Developing New Abilities for Humanoid Robots with a Wearable Interface

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1. Introduction

A humanoid robot is a robot that has a similar appearance with humans. Although appearance is the one of the important features of humanoid robots, human-like behaviors and task solving abilities are more meaningful features in daily life. To make humanoid robots more useful, they should have the capacity to learn new abilities. However, today's humanoid robots are not smart enough to adapt to their working environments. In this paper, we propose a method to develop new abilities of humanoid robots on the basis of imitation, one of the most powerful methods to learn a new skill, not only for humans but also for humanoid robots.

To achieve this goal, we designed and implemented a wearable interface to teach humanoid robots via user demonstration. Magnetic markers and flex sensors are applied for capturing human motion. A head mount display and a microphone are used for communicating with the partner robot. A vision channel and speech channel are employed to communicate with the partner robot. The wearable system assists the user and enhances interaction with the robot through an intuitive motion imitating method and multimodal communication channels via which commands are given and sensory feedback is received.

A vision channel is used to complement the weakness in recognizing surrounding states. A human teacher can sense the environment by sharing the robot's sight using the head mount display and he or she can decide the most appropriate behavior for the observed situation. When the teacher concludes that there is no proper behavior among the robot's abilities, a new ability can be trained through demonstration by the teacher. We conducted a kinematic analysis on both a human user and a partner robot to overcome the joint difference problem when transferring motion from the human user to the robot. We used the humanoid robot AMIO as a test bed to validate the wearable interface and found that we could make the robot more intelligent with the wearable interface.

2. Related Work

Many researchers are trying to develop a novel way to enhance the abilities of humanoid robots. There have been some worthy researches on robotics which used motion capture data to transfer human motion to a partner robot. Zhao et al., generated a new motion for a robot by mapping motion capture data to a robot model with employing similarity evaluation (Zhao et al., 2004). Nakazawa et al., proposed a method to generate new motions for humanoid robots by using motion primitives extracted from motion capture data (Nakazawa et al., 2002). Matsui et al., tried to minimize the motion difference between a human user and a partner robot by capturing motion from both the user and the robot (Matsui et al., 2005). Inamura et al., controls their robot by using voice command and motion capture data (Inamura et al., 2005). Kanzaki et al., used a wearable system instead of conventional motion capturing devices for generating new motions for humanoid robots. (Kanzaki et al., 2004).

Programming by demonstration (PbD) or learning by imitation is the one of the most popular approaches that a robot learns a new ability from an user's demonstration. Movement primitive based motion reproduction is a major research issue in PbD. Schaal et al., applied dynamic movement primitives for controlling actuators of their humanoid robot. (Schaal et al., 2004). Jenkins and Mataric proposed a system that extracts action units from motion capture data and they generated new motions for their robot based on action units. (Jenkins and Mataric, 2002). Stochastic motion modelling is another major research issue in PbD. Most researches adopted hidden Markov model (HMM) to handle the motion data as a time series data. Inamura et al. proposed a method to represent the original motion using HMM (Inamura et al., 2003). Calinon et al. used PCA, ICA and HMM for encoding the motion data (Calinon et al., 2005). Kwon et al. proposed a method to find the best combination of motion primitives using HMM (Kwon at el., 2006).

Motion capturing devices are very effective in terms of capturing precise motions from human user for generating humanoids' motion. But they are not appropriate for users to interact with a humanoid robot in daily life. Therefore we focused on enhancement of HRI using a wearable interface which is very easy to use in daily life. Motion primitive based motion reproduction methods have advantages of generalizing the task to be learned by a robot for later use but the methods cannot generate motions with variations. And HMM based motion generation methods need a lot of training data and a lot of time. So we propose a new method for extracting motion primitives from an user's demonstration and generating motions with variations for humanoid robots.

3. Wearable Interface

3.1. Wearable Interface Prototype

Motion capture devices are widely used for researches on human motions. But those devices are very expensive and difficult to use in daily life. Therefore we developed a wearable interface platform with some inexpensive sensors - inclinometer sensors, magnetic sensors and flex sensors. Our wearable interface is designed for the interaction between a human user and a partner robot in daily life, so it should be very easy to wear and easy to use. The prototype of our wearable interface platform is shown in Fig. 1.

A head mount display (HMD), PC Eye-Trek manufactured by Olympus Optical is used to interact with a partner robot. With the HMD, an user can share the sight of the robot. An earphone and a microphone are attached to the HMD for the interaction between the user and robot by speech channel.

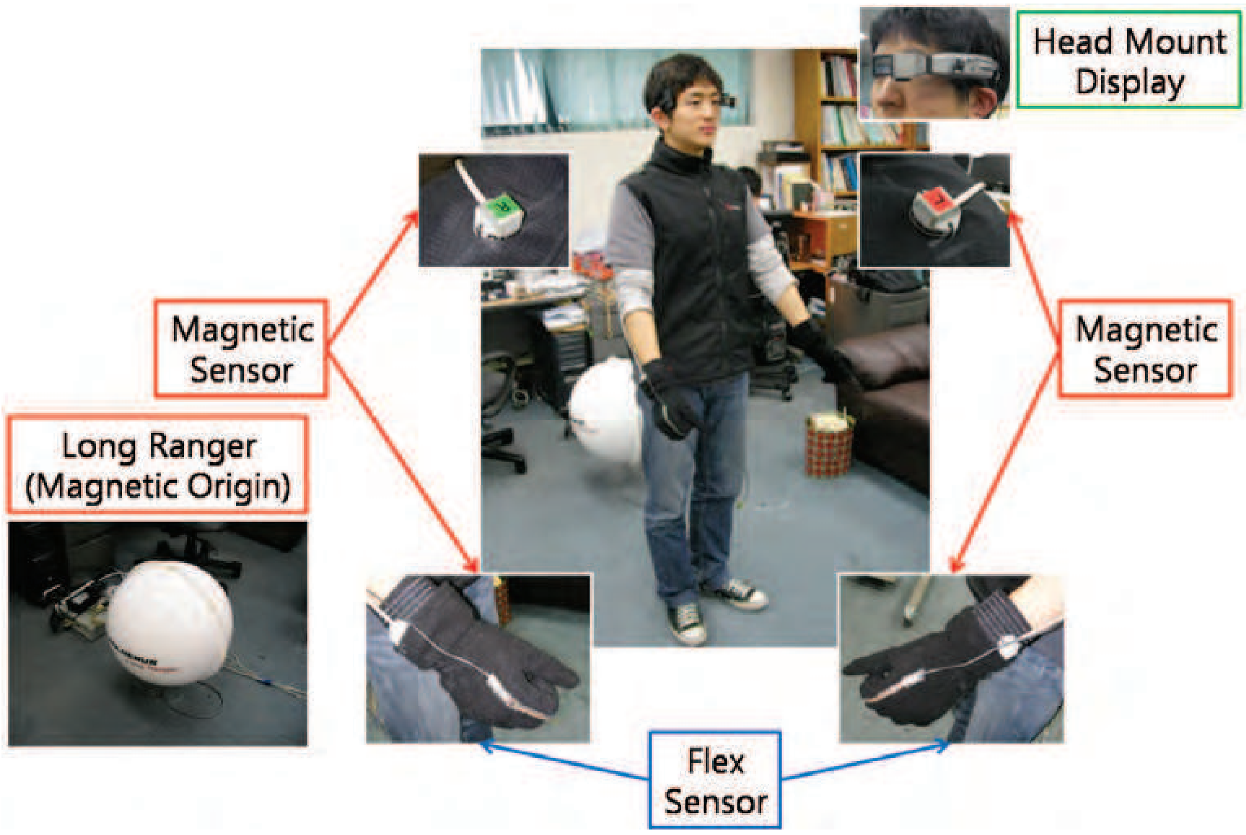

Fig. 1. Wearable Interface Platform Prototype

A Polhemus Fastrak system with a long range origin is used as magnetic sensor. Each magnetic marker can measure the 3-axis rotation angles and the distance from the origin. The effective workspace is 4.6 meters from the origin. The static accuracy for the position is 0.08 centimeters, and the static accuracy for the orientation is 0.15 degrees. Data acquisition rate is 40Hz with 4 markers, so it is fast enough to capture human motion. Four magnetic markers are used, two for shoulders and other two for wrists. By measuring the position and orientation of each shoulder and wrist, we can capture the human motion to generate a new behaviour for a humanoid robot. Two FLX-01 sensors manufactured by Abrams Gentile are attached to gloves for measuring bending degrees of human fingers. A MI-A3330LS 3-axis gyroscope sensor made by MicroInfinity is used to measure human head motion. Because our robot platform has a neck with 2 degrees of freedom, we measure the rotation angles of yaw axis and pitch axis. The sensors we used to develop our wearable interface are shown in Fig. 2.


Fig. 2. Sensors

3.2. Motion Capture using Wearable Interface

We used our wearable interface as a motion capturing device to extract motion data from the human user's demonstration. The motion of neck is measured by a gyroscope sensor attached to HMD and the motion of each hand is measured by flex sensor attached to gloves. Four magnetic sensors are used for gathering the position and orientation information of each shoulder and each wrist.

The motion of neck and hands can be applied directly to the robot because the degrees of freedoms which those sensor can measure are exactly same as the robot's ones. But in the case of arm motions, kinematic analysis must be done before applying arm motion to the robot because the control input and the measured information cannot be matched directly. The analytic solution for the inverse kinematics problem is hard to find and it makes multiple solutions. Therefore we tried to find a single solution by using geometrical information of the robot arms. After solving inverse kinematics problem, we can get 4 angle trajectories representing each arm motion. The angle trajectories of neck, hands and arms are used as the original motion data for the user's demonstration.

3.3. Human-Robot Interaction using Wearable Interface

A humanoid robot should have autonomy with a self-contained anthropomorphic body. it must have abilities to sense its surrounding environments. Furthermore, it must have sufficient intelligence to perform its task successfully. However, today's humanoid robots don't have enough abilities to have autonomy because the current limitations of robotic technologies. So we focused on the interaction with humanoids using our wearable interface with multi-modal communication channels to complement the limitation of humanoid robots' autonomy (Seo et al., 2007).

Fig. 3. HRI using the wearable interface

An user wearing the wearable interface gives commands to the partner robot through multi-modal communication channels – visual channel and speech channel. The user can see what the partner robot sees by sharing the scene from cameras in the robot's head. And then the user can choose the operation mode of robot – automatic and manual. The user can make the robot perform its task autonomously by sending speech command when the robot can solve that task by itself. If the task is too complex for the robot to solve by itself, the user can control the robot's movement manually by conducting demonstration for that task. Fig. 3 shows an example of human-robot interaction using our wearable interface.

4. A Humanoid Robot, AMIO

A humanoid robot AMIO is used as a partner robot in our experiments. AMIO is a humanoid robot developed in 2006 by Yang at el. (Yang at el. 2006). AMIO is designed to test biped walking algorithms and to imitate natural human motions. With a built-in Lithium-Polymer battery, it can operate its work up to 30 minutes without external source of electricity. AMIO has height of 150cm and weight of 45kg and it can walk at speed of 1km/h. It has a self-contained body, head, two arms with five finger hands, and two legs. The total degrees of freedom of the robot are 36 – 2 for neck, 5 for each arm, 6 for each hand, and 6 for each leg. The shape and the degrees of freedom of AMIO are shown in Fig. 4.
There exist two CCD cameras in its head and it can recognize human users and sense its surrounding environments using the stereo vision mechanism. AMIO can express its emotion using 3D characterized virtual face through a LCD screen in its chest, and it can recognize human speech command using a simple speech recognizer.

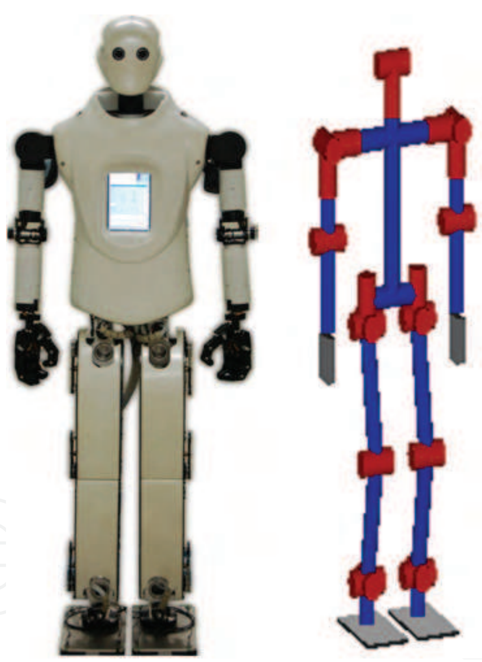

Fig. 4. A humanoid robot AMIO and its degrees of freedom

5. Developing New Abilities

5.1. Overview

We focused on generating new upper-body motions from user's demonstrations to enhance the robot's ability. It is intractable to generate new motions for a robot based on original motion data because the motion data is dense sequence of motion frames which is very hard to modify. Therefore we adopted the concept of motion primitives for representing motion sequences. The original demonstrated motion can be expressed with motion primitives and various new motions can be generated based on those motion primitives. For extracting motion primitives, we used a curve simplification algorithm and a clustering algorithm. After simplifying motion sequence, we conducted a clustering algorithm to cluster similar keyframe motions and we constructed motion primitives based on these motion clusters. The whole process of generating new motion is shown in Fig. 5.

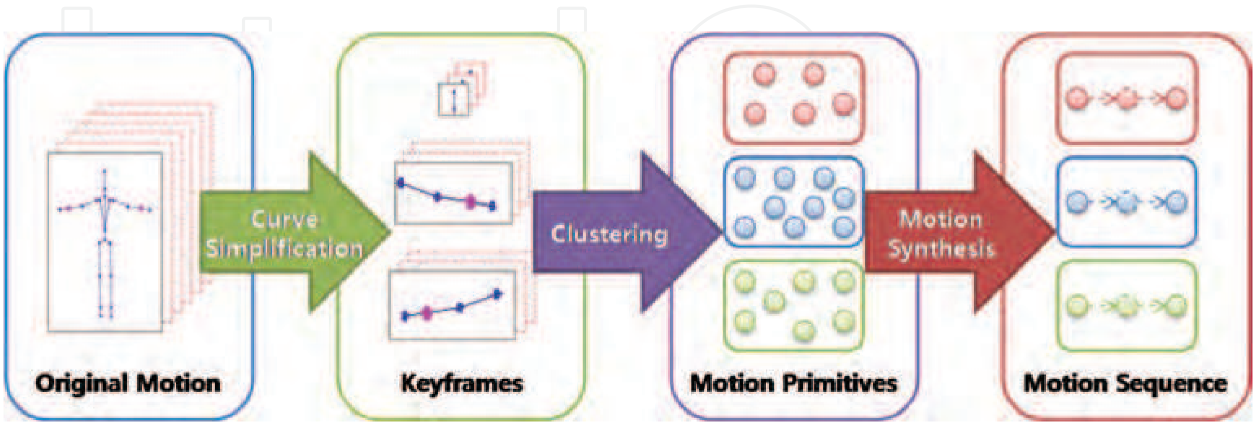

Fig. 5. Whole process for generating new motions from original motion

5.2. Motion Primitives

We simplified the original motion sequence using a curve simplification algorithm proposed by Lowe (Lowe, 1987). Lowe's algorithm converts the original curve into a set of vertices. We used the curve simplification algorithm for extracting keyframe motions from the original motion sequences. After then, we conducted a clustering algorithm to group the similar keyframe motions into the same cluster. The total number of cluster is unknown parameter, so we used adaptive resonance theory (ART) to cluster the keyframe motions (Alpaydin, 2004) (Bishop 2006). Each cluster is represented as a Gaussian distribution with its mean and variance, and it is a representative of similar keyframe motions. We used the clusters as motion primitives. The specific process of constructing motion primitives is shown in Fig. 6.

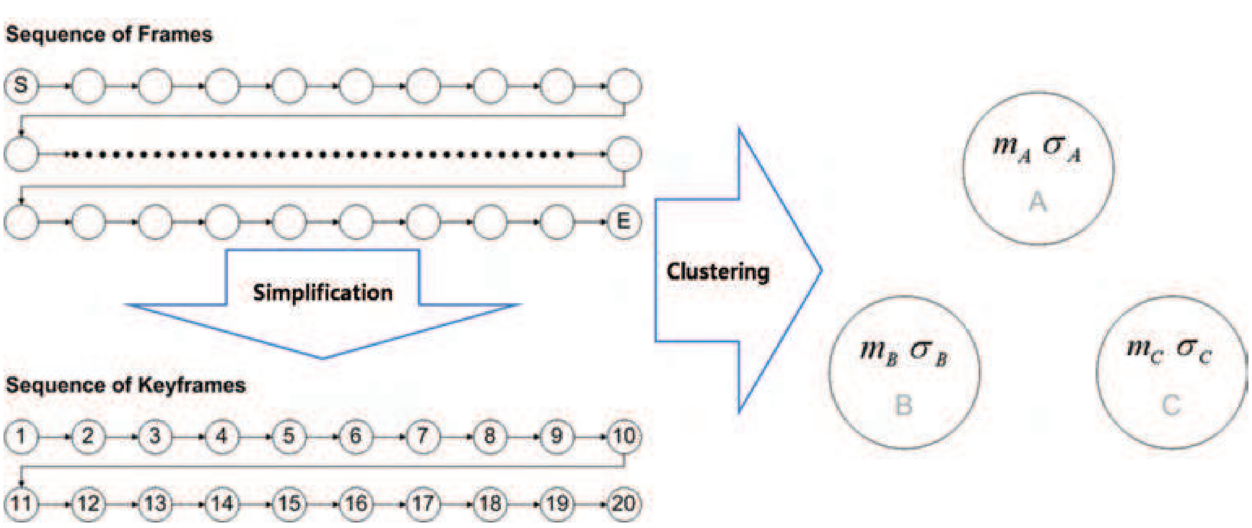

Fig. 6. Constructing motion primitives

5.3. Generating New Motions

The sequence of keyframe motions can be written as a sequence of motion primitives and we can calculate the transition probabilities among all the clusters. The transitions can be represented as a weighted directed graph. We used the graph as a model of a motion sequence for the user's demonstration. New motions can be generated by writing a new sequence with following the transitions of the model. We can create a new motion from multiple motion models. The transitions among multiple models can be only caused between the similar motion primitives and motion frame interpolations are conducted to complement the surprise changes in transitions between different motion models.

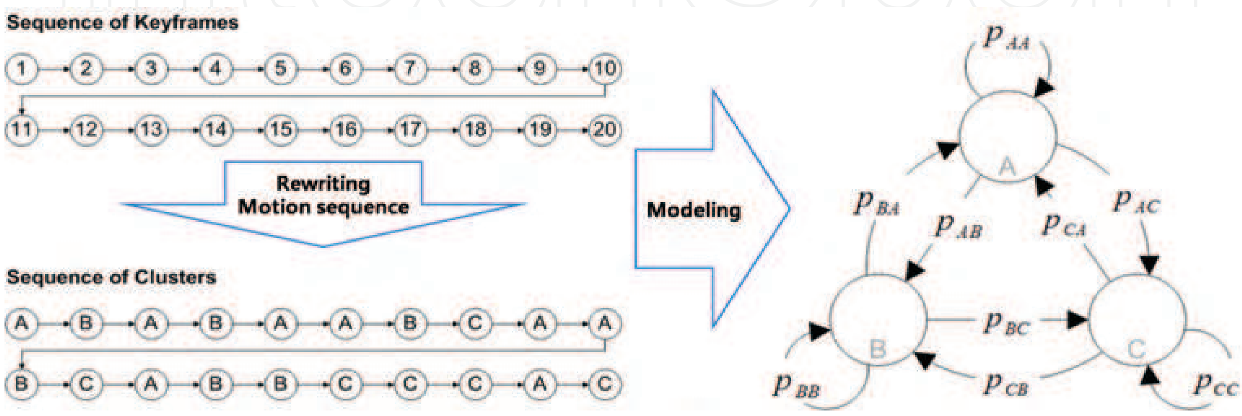

Fig. 7. Creating motion model using motion primitives

6. Examples

We tested our motion generation method using our humanoid robot, AMIO. After finishing the motion capture from the user demonstration, our system extracted motion primitives and made a motion model for the demonstrated motion. We implemented a simulator to check the validity of generated motion before applying to real robot platform like Fig. 8. An example of motion tracking using the wearable interface is shown in Fig 9.

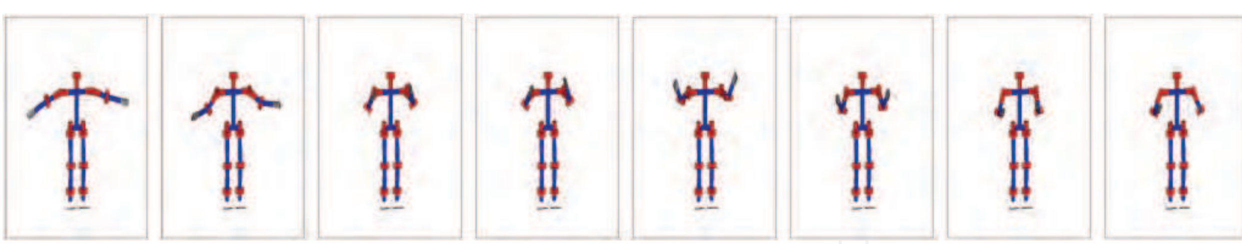

Fig. 8. An example of simulated motion

Two simple motions are demonstrated by an user – a simple heart drawing motion and a simple boxing motion. A heart drawing motion is used to test our wearable interface's motion capturing capability. The AMIO's heart drawing motion is shown in Fig. 10. And for generating new motions for AMIO, a basic boxing motion was demonstrated by an user and AMIO generated its modified motion based on the motion primitives from the demonstrated motion. Then the robot started to generate a new motion based on the motion model. The generated boxing motion for AMIO is shown in Fig. 11.


(a) (b) (c)
Fig. 9. Motion tracking from user demonstration

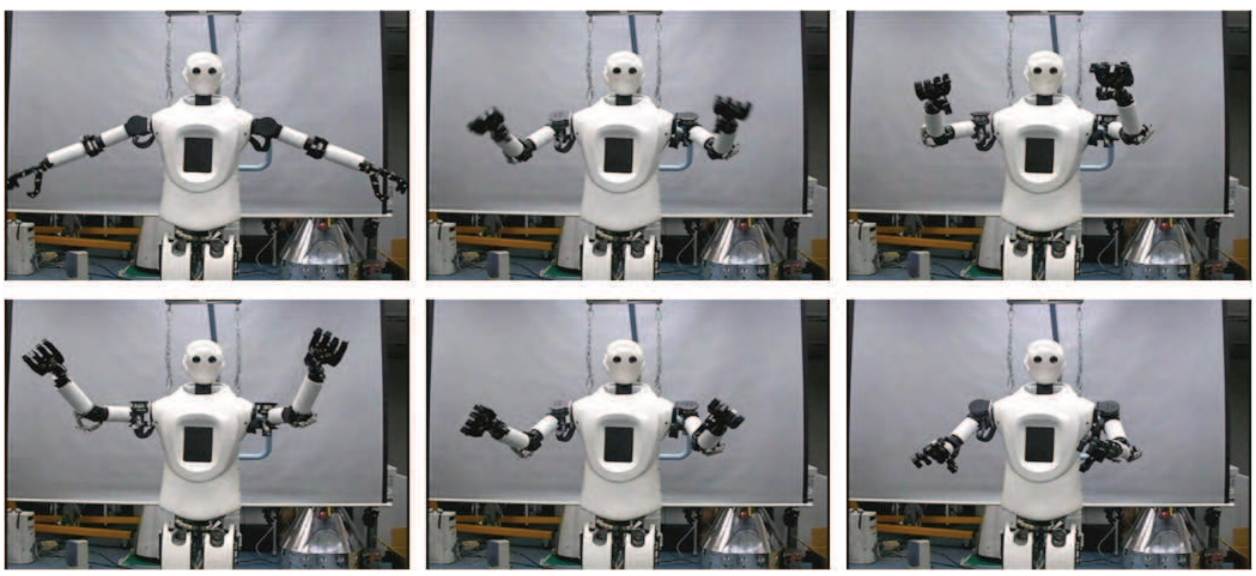
Fig. 10. A heart drawing motion

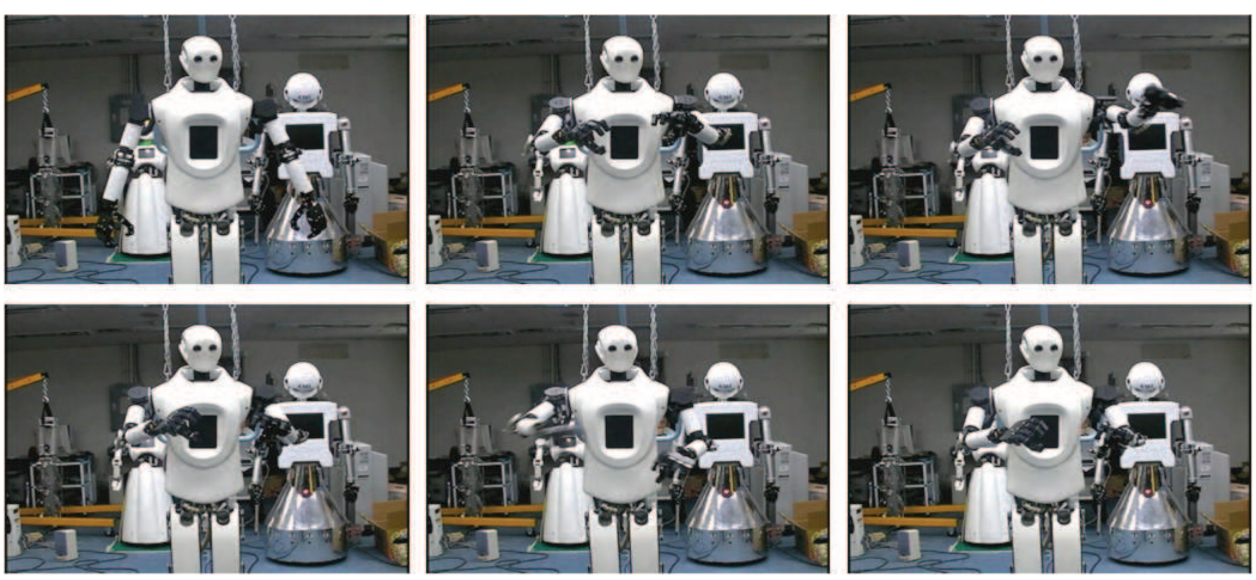
Fig. 11. A boxing motion

7. Conclusion

We focused on a method to enhance the abilities of humanoid robots by paying attention to the fact that imitation is the best way to learn a new ability. We designed and developed a wearable interface which is lightweight and presents multi-modal communication channels for interacting with robots. And we proposed a method to build motion primitives from the user demonstrated motion using curve simplification and clustering. A stochastic process is used for modelling motions and generating new motions. The stochastic model presents the way of generating various motions not monotonous repetition of demonstrated motions. And we tested our method by using a humanoid robot AMIO.
The limitations of our work are 1) limited working space of human user because our wearable interface uses magnetic sensors which can be operated near the origin sensor, and 2) the motions that we generated are not considering the meaning of the task. For the further work, we will replace the magnetic sensors with the other positioning sensors that do not have any spatial limitations. And for improving the intelligence of humanoid robots, defining task descriptors and extracting task descriptors from a demonstrated task are indispensable. We are planning to conduct a research on task description method for generating tasks with ease.

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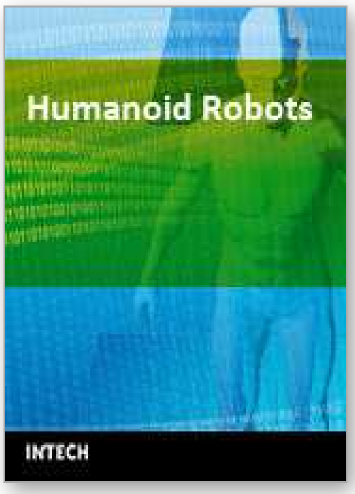

Humanoid Robots

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Humanoid robots are developed to use the infrastructures designed for humans, to ease the interactions with humans, and to help the integrations into human societies. The developments of humanoid robots proceed from building individual robots to establishing societies of robots working alongside with humans. This book addresses the problems of constructing a humanoid body and mind from generating walk patterns and balance maintenance to encoding and specifying humanoid motions and the control of eye and head movements for focusing attention on moving objects. It provides methods for learning motor skills and for language acquisition and describes how to generate facial movements for expressing various emotions and provides methods for decision making and planning. This book discusses the leading researches and challenges in building humanoid robots in order to prepare for the near future when human societies will be advanced by using humanoid robots.

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