Human-robot Interaction Oriented Human-in-the-loop Real-time Motion Imitation on a Humanoid Tri-Co Robot

Wenbin Xu[1], Xudong Li[1], Wenda Xu[1], Liang Gong[1], Yixiang Huang[1], Zelin Zhao[1], Lujie Zhao[1], Binhao Chen[1], Haozhe Yang[1], Li Cao[2], Chengliang Liu[1]

Abstract—**Inspired by the concept of Tri-Co Robots, a real-time motion imitation based human-robot interaction method is proposed to telemanipulate a life-size humanoid robot. First, a motion capture system is established to retarget the accurate motion data to a skeletal model. Second, the real-time data transfer for a human-in-the-loop control system is realized through the publish-subscribe messaging mechanism in ROS (Robot Operating System). Third, a fast mapping algorithm is developed to convert BVH (BioVision Hierarchy) data into corresponding joint angles which are then encapsulated in a designed communication protocol and sent to a low-level slave controller through a serial port. Finally, visualization terminals render it more convenient to make comparisons between two different but simultaneous motion systems. Experimentation on complicated gesture imitation shows the feasibility of the proposed methodology, and the synchronous latency of less than 0.5 seconds validated its real-time performance. The proposed human-in-the-loop imitation control method enhances robot interaction capability in a more natural way and improves robot adaptability to uncertain and dynamic environments.**

Index Terms—**Motion Imitation, Life-size Humanoid Robot, BioVision Hierarchy, Motion Capture, Human-in-the-loop Control, Human-robot Interaction**

I. INTRODUCTION

With the rapid development of technology, robots have experienced great changes in many aspects since the invention of the first industrial robot in 1959. Faced with different missions, various robots, such as sweeping robots to educational robots, have been developed. To improve the cooperation between human and robots, human-robot interaction (HRI) has risen as a research area, attracting attention from academics and industry. [1] In 2017, the National Natural Science Foundation of China (NSFC) has launched the Tri-Co Robot (i.e. the Coexisting-Cooperative-Cognitive Robot) major research program to enhance robot interaction capacities, one of which is HRI capacity. [2] Hence, the ubiquitous applications of robots, effective coordination with other agents and adaptability to uncertain and dynamic environments are respectively ensured.

Human society and most scenes in the world are constructed according to our scale, demands and capacity, which means if parts of, or even complete human functions are to be substituted or to be strengthened, robots equipped with human morphology are required. With respect to HRI, humanoid robots have numerous advantages. First, since humanoid robots possess human-like structures and scales that have evolved for millions of years on human bodies, they are completely capable of integrating themselves into daily life, human society and uncertain environments seamlessly to emulate human behaviors, and at the same time acquire necessary knowledege and skills. Second, humanoid robots can provide a direct and natural platform for HRI. Since they are entirely able to mirror human motion, manipulators can obtain overall comprehensive cognition of the surroundings, analyze complicated information and make strategies for humanoids from the first-person view so that robots can be gradually endowed with the ability to repeat similar processes. Through such natural teaching, they are even capable of making autonomous decisions. Third, humanoid robots can resort to the rich fruits of ontology and the epistemology of human civilization to accumulate necessary knowledge, which renders the cost of HRI lowest and achieves the most satisfactory performance.

To facilitate the interaction between human and humanoid robot under social and industrial circumstances, novel behaviors that are commonly used in human life but not pre-programmed to humanoid robots should be taught to them by a natural mean, which resembles the learning process of children. To acquire inspiration, we look to successful strategies adopted by people, such as imitation, where people observe the behavior of another, and reproduce it. [3] After human demonstrations, imitation of this behavior is usually more convenient for humanoid robots than manually programmed controllers. [4] Hence in this regard, human imitation is of increasing importance: human-like behavior, emotionally and aesthetically pleasing action, and expressive motion are fundamental. [5]

Related works has been in process over the past few years. Marcia Riley proposed a framework where external cameras and head-mounted cameras are used to capture body postures and joint angles are computed through a fast full-body inverse kinematics (IK) method. [3] The full-body IK problem is divided into many sub-problems to realize real-time imitation on a Sarcos humanoid robot with 30 degrees of freedom (DOF). Besides, several articles ([1], [6], [7]) utilize Kinect for gesture recognition and then perform similar actions on robots through different algorithms. Additional to vision, other sensory methods are also adopted. Abhay Bindal fixes IR sensors and accelerometer motion sensors to human legs and achieve real-time control of gaits through an Arduino ATmega

[1]School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai, China
[2]Rui Jin Hospital, Shanghai Jiao Tong University School of Medicine, Shanghai, China
Corresponding author: gongliang_mi@sjtu.edu.cn

This study was supported by the Natural Scientific Foundation of China under Grant NO.51775333 and the Foundation of Cross-disciplinary Research on Medicine and Engineering under Grant NO. YG2016MS64.

2560 based microcontroller on a biped humanoid robot. [8] Akif DURDU attaches potentiometers to human joints and the collected data are classified with the assistance of ANN to perform movements on the robot. [4] However, there are some demerits in the existing work. First, conventional vision-based motion recognition methods are not completely reliable due to their sensibility to lighting conditions and cluttering of the background. Numerous cameras can indeed increase the reliability but also the expenses. Through wearable sensors, more accurate motion can be captured. Second, the real-time feature will be negatively affected if the full-body IK problem is yet to be solved. Hence an algorithm with less calculation amount is desired. Third, motion imitation has rarely been applied to humanoid robots with human dimensions due to the complicated structure and the great difficulty of control.

In this paper, we present a human-in-the-loop system where a life-size humanoid robot whose establishment is based on InMoov, an open-sourced 3D printing humanoid robot, can imitate real-time motion of human's upper limber. The humanoid robot has a similar structure with human and is equipped with 29 DOF, 22 of which are controlled in this system. The process of motion imitation is illustrated as follows. To begin with, a set of wearable sensors is employed to capture the motion of human and the collected motion data are presented in BVH (BioVision Hierarchy) format. Then these data are transmitted to an industrial PC with Ubuntu running on it through TCP/IP and parsed according to BVH format. Next, the parsed euler angles are converted to the corresponding joint angles with mathematical techniques and encapsulated in a communication protocol. Lastly, the industrial PC sends joint angles to the low-level slave controller to control the robot. This human-in-the-loop system has paved a novel, real-time and accurate way for human motion imitation on humanoid robots.

This paper is organized as follows. Section 2 introduces the motion capture system. Section 3 discusses the setup of the humanoid robot. Section 4 presents the realization of real-time motion imitation on the humanoid robot. Section 5 performs several experiments on complicated gesture imitation processing through our proposed method. Finally, section 6 deals with the conclusion about our work.

II. Motion Capture System

This section gives an introduction to the motion capture system. The system is composed of a motion sensor used to capture real-time human motion and a human motion retargeting method which enables us to map these data to a simplified skeletal model.

A. Motion Sensor

A modular system composed of 32 9-axis sensors is adopted as the motion sensor. It is a set of wearable sensors designed by Noitom Technology Ltd to deliver motion capture technology. Characteristics of the whole modular system include being small, adaptive, versatile and affordable. It contains 32 IMUs (Inertial Measurement Unit), each of which is composed of a 3-axis gyroscope, 3-axis accelerometer and 3-axis magnetometer. The system is operated with Axis Neuron Pro(ANP) running on Windows OS for calibration and management. Besides, a skeleton model is visualized in ANP to reflect real-time human motion. Another important feature of ANP is to broadcast BVH data through TCP so that other programs can obtain and analyze these data through specified IP and port using SDK provided by Noitom Technology Ltd.

```
HIERARCHY
ROOT Hips
{
    OFFSET 0.00 104.19 0.00
    CHANNELS 6 Xposition Yposition Zposition Yrotation Xrotation Zrotation
    JOINT RightUpLeg
    {
        OFFSET -11.50 0.00 0.00
        CHANNELS 6 Xposition Yposition Zposition Yrotation Xrotation Zrotation
        JOINT RightLeg
        {
            OFFSET 0.00 -48.00 0.00
            CHANNELS 6 Xposition Yposition Zposition Yrotation Xrotation Zrotation
            JOINT RightFoot
            {
                OFFSET 0.00 -48.00 0.00
                CHANNELS 6 Xposition Yposition Zposition Yrotation Xrotation Zrotation
                End Site
                {
                    OFFSET 0.00 -1.81 18.06
                }
            }
        }
    }
MOTION
Frames: 2
Frame Time: 0.04166667
-9.533684 4.447926 -0.566564 -7.757381 -1.735414 89.207932 9.763572
```

Fig. 1. An example of BVH format

B. Human Motion Retargeting

Motion retargeting is a classic problem which aims to retarget motion from one character to another while keeping styles of the original motion. [9] With this method, real-time human motion can be reflected on the skeletal model in ANP through BVH data, developed by the BVH company for motion description. As a universal human feature animation file format usually adopted in skeletal animation models, it can store motion for a hierarchical skeleton, which means that motion of the child node is directly dependent on the motion of the parent one. [10] A normal BVH file will consist of several parts as follows.

- HIERARCHY signifies the beginning of skeleton definition.
- ROOT gives the first defined joint which is also the root of the whole skeleton.
- OFFSET specifies the deviation of the child joint from the parent joint, which remains constant due to the unchanged lengths of human limbers.
- CHANNELS contains several parameters. The first parameter, which is 6 in Fig. 1, indicates the number of DOF. Usually only the root joint has both position data and rotation data. The rest only contains rotation data because positions of other joints are obtained from the fixed values of OFFSET. Besides, these rotation data are Euler angles and the sequence of rotation hinges on

the sequence mentioned in CHANNELS. In Fig. 1 , the rotation is carried out in YXZ order.

- End Site is only tagged in the definition of an end-effector and describes the lengths of the bone through OFFSET.
- MOTION represents the beginning of another section which describes states of each joint at each moment.
- Frames stands for the current order of frames and Frame Time is the duration of each frame. The rest data are real-time states of each joint described sequentially in the HIERARCHY section. The number of these data is equal to the total number of channels defined in the HIERARCHY section.

We adopt BVH with no position channels. Hence three rotation values are obtained for each joint since position value keeps constant. Accordingly, we can figure out human gestures through these three rotation angles based on the assumption that wearable sensors are fixed with respect to human body.

III. Setup of Humanoid Robot

To realize real-time motion imitation on robots, a humanoid robot is set up since they possess human-like design and are able to mimic human motion. [11] However, due to the complicated structure of the robots and various constraints of conventional manufacturing methods, it is difficult to fulfill an elegant design of a dexterous humanoid robot. Fortunately, with the rapid advancement in 3D printing technology, 3D printing turns to be more cost-effective. Also, 3D printing element is also becoming more accurate, more complex and stronger. 3D-printed humanoid robots like InMoov, Flobi and iCub have been created to serve as experiment platforms where research on HRI is conducted.

In this paper, a 3D-printed life-size humanoid robot is established based on InMoov initiated by Gael Langevin, a French sculptor in 2012. [12] The whole structure as well as other necessary backgrounds have been illustrated in the previous work. [13] 22 out of 29 DOF are controlled during motion imitation, including 5 DOF for each hand, 4 for each arm, 3 for each shoulder and 2 for the neck, as shown in Fig. 2. As for control, the low-level slave controller is composed of 4 small Arduino Nano control core boards, each of which can drive 6 servos with corresponding angles through PWM wave, and an Arduino Mega 2560 master board which communicates with the aforementioned nano nodes via 485 Hub based on the Modbus RTU control.

IV. Real-time Imitation of Human Motion

Several functional components are developed to realize real-time human motion imitation. The whole structure of the proposed method is shown in Fig. 3. First, the publish-subscribe messaging mechanism and the designed communication protocol ensures the safety of data transfer. Second, a key point to the accomplishment of motion imitation is the fast mapping algorithm which converts euler angles in BVH data into corresponding joint angles. Then, visualization terminals make it possible to make comparisons between different but simultaneous motion systems.

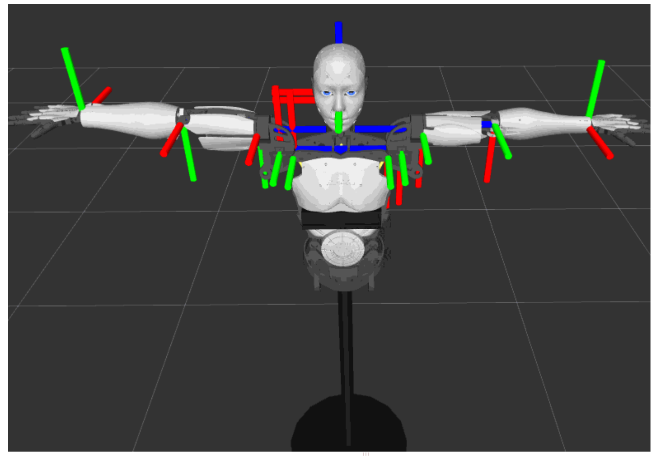

Fig. 2. DOF of the humanoid robot (DOF of fingers are not displayed)

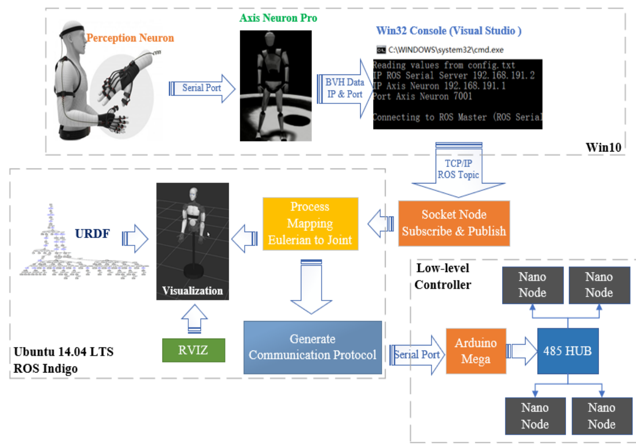

Fig. 3. Whole structure of the proposed method

A. Data Transmission

Nodes, which are executables after compilation, can subscribe to or publish new messages to a topic in ROS (Robot Operating System). [14] This publish-subscribe messaging mechanism is one of the most important features of ROS. Data streams are enabled mainly through topics in this paper. The whole data stream is visualized in Fig. 4, where ellipses stand for nodes and squares represent topics.

- rosserial_server_socket_node connects with the win32 console through TCP/IP and then advertises the topic, perception_neuron/data_1
- perception_neuron_one_topic_talk_node subscribes to the previous topic and then converts euler angles in BVH data to joint angles, which are then published to another topic called Controller_joint_states.
- joint_state_publisher subscribes to the previous topic and realizes the real-time simulation of robot model.
- perception_serial will send joint angles to the low-level slave controller through a serial port after obtaining them from Contoller_joint_states

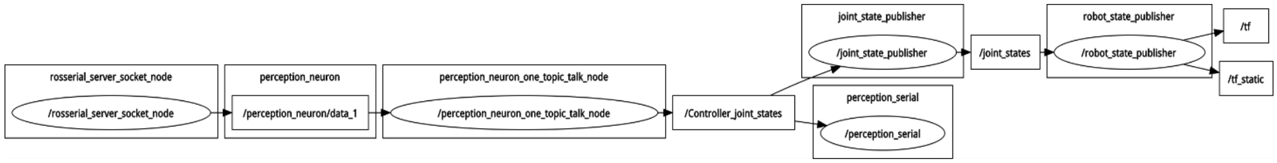

Fig. 4. Visualized data stream through ROS publish_subscribe messaging

Fig. 5. Designed Communication Protocol

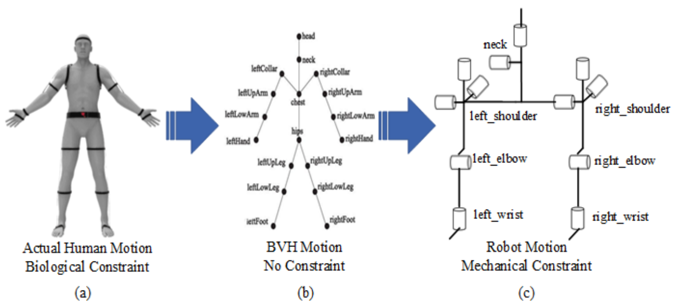

Fig. 6. Three motion systems with different constraints

While topics have been successfully adopted mainly in the data transfer process on Ubuntu, to control the robot, we still need to transmit joint angles to the low-level slave controller through a serial port. In case packet loss or data dislocation takes place during transmission, a specific communication protocol is designed, as shown in Fig. 5. Before transmission, all these data including time stamp and joint angles are converted to integers. The communication protocol contains 2 bits of time stamp data, 22 bits of position data corresponding to each joint, and 2 bits of CRC16 check code which are generated according to prior 27 bits to ensure the safety of data transfer.

B. Mapping Algorithm

To make the robot imitate human motion, the key is to send corresponding joint angles computed from BVH data. BVH has provided us with three euler angles for each node, enabling us to ascertain the rotation matrix between child and parent links. Denote euler angles with a rotation order of ZYX as φ, θ, ψ, the rotation matrix of child frame with respect to parent frame is

$$R_{child}^{parent} = \begin{pmatrix} cos\varphi & -sin\varphi & 0 \\ sin\varphi & cos\varphi & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} cos\theta & 0 & sin\theta \\ 0 & 1 & 0 \\ -sin\theta & 0 & cos\theta \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ 0 & cos\psi & -sin\psi \\ 0 & sin\psi & cos\psi \end{pmatrix} \quad (1)$$

Fig. 7 shows the mapping problem. Human, with biological constraints, cannot have 3 rotational DOFs at each joint and some of them are not completely independent. With mechanical constraints, many joints of humanoid robots are also unable to rotate in three independent directions. The main difficulty is to eliminate the differences between the robot and human body. Thus, there is no universal algorithm for each joint and we need to specify the algorithm for each certain case. The first case is the conversion from 3 human DOF to 3 robot DOF. Take the shoulder as an example. There are 3 DOF on each shoulder part of InMoov and their axes of rotation can be approximately treated as perpendicular to each other. Denote the joint angles of 3 shoulder joints as respectively α, β, γ and the rotation matrix of the arm link with respect to the shoulder link can be similarly expressed as

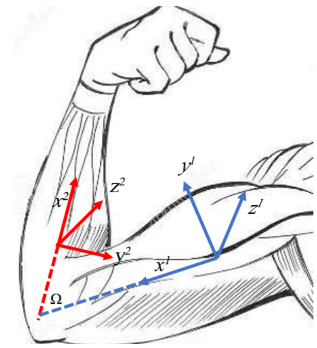

Fig. 7. Elbow conversion from 2 DOF to 1 DOF

$$R_{arm}^{shoulder} = \begin{pmatrix} cos\alpha & -sin\alpha & 0 \\ sin\alpha & cos\alpha & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} cos\beta & 0 & sin\beta \\ 0 & 1 & 0 \\ -sin\beta & 0 & cos\beta \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ 0 & cos\gamma & -sin\gamma \\ 0 & sin\gamma & cos\gamma \end{pmatrix} \quad (2)$$

Then we only need to equal φ, θ, ψ obtained from the motion sensor and α, β, γ used to control the robot. But there's still one thing that needs to be noticed. Since the mechanical structure of the robot has determined the rotation order of three joints between shoulder and arm, the rotation order of euler angles in BVH should be set to be the same (in our case, ZYX), or this method will be invalid.

The second one is conversion from 2 human DOF to 1 robot DOF. The example is elbow. Human elbows are able to bend and rotate while those of the robot can only bend. Then we need to compute the joint angle for bending, which is Ω, as shown in Fig. 7. With the assumptions that sensors are fixed with respect to human body and the x-direction is along the links, we can derive the following equations with the rotation matrix (1). R_2^1 stands for the rotation matrix of frame $x_2y_2z_2$ with respect to $x_1y_1z_1$. $\hat{\boldsymbol{x}_1}^1$ is the description of unit vector of $\boldsymbol{x_1}$ in frame $x_1y_1z_1$.

$$\hat{\boldsymbol{x}_2}^2 = (1, 0, 0)^T \quad (3)$$

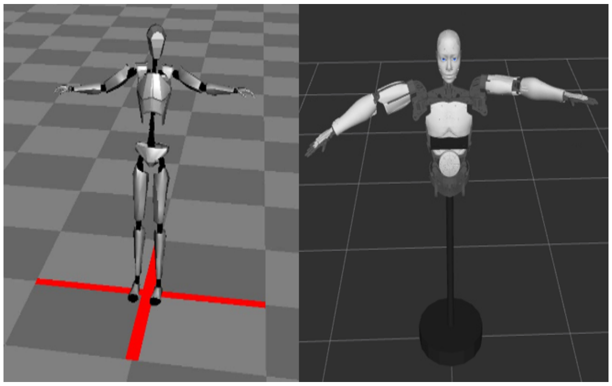

Fig. 8. Different visualization terminals for different motion systems

Fig. 9. Experiments of different gestures with arms and head

$$\hat{\boldsymbol{x}_2}^1 = R_2^1 \hat{\boldsymbol{x}_2}^2 = (cos\theta cos\psi, cos\theta sin\psi, -sin\theta)^T \tag{4}$$

$$< \hat{\boldsymbol{x}_2}^1, \hat{\boldsymbol{x}_1}^1 >= arccos(cos\varphi cos\theta) \tag{5}$$

$$\Omega = \pi - < \hat{\boldsymbol{x}_2}^1, \hat{\boldsymbol{x}_1}^1 >= \pi - arccos(cos\varphi cos\theta) \tag{6}$$

The last case is conversion from 3 human DOF to 2 robot DOF like the neck joint. The solution to this case resembles that for the shoulder joint and we only need to take 2 out of 3 euler angles in the corresponding order.

C. *Different Visualization Terminals*

On one hand, in the display of human motion, ANP can visualize a skeletal model where each joint has three rotational DOF regardless of human's physiological structures or the humanoid robot's DOF, as shown in Fig. 8. The skeletal model mainly utilizes the euler angles to reflect the actual human gestures and the length of each link is fixed for one chosen body size.

On the other hand, to visualize the robot model and to make simulation more convenient, another visualization scheme is provided with the assistance of ROS. A 3D visualization model is created in URDF (unified robot description format), a language based on XML and designed to describe the robot simulation model universally in ROS system, including the shape, size and colour, kinematic and dynamic characteristics of the model. The basic grammars are mentioned in [14]. However, the complicated structure of InMoov makes it arduous to write a URDF manually. Hence we resort to a powerful tool called Xacro (XML Macros). Xacro is also an XML macro language adopted to reuse one structure for two different parts, i.e. left arms and right arms and to auto-generate a URDF file. Some fundamental grammars are shown in Table I. Also, open-sourced *.STL files can be imported in URDF after scale adjustment. After finishing a URDF file, we need to invoke RVIZ, a 3D visualization tool in ROS and a node called joint_state_publisher subscribing to a topic which publishes joint angles in sensor_msgs/JointState format. Then the robot model will be visualized in RVIZ and operate with the computed joint angles, as shown in Fig. 8.

Fig. 10. Comparison between fingers

V. Experiment

This section presents the experimental results using the proposed method based on the humanoid robot. The results can be seen from Fig. 9 -Fig.10. To verify the feasibility of the system, photos for various poses were taken from the human motion imitation system, including different positions of two arms, face orientations and movements of fingers. These gestures are complicated because imitation of these gestures entails the rotation of most revolute joints at the same time rather than one or two. Also, the high degree of similarity between the wearer and the humanoid robot has demonstrated that the robot has successfully followed the wearer's upper limber motion of the wearer., thus proving the feasibility of our proposed method. Besides, the synchronous latency of less than 0.5 seconds validates the real-time performance.

To illustrate accuracy, we take one DOF of the right shoulder as an example. Fig. 11 shows the comparison between different trajectories of the same motion on human and the humanoid robot. The trajectory can be approximated as an arc and the central angle of the arc represents the accuracy of the proposed method. The error is nearly 3°, which is 6.1% based on the rotation angle of the human arm. The relatively small error has further demonstrated the high accuracy of our method.

However, there are still some limitations. The first one is the

TABLE I
FUNDAMENTAL GRAMMARS OF XACRO

Command	Definition	Usage
Property	<xacro:property name=“pi” value=“3.14” />	< ··· value =“ ${2*pi}”···/>
Argument	<xacro:arg name=“use_gui” default=“false”/>	< ··· use_gui:= true ···/>
Macro	<xacro:macro name=“arm” params=“side”/>	<xacro:arm side=“left”/>
Including	<xacro:include filename=“other_file.xacro” />	

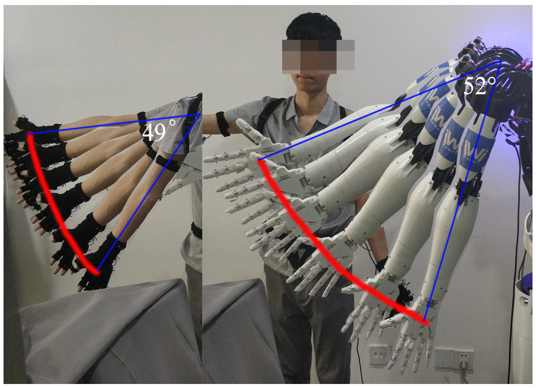

Fig. 11. Snapshots for motion trajectory

difference of structure between human and robot. Each of our arm has 7 DOF but the robot has only 5 and the rotational axes of their wrists are not the same. Also, the rotational angles of some robot joints are limited due to its mechanical design. (i.e. The arm of the robot cannot get over its shoulder.) The second one is the mismatch between the skeletal model visualized through BVH data and the wearer’s real motion. As we all know, the revolution of each joint is achieved through skeletons in human body, while the wearable sensors can only be kept fixed to the skin or the clothes and there exists relative angular displacement between our skin and skeletons. Hence errors are obvious when we carry out particular behaviors. Other factors include the accumulated drift errors and different positions of wearable sensors relative to human bodies. Nevertheless, there are still some possible solutions to these limitations. For example, sensors can be bound tightly to limbs in case of relative displacement between sensors and skin. Human motion can be confined to a certain range to achieve a higher accuracy. Besides, reasonable compensations for errors resulting from relative angular displacements between skins and skeletons can render the motion retargeting more reliable.

VI. CONCLUSIONS

In this paper, a novel human-in-the-loop system for human motion imitation on a humanoid robot is proposed. The system enables real-time imitation through an accurate motion capture system, visualization terminals for different motion systems, fast mapping algorithms and reliable data transfer methods. Experiments with different gestures have demonstrated that the system is feasible, real-time and accurate. Future work will lay more emphasis on the development of mapping algorithms and the accuracy of human motion imitation on a humanoid robot. Encouraged by Tri-Co Robot Initiative, we hope this work will further contribute to the enhancement of robot interaction capacity.

REFERENCES

[1] E. Yavan and A. Uar, “Gesture imitation and recognition using kinect sensor and extreme learning machines,” *Measurement*, vol. 94, pp. 852–861, 2016.

[2] H. Ding, X. Yang, N. Zheng, M. Li, Y. Lai, and H. Wu, “Tri-co robot: a chinese robotic research initiative for enhanced robot interaction capabilities,” *National Science Review*, p. nwx148, 2017. [Online]. Available: http://dx.doi.org/10.1093/nsr/nwx148

[3] M. Riley, A. Ude, K. Wade, and C. G. Atkeson, “Enabling real-time full-body imitation: a natural way of transferring human movement to humanoids,” in *IEEE International Conference on Robotics and Automation, 2003. Proceedings. ICRA*, 2003, pp. 2368–2374 vol.2.

[4] A. Durdu, H. Cetin, and H. Komur, “Robot imitation of human arm via artificial neural network,” in *International Conference on Mechatronics - Mechatronika*, 2015, pp. 370–374.

[5] S. H. Hyon, J. G. Hale, and G. Cheng, “Full-body compliant human-humanoid interaction: Balancing in the presence of unknown external forces,” *IEEE Transactions on Robotics*, vol. 23, no. 5, pp. 884–898, 2007.

[6] I. J. Ding, C. W. Chang, and C. J. He, “A kinect-based gesture command control method for human action imitations of humanoid robots,” in *International Conference on Fuzzy Theory and ITS Applications*, 2014, pp. 208–211.

[7] A. Bindal, A. Kumar, H. Sharma, and W. K. Kumar, “Design and implementation of a shadow bot for mimicking the basic motion of a human leg,” in *International Conference on Recent Developments in Control, Automation and Power Engineering*, 2015, pp. 361–366.

[8] S. Gobee, M. Muller, V. Durairajah, and R. Kassoo, “Humanoid robot upper limb control using microsoft kinect,” in *2017 International Conference on Robotics, Automation and Sciences (ICORAS)*, Nov 2017, pp. 1–5.

[9] X. Meng, J. Pan, and H. Qin, “Motion capture and retargeting of fish by monocular camera,” in *International Conference on Cyberworlds*, 2017, pp. 80–87.

[10] H. Dai, B. Cai, J. Song, and D. Zhang, “Skeletal animation based on bvh motion data,” pp. 1–4, 2010.

[11] N. E. N. Rodriguez, G. Carbone, and M. Ceccarelli, “Antropomorphic design and operation of a new low-cost humanoid robot,” in *Ieee/ras-Embs International Conference on Biomedical Robotics and Biomechatronics*, 2006, pp. 933–938.

[12] G. Langevin, “Inmoov,” http://www. inmoov.fr/project, 2014.

[13] L. Gong, C. Gong, Z. Ma, L. Zhao, Z. Wang, X. Li, X. Jing, H. Yang, and C. Liu, “Real-time human-in-the-loop remote control for a life-size traffic police robot with multiple augmented reality aided display terminals,” in *2017 2nd International Conference on Advanced Robotics and Mechatronics (ICARM)*, Aug 2017, pp. 420–425.

[14] Z. Wang, L. Gong, Q. Chen, Y. Li, C. Liu, and Y. Huang, *Rapid Developing the Simulation and Control Systems for a Multifunctional Autonomous Agricultural Robot with ROS*. Springer International Publishing, 2016.