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Preliminary Study in Motion Assistance of Soft Exoskeleton Robot based on Data-driven Kinematics Model Learning

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***Abstract* - Exoskeleton is widely used to enhance human mobility. Especially in recent years, the soft exoskeleton robots have developed rapidly, which could realize natural human-machine physiological coupling. However, the motion patterns and physiological parameters are significant various between different subjects. The parameters of the soft exoskeletons change differently during motion. In this paper, we proposed kinematics model based on data-driven model learning. The proposed model learning method not only has the fast learning ability of model-based controller, but also has the adaptability of sensor-based controller. Firstly, we use the data of the rigid model to pre-train the kinematics model network, which can make the output of the network consistent with the kinematics model. Then, we use the sensors to collect the actual motion data and send the motion data into the pre-trained neural network model. By increasing the iteration times of training, the network model outputs model parameters that are consistent with the trend of the simulation model. Through the training and learning of the bionic motion platform, the speed of learning adaptation in human body can be accelerated.**

Index Terms-Bio-Inspired soft exoskeleton robot, Personalized assistive strategy, Data-driven, Model-based learning

I. INTRODUCTION

The hard exoskeleton structure of animals like shrimp and crab can effectively protect its own security and enhance sports ability. Inspired by these exoskeleton structures, the exoskeleton robots are designed with bionic design, which intended to improve human locomotor performance [1], lower the energy expenditure of human walking [2-4] and assist the rehabilitation of stroke patients [5, 6]. Exoskeleton can be divided into rigid exoskeleton and soft exoskeleton according to structural materials [7, 8]. The initial researches of exoskeleton robots were on rigid exoskeleton, which have the characteristics of structural stability and large load capacity. However, the application and development of rigid exoskeletons are restricted by the problems of misalignment of human-robot motion axes [9, 10], poor dynamic response and lack of intrinsic safety. Therefore, more and more researchers have carried out the research of soft exoskeleton robots using soft materials in recent years. Soft exoskeleton robots [11], like clothes, are attached to the human to assist the wearer which has the advantages of being portable and not restricting the natural movement of the human. Therefore, the motion parameters of the soft exoskeleton robot are affected by the wearer's own motion parameters. As we all know, everyone has different sports habits and parameters and may change over time [12]. Meanwhile, wearable robots such as soft exoskeleton robots need to cooperate with the motion system of human. Hence, exoskeleton robots need personalized assistance according to the motion parameters and habits of wearers to adapte themselves to the level of the skill of the wearers improve the assisting effect and human-machine compatibility.

There have been some successes in personalized assistive strategies for assistive robotics, including exoskeleton robots and prosthesis [13]. At present, the main of these studies are via model-based and sensor-based controllers with physical human-robot interaction (HRI). However, these studies lack the input of prior experience and the optimization of model-based in kinematics. Some researchers use model-based

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controllers of traditional control theory to solve the problem. The soft exoskeleton glove consider its HRI to match hands of different sizes and shapes by establishing a human-robot hybrid model to control of the robot. [14]. However, in many cases, it is difficult to establish a human-computer hybrid model, especially for the soft exoskeleton robots with nonlinear time-varying model. The sensor-based controllers of HRI data-driven approach could avoid this problem. The ankle exoskeletons explored effectively the different gait parameters during a variety of conditions, including walking and running for optimizing muscle activity and lower the energy economy optimization [1]. Later, researchers applied similar ideas to a soft exoskeleton of hip joint [15, 16]. The human-in-the-loop (HIL) algorithm is used to assist different motion modes, which achieves better assistant effect than before. The decline margin of energy consumption increases by more than 10% compared to no torque. Some other researchers use the idea of learning to solve this problem. A data-driven learning approach of assistive strategies for the elbow exoskeleton robot from human-robot interaction [17]. Their method could explore proper assistive strategies that with only 60 seconds of the bidirectional HRI based on the reinforcement learning. The reinforcement learning method has also achieved good results in adjusting the motion control parameters of the robot to adapt to different individuals in an average of 300 gait cycles or 10 min of motion [18]. They first proposed the ADP method to realize the clinical application of individualized assisted robotic prosthesis. Soft exoskeleton robots are attached to the human surface, whose motion parameters are affected by the individual differences of the wearer. Meanwhile, the complexity of the human is too vast to accurately predict the response to a novel assistive device. However, these above methods have not been thoroughly studied on the kinematics parameters and deformation of soft exoskeleton, which will affect the control accuracy and assistant effect of soft exoskeleton.

In this paper, we proposed personalized motion assistance strategy based on model-based learning to combine the advantages of sensor-based and model-based controllers, which aims to handle varying interaction kinematics of soft wrist exoskeleton robot. This control strategy is based on rigid kinematic model, and combined with HRI sensor data for learning, which plays a priori knowledge role in the adaptation process of soft exoskeleton robot and can accelerate the learning process. In other words, the assistance strategy not only has the fast learning ability of model-based controller, but also has the adaptability of sensor-based controller. We use artificial neural network (ANN) to study the rigid kinematics model. The output of the network is highly similar to the actual kinematics model. Then we use the inertial measurement unit (IMU) to collect the motion data of the robot, and learn and adapt the kinematics model of the robot based on the motion data. Based on the rigid model and the learning of the motion data, the difficulty of obtaining kinematic parameters and the uncertainty caused by the deformation of the soft materials during the movement can be solved.

II. METHOD AND MATERIAL

A. Bionic Design of Hardware Platform

Human joint movement is the rotation of joint caused by muscle contraction. Wrist joint is an important joints at the end of human body. Especially for stroke patients, rehabilitation medicine shows that the closer to the trunk end of the joint, the greater the difficulty of recovery. At present, the traditional wrist exoskeleton has a large structure and complex design. It can only provide rehabilitation training and can't realize daily activities. A portable and wearable wrist exoskeleton can quickly acquire motor ability, provide life confidence and self-care ability before patients recover their wrist ability. So the wrist exoskeleton robot was chosen as a platform to validate the algorithm.

First of all, the musculoskeletal model of wrist was anatomically analyzed. There are mainly six muscles[10]: ulnar flexor carpi (UFC), radial extensor carpi longus (RECL), radial flexor carpi (RFC), ulnar extensor carpi (UEC), palmar longus (PL) and radial extensor carpi brevis (RECB). The main functions of wrist joint in 2-DOF movement are: UFC, RECL, RFC, UEC. And, the tension lines are arranged according to the corresponding position and distribution of muscles to achieve good human-robot coupling. When the muscle loses the motion ability, the limbs could be driven by the external power of robots.

(a) (b) (c)

Fig. 1 (a, b) the corresponding diagram of human musculoskeletal model and robot; (c) three different sizes of motion platforms.

Human skin is a soft structure, which can protect and buffer human body. In order to better adapt to the human body, the structural parts of the robot are made of commercial protective materials (McDavid, Woodridge, Illinois, USA), which have good wearable comfort and ergonomic coupling. The tension lines adopted the nylon wires with flexibility and tensile strength. The driver part circuit was designed based on the Ethecat bus protocol. The driving force output system adopts Elmo driver to drive DC motor (Maxon Motor Ag., Sachseln, Switzerland), and the position of motor shaft are measured by the absolute value encoder (Scancdn Industrial Encoders., Huginsvej, Denmark). In order to represent people with different body parameters, we used the same principle to create three different sizes of motion platforms representing three different heights of human bodies, as shown in Fig. 1 (c).

B. Bionic Kinematics Model

The system adopts the bionic skeletal muscle tension line drive mode, which is different from the traditional mechanical arm motor direct drive joint. The traditional articulated robot controls the task space based on the DH kinematics model. However, the tension lines of the soft exoskeleton are across the degree of freedom (DOF). By controlling the length of the tension lines, the wrist joint angles can be controlled. Then, the position and hand could be adjusted via joint angles based on the DH model. Thus, the kinematics under muscle-like configuration is finally realized.

The Kinematic characteristics of wrist joint include two DOFs [19]. The specific layout is as follows:

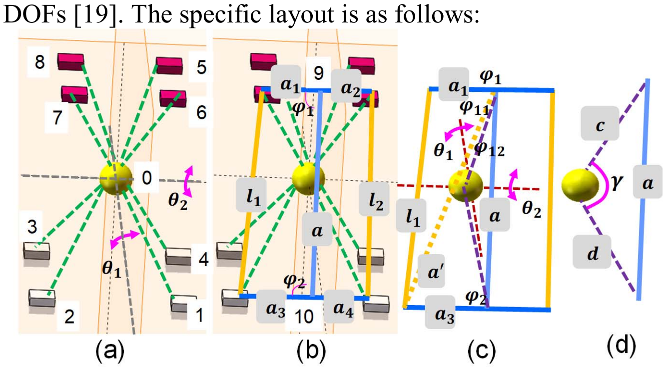


Fig. 2 (a) Bionic configuration diagram; (b) Connection diagram under bionic configuration; (c) Configuration diagram of pull point of front view; (d) Rotation center connection of side view. The dotted green line represents the line from the center of rotation to the tension line; The orange line represents the tension line.

TABLE I
SYMBOLIC INDEX IN THIS STUDY

Symbol	Elucidation
Point 0	Wrist rotation center
Points 1-10	The end points of tension lines
Line l_{1-2}	Two tension lines in front of the wrist
$a_{,1-4}$	The lines connecting two points
φ_{1-2}	the angle of the sagittal line and the connecting lines
θ_{1-2}	Two DOFs angle of wrist joint
c, d,	The connection of the intersection point of sagittal plane of wrist joint with the center of rotation
γ	Inclusion angle of sagittal intraplane intersection of wrist joint

Because the configuration of the four tension lines is similar, we take l_1 as an example to solve the relationship between the tension lines and the joint angles. The length of tension line l_1 was obtained from Fig. 2.

In Fig. 2 (c), l_1 can be obtained by using geometric relations through two triangles composed of l_1, a_1, a', a_3 and a. Meanwhile, according to the geometric relationship of Fig. 2 (d), a can be obtained from c, d and γ. φ_2 and γ are related to θ_1 and θ_2, respectively, and other length values are measured according to the initial values.

C. Motion Test of Bionic Platform

In order to better verify the kinematics model and collect motion data, the motion tests of the motion platform were carried out. The single DOF motion and circular motion were carried out. The specific movement process was smooth, and the 2 DOFs motion could be completed successfully. The ulnar flexion and radial flexion motion showed the movement process as Fig.3.

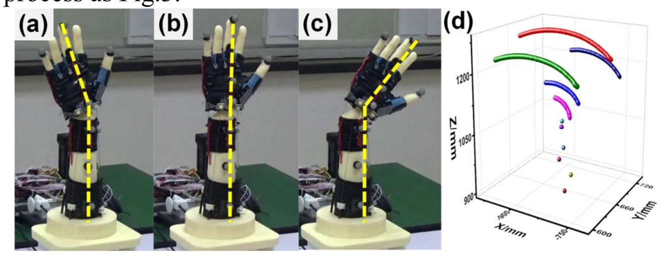


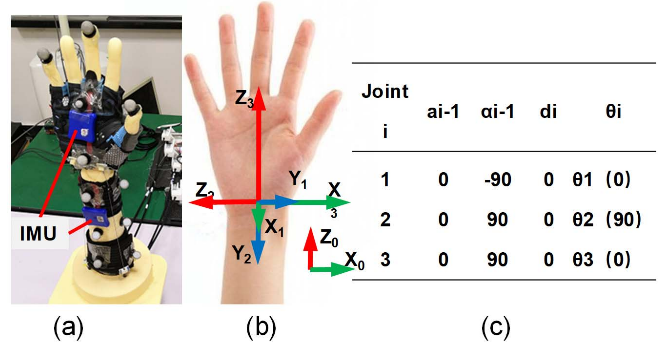
Fig. 3 (a-c) Radial and ulnar flexion of motion model; (d) Vicon collects motion data and reproduces trajectories.

The trajectory that the motion process is smooth and there is no carton phenomenon. The range of motion satisfies the requirement of human daily life, and can be used for daily wear.

D. Data Acquisition

a) Simulation Data Extraction: The above-mentioned bionic kinematics model is based on rigid kinematics. Firstly, we use software to collect the simulation data, obtain the initial data, and pre-train the later learning model, which can speed up the learning process of the actual motion data.

b) Simulation Data Extraction: We use the Inertial Measurement Unit (IMU) to collect the actual motion data. Two IMUs are placed on the hand and forearm respectively. By calculating the rotation angles between the two IMUs, the angles θ_1, θ_2 of the two DOFs can be obtained.



Joint i	ai-1	αi-1	di	θi
1	0	-90	0	θ1 (0)
2	0	90	0	θ2 (90)
3	0	90	0	θ3 (0)

Fig. 4 (a) Data Acquisition Platform with IMU; (b) The model of the wrist with the DOFs; (c) DH Kinematics Model Parameters.

Firstly, we build the model of the wrist joint to solve the relationship of the two angles of IMU, as shown in Fig. 4. Then we use the rotation matrix between wrist angles and the quaternion returned by two IMU sensors to calculate the angles θ_1, θ_2 as shown in Equation (1, 2).

$$R = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix} \quad (1)$$

$$R_1^{-1}R_2 = {}_3^0T = \begin{bmatrix} c_1c_2c_3 + s_1s_3 & -c_1c_2s_3 + s_1c_3 & c_1s_2 & 0 \\ s_2c_1 & -s_2s_3 & -c_2 & 0 \\ -s_1c_2c_3 + c_1s_3 & s_1c_2s_3 + c_1c_3 & -s_1s_2 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (2)$$

In Equation 2, $c_x = \cos\theta_x, s_x = \sin\theta_x, x = 1,2,3$.

E. Data Training Framework for Kinematics Model

The kinematics of rigid exoskeleton structure is modeled above. There are many parameters involved, the measurement error of which increases the uncertainty of the model. In addition, the kinematics parameters of each wearer are different, so it is very difficult to measure each wearer in advance. At the same time, the errors deformation and position movement caused by soft material during motion are difficult to model with conventional methods. The artificial neural network (ANN) has regression characteristics and can accurately fit complex functions. Therefore, we set up a multi-layer neural network to learn and train motion interaction data of the wearers, and obtain the individualized auxiliary parameters for different individuals. Schematic diagram of our approach is shown in Fig.5.

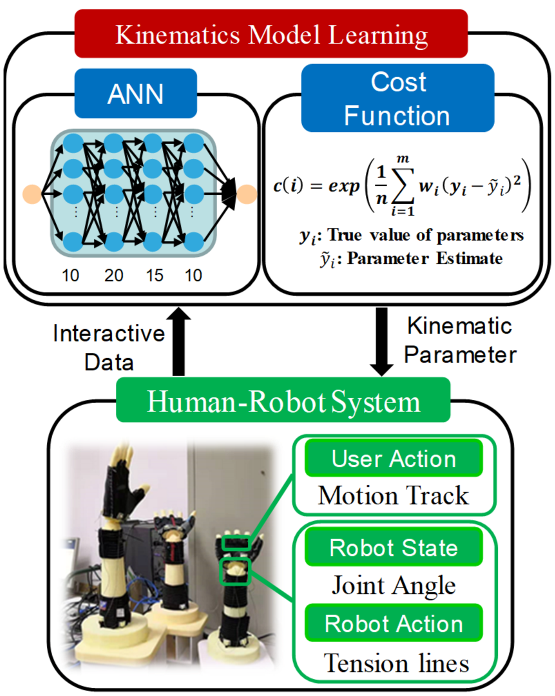


Fig. 5 Schematic diagram of kinematics model parameter training and learning framework

The exoskeleton robot is physically coupled with the wearers. We formulated kinematics model parameter training and learning framework based on human-robot integrated system and joint angles cost function and adopted ANN to Learning and adapting to different individual specific kinematics models.

III. RESULT

A. Training Results of Simulation Model Data

The rigid kinematics model established before can be used as a model reference for the generation of kinematics parameters of soft exoskeleton, which has two specific functions: 1) The established mathematical model can generate simulation motion data, which can be used to pre-train the learning network to improve the adaptability of the learning network to actual motion data; 2) The rigid kinematics model can play a guiding role in the movement of the soft robot, which enables the soft exoskeleton to achieve preliminary motion without obtaining a complete and accurate kinematics model, so as to achieve the acquisition of its motion data. Therefore, we first collect the kinematics data generated by the rigid model, and use these simulation kinematics model data to pre-train the learning network. Each individual has its own kinematics surface, so here we take the fitting of kinematics surface as an intuitive measure of learning effect. The network learning effect of simulated motion data is shown in Fig. 6.

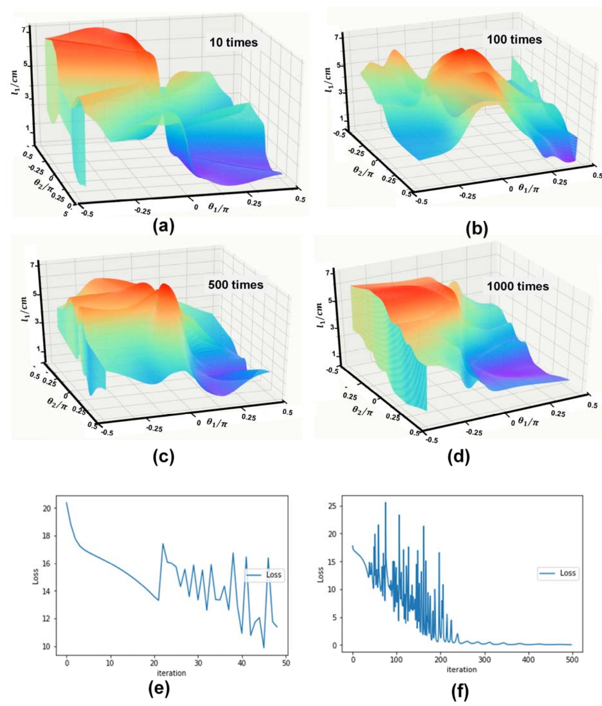


Fig. 6 Network learning of kinematics model parameters based on simulated motion data. (a-d) The change of kinematics model surface with the increase of training times; (e, f) Loss value decreases with training times; The horizontal axis shows a value every 10 training sessions.

From the figure 7, it can be seen that with the increase of training times, the neural network model can fit the ideal kinematic surface well, and the loss value decreases obviously, which also proves the effectiveness of the training model.

B. Training Results of Actual Motion Data

After completing the training of simulation data, we carried out the training of actual motion data. The joint motion angle of exoskeleton is obtained by IMU, and the stretch line is obtained by motor encoder. We collect the movement data in the actual movement process and send it into the training network model. The specific training results are shown in Fig. 8.

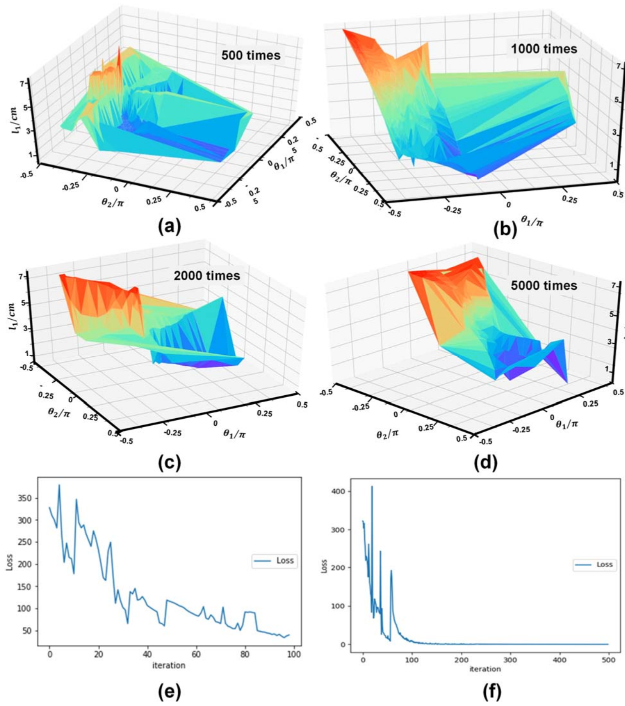


Fig. 7 Kinematics model training based on actual motion data. (a-d) The change of kinematics model surface with the increase of training times; (e, f) Loss value decreases with training times; the horizontal axis shows a value every 10 training sessions.

As shown in Fig. 7, it can be seen that the kinematics model surface of the soft exoskeleton gradually approximates the kinematics model with increasing the number of training, which proves the validity of the learning process. However, due to the deformation and movement of soft structure, there are differences between the real kinematics model and the rigid kinematics model, so the output surface of learning network is uneven. Meanwhile, due to the limitations of less actual motion data and sensor measurement errors, the instability of the kinematics model surface of the network is also aggravated. So in the next work, we will improve the method of data acquisition, improve the quality and quantity of sensor data, and improve the learning effect by generating countermeasures network.

IV.CONCLUSION

In this study, we proposed motion assistance strategy based on data-driven kinematics model learning by artificial neural network. Different wearers of exoskeleton robot have their own unique kinematic parameters and models. And, the deformation and movement of soft materials aggravate the uncertainty of individual kinematics model, which seriously restrict the practical application of soft exoskeleton robots. The proposed data-driven kinematics model learning method based on rigid model has the following two advantages: 1) *combining the advantages of accurate control of model reference controller*: the rigid kinematics model can be used to pre-train the training learning model. At the training stage of data acquisition, it could also play a guiding role in the trend of robot motion; 2) *having the adaptability of the motion of the robot based on the learning network*: the sensor-based control method could increase the adaptability of the model by data-driven, especially it can solve the uncertainty kinematics model of the soft structure. We train the simulation data and the human-robot interaction motion data through neural network to fit the kinematics model. The preliminary results show that the network output model can match the expected kinematics model well, which proved that the model-based learning model could realize the learning of the kinematics model of the soft exoskeleton robot, so as to realize the personalized assistance for different individuals. Currently, there are still some limitations, which will be addressed in future studies. For example, the number of HRI motion data and the poor quality of data caused by sensor errors affect the effect of kinematics model training. In the future, related work will be carried out to improve the speed of sensor acquisition and data quality to speed up the learning speed.

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