STUDY ON FINE HAND MOVEMENT BASED ON HIDDEN MARKOV MODEL

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How to achieve effective human-computer interaction is the shackle of the development of the assistive hand because it lacks information connection with the human brain. Aiming at the real-time opening and closing control of single-degree-of-freedom assistive hand's continuous motion, a supervised learning control algorithm for assistive hand based on Markov chain was proposed in this paper. Firstly, the motion information of the upper limb arm and forearm of the disabled person was used as the basis of human action intention recognition, and an algorithm which can greatly reduce the data storage structure of the state transition matrix was proposed. Then, the Markov model of the assistive hand control was established. Finally, a supervised learning data acquisition device, a data processing method and a model training method were designed based on wearable devices. The experimental results show that the Markov chain can effectively describe the complex daily behaviors and processes of human beings and has good sensitivity and reliability when applied to the control of assistive hands.

Keywords: Markov chain; assistive hand; supervised learning; degree-of-freedom; data glove

1. Introduction

According to the results of the sixth national population census and the second national sampling survey of the disabled in 2010, there were more than 85 million disabled people in China at the end of 2010, including about 24.72 million with physical disabilities [1]. Among the patients with physical disabilities, 13.15% are likely to have upper limb dysfunction, of which 43.16% are disabled above grade III [2]. People with upper limb dysfunction not only lack the ability to work, but also have many inconveniences in daily life. The patients themselves and their families are under considerable pressure.

As a tool to improve the incomplete shape and function of disabled patients, assistive limbs are a hot issue in the field of assistive robots. Grasping is the most basic function of a dexterous hand for the disabled, and its basic condition is force balance between each finger through grasping objects, which

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requires accurate measurement and control of finger position and force [3,4]. Another difficulty of the dexterous hand for the disabled is that the movement of the assistive hand must correctly reflect the movement consciousness of the human brain, so as to give full play to its function of helping the disabled. Many researchers can identify the signs on the hands or arms, the skin color of the human body and the shape features of the limbs by using the method of machine vision and finish the task planning of the arms and dexterous hands by using the method of machine learning [5-7]. However, this method needs a camera around the disabled patient, which is not very convenient to use, and similar problem exists in dexterous hand control technology based on speech recognition technology [8].

Another research focus of disability assistance is to control the assistive hand using the human body's own signals, such as myoelectric signals [9], electroencephalogram signals, and even the implanted nervous system. In 2008, Duke University in the United States realized walking by controlling a robot with monkeys' thinking activities. In 2015, Gregg A. Tabot and others from the University of Chicago verified the possibility of human hand tactile reconstruction based on brain-computer interface [10], and the importance and possibility of tactile reconstruction were also explained in the reference [11] from different angles. Therefore, it is possible to develop a "real" hand for assisting the disabled based on the control of the human brain's nervous system in the future, but it is still a long way off. The electrical signals excited by the human nervous system are the results of billions of years of evolution. The recognition rate of human movements by both myoelectric and electroencephalogram signals is still limited and unstable, and far from being competent for the needs of assistive hands. Many assistive hands are equipped with myoelectric control signals, but they are not stable enough. Therefore, the myoelectric prosthetic hand is also equipped with a switch button for controlling the opening and closing of the mechanical prosthetic hand. Although the button control is reliable, it is extremely inconvenient to use. Regardless of single degree-of-freedom or multiple degrees of freedom, how to realize effective human-computer interaction is the fetter for the development of assistive hands.

In recent years, the recognition of daily movements based on wearable devices has attracted much attention. Some representative studies include: in 2016, Wu Donghui of Dalian University of Technology studied the recognition of people standing, walking, running and jumping [12], and achieved good accuracy. In 2017, Wu Rongrong of xidian university studied 21 gestures related to writing [13]. In 2018, Yu Shilong of National University of Defense Technology studied the recognition of part of human motions in the kitchen [14]. In recent years, there are many studies combining speech and gesture to achieve effective control of an object based on hidden Markov model (HMM) [15, 16]. These studies focus on the recognition of single action types of people in different scenes. For the assistive hand, it is more urgent to identify the posture that should be taken in a continuous movement process, especially the posture that "finger" should take in the process of contact with tools or objects.

As the human hand performs all kinds of daily actions under the traction of the arm, the motion state of the arm is the direct response of the human brain's intention, it is possible to understand the brain's intention to use the hand by observing the motion law of the arm, that is, in the absence of accurate expression of the human brain's intention, it is the result of arm motion to directly view the human hand's action. In this paper, the MPU6050 inertial sensor was installed on the upper arm and forearm of a person, which constitutes a wearable motion data acquisition device, as shown in Fig. 1, also known as a data glove, used to collect the motion and attitude data of the upper arm and forearm, including angular velocity and acceleration. And these data were used as the information to "drive" the hand. Obviously, these data had nothing to do with the arm span of a person. A data glove with a tactile sensor was used to measure the opening and closing information of a healthy human hand when grabbing an object as a result of "driving". Based on these two types of data, a supervised learning HMM model for healthy people to capture objects was constructed to express and learn the coordination relationship of body movements when healthy people ingest objects.

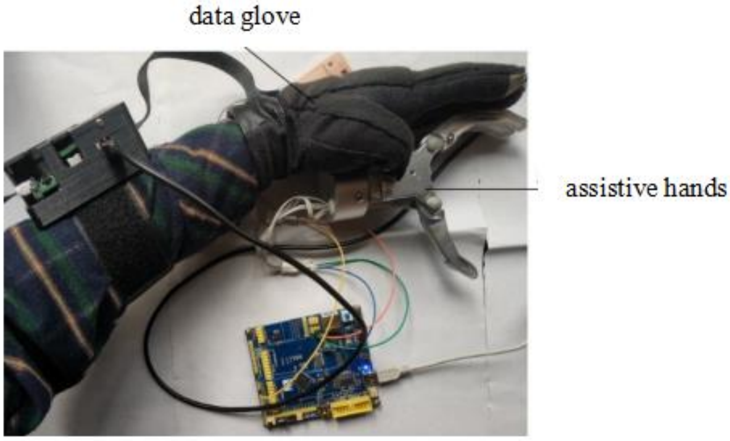

Fig.1. Experimental device

As long as the human hand has a thumb and an index finger, most of the daily actions can be completed, which is more similar to a two-finger or three-finger hand with single degree-of-freedom. Based on the above methods and assumptions, an experimental study on real-time control of a single degree-of-freedom hand with an assistive hand by hidden Markov model was carried out in this paper.

2. HMM Model of Daily Hand Movements

The observation of the movements of human upper limbs reveals that the processes of different actions completed by each person are random due to their habits, situations, etc. The purpose and degree of the actions completed by each person depend on the instantaneous instructions of the human brain. Therefore, the movements of the arms have no aftereffect, and the Markov model can be used to describe the human hand habits.

The commonly used data glove can directly measure the angular velocityω, angular acceleration ε and other parameters of the upper arm, forearm and palm. At time t, the state quantity of upper arm movement is Q_{Bt}=[ω_{BPt}, ω_{BRt}, ω_{BYt},ε_{BPt}, ε_{BRt}, ε_{BYt}], and that of forearm is Q_{Ft}=[ω_{FPFt}, ω_{FRt}, ω_{FYt}, ε_{FPt}, ε_{FRt}, ε_{FYt}], where the angle mark B represents the upper arm, and F represents the forearm. P, R and Y represent the pitch angle, roll angle and heading angle of the arm movement, respectively. The set of upper limb movement state quantity is: Q={ Q_B Q_F}. In actual observation, these quantities have been filtered and averaged, so Q is actually the average value in a certain period of time. Connecting these averages will express the path information of the arm movement process, which also reflects people's habit of using hands.

Firstly, the transition probability matrix between arm motion states was established.

As mentioned earlier, there are 6 measurable state quantities of arm movement, and the upper arm and forearm totally have 12 state quantities. Therefore, a compromise is needed between the accuracy of the model and the computational resources used, mainly considering the dimension and depth of the state features. Firstly, each quantity is simplified to 10 grades according to its numerical value, and the combination of 12 state quantities has 10^{12} state values, while Markov's state transition matrix is a square matrix with a scale of $10^{12}\times10^{12}$, which is obviously not easy to realize.

Considering that acceleration is the derivative of velocity, and the difference between two adjacent states in time series can represent the change of acceleration, only angular velocity is selected as the representation quantity, which is recorded as Q_t=[ω_{BPt} ω_{BRt} ω_{BYt} ω_{FPFt} ω_{FRt} ω_{FYt}]. The scale of state transition probability matrix of Markov chain is reduced to $10^6\times10^6$, which is still very large for storage.

Considering the continuity of motion, the velocity of the motion cannot be abruptly changed. As long as the sampling is sufficiently dense, the current state will only transition before the "proximity state". Between two adjacent states, there is at least one-dimensional angular velocity value +1 or -1 changed in Q_t. Thus, a sequence Δ is constructed:

Δ=（-1，-1，-1，-1，-1，-1，1，1，1，1，1，1，0，0，0，0，0，0）

Any 6 numbers from Δ constitute a vector ΔQ, which is added to Q_{t-1}, i.e.

$$Q_t = Q_{t-1}+\Delta \quad (1)$$

Note that the elements in Δ are -1, 0, and 1, so the number of adjacent states cannot be calculated from the combination $N = C_{18}^{6} = 18564$ (the state transition matrix in Table 1 does not have 18,564 columns). Take unit vector:

$$I=[1,1,1,1,1,1]$$

$$\Delta Q'=\Delta Q+I \quad (2)$$

Then

$$Q_t= Q_{t-1}+\Delta Q' \quad (3)$$

Then $\Delta Q'$ is a vector regularized after Δ translation. Only three values of 0, 1 and 2 of elements in $\Delta Q'$ can generate a "3" decimal number from $\Delta Q'$, which is defined as offset:

$$Offset=\Delta Q'(1)\times 3^5+\Delta Q'(2)\times 3^4+\Delta Q'(3)\times 3^3+\Delta Q'(4)\times 3^2+\Delta Q'(5)\times 3+\Delta Q' \quad (4)$$

By examining the value range of Offset, the number N of adjacent states can be obtained as $N=3^6=729$.

A decimal modulus value q_{ot} of Qt is defined to represent the size of Qt:

$$q_{ot}=Q_t(1)\times 10^5+ Q_t(2)\times 10^4+ Q_t(3)\times 10^3+ Q_t(4)\times 10^2+ Q_t(5)\times 10^2+ Q_t \quad (5)$$

Q_t sorted by q_{ot}: Of the 729 possible transition states for Q_t, the first 364 state values are less than Q_{t-1}, the 365th state value is the same as Q_{t-1}, and the following 364 state values are greater than Q_{t-1}.

A $10^6\times 729$ matrix is defined according to Table 1, wherein the first column of the matrix represents the number q_{ot} of all 10^6 state quantities, which is also the line number 0-99999; Each row has 729 possible migration states corresponding to this state quantity, with proximity state number 0-728 listed in the first row.

The elements in each row in the table represent the probability or frequency of transition from one state to another state in the vicinity, where the first 364 columns of the first row are constant zeros, the first 363 columns of the second row are constant zeros, and so on. From rows 365-99,635, the elements in each column may not be zero. Column 729 in line 99,635 is always zero, columns 728 and 729 in line 99,636 are also always zero, and so on. In line 999,999, all columns after 365 are always zero, i.e. a total of 365×729 cells in the matrix are always zero. Cells with a constant value of zero represent mathematically possible migration states, but have no physical significance, and the number proportion is only 0.0365%, so no special treatment is required.

Table 1

Calculation of state transition probability matrix A

a_{ij} / q_{ot}	Transition probability A or frequency a_{ij}									
	0	2	3		363	364	365		727	728
[000 000]	0	0	0	…	[000 000]	[000 001]	[000 010]	…	[111 110]	[111 111]
	……									
[555 555]	[444 445]	[444 455]	[444 456]	…	[555 555]	[555 556]	[555 565]	…	[666 665]	[666 665]
	……									
[999 999]	[888 888]	[888 889]	[888 899]		[999 999]	0	0	0		0
Note：	The values listed in [] in this table are the numbers of the corresponding transition states, but the initialization value of a_{ij} is 0.									

At this point, the state transition probability matrix of HMM model is defined:

$$A=[a_{ij}]。 i= q_{ot} =0\sim999999， j =0\sim728$$

The data glove can also measure the bending angle of five fingers. Considering that the normal working state of the assistive hand with single degree-of-freedom is two states of opening and closing controlled by force, but the degree of opening and closing depends on the size of the grasped object, it is stipulated that the force on the tip of the finger, where the thumb and forefinger are open and the other fingers are stretched, is zero, and that the force on the tip of the finger when the thumb and forefinger are closed and the other fingers are bent is not zero. Reading the bending angle of the index finger and specifying that the bending angle is greater than 100 degrees or the force is zero, the finger is considered to be open. In addition, considering the practical application, it is stipulated that the assistive hand cannot be closed for a long time, which will be recorded as an error. If an error occurs, the system will automatically change to open after identification. These three quantities are recorded as V={0,1,2} as observed values, as shown in Table 2, and the observation probability matrix B is established:

Table 2

Observation probability matrix

V	Q_0	Q_2		Q_{999999}
0				
1				

The initial state probability vector is defined $\pi=(\pi_i)$,i=0-999999:

$$\pi_i = \begin{cases} 0 & i \neq 555555 \\ 1 & i = 555555 \end{cases} \tag{6}$$

It means that the motion state of the arm at the initial position of the upper limb is the static state numbered [555555], and it is stipulated that the upper limb will naturally droop, and the fingers will open at this time.

Therefore, the HMM model is expressed as: $\lambda = (A, B, \pi)$

3. Model Training

The data glove is used as the data acquisition equipment, and the HMM control model of hand movement can be trained by using supervised learning.

3.1 Hardware device with tactile perception

Wearing data gloves, a universal man-machine interface, can obtain the posture data of the wearing parts in the movement process in real time, track the gestures of the wearer, locate the spatial information and so on. In this paper, DN-02A data glove made in China by Chengdu Big Bird Intelligent Technology Co., Ltd. is selected, which can capture the degree of bending of five fingers in both left and right hands, and the attitude angle data of palm, upper arm and forearm at the same time, including acceleration, angular velocity and angle, and feedback from eight motion nodes in each hand. The control part of the data glove can communicate with the host computer through USB or wireless Bluetooth. In this paper, the motion parameters of fingers and arms are measured through data gloves, which are transmitted to the PC for background processing, as shown in Fig. 2:

Fig. 2. DN-02A data glove

3.2 Force tactile sensor

A201 thin-film piezoresistive sensor of FlexiForce Company is selected to measure the tactile information of fingertip by attaching it to the thumb tip of data glove, and a comparator is designed to measure the opening and closing of finger. The closing of the finger only refers to whether the thumb "pinches" the operated object in cooperation with other fingers. Since the human hand has adaptive force balance ability in grasping, so does the assistive hand due to its shape, attention is only paid to whether it is "pinched" to form state observed quantities 0 and 1, as shown in Fig. 3:

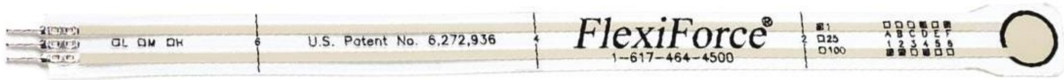

Fig. 3. Shape of FlexiForce A201 pressure sensor

3.3 Data acquisition and processing

Due to the large range of the data glove, the angular velocity of the subject's arm under daily conditions is observed to be no more than 80°/s in many experiments. While recording and archiving the original data, the data are translated, oriented, rounded and graded according to the following formula:

$$\omega' = [(\omega + 100.05)/200] \times 10 \ (^\circ/s) \tag{7}$$

For example, in the initial state, the upper limbs naturally droop and the fingers open, $\omega \approx 0$, and $\omega' = 5$ is calculated, so the initial state $Q_0 = [5\ 5\ 5\ 5\ 5\ 5]$.

Suppose that a state vector Q_{t-1} is obtained after ranking the data measured at the t-1th sampling:

$$Q_{t-1} = [\omega_{BPt-1}\ \ \omega_{BRt-1}\ \ \omega_{BYt-1}\ \ \omega_{FPFt-1}\ \ \omega_{FRt-1}\ \ \omega_{FYt-1}] \tag{8}$$

And the observed quantities: V_{t-1}, $V_{t-1} \in \{0,1,2\}$

to calculate the line No. *i*:

$$i = \omega_{BPt-1} \times 10^5 + \omega_{BRt-1} \times 10^4 + \omega_{BYt-1} \times 10^3 + \omega_{FPFt-1} \times 10^2 + \omega_{FRt-1} \times 10 + \omega_{FYt-1}] \tag{9}$$

The t-th sample data is graded to get a state vector:

$$Q_t = [\omega_{BPt}\ \ \omega_{BRt}\ \ \omega_{BYt}\ \ \omega_{FPt}\ \ \omega_{FRt}\ \ \omega_{FYt}] \tag{10}$$

The difference between the state vectors is calculated to get a vector whose element is 0 or 1:

$$\Delta Q_t = Q_t — Q_{t-1} = [\Delta\omega_{BPt}\ \Delta\omega_{BRt}\ \Delta\omega_{BYt}\ \Delta\omega_{FPt}\ \Delta\omega_{FRt},\ \Delta\omega_{FYt}] \tag{11}$$

The column No. *j* is calculated:

$$j = \Delta\omega_{BPt} \times 3^5 + \Delta\omega_{BRt} \times 3^4 + \Delta\omega_{BYt} \times 3^3 + \Delta\omega_{FPFt} \times 3^2 + \Delta\omega_{FRt} \times 3 + \Delta\omega_{FYt} + 365 \tag{12}$$

The frequency of state transition is calculated: $a_{ij} = a_{ij} + 1$, where the initialization value of a_{ij} is 0. The frequency of observation is calculated: $b_{ji} = b_{ji} + 1$, where the initialization value of b_{ij} is 0; *i* is the same as above, and $j=V_t$. Thus, the frequencies of the state transition matrix A and the observation matrix B are obtained respectively.

3.4. Model training method

The purpose of HMM model training is to obtain the state transition probability matrix A and observation probability matrix B. the method is as follows：

1. Obtain measurement data. Experiments were conducted according to 3.1 and 3.2 above to obtain the arm motion data of N groups of people when completing daily movements, and the data were processed according to 3.3.

2. Calculate the state transition matrix

The probability value in row I and column J of the state transition matrix A is recorded as P_{Aij}, which represents the probability that the ith state will migrate to the jth state in the data sequence of a daily action. The calculation method is as follows:

$$P_{Aij}=a_{ij}/\sum_{j=0}^{n} a_{ij}$$

3. Calculate the state observation matrix

The probability value in row I and column J of the state observation matrix B is recorded as P_{Bij}, which indicates that in the data sequence of a daily action, the observed value is the probability of the ith observation in the jth state. The calculation method is as follows:

$$P_{Bij}=b_{ij}/(b_{0j}+b_{1j})$$

4. Control method of disabled hands based on HMM model

HMM model has two possible uses for helping the disabled: (1) because people's daily actions are "habitual repetition", integrating the state value converted by the angular velocity of the upper limb in Table 1 with time represents a spatial path when people complete the action, and this path also corresponds to the state sequence in table 1 of HMM state transition matrix A, which can be used to distinguish the types of actions that people complete; (2) The observation matrix B represents the opening and closing state of the disabled hand in a complex action, which can be used to control the disabled hand. This article only discusses and verifies the second use.

4. Analysis of Experimental Results

In this paper, the model simulation experiment and the comparative experiment of single degree-of-freedom assistive hand were made.

4.1. Data analysis of model simulation experiment

Experimental process: The test set data collected in 3 were analyzed and compared. Five subjects were selected, and each group received 50 trials in different time periods. The first 40 trials were used as the training set, and the last 10 trials were used as the test set. During the test, the subjects first kept standing still with their arms naturally drooping, opened their thumb and forefinger, and started the experiment according to the command to move their right hand naturally to the abdomen to hold the zipper, close it, and loosen their fingers. An experiment was over. During the experiment, the data glove recorded each group of data at the sampling rate of 50Hz. The duration of each experiment was generally not more than 3 seconds, and the amount of data collected each time was about 140 groups. Matlab was used for data processing and the experimental data curve was drawn. A typical zipper pulling process is shown in Fig. 4. The abscissa in the figure shows the order of data acquisition.

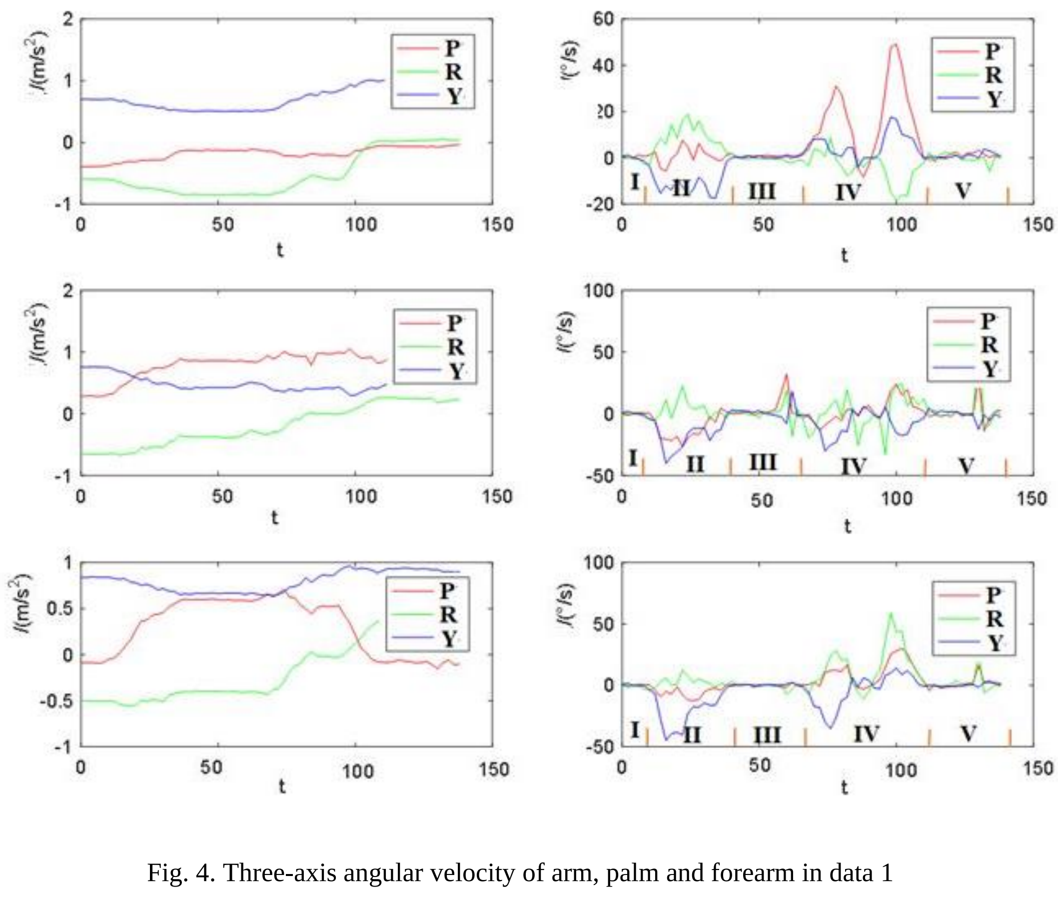

Fig. 4. Three-axis angular velocity of arm, palm and forearm in data 1

Five processes in the whole zipper pulling process are marked in Fig. 4. Part I represents the initial state of rest readiness; Part II is the process before the hand moved to the lower abdomen; Part III is the process to close the finger and tighten the zipper; Part IV is the zipper pulling process, during which slight and short-term zipper stuck sometimes occurs, which is characterized by slight oscillation of the arm; Part V is the pause after the zipper pull is completed when the fingers are released and ready to move away. By comparing the acceleration diagram with the angular velocity diagram, it is found that the expression of acceleration for the zipper pulling process is not as intuitive as that of angular velocity. The test set data is deduced by the trained model and compared with the actual test data. The results are shown in Table 3 below:

Table 3

Data comparison

Data set	*Data 1*	*Data 2*	*Data 3*	*Data 4*	*Data 5*	*Total data*
Total number of sampling points	1393	1451	1423	1405	1413	7085
Number of points for judging the correct state	1329	1389	1361	1386	1354	6810
Accuracy (%)	95.4	95.7	95.6	98.6	95.8	96.2

4.2 Simulation experiment of assistive hand control

Five subjects were respectively equipped with data gloves and held the assistive hand to simulate the zipper pulling action of the disabled hand. The movement of the upper limb was collected at a rate of 5Hz, and the opening and closing instructions of the computer to the assistive hand were used to replace the aforementioned closing data of the hand. Another observer was asked to control the opening and closing of the assistive hand through the cable, and the process of the observer controlling the assistive hand was taken as a theoretical process.

In order to avoid the experiment failure caused by the stuck zipper caused by the quality, it is set as the blocking state (observed value π=2) when the finger closing time exceeds 2s and the arm state is [555555]. At this time, the assistive hand will be automatically opened since it is designed as a failure in task. The simulation curves of five subjects are shown in Fig. 5:

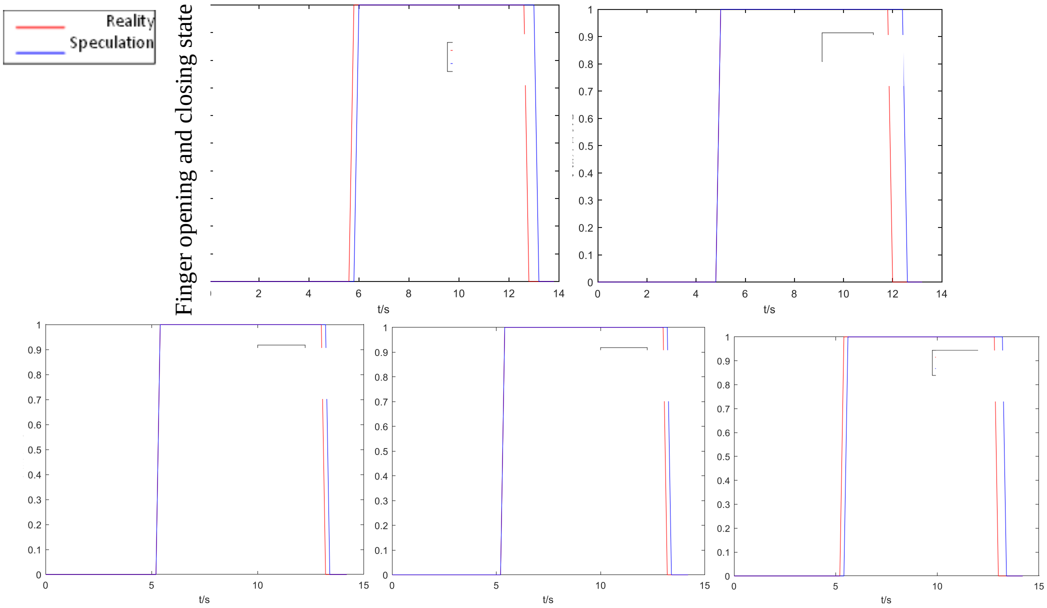

Fig. 5. Curves of simulation experiment

By analyzing the above figures, the control method of assistive hand based on HMM model basically coincides with that of observer, but the response of assistive hand controlled by HMM model to action is more sensitive than that of observer, and there are observable advances in the beginning of closing and pinching and the end of opening, as shown in the following Table 4:

Table 4

Test data

	Test 1	*Test 2*	*Test 3*	*Test 4*	*Test 5*
Closing at the beginning	-0.2s	0	—	—	-0.2
Opening at the end	-0.4	-0.5	-0.6	-0.2	-0.3

5. Conclusions

In this paper, a control algorithm for the assistive hand based on Markov chain was proposed, including establishing a Markov model and improving the data structure of state transition matrix, which effectively reduces the storage space of state transition matrix. The data collection and processing method, experimental equipment and model training method of supervised learning were put forward. The results show that Markov chain can effectively describe people's complex daily behaviors and processes, and it has good sensitivity and reliability when applied to the control of assistive hands. In the future, it may be further expanded to enable assistive hands to smoothly complete other daily actions, so as to become a general control method for assistive hands.

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REFERENCES

[1] China Disabled Persons'Federation, The Total Number Of People with Disabilities and the Number of People with Different Types and Grades of Disabilities in the Country at the End of 2010, https://www.cdpf.org.cn/zwgk/zccx/cjrgk/4c0d47abe6a3144790d4ee786553fb65.htm

[2] China Disabled Persons'Federation, Data of National Sample Survey of Disabled Persons in 1987-Basic Situation of Physically Disabled Persons https://www.cdpf.org.cn/zwgk/zccx/cjrgk/2a9a6fbad9c84b81ada3eed52176008b.htm

[3] *Yu Yangyang*, Research on the Design and Control of Dexterous Hands [D], Master's Degree Thesis of Beijing University of Chemical Technology, June 2019

[4] *Xu Tongtong*, Research on Dynamics and Operation Control Technology of Multi-fingered Dexterous Hand, Master's Degree Thesis of Nanjing University of Aeronautics and Astronautics, March 2019

[5] *M. HUser, T. Baier, 1. Zhang*; Learning of demonstrated Grasping Skills by stereoscopic tracking of human hand configuration, IEEE IntI. Conference on Robotics and Automation, 2795-2800, 2006

[6] *H. Kjellstrom, I. Romero, D. Kragic*, Visual Recognition of Grasps for Human-to-Robot Mapping, Proc. 2008 IEEEIRSl International Conference on Intelligent Robots and Systems, 3192-3197, 2008

[7] *Qi Jinxian*, Research on Grabbing Posture of Dexterous Hand Based on Stereo Vision Guidance, Master's Thesis of Wuhan University of Science and Technology, May 2020

[8] *Wang Dong*, Design of Control System for Assistive Forearm Manipulators Based on Speech Recognition of Specific Person. Master's Thesis of Shandong University of Science and Technology, April 2018

[9] *WenRS, WangQ , Li ZB*, Human hand movement recognition using infinite hidden Markov model based sEMG classification Biomedical Signal Processing and Control. Volume 68, July 2021, 102592

[10] *Gregg A. Tabota, Sung Shin Kimb, Jeremy E. Winberryb, Sliman J. Bensmaia*, Restoring tactile and proprioceptive sensation through a brain interface Neurobiology of Disease Vol 83, November 2015, Pages 191–198

[11] *HC Kuo，AM Gordon，A Henrionnet，S Hautfenne，KM Friel*, The effects of intensive bimanual training with and without tactile training on tactile function in children with unilateral spastic cerebral palsy: A pilot study. Research in Developmental Disabilities，2015， 4950:27-39

[12] *Wu Donghui*, Research on Human Daily Action Recognition Based on Inertial Sensor Data, Ph.D. Thesis of Dalian University of Technology, November 2016

[13] *Wu Rongrong*, Research on Fine Gesture Recognition Method and Its Application Based on EMG and FSR, Master's Thesis of Xidian University, June 2017

[14] *Yu Shilong*, Research on Human Motion Recognition Technology Based on Inertial Sensors. Master's Thesis of National University of Defense Technology, June 2018

[15] *Glory Evangelin N，Vijayalakshmi P，Kumar Satheesh G,*Development of Speech and Gesture Enabled Wheelchair System for People with Cerebral Palsy: IEEEICSPC'21: 2021 3RD INTERNATIONAL CONFERENCE ON SIGNAL PROCESSING AND COMMUNICATION P 620-624 DOI10.1109/ICSPC51351.2021.9451712

[16] *Lopez-Casado Carmen，Bauzano Enrique，Rivas-Blanco I，Perez-del-Pulgar Carlos J，Munoz, Victor F,*A Gesture Recognition Algorithm for Hand-Assisted Laparoscopic Surgery. SENSORS Vol 19 No23 DEC 2019 DOI10.3390/s19235182