear model can potentially improve the estimation of force and dynamic parameters, which in itself will improve the performance of many robotic, haptic, and tele-robotic tasks. However, fast and accurate identification of HC nonlinear models remains a challenge, and in real-time parameter estimation is more sensitive to the initial conditions of the parameters [10], and the control algorithm is prone to slow convergence, persistent excitation, and large computational effort. Therefore, in this paper, we consider a Kelvin-Voigt model with a quality factor and devise a method to adjust the forgetting factor following the change of force error. Its muscle tissue model is defined as follows:

$$F_e = M_e(\ddot{x}_e - \ddot{x}) + B_e(\dot{x}_e - \dot{x}) + K_e(x_e - x) \tag{1}$$

where F_e denotes the environmental force on the robot in the Z-axis direction, as obtained by the force/torque sensor; M_e is the mass factor, B_e is the damping factor, K_e is the stiffness factor; x is the real-time position of the robot end; x_e is the initial environment position, $\delta x = x_e - x$ is soft tissue deformation. Based on the literature [14] a bilinear transformation is used to transform (1) into the discrete time counterpart equation:

$$F_e = [M_e(\frac{2}{T})^2(\frac{1-z^{-1}}{1+z^{-1}})^2 + B_e(\frac{2}{T})(\frac{1-z^{-1}}{1+z^{-1}}) + K_e]\cdot \delta x \tag{2}$$

where T is the sampling period. By recognizing that z^{-1} represents a shift of one step in the time domain, and letting k describe the time-step index, the corresponding difference equation is:

$$\begin{aligned} &F_{e[k]} + 2F_{e[k-1]} + F_{e[k-2]} \\ &\quad = [M_e(\frac{2}{T})^2 + B_e(\frac{2}{T}) + K_e]\delta x_{[k]} \\ &\qquad + 2[K_e - M_e(\frac{2}{T})^2]\delta x_{[k-1]} \\ &\qquad + [M_e(\frac{2}{T})^2 - B_e(\frac{2}{T}) + K_e]\delta x_{[k-2]} \\ &\quad = L_1\delta x_{[k]} + L_2\delta x_{[k-1]} + L_3\delta x_{[k-2]} \end{aligned} \tag{3}$$

Equation (3) can be transformed into a regression function, which is based on a recursive least squares method [28].

$$\phi_k = \psi_k \Theta_k \tag{4}$$

where $\phi_k = F_{e[k]} + 2F_{e[k-1]} + F_{e[k-2]}$, $\psi_k = [\,\delta x_k \ \delta x_{k-1} \ \delta x_{k-2}\,]$, The performance index parameter that determines the muscle tissue parameters is $\theta_k = [\,L_1 \ L_2 \ L_3\,]^T$, establishing the minimum cost function is

$$\min J_k(\theta) = \min \sum\nolimits_{i=i_0}^{k} (\phi_k - \psi_k\Theta_k)(\phi_k - \psi_k\Theta_k)^T \tag{5}$$

Its parameter estimates are

$$\theta_k = \theta_{[k-1]} + K_k(\phi_k - \psi_k\Theta_{k-1}) \tag{6}$$

where K_k is the matrix of adaptive gain coefficients at moment k; P_k is the parameter identification covariance matrix at moment k, this formula are as follows:

$$K_k = \frac{P_{[k-1]}\psi_{[k]}^T}{\lambda + \psi_{[k]}P_{[k-1]}\psi_{[k]}^T} \tag{7}$$

$$P_k = \frac{1}{\lambda}(P_{[k-1]} - \frac{P_{[k-1]}\psi_{[k]}^T\psi_{[k]}P_{[k-1]}}{\lambda + \psi_{[k]}P_{[k-1]}\psi_{[k]}^T}) \tag{8}$$

B. ADJUSTMENT OF FORGETTING FACTOR

In the original parameter estimation algorithm, the forgetting coefficients are unchanged, which poses some problems. When the robot responds to rapid changes in the contact position or material, it can lead to a large change in the contact force, which can cause large errors in the parameter estimation system. Now, we hope the system to quickly forget this segment of data to avoid affecting the accuracy of parameter estimation in the next moment. The forgetting factor does not need to be large when the robot is stabilizing the contact, enabling the robot to continue to remain stable. For this purpose, the forgetting factor is dynamically calculated based on the error between the estimated and measured forces [9].

$$\lambda = 1 - \alpha_1(\frac{1}{\pi}\cdot \arctan(\alpha_2(\left|\phi_k - \hat{\phi}_k\right| - \alpha_3) + \frac{1}{2})) \tag{9}$$

where $\hat{\phi}_k = \psi_k\Theta_{k-1}$, α_1 represents the value of the forgetting factor for the maximum error; α_2 represents the magnitude of the transition zone; α_3 represents the threshold between the small and large error conditions. In particular, when the error is small, the forgetting factor is close to 1, indicating that the weight of the previous moment value on the system is large, while when the error is large, the forgetting factor decreases and the weight associated with the old sample decays.

IV. ADAPTIVE ATTITUDE REGULATION AND CONTACT FORCE CONTROL

At the beginning of the robot massage, position control method is used to control the robot to move downward until it touches the human skin tissue. After contact, the control system in the contact direction switches from position control to impedance control. During the massage process, the position controller achieves the tracking of the massage trajectory during the force control in the vertical direction of the body shape. In order to maintain the massage robot posture adjustment and stabilize the contact force, a force-position hybrid control framework is proposed based on the human muscle model and impedance control algorithm, as shown in Fig. 3.

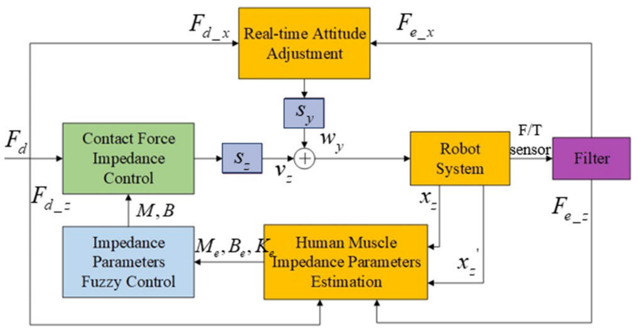

FIGURE 3. Adaptive hybrid force-position control strategy for massage robots.

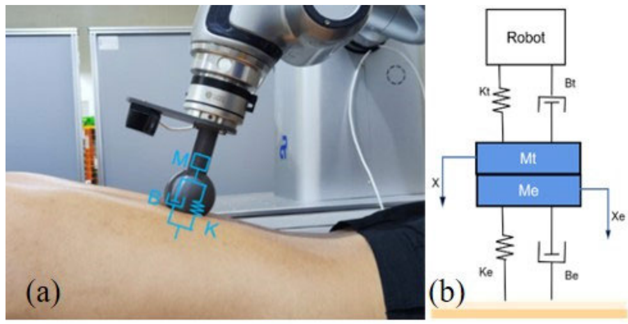

FIGURE 4. (a) System impedance modeling during robot contact; (b) Impedance model of contact between massage robot and human muscle tissue.

A. MODELING OF MASSAGE ROBOT-HUMAN CONTACT

The basis of robot-environment contact control is to establish a contact process model, the robot and the environment contact model are used in the mass-spring-damping model, the impedance model is shown in Fig. 4(a). In this part, position-based impedance control is used to accomplish the massage force tracking, and the robot environment contact model is established as shown in Fig. 4(b).

To achieve the contact force tracking control, a desired force F_d in the Z-axis is introduced, and the difference between it and the actual Z-axis contact force is obtained as $\Delta F = F_z - F_d$, A second-order dynamic relationship between the contact force error and the position error in the z-axis direction can be established:

$$M(\ddot{x} - \ddot{x}_d) + B(\dot{x} - \dot{x}_d) + K(x - x_d) = \Delta F \tag{10}$$

where x_d is robot desired position, M, B and K represent the mass, damping and stiffness coefficients of the robot control system. During the contact interaction, the robot's desired position is not available, so x_d is replaced by the initial environment position x_e, $e = x - x_e$, and $F_e = F_z$ in the system. The equation (1) can be put into equation (9) to obtain the following equation:

$$-M_e\ddot{e} - B_e\dot{e} - K_e e - F_d = M\ddot{e} + B\dot{e} + Ke \tag{11}$$

Since there is no need for the robot to have resilience force in the massage interaction. Therefore, the robot stiffness coefficient K was set to 0. The details of this can be found in [11] and [29]. This avoids the effects of unknown environmental positional, and can also greatly ensure the safety of people. Eq. (10) can be obtained after simplification and Laplace transformation:

$$s^2 + (M_e + M)^{-1}(B_e + B)s + (M_e + M)^{-1}K_e = 0 \tag{12}$$

1) DETERMINATION OF ROBOT IMPEDANCE PARAMETERS

In the robot-human back interaction, dynamic changes in organizational status, the relationship between the impedance parameters of the robot system and the tissue model is difficult to establish a specific mathematical model, but there is a corresponding trend of its change. Therefore, fuzzy control algorithms are used so that the mass and damping coefficients can be self-adjusted in real time according to different contact environment.

Based on the fuzzy control theory, the human muscle tissue model parameters: damping coefficient B_e and stiffness coefficient K_e are fuzzified to establish a dual-input and dual-output fuzzy controller.

First, the fuzzification of variables. Let the range of values of B_e be $[B_{e.\min}, B_{e.\max}]$. Define the fuzzy set of the human muscle tissue model parameters B_e and as {NB, NS, ZO, PS, PB}; Let the range of values of K_e be $[K_{e.\min}, K_{e.\max}]$. Define the fuzzy set of the tissue model parameter K_e as {NB, NS, ZO, PS, PB}; Similarly, the quantization level of the system U has fundamental domain $[-2, 2]$ and the fuzzy set as {NB, NS, ZO, PS, PB}.Choose a Π-type membership function for the rectangular distribution.

Second, a fuzzy control rule table is created. Designing impedance controllers in which the mass coefficient M and damping coefficient B vary with the environmental parameters of muscle tissue (K_e, B_e) as fuzzy inference rules, obtain a deterministic relationship between the fuzzy control inputs variate and the quantization level of the system control quantity U. The discrete control method is used to establish the fuzzy rule table as follows:

Finally, defuzzification. Setting the true adjustment range $([M_{\min}, M_{\max}], [B_{\min}, B_{\max}])$ of the output variables (M, B). The mapping of the mass and damping coefficients in the fuzzy output quantities corresponding to the actual demand range is given in (13)(14), where n = 1.

$$B = \frac{B_{\min} + B_{\max}}{2} + \frac{B_{\max} - B_{\min}}{2n} * U \tag{13}$$

$$M = \frac{M_{\min} + M_{\max}}{2} + \frac{M_{\max} - M_{\min}}{2n} * U \tag{14}$$

2) STABILITY OF THE CONTROL SYSTEM

The robot impedance model established by the equation (10) is a second-order system, and system damping coefficient

TABLE 1. Fuzzy logic rules.

B_e、K_e、U	NB	NS	ZO	PS	PB
NB	NB	NB	NS	NS	PS
NS	NB	NS	NS	ZO	PS
ZO	NB	NS	ZO	PS	PB
PS	NS	ZO	PS	PB	PB
PB	NS	ZO	PS	PB	PB

determines the response and oscillation form of the system, and to establish the undamped frequency and damping ratio as follows:

$$w_n = \sqrt{(M_e + M)^{-1} K_e} \tag{15}$$

$$\xi = \frac{B_e + B}{2\sqrt{(M_e + M)K_e}} \tag{16}$$

When $\xi = 1$, the system is in a critically damped state, the system just does not oscillate. In order to ensure the stability and safety of the interactive system, the damping ratio should be maintained at all times at not less than 1.

B. HYBRID FORCE-POSITION CONTROL STRATEGY FOR MASSAGE ROBOTS

This paper considers the two dimensions of force control in the z-axis direction and attitude control around the y-axis direction. The control actions are decoupled in the coordinate system of the end-effector. The contact force F_z is used as feedback of the controller to adjust the contact depth, and the lateral forces F_x are used as feedback of the controller to adjust the normal orientation, as shown in Fig. 3.

1) STABILIZATION OF CONTACT FORCE CONTROL

The unstable contact force at the end of a massage robot is mainly caused by changes in the mechanical characteristics of human muscles and the position of the skin surface. Impedance control algorithms can be well suited for contact interaction force control at the massage robot. During the contact between the massage robot and the environment, we only apply the force to the human muscle normal direction, and at the same time, the information of each dimension is decoupled under the Cartesian space, so only the impedance model in the direction of single degree of freedom is considered here, and the force tracking error is shown as follows:

$$m(\ddot{x} - \ddot{x}_e) + b(\dot{x} - \dot{x}_e) + k(x - x_e) = f_e - f_d \tag{17}$$

where $f_e - f_d$ is the error between the robot's true contact force and the desired contact force, x and x_e represents the robot's true position and environmental position, where the stiffness coefficient is 0, the speed control output of the z-axis can be expressed as:

$$\dot{v}_z(k) = (\ddot{x}_e(k) + (\Delta f - b\dot{x}(k)))/m \tag{18}$$

$v_z(k)$ can be obtained by integrating $\dot{v}_z(k)$ over time (period t), the stabilization of the contact force in the axis direction will be controlled by $v_z(k)$.

2) ADAPTIVE ATTITUDE ADJUSTMENT

When the human body lies on the massage bed, the back usually has a large surface curvature, causing the robot to form a human skin buildup in areas with rapid curvature changes, such as the waist, as shown in Fig. 5(a). This leads to a greater forward resistance and also causes some difficulty in stabilizing the robot for contact. Therefore, the massage robot attitude is designed to adaptively follow the back surface changes. As shown in Fig. 5, the comparative effect of the massage robot attitude before and after adjustment within the sagittal plane of the human body is demonstrated.

During the movement of the end-effector, $\Theta_y \neq 0$, $F_x \neq 0$, the direction of movement does not change. At this time, the robot is subjected to forward resistance F_{f2}, the robot's forward direction is changed by adjusting the attitude to deflect in the y axis, the forward resistance is mainly sliding friction F_{f1}.

$$w_y = \frac{F_x - F_f}{F_z} \cdot t \cdot \beta = C_y \cdot \frac{F_x - F_f}{F_z} \tag{19}$$

where, F_f is the sensitivity of robot attitude adjustment, t is the robot control period, and β is the attitude deflection damp factor, which affects its rate of change.

3) SECURITY POLICY PROTECTION

Since the object of massage is the human body, the safety strategy of the massage robot is a must. During the massage process the person's body will move or change, the adaptive hybrid force position control can well control the massage position and adjust the massage force. It is not desirable to adopt the same impedance control parameter for different states of muscle tissue. In practice, the massager will also judge the softness and hardness of the muscle by the feel of the hand and make a suitable choice. The advantage of adaptive fuzzy impedance control is to give the massage robot a better safety performance.

V. RESULTS OF THE EXPERIMENT

A. VALIDITY OF PARAMETER ESTIMATES

The reference input force was given by the massager wearing thin-slice sensor measurements, in which 30 testers were selected for force data acquisition and massage muscle parameter estimation tests, Body mass index (BMI) in the range [24, 18.5]. The final choice was to set the desired force to 13 N, parameter estimation was performed 1s from the beginning of the massage (the robot was not in contact with the environment for the previous second). α_1, α_2 and α_3 in the formula of variable forgetting factor respectively are 0.08, 0.2 and 8. The experimental time was 10 [s] and the sampling time was 2 [ms]. Fig. 6 shows the measurement locations for measuring the impedance of the human arm (a) and hand

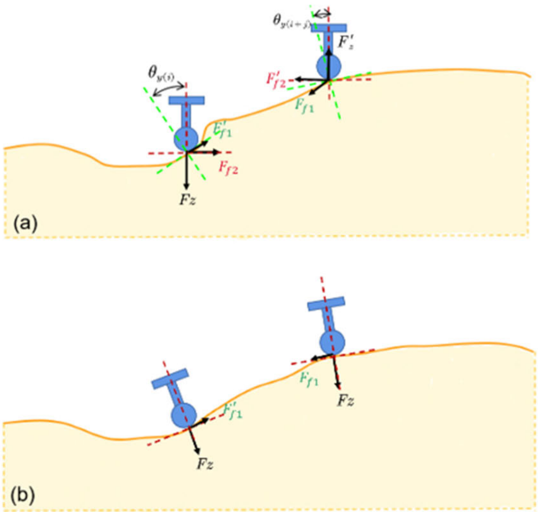

FIGURE 5. Force diagrams of the human body and massage head without postural adjustment (a) and after postural adjustment (b).

(b). The estimated parameters of human muscle tissues under different parts of the body are shown in Table 2. Fig. 7 shows the identification experiment of arm muscles, where the force error represents the comparison between the observed values in the real experiments and the estimated values calculated form model of Equation (1) using the estimated parameters. Final identification results have a mean error of 0.3406 N and Relative Root Mean Square Error (RMSE%) value of 9.6041, which can satisfy the basic level of identification.

As shown in Fig. 8, the same recognition procedure as before was used, with the difference that after 12 seconds of recognition in the first body part, the robot quickly moved to the second part for another 12 seconds, obtaining in the model's online parameter identification experiment for the different contact tissues. It can be clearly seen that the parameter of the model identification is dynamic and converges to a level corresponding to when the robot touches each tissue individually, and that the previous estimation does not affect the final value. Comparing the results of online identification with and without adaptive adjustment of the forgetting factor, the former can rapidly converge within 2 s when changing the contact part, and the maximum force error during the period is 3 N, and then stably stays within 1 N after that.

B. VALIDITY OF SURFACE NORMAL ADJUSTMENT

This experiment is carried out using the force-velocity hybrid control strategy described in Section IV, The initial parameters of the impedance controller were set to mass factor $M = 1.0\ kg$, damping factor $B = 340\ Ns/m$, stiffness factor $K = 0\ N/m$, and $C_y = 0.05$. The robot moves along the massage path with or without normal adjustment and the experimental results are shown in Figs. 9-11. The required contact force is set to 13N, the force sensitivity on the X-axis is 1.3N (set according to the actual situation), and the X-axis massaging

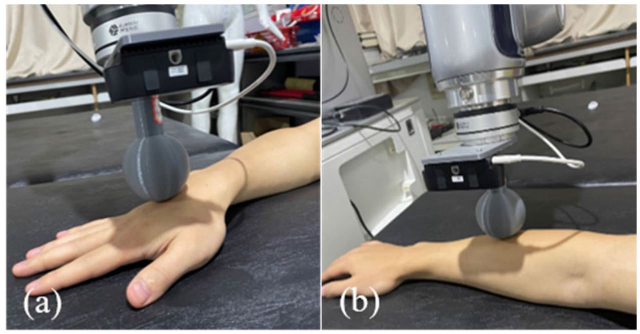

FIGURE 6. Selected locations for parameter estimation of human muscle tissue models. (a) is the hard part of the hand and (b) is the soft part of the human arm.

TABLE 2. Table of tissue model parameters for different parts of the human body.

test parts	M_e	B_e	K_e
Harder muscle parts	0.0070	4.3869	671.5814
Softer muscle parts	0.0053	1.5847	376.7202
bony parts	0.0112	6.4894	1185.653
arm muscle	0.0064	1.9795	539.4812

speed is set to 20mm/s. From Figs. 9 and 10, it can be seen that in the flat (before 3s of robot motion) region, the force in the X-axis direction has a small force error, regardless of whether the force is adjusted or not. When the robot reaches the lumbar region, the force without attitude adjustment increases rapidly because of the soft human musculature in this region, which generates a high forward resistance due to the constant skin buildup. The advantage of our proposed normal probe orientation adjustment is evident in steep areas, where tissue thickness is different at different locations, the adjustment can make it easier for the robot to leap over these areas. When $F_d = 13N$, the forward resistance is large without adjustment, with a maximum of -10.56 N along the X-axis and -2.94 N after orientation adjustment; The average force error in the X-axis respectively are -5.74 N and -1.32 N. The lateral maximum force tracking error was reduced by 73.2% and the average force error was reduced by 73.1%. When $F_d = 7N$, the maximum forward resistance is -1.61 N and the average force is very small after orientation adjustment. In Fig. 8. it is seen that the resistance of the lumbar region better when the expected force is larger, with better advantage. From Fig. 12, it is demonstrated that the proposed massage robot end orientation adjustment controller maintains the normal direction when interacting with human skin. Combined with Table 3, the axial force on the human body is obviously reduced after the addition of adaptive attitude adjustment.

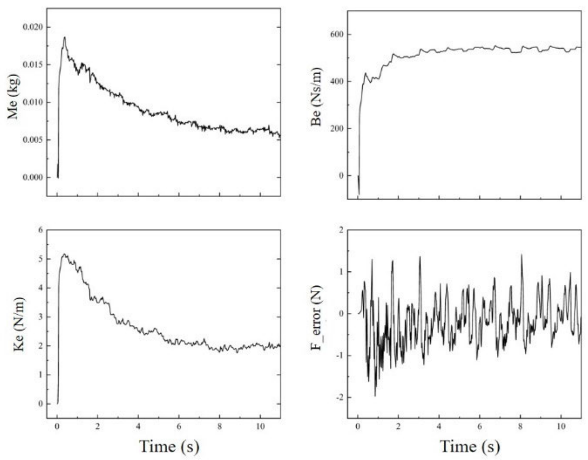

FIGURE 7. Experimental result of model parameters at arm muscles.

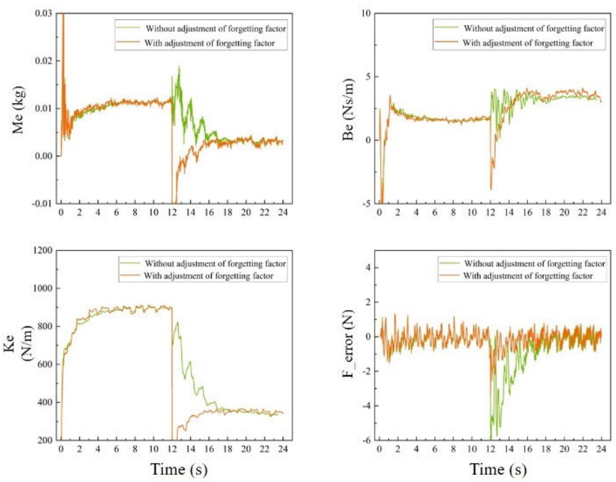

FIGURE 8. Experimental result between two different tissues in the human body.

TABLE 3. Optimization effect of X-axis force under different massage forces.

	X-force	pre-adjustment	after adjustment	effect
Max_F	$F_d = 13N$	-10.56 N	-2.94 N	73.2%
Ave_F		-5.74 N	-1.32 N	73.1%
Max_F	$F_d = 7N$	-5.03 N	-1.61 N	68.0%
Ave_F		-2.19 N	-0.59 N	73.1%

C. EFFECTIVENESS OF CONSTANT CONTACT FORCE ON HUMAN SURFACES

A path on the back of the human body was chosen to verify the effectiveness of end force contact stabilization of the massage robot, as shown in Fig. 12. The initial parameter settings of the impedance controller are the same as in the previous section, and the stabilizing force control experiments

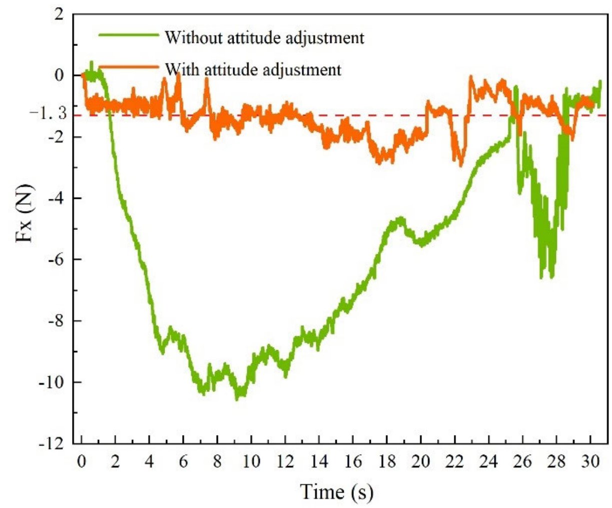

FIGURE 9. Posture adjustment effectiveness experiment, X-axis force tracking performance when $F_d = 13N$.

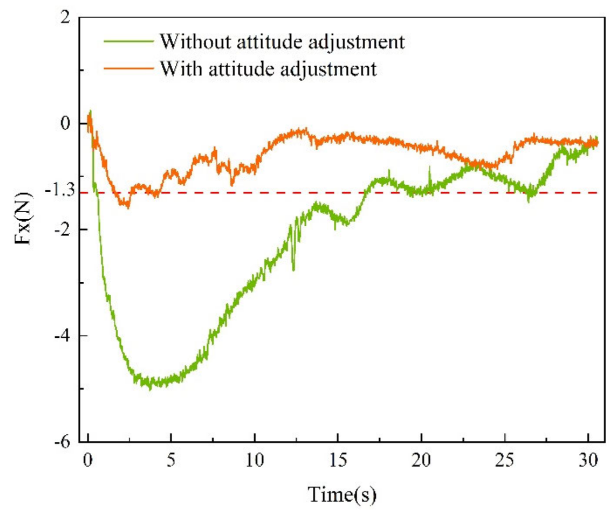

FIGURE 10. Posture adjustment effectiveness experiment, X-axis force tracking performance when $F_d = 7N$.

respectively are performed on the paths with and without adaptive parameter adjustment. Figs. 13 and 14 shows the contact forces recorded in the comparison experiment. Massage contact force errors with and without adaptive parameter adjustment were similar in initial regions where human skin tissue changes were small. However, the method in this paper is superior in the area of muscle-bone changes in the upper back (scapular region) and at the ribs below the scapular region. When $F_d = 13N$, the maximum contact force error for the unadjusted impedance parameter was 5.97 N, with an average error of 1.27N. And the maximum contact force error after adaptive impedance parameters is only 2.04N, and the average error is 0.21N. In comparison, the stabilized contact force control reduced the maximum contact force error by 66.8% and the average error by 83.5%. Similarly when $F_d = 7N$, the maximum error is 0.96 N and the average error is only

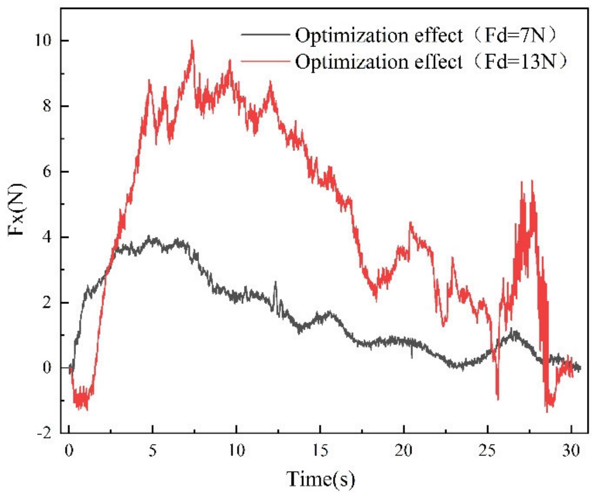

FIGURE 11. Comparison of x-axis force tracking optimization effect under different desired forces.

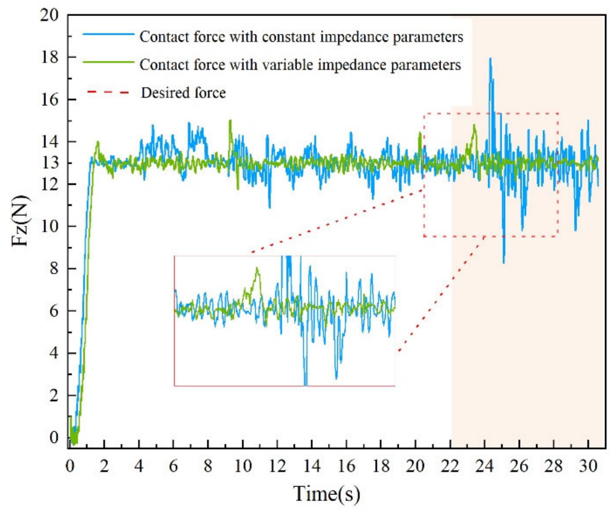

FIGURE 13. Contact force tracking performance when $F_d = 13N$.

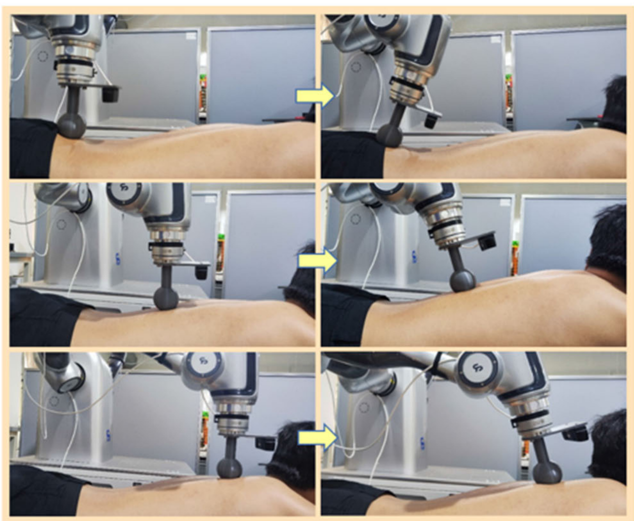

FIGURE 12. Attitude adjustment comparison graph.

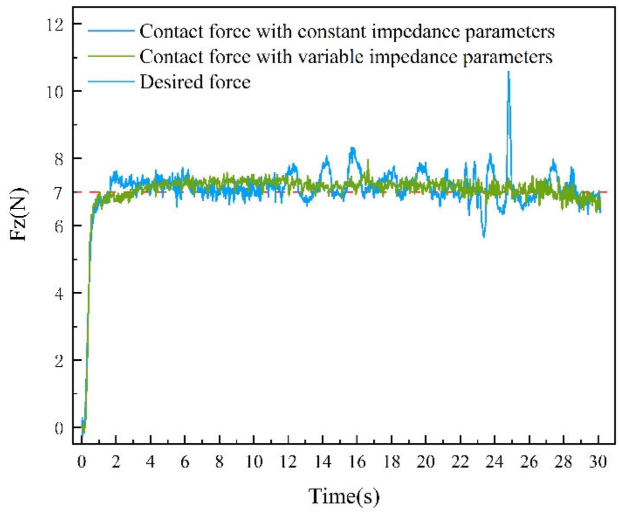

FIGURE 14. Contact force tracking performance when $F_d = 7N$.

0.27 N after adjustment. In Fig. 15 it is seen that the algorithm performs better when the expectation force is larger. These results validate the robustness of our proposed fuzzy adaptive force control under different tissue characteristic and external disturbances.

Adjustable impedance parameters are necessary. Tested through experimentation, if the impedance control is not adjusted with variable impedance parameters, the tracking force value can reach a maximum of about 30N, and the value will also increase with the increase of the desired force, which will cause great harm to the human body. Therefore, we have established an impedance control algorithm with adaptive impedance parameter adjustment so that the robotic arm always maintains the adaptability of the human environment, the constant force tracking requirement, and most importantly the full assurance of massage safety requirements.

VI. CONCLUSION

In this study, a human-massage robot interaction fuzzy adaptive impedance control system based on the Kelvin–Voigt model is proposed, which is able to cope with different massage parts of different massage subjects. For the unknown human muscle tissue state, a human muscle tissue model is introduced, which is used to sense skin muscle softness and hardness by online identification of model parameters. The fuzzy logic system of the muscle tissue model and contact dynamics model was established to solve the problem that the impedance controller parameters are difficult to determine when the robot massages the human body. To make the robot satisfy the massage demand, an adaptive force-position

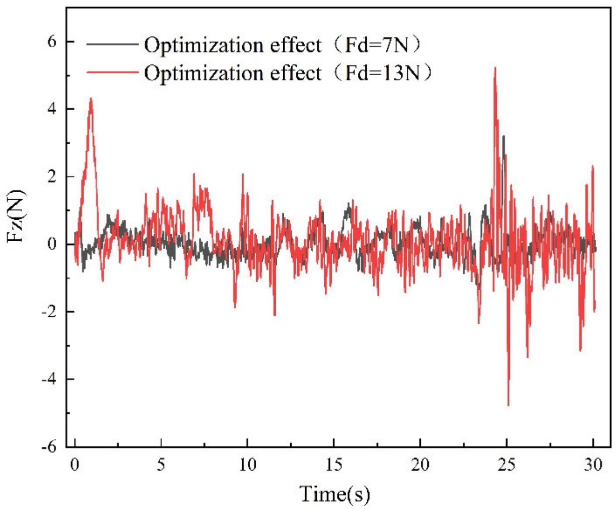

FIGURE 15. Comparison of z-axis force tracking optimization effect under different desired forces.

hybrid control strategy is proposed to keep the massage path of the massage head with normal attitude and constant contact force. Meanwhile, the adaptive control strategy adopted in this paper significantly enhances the safety during the contact task and satisfies the force requirements of different parts of the robot. The effectiveness and feasibility of a hybrid force-position control massage system adapted to the variation of human skin-muscle stiffness has been verified through experiments on the control system of a massage robot. Later, the end structure can be redesigned and generalized for use in other massage and physiotherapy robots as well as surgical robots.

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