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Associative Motion Generation for Humanoid Robot Reflecting Human Body Movement

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Abstract

This paper proposes an intuitive real-time robot control system using human body movement. Recently, it has been developed that motion generation for humanoid robots with reflecting human body movement, which is measured by a motion capture. However, in the existing studies about robot control system by human body movement, the detailed structure information of a robot, for example, degrees of freedom, the range of motion and forms, must be examined in order to calculate inverse kinematics. In this study, we have proposed Associative Motion Generation as humanoid robot motion generation method which does not need the detailed structure information. The associative motion generation system is composed of two neural networks: nonlinear principal component analysis and Jordan recurrent neural network, and the associative motion is generated with the following three steps. First, the system learns the correspondence relationship between an indication and a motion using training data. Second, associative values are extracted for associating a new motion from an unfamiliar indication using nonlinear principal component analysis. Last, the robot generates a new motion through calculation by Jordan recurrent neural network using the associative values. In this paper, we propose a real-time humanoid robot control system based on Associative Motion Generation, that enables user to control motion intuitively by human body movement. Through the task processing and subjective evaluation experiments, we confirmed the effective usability and affective evaluations of the proposed system.

Key Words: Humanoid Robot Control System, Human Body Movement, Kinect, Nonlinear Principal Component Analysis, Jordan Recurrent Neural Network

1. Introduction

Research field in robotics has been advanced, and mutual interaction between humans and robots are especially researched [1]. Then, humanoid robots have been focused and researched due to its effectiveness for user's affection and usability. Then, the robot can communicate with human using its motions: body language, gestures, eye contact and so on [2]. And motion generation system reflecting human body movement also has been developed for humanoid robot, which is mostly measured by a motion capture.

It is thought that the robot motion generation using the motion capture is superior to general controller such as a joystick in providing anyone with intuitive and careful control of robot motions. However, for adapting the human body movement to humanoid robot motion, it is necessary to consider the difference between human and robot: kinematics, self interference and so on. In the existing studies about robot control system by human body movement [3, 4], the detailed **structure information of the robot** (e.g., degrees of freedom, the range of motion and forms) must be examined in order to calculate inverse kinematics. Meanwhile, in our previous study, we proposed Associative Motion Generation (**AMG**) [5] as humanoid motion generation method, which does not need detailed robot's structure information.

In this paper, we propose the real-time robot control system based on AMG, that enables user to intuitively control humanoid robot motion by human body movement. Figure 1 shows the general of the proposed system, and this system works as the following procedures:

1. Observe human body movement by Kinect[6] and extract representative physical coordinate points.

2. By using AMG, control the robot motion from the extracted coordinate points.

In this paper, we focus on coordinates of both arms as

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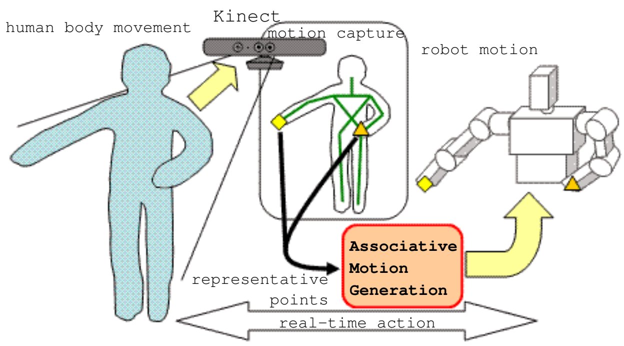


Figure 1: General idea of the proposed system.

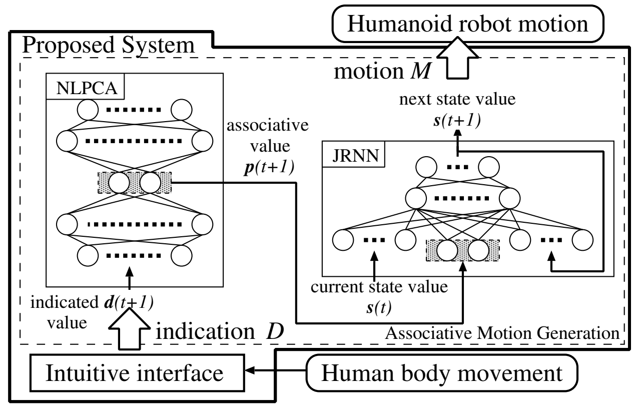


Figure 2: General description of the proposed system. NLPCA is connected with JRNN by an associative value, and the system can generate the corresponding motion to each indication.

representative physical coordinate points, and construct the robot control system to generate the motion of a robot's upper body. Through the task processing and subjective evaluation experiments, we verify the effective usability and affective evaluations of the proposed system.

2. Related Work

To achieve human like movement of the robot, Matsui et al. [7] focused on not only robot's joint angle but also robot's surface movement. And they proposed the motion generation system for imitating the posture of the appearance between the robot and human by using neural network. However, their system assumed the joint structure of robot resembling human being, thus it is difficult to apply the system to various robots.

Kurihara et al. [8] considered the human body movement to movement of some representative points, e.g., both hands, both legs, trunk and head. They proposed the system to convert an observed human body movement into a natural motion of the robot by the inverse kinematics using constraint representation with the virtual link and the singularity low-sensitive motion resolution. However, in their system, the detailed structure information of the robot must be examined in order to set the constraint representation. Thus, it is thought that their system is hard to use and unfamiliar to public.

3. Associative Motion Generation (AMG)

Figure 2 shows general structure of the proposed system. An indication is time sequence of coordinate values that the robot obtains through a sensor. And it is defined as three-dimensional coordinate values of the indicator's both arms in this paper.

In this study, the generated robot motion corresponding to an indication is defined as a **corresponding motion**. AMG learns correlations between indications and the corresponding robot motions. For unfamiliar indication, AMG associates the corresponding motion with the similarity between the indication and the learned indications, and newly generates the motion. In fact, AMG has the following functions for the unfamiliar indication:

1. **Motion association**: the system relates an indication with the joint angles of the robot's posture.

2. **Motion generation**: the system generates a motion which is a time-series of posture.

AMG is composed of two kinds of neural networks: nonlinear principal component analysis (NLPCA) [9, 10] and Jordan recurrent neural network (JRNN) [11]. NLPCA is used for motion association, which is the five-layer sandglass neural network that has the function of the principal component analysis with non-linear bases. By NLPCA, **associative value** is calculated with reflecting the similarity between the given indication and the previously learned indications, and the calculated value is used for the motion generation. JRNN is used for motion generation, which has feedback from the output layer to the input layer and a property that the current output value influences the next output value. Therefore, as the joint angle on each Δt (t means the minimum unit of robot motion) is used for input and output, consecutive postures are obtained as output vectors.

Figure 3 shows an overview of AMG. AMG has three phases: learning, association and generation. In the learning phase, the robot learns indications and their corresponding motions using training data, and the connection weights of each network are updated. After the learning, the indicator gives a new indication that the robot has not experienced. In the association phase, the robot inputs the

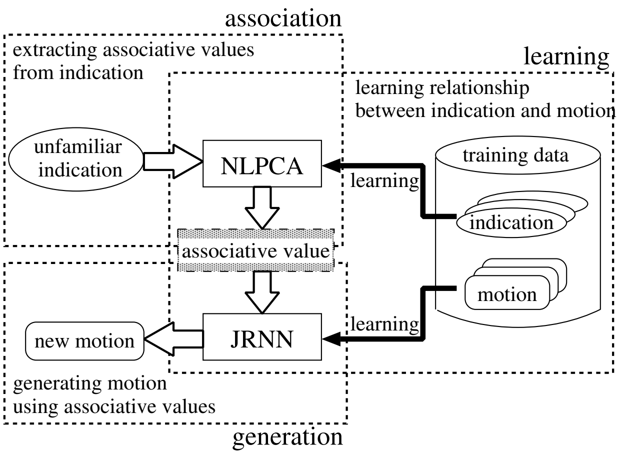


Figure 3: Overview of Associative Motion Generation.

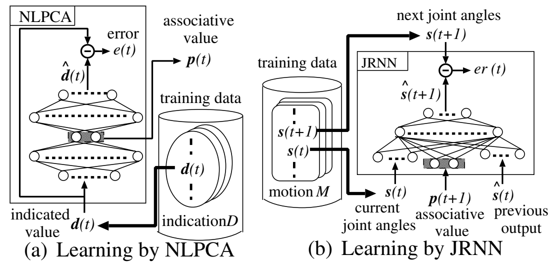


Figure 4: Learning phase.

new indication to NLPCA and extracts the associative values. In the generation phase, the motion corresponding to the unfamiliar indication is associated and newly generated by inputting the associative value to JRNN.

3.1 Learning Relationship Between Indication and Motion

NLPCA and JRNN learn the relationship between an indication as input and a motion as output using training data: pairs of an indication and its corresponding motion. The connection weights of each network are updated using the back-propagation algorithm [12].

3.1.1 Formulation of Associative Space

NLPCA learns an identity mapping that output $\hat{\boldsymbol{d}}(t)$ is approximated to input $\boldsymbol{d}(t)$ when the indicator gives an indication $D = [\boldsymbol{d}(1), \cdots, \boldsymbol{d}(T)]$ to the robot. The squared error $e(t) = ||\hat{\boldsymbol{d}}(t) - \boldsymbol{d}(t)||^2$ is minimized by learning. NLPCA acquires a function to extract the value representing a feature of the input from the input layer to the middle layer because units of the middle layer are less than those of the input layer. In this paper, we define the middle layer of NLPCA as an *association layer* and its output at t as *associative value* $\boldsymbol{p}(t) = (p_1(t), \ldots, p_n(t))^{\mathrm{T}}$. Moreover, n-dimensional space in which associative values are plotted is defined as *associative space*. The associative values are calculated as follows:

$$\boldsymbol{p}(t) = sig(\boldsymbol{w}_2 sig(\boldsymbol{w}_1 \boldsymbol{d}(t))), \quad (1)$$

where $\boldsymbol{w}_1$ and $\boldsymbol{w}_2$ are weight matrices between two layers from the input layer to association layer and sig is the sigmoidal function. If two arbitrary indication values $\boldsymbol{d}(i)$ and $\boldsymbol{d}(j)$ are close to each other, two associative values $\boldsymbol{p}(i)$ and $\boldsymbol{p}(j)$ will also be close by sigmoidal continuity in Equation (1). That is, topological relationships of input values are maintained in the associative values. This continuity is an effective property for recognizing the similarity of indications in the associative space. The learning by NLPCA is shown in Figure 4(a). After this learning, associative values $P = [\boldsymbol{p}(1), \cdots, \boldsymbol{p}(T)]$ are extracted from each indication D based on Equation (1).

3.1.2 Construction of Motion Generator

The inputs of JRNN are the associative values and joint angles of the robot in a corresponding motion. JRNN has feedback that inputs the previous output as partial units of the input layer. The robot acquires the joint angles retaining time continuity because its next output posture depends on the previous posture through the feedback. Consequently, JRNN learns to predict the next joint angles $\boldsymbol{s}(t+1)$ on the basis of the input current joint angles $\boldsymbol{s}(t)$ and next associative value $\boldsymbol{p}(t+1)$. The squared error $er(t) = ||\hat{\boldsymbol{s}}(t) - \boldsymbol{s}(t)||^2$ is minimized by learning. The predictive learning of JRNN is shown in Figure 4(b). By this predictive learning, JRNN becomes an associative motion generator. The units to which the associative value is input are called *association layer*.

3.2 Association and Motion Generation

When the indicator gives unfamiliar indication to the robot, the robot generates a corresponding motion through two phases: extracting the associative value using NLPCA and generating the associative motion using JRNN.

3.2.1 Analogically-Based Associative Value

The left of Figure 5 presents the extraction of associative values P^{unf} from an unfamiliar indication D^{unf} that the robot has not experienced. When the unfamiliar indication $D^{unf} = [\boldsymbol{d}^{unf}(1), \cdots, \boldsymbol{d}^{unf}(T)]$ is given to the robot, associative values $P^{unf} = [\boldsymbol{p}^{unf}(1), \cdots, \boldsymbol{p}^{unf}(T)]$ is extracted based on Equation (1). The similarity between the unfamiliar indication and a learned one can be replaced by

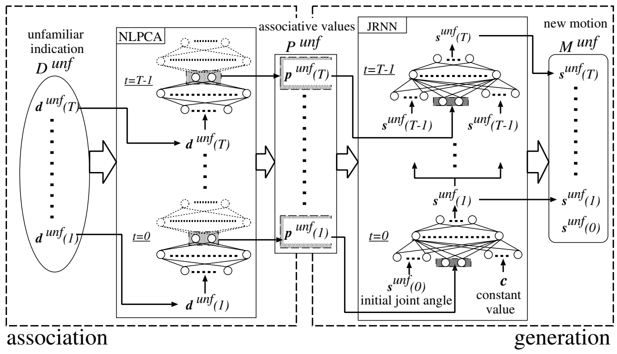
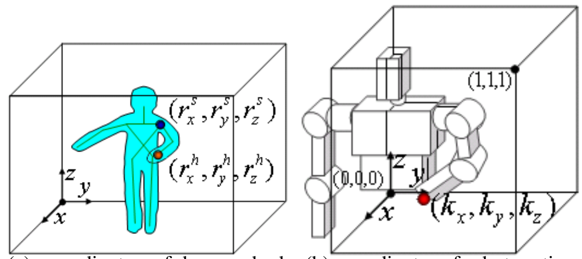


Figure 5: Association phase (left) and generation phase (right).



(a) coordinates of human body movement.
(b) coordinates of robot motion.

Figure 6: Conversion of coordinates from human body movement to robot motion (left arm).

degrees of similarity with learned associative values in the associative space of P^{unf}. In this study, the robot generates the motion corresponding to a given unfamiliar indication D^{unf} by this property.

3.2.2 Generation of Corresponding Motion

The right of Figure 5 presents the generation of the new motion M^{unf} corresponding to the unfamiliar indication D^{unf}. The corresponding motion to the unfamiliar indication is generated by repeating forward calculation of JRNN using the series of associative values P^{unf} as input of the associative layer in JRNN. Joint angles of the next posture $\boldsymbol{s}^{unf}(t+1)$ are obtained as output of JRNN by inputting the current joint angles $\boldsymbol{s}^{unf}(t)$ and the associative value $\boldsymbol{p}^{unf}(t+1)$ to produce the next posture. The joint angles of the initial posture are given at $t = 0$. The following calculation is repeated from 0 to $T-1$.

$$\boldsymbol{s}^{unf}(t+1) = \begin{cases} f(\boldsymbol{s}^{unf}(t), \boldsymbol{p}^{unf}(t+1), \boldsymbol{c}) & \text{if } t=0 \\ f(\boldsymbol{s}^{unf}(t), \boldsymbol{p}^{unf}(t+1), \boldsymbol{s}^{unf}(t)) & \text{if } 1 \le t \le T-1, \end{cases} \quad (2)$$

where f is the map function that JRNN acquired by learning, and its arguments are input to the input layer, association layer, and context layer that receives feedback from the output. $\boldsymbol{c}$ is a vector value constant at $t = 0$. The series of joint angles $M^{unf} = [\boldsymbol{s}^{unf}(0), \cdots, \boldsymbol{s}^{unf}(T)]$ is acquired by this calculation. The corresponding motion to the unfamiliar indication is M^{unf}.

3.3 Related Methods

Aoyama et al. [13] used the clustering property of Self-Organizing Map and aimed at generating the appropriate output to the input that the robot had not learned. As a result, their robot acquired output voices imitating some unknown input voices in a vocal imitation experiment. However, it could not generate an output motion corresponding to an unknown input in a motion imitation experiment. In our method, the robot is able to generate a motion corresponding to an indication unfamiliar to the robot because we used associative values in which topological relationships of input values are maintained for motion generation. Moreover, it generated the motions that were not represented as a combination of learned motions by calculation using the nonlinear function.

Lee et al. [14] proposed a method to associate whole body motion of tool-usage from the trajectory of a tool that a human was grasping by partial observation using Hidden Markov Model (HMM). In this method, when their robot observed an unknown tool trajectory, it selected the most similar body motion knowledge from a database of learned motion depending likelihood of HMM. However, generation of a new motion was not considered when an observed tool trajectory was not similar to learned trajectories. In our method, when the robot is given an unfamiliar indication, it generates a new motion corresponding to the indication by a motion generator that was constructed during a learning phase. The unfamiliar indication is quite different from learned indications (see lower of Figure 10).

4. Intuitive Motion Generation

In this paper, we developed the intuitive interface with Kinect to input the indication, that is human body movement, into AMG (**Kinect+AMG**), Kinect is a motion capture device made by Microsoft, which has two RGB cameras and a depth sensor which can obtain human forms and gestures without any markers, and enables human to control operational objects by their body movement.

4.1 Indication Generation by Human Body Movement

Figure 6(a) and Figure 6(b) each shows coordinate of the human structure observed by Kinect and the robot structure

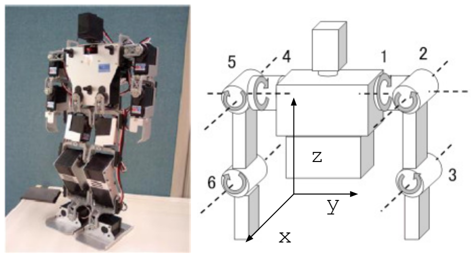


Figure 7: Humanoid robot KHR-2HV, and its link model.

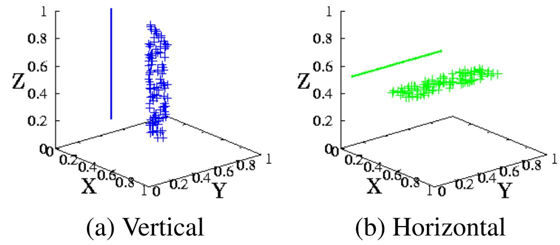


Figure 8: Indicated trajectories in training data for NLPCA.

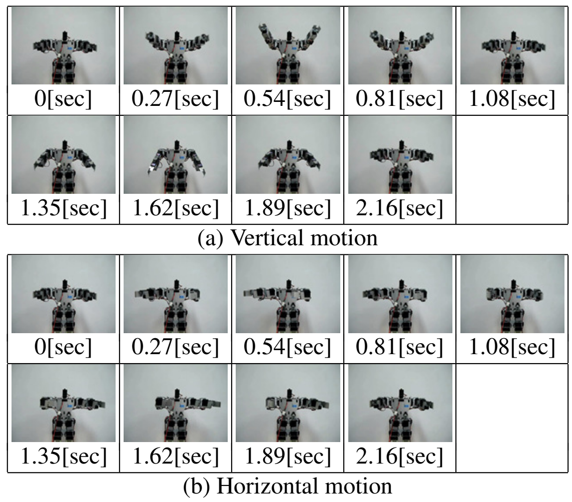


Figure 9: The corresponding motions in training data for JRNN.

in AMG, respectively. In this paper, the range of indication value is $[0, 1]$ on AMG. Hence the human structure information is converted to the indication by following equation, and inputted into AMG.

$$\boldsymbol{p}(t) = sig(\boldsymbol{r}^h(t) - \boldsymbol{r}^s(t)), \tag{3}$$

where, $\boldsymbol{p}(t)$ shows the indication on the given time t, and $\boldsymbol{r}^h$ and $\boldsymbol{r}^s$ each shows three-dimensional coordinate of both human hands and shoulder, respectively. And sig shows sigmoid function. The distance between hand and shoulder is calculated and gap of human and robot structure is minimized. Moreover, sigmoid function standardizes individual differences such as a length of arms. These are applied to both arms, and it enables anyone to operate both arms of robot with their body movements. In fact, the purpose of AMG is summarized as to achieve $\boldsymbol{p}(t) \fallingdotseq \boldsymbol{k}(t)$, where, $\boldsymbol{k}$ shows the coordinates of robot's hand in AMG.

4.2 Real-time Motion Generation Demonstration

We conducted real-time motion generation demonstration with KHR-2HV (17 DOFs, 353×183[mm],1.27[kg]) as the operational humanoid robot to test the effectiveness of our proposed system. KHR-2HV has three degrees of freedom in each arm, and the arms are used for motion (Figure 7). The coordinate system complied with the right-hand rule based on the robot.

4.2.1 Experimental Setup

We set NLPCA have 3 units in its input/output layer, 2 units in its association layer, and 9 units in its hidden layer. And the indication on the given time, which is converted from the three-dimensional coordinate of human hand by Equation (3), is inputted into NLPCA. We set JRNN have 6 units in its each input, output and context layer, 2 units in its association layer, and 20 units in its middle layer. Input values to JRNN are normalized, and the joint angles of the robot's arms become $[0, 1]$. The outputs of the association layer of NLPCA are inputted into the one of JRNN.

As the training data, we prepared the two pairs of indications and its corresponding motion: 'Vertical' and 'Vertical motion,' and 'Horizontal' and 'Horizontal motion.' 'Vertical' and 'Vertical motion' each shows the parallel trajectories to the Z-axis and that robot moved its arms up and down, respectively. 'Horizontal' and 'Horizontal motion' each shows the parallel trajectories to the Y-axis and that robot moved its arms from left to right, respectively.

NLPCA was trained with indications. Three-dimensional coordinate points are used as the indications of the training data, and are shown in Figure 8. In Figure 8, the shape of a trajectory were represented on the Y-Z plane, and the solid lines which are projected trajectories are shown. The X-coordinate values of a trajectory were random. JRNN was trained with corresponding motions. The two types of the corresponding motions in the training data are shown in Figure 9.

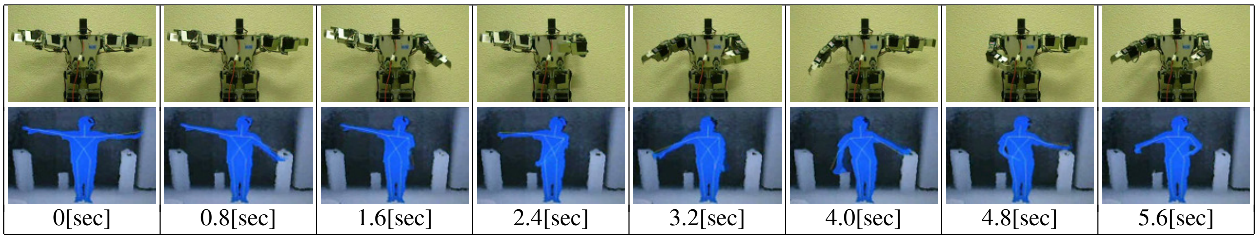
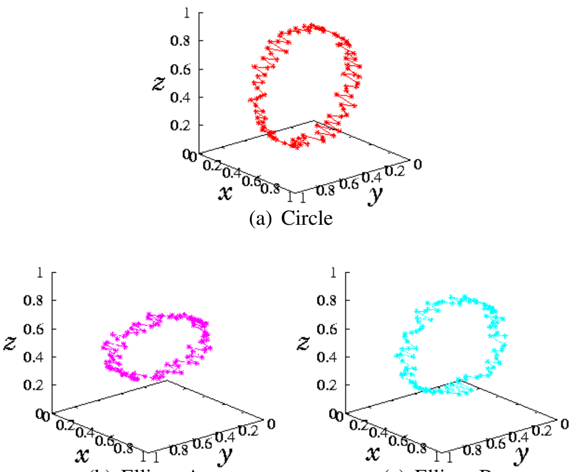


Figure 10: Snapshots of demonstration.



(a) Circle (b) Ellipse A (c) Ellipse B

Figure 11: Unfamiliar indications.

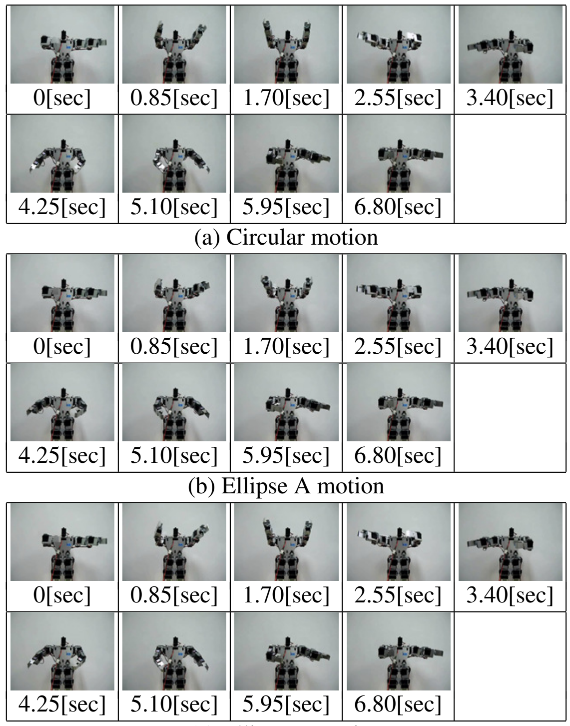
4.2.2 Generating New Motion from an Unfamiliar Indication

We conducted motion generation demonstration to verify whether the robot can generate motions corresponding to unfamiliar indications in real-time or not. Figure 10 shows the snapshots of the human movement and the corresponding robot motion in the demonstration. Through the demonstration, we confirmed that the humanoid robot motion could be controlled by human body movement in real-time.

4.3 Evaluation of Corresponding Motion

We conducted another experiment to verify whether differences in indications were correctly reflected in the generated motions. The corresponding motions we evaluated were generated from the following indications:

- Circle: a circular trajectory.
- Ellipse A: an elliptical trajectory whose minor axis was **0.5** times the diameter of 'Circle'.
- Ellipse B: an elliptical trajectory whose minor axis was **0.8** times the diameter of 'Circle'.



(a) Circular motion (b) Ellipse A motion (c) Ellipse B motion

Figure 12: Corresponding motions.

The centers of the indications were the same point as 'Circle' and their major axes were the same length as the diameter of 'Circle'. Their trajectories are shown in Figure 11.

Result. The generated corresponding motions from their indications are shown in Figure 12. The tracks of the robot's left hand in generated corresponding motions are shown in Figure 13. The tracks were plotted in the same way as previously described, and the track of 'Circular motion' is included for comparison. The red-colored line represents 'Circle', the pink-colored line represents 'Ellipse A', and the aqua-colored line represents 'Ellipse B'. As can be seen from Figure 13, the movement of the robot's arm became smaller in the order of 'Circular motion', 'Ellipse B motion' and 'Ellipse A motion'. The minor axis of indications 'Ellipse A' and 'Ellipse B' corresponded to the up-and-down movement of the robot's arm. Therefore, there

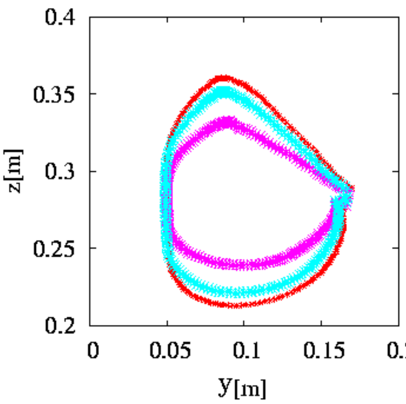


Figure 13: Trajectories of left hand in motion: 'Circular motion' (red), 'Ellipse A motion' (pink), and 'Ellipse B motion' (aqua).

Table 1: Ratio of Minor Axis of Ellipse to Diameter of Circle.

Ellipse A motion	Ellipse B motion
0.63	0.87

were appropriate changes in the generated motions. Table 1 presents the two ratios of the minor axes of 'Ellipse A motion' and 'Ellipse B motion' to the Z-axial diameter of 'Circular motion' in Figure 13. The ratios of the indications of 'Ellipse A' and 'Ellipse B' to 'Circle' were 0.5 and 0.8, respectively. Accordingly, we expected that the ratios in the generated corresponding motions would be similar. We can see from Table 1 that the robot reflected the difference of the indications in two generated motions within the range that can be allowed.

5. Subjective Evaluation Experiment

To verify the availability of the proposed system, we conducted two types of subjective evaluation experiment: the effect on the operator's affection, and the controllability for humanoid robot motion. We compared the proposed system with M-editor and Stick+AMG. Figure 14 shows Graphical User Interface (GUI) of M-editor. In M-editor, the robot motion is assumed as the time series of static behavior. The M-editor is the method that directly input the each joint angle and transition time from a static behavior to the next one. Stick+AMG is the method to use analog stick shown in Figure 15 as input of AMG instead of the human body movement.

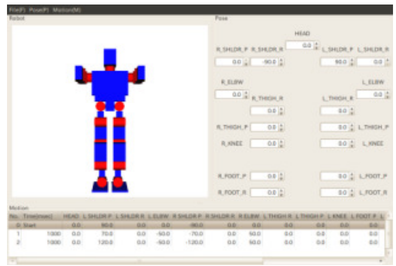


Figure 14: GUI of M-editor.

Figure 15: Analog stick.

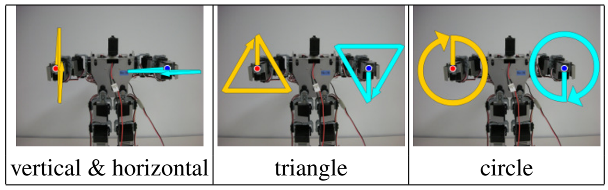


Figure 16: Designated motion.

5.1 Designated Motion Generation Experiment

We conducted the subjective evaluation experiment to verify the effect on the operator's affection. In the experiment, eight males and females were participated. They were asked to operate KHR-2HV with each interface in random order as following steps, and evaluated the impressions from the operating.

1. Listen to explanation of interface and how to operate the robot.
2. Operate the robot as it moves in the designated motion, which is shown in Figure 16.
3. Evaluate impressions from the operating.

A participant evaluates all three interface in random order. The fixed designated motion is used to unify the impressions from the robot motion, and clarify the difference between the impressions from each interface. We used the Semantic Differential (SD) method [15] to evaluate impressions for the prepared six pairs of adjectives on a scale of one to seven, which are listed in Table 2.

Result. Figure 17 shows the average and the standard error of the evaluation of all participants for each interface. The parenthetical adjectives significantly deffer with Tukey's test [16] (5% significance level). As shown in Figure 17, Kinect+AMG significantly gives positive impressions to the participants for all adjectives in comparison with M-editor. And in comparison with Stick+AMG, Kinect+AMG significantly gives positive impressions in all

Table 2: Prepared adjectives in the designated motion generation experiment.

Bright – Dark
Excitable – Calm
Boisterous – Lonely
Fulfilling – Boring
Pleasurable – Painful
Cheerful – Gloomy

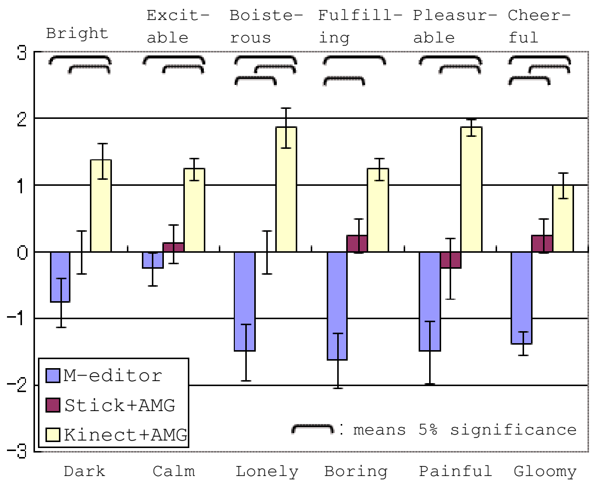


Figure 17: Subjective evaluation results in designated motion generation experiment.

adjectives except 'Fulfilling.' Therefore, it is confirmed that the Kinect+AMG gives significantly effective influences on the psychology to the operator.

5.2 Task Processing Experiment

We conducted the subjective evaluation experiment to verify the controllability of the proposed system. In the experiment, sixteen males and females were participated. They were asked to operate KHR-2HV and achieve block-lifting task shown in Figure 18 with each interface in random order, and evaluated the impressions. To evaluate impressions, we also used the SD method for the prepared six pairs of adjectives listed in Table 3. Figure 19 shows a snapshot of the task processing experiment. The goal of the block-lifting task is "grab the block on the front of the robot with robot's both hand, and lift it up to the robot's head height."

Result. Average time to achieve a task of each interface is shown in Table 4. As shown in Table 4, it was confirmed that Kinect+AMG achieved the task in the shortest times. M-editor took so long times because it needed to manually

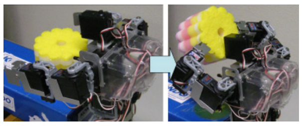


Figure 18: Block lifting task.

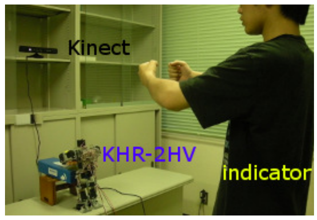


Figure 19: Appearance of experiment.

Table 3: Prepared adjectives in the task processing experiment.

Good – Bad
Easily-handled – Hardly-handled
Intuitive – Non-intuitive
Affinitive – Non-affinitive
New – Old
Accustomed – Unaccustomed

set each joint angle of the robot.

Figure 20 shows the subjective evaluations of the each interface after processing the task. The parenthetical adjectives significantly deffer with Tukey's test (1% significance level). As shown in Figure 20, in comparison with M-editor, both Stick+AMG and Kinect+AMG get more positive impressions. In comparison with Stick+AMG, Kinect+AMG significantly gets positive impressions in adjectives 'Intuitive' and 'Affinitive.'

The results suggested that the task was quickly processed by the proposed system because the operators could intuitively control the robot by their body movement in real-time; it seemed that the proposed system, in which the robot was controlled like their own human bodies, provided them with some positive impressions.

5.3 Summary of Experimental Result

As explained in section 3, AMG can operate the robot without their detailed structure information. Through the task processing and subjective evaluation experiments, it was confirmed that the proposed system controlled the robot intuitively, and gave significantly effective influences on psychology to operators in real-time. From these results, it is suggested that the proposed system is useful as a real-time humanoid robot control system, which does not need any detailed robot structure information.

6. Conclusion and Future Works

In this paper, we proposed a real-time humanoid robot control system reflecting human body movement. The sys-

Table 4: Average time to achieve a task.

M-editor	Stick+AMG	**Kinect+AMG**
139.32[sec]	8.95[sec]	**7.33**[sec]

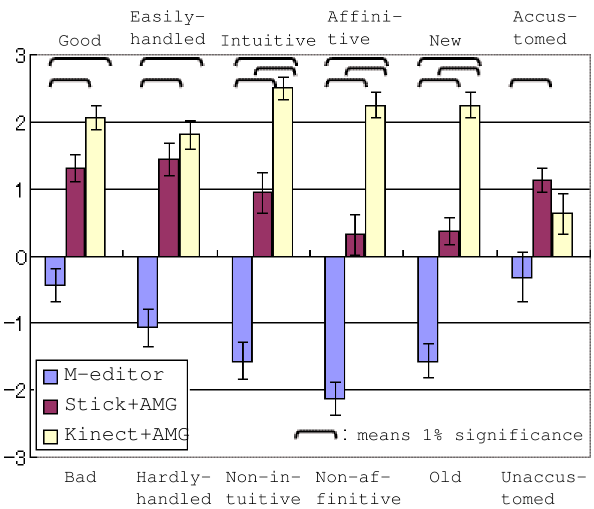


Figure 20: Subjective evaluation results of interface in the task processing experiment.

tem enables user to intuitively control the robot's motion as if the robot motion is human own body movement. In the proposed system, AMG is used as the learning and generation mechanism. AMG can generate unfamiliar robot motion from simple and few learning data, then AMG associates the inexperienced motion from the learned indications. That is to say, AMG can dynamically generate the robot motion corresponding to user's free body movement, and it realizes intuitiveness on robot control.

Through task processing and subjective evaluation experiments, we confirmed the effective usability and affective positive evaluations of the proposed system. In particular, the proposed system provided user with intuitiveness and affinity on operation. Using the proposed system, it is expected that the robot operation is not only just an operation but also entertainment because it was confirmed that the proposed system impressed so many positive evaluations through the experiment.

In this paper, the proposed system did not care the centroid of the robot and the stability were not covered. Thus, in the future, not only upper body but also whole body of the robot will be under the control, and practical utility and more freely robot control will be realized. Moreover the three-dimensional motion can be realized as covering the X-coordinate values, and it is expected that the robot can perform the user's movement more directly. And we will test the proposed system with some other robot, and verify its effectiveness and general versatility.

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