Clustering Observed Body Image for Imitation based on Value System

Yoshihiro Tamura, Yasutake Takahashi, and Minoru Asada

Abstract— **In order to develop skills, actions, behavior in a human symbiotic environment, a robot is going to learn something from behavior observation of predecessors or humans. Recently, robotic imitation methods based on many approaches have been proposed. We have proposed reinforcement learning based approaches for the imitation and investigated them under an assumption that the observer recognizes the body parts of the performer and maps them to the ones of its own. However, the assumption is not always applicable because the body of the performer is usually different from the observing robot. In order to learn various behaviors from the observation, the robot has to cluster the observed body area of the performer on the image and maps the clustered parts to its own body parts based on reasonable criterion for itself and feedback the data for the imitation.**

This paper shows that the clustering the body area on the camera image into the body parts of its own based on the estimation of the state value in the framework of reinforcement learning as well as it imitates the observed behavior based on the state value estimation. The clustering parameters are updated based on the temporal difference error, in an analogous way such that the parameters of the state value of the behavior are updated based on the temporal difference error. The validity of the proposed method is investigated by applying it to a imitation of a dynamic throwing motion of an inverted pendulum robot and human.

I. Introduction

In order to develop skills, actions, behavior in a human symbiotic environment, a robot is going to learn something from behavior observation of predecessors or humans. Observation of others make the behavior learning rapid and therefore much more efficient [1], [2], [3]. Recently, robotic imitation methods based on many approaches have been proposed (for example, [4], [5]). It is desirable to acquire various unfamiliar behaviors with some instructions from others, for example, surrounding robots and/or humans in real environment because of huge exploration space and enormous learning time to learn. Therefore, behavior learning through observation has been more important.

Reinforcement learning has been studied well for motor skill learning and robot behavior acquisition in both single and multi-agent environments [6]. The reinforcement learning generates not only an appropriate behavior (a map from states to actions) to achieve a given task but also a utility of the behavior, an estimated discounted sum of the reward value that will be received in the future while the agent is taking an appropriate policy. This estimated discounted sum of the reward is called "state value." Estimation error of the state value is called "temporal difference error" (hereafter TD error) and the agent updates the state value and the behavior based on the TD error. Eventually, the agent represents its behavior based on the state value.

On the other hand, Meltzoff suggests [7] "Like me" hypothesis that a child uses the experience of self to understand the actions, goals, and psychological states of a performer including its caregiver. From a viewpoint of reinforcement learning framework, this hypothesis indicates that the reward and state value of the performer might be estimated through observing the behavior. Takahashi et al. proposed a method to understand observed behavior based on the state value estimation [8] and a method for mutual development of acquisition and recognition of observed behavior [9][10].

The imitation based on reinforcement learning approaches has been investigated them under an assumption that the observer recognizes the body parts of the performer and maps them to the ones of the observer. However, the assumption is not always applicable because the body of the performer is usually different from the observing robot. In order to learn various behaviors from the observation of different types of performers, the robot has to cluster the observed body area of the performer on the camera image and maps the clustered parts to its own body parts based on reasonable criterion for itself and feedback the data to behavior learning by itself.

When a human child learns dynamic behavior through the observation of the caregiver's motion, the caregiver intentionally takes the action that the child can easily execute. For instance, when the caregiver plays catch with the child, it is usual not to throw a ball quickly but to throw it slowly, in order to show his/her throwing motion to the child so that the child easily imitate the caregiver's throwing motion. This action is called "motionese". The motionese can be thought that it becomes easy for the child to estimate the caregiver's error of reward, and there is an effect of taking the matching of the body part with the caregiver as a result. Nagai et al.[11][12] points out that Motionese is analyzed by using the attention model based on saliency, and it is effective for the task learning of the robot.

As our imitation methods are based on reinforcement learning, especially value function, clustering the body area on the camera image based on the value system is investigated. This paper shows a method for clustering performer's

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body area on the camera image for the imitation of the observed behavior based on a value system from which values can be obtained by reinforcement learning. The clustering parameters are updated based on the temporal difference error (hereafter TD error: estimation error of the state value) in an analogous way such that the parameters of the state value of the behavior are updated based on the TD error. Preliminary investigation results by applying it to a imitation of a dynamic throwing motion of an inverted pendulum robot are shown.

II. Clustering Observed Body Region based on TD Error

A scenario of our experiment is shown first. Then we describe the reinforcement learning scheme, the state/action value function, throwing motion learning, representation of links forming a body, and clustering observed body region based on TD error.

A. Scenario of Experiment

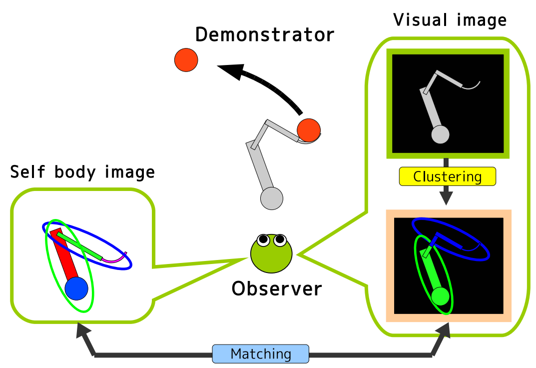


Fig. 1. Scenario of Mapping an Observed Body Image to Its Own: An observer watches an inverted pendulum robot throwing a ball and maps the body parts of the performer to its own

Fig. 1 shows the scenario of our experiment. There are two inverted pendulum robots in the environment. Each robot has an arm on the torso for throwing a ball and two actuators, one for wheels and one for the joint between the torso and the arm. Each robot has independently acquired behavior of throwing a ball and maintains a value system based on reinforcement learning. After learning the behavior, one of the players becomes a performer and shows the throwing motion. The other player, an observer, tries to map the observed body area of the performer to it own links of the body. Parameters of the clustering of the observed body area for mapping the clusters to the observer's links of the body have to be estimated accordingly. The mapping enables the observer to understand and imitate the observed behavior based on state value function as proposed in [8][13][10].

B. State Value and TD error

A robot is supposed to discriminate a set S of distinct world states. The world is modeled as a Markov process, making stochastic transitions based on its current state and the action taken by the robot based on a policy π. The robot receives reward r_t at each step t after it follows the policy π. State value at state s_t, $V(s_t)$, the discounted sum of the reward received over time under execution of policy π, will be calculated as follows:

$$V(s_t) = E[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \cdots] \ . \tag{1}$$

where $0 < \gamma < 1$ is a discount rate. The robot receives a positive reward if it reaches a specified goal and zero otherwise, therefore, the state value increases if the robot follows a good policy π. The robot updates its policy through trial and error in order to receive higher positive rewards in the future. From 1, the state value V_t can be derived as:

$$V(s_t) = E[r_t] + \gamma V(s_{t+1}) \ . \tag{2}$$

Then the state value V_t can be updated iteratively by:

$$\begin{aligned} V(s_t) &\leftarrow V(s_t) \quad + \alpha \Delta V(s_t) && (3) \\ \Delta V(s_t) &= r_t + \gamma V(s_{t+1}) - V(s_t) && (4) \end{aligned}$$

where $\alpha (0 < \alpha \leq 1)$ is the update ratio. The $\Delta V(s_t)$ is called Temporal Difference error (TD error) and it is used for updating the parameter of estimation of the state value function and the policy. Fig. 5(a) shows a diagram of the state value updating procedure. For further details, please refer to the textbook by Sutton and Barto [14] or a survey of robot learning [6].

C. Throwing Motion Learning

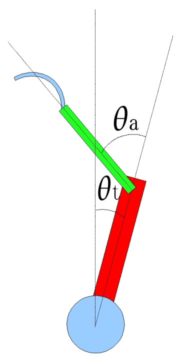


Fig. 2. Model of an inverted pendulum mobile robot with an arm

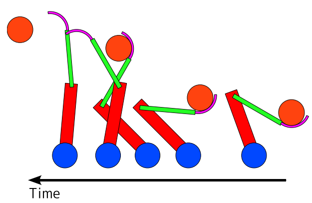


Fig. 3. Throwing motion

Fig.3 shows the throwing motion learned by the observer. Fig.2 shows the model of the inverted pendulum mobile robot with an arm. θ_a and θ_t are angle from the torso to the arm and angle between the torso and the direction of gravity, respectively. The state variables for representing state value of the throwing motion are θ_a, $\dot{\theta}_a$, θ_t and $\dot{\theta}_t$.

The state value function is approximated with a tile coding system, a 4-dimension table. θ_a and θ_t spaces are quantized into 8 and the other state variables' spaces into 10.

The robot learns the throwing motion through trial and error while it receive positive reward when it successfully threw the ball and zero reward else. It updates the state value functions over the trials based on the rewards.

D. Representation of Links of Observed Body

The inverse pendulum throwing robot has two links, that is, the torso and the arm. The observer watches the performer with a camera on the robot and acquires a camera image. It extracts a silhouette of the performer by subtracting the background image. The silhouette contains the torso and the arm of the performer. The observer has to segment the silhouette region into the two links. A link is modeled with an ellipsoid and it can be clustered based on Mahalanobis distance. A link has a center $\boldsymbol{\mu}$ and a covariance of the region Σ. The Mahalanobis distance D to the link is

$$D(\boldsymbol{x}) \quad = \quad \sqrt{(\boldsymbol{x}-\boldsymbol{\mu})^T \Sigma^{-1} (\boldsymbol{x}-\boldsymbol{\mu})} \ . \tag{5}$$

The robot body consists of a torso link and an arm link. The Mahalanobis distance from an arbitrary point $\boldsymbol{x}$ to the torso link D_t can be calculated using Eq.5 with the center $\boldsymbol{\mu_t}$ and the covariance Σ_t. The distance to the arm link is calculated as D_a with the center $\boldsymbol{\mu_a}$ and the covariance Σ_a of the arm link, as well. The point x on the silhouette region is classified into the torso link If $D_t < D_a$, and it is classified into the arm link else. Fig.4 shows the representation of links of observed body based on the Mahalanobis distance. The center vectors and covariance matrices of the two links are actually the clustering parameters that are updated based on state value function, more specifically, TD errors.

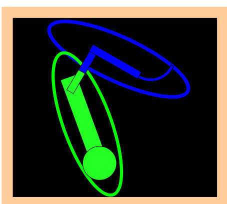
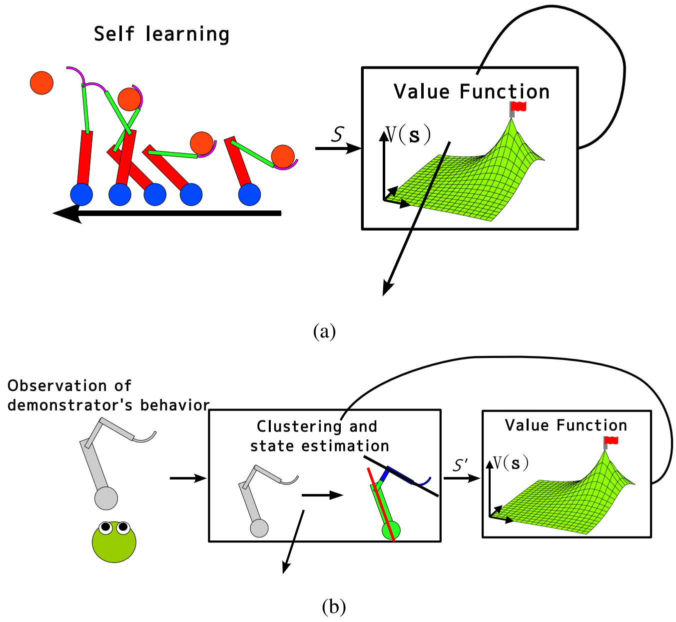


Fig. 4. Representation of links of observed body based on Mahalanobis distance

After the clustering parameters and the body region on the observed image are defined as shown in Fig.4, then, the posture parameters, θ_a, ξ_a, θ_t and ξ_t, are estimated as followings. First, pixels of the body region on the observed image are clustered with the clustering parameters based on the Mahalanobis distance into the torso and the arm regions.



(a)

(b)

Fig. 5. (a)Update of state values based on TD error through trial and error, (b)Update of link representation parameters based on the TD error

Then, the postures of the arm and the torso are calculated with the clustered pixels. The posture of the torso region can be calculated as:

$$\theta = \frac{1}{2} \arctan\Bigl(\frac{2M_{11}}{M_{20} - M_{02}}\Bigr) \tag{6}$$

where M_{pq} is a moment of the torso region:

$$M_{pq} = \sum_i \sum_j (i - i_G)^p (j - j_G)^q f(i,j) \tag{7}$$

(i_G, j_G) is the center of the region and $f(i,j)$ is pixel value on the point (i, j) which is 1 if the point on the silhouette of the performer, otherwise zero.

The angular velocity of the torso $\dot{\theta}$ is estimated with a simple numerical differentiation with Eq.8.

$$\dot{\theta} = \Bigl(\frac{\theta_t - \theta_{t-1}}{T}\Bigr) \tag{8}$$

where T is time step size.

E. Observed body segmentation based on TD error

Fig. 5(b) shows a sketch of the parameter update of the link representation parameters based on TD error. TD error feedbacks do not update of state value function because the state value function is supposed to be acquired beforehand. The observer watches performer's behavior, first. It estimates the postures of the links of the performer. More specifically, it updates the clustering parameters μ_i and Σ_{ij} of each link of the performer based on the estimated TD error $\Delta\hat{V}_t$ as follows:

$$\mu_i \quad \leftarrow \quad \mu_i - \beta \frac{\partial |\Delta \hat{V}_t|}{\partial \mu_i} \tag{9}$$

$$\Sigma_{ij} \quad \leftarrow \quad \Sigma_{ij} - \beta \frac{\partial |\Delta \hat{V}_t|}{\partial \Sigma_{ij}} \tag{10}$$

where, i, j and $\beta(0 \leq \beta \leq 1)$ are indexes of the parameter and update ratio, respectively. The condition that the TD error is zero means that the posture sequence of the performer perfectly matches to the one of the throwing motion of the observer. Therefore, minimizing the TD error by updating the clustering parameters indicates that the observer maps the clustered links to its own links to represent the throwing motion of its own successfully.

The estimated TD error is calculated as below:

$$\Delta \hat{V}_t = \hat{r}_t + \gamma \hat{V_{t+1}} - \hat{V}_t \tag{11}$$

where

$$\begin{aligned} \hat{r}_t &= r(\hat{s}_t) \\ \hat{V}_t &= V(\hat{s}_t) \\ \hat{s}_t &\leftarrow F^{hash}(\boldsymbol{x}_t) \end{aligned}$$

$\hat{s}_t$, $\hat{r}_t$, and $\hat{V}_t$ are estimated state, reward, and state value at time t. F^{hash} is a hash function that maps from sensory values ${}^{d}\boldsymbol{x}_t$ to a state $s \in \boldsymbol{S}$.

In the following experiments, the state space is quantized into a set of discrete states and the state value function is represented in this space. When the differential of the state value is calculated, in order to avoid a problem of the discontinuity of the function, the state value is interpolated linearly and the TD error of (11) is calculated with the interpolated state value. Then, $\frac{\partial|\Delta\hat{V}_t|}{\partial\mu_i}$ and $\frac{\partial|\Delta\hat{V}_t|}{\partial\Sigma_{ij}}$ are calculated in a numerical manner as below:

$$\frac{\partial|\Delta\hat{V}_t|}{\partial\mu_i} \leftarrow \frac{|\Delta\hat{V}_t(\boldsymbol{x}_t|^{\mu_i+\delta\mu_i})| - |\Delta\hat{V}_t(\boldsymbol{x}_t|^{\mu_i-\delta\mu_i})|}{2\delta\mu_i} \tag{12}$$

$$\frac{\partial|\Delta\hat{V}_t|}{\partial\Sigma_{ij}} \leftarrow \frac{|\Delta\hat{V}_t(\boldsymbol{x}_t|^{\Sigma_{ij}+\delta\Sigma_{ij}})| - |\Delta\hat{V}_t(\boldsymbol{x}_t|^{\Sigma_{ij}-\delta\Sigma_{ij}})|}{2\delta\Sigma_{ij}} \tag{13}$$

where $\boldsymbol{x}_t|^{\mu_i+\delta\mu_i}$ and $\boldsymbol{x}_t|^{\mu_i-\delta\mu_i}$ ($\boldsymbol{x}_t|^{\Sigma_{ij}+\delta\Sigma_{ij}}$ and $\boldsymbol{x}_t|^{\Sigma_{ij}-\delta\Sigma_{ij}}$) are estimated state value vectors $(\theta_a, \xi_a, \theta_t, \xi_t)$ of the performer while μ_i (Σ_{ij}) is increased or decreased by $\delta\mu_i$ ($\delta\Sigma_{ij}$), respectively.

The procedure of the clustering parameter learning becomes as follows:

1. Initialize the clustering (body segmentation) in an arbitrary way
2. Update the clustering parameters in order to reduce the TD error
3. Cluster pixels on the observed body image based on the Mahalanobis distance with the clustering parameters
4. Update the clustering parameters again with the clustered pixels
5. Exit if TD error converged, goto 2. else.

F. Extrapolation of state value

The TD error from the observed trajectory is not often available because the estimated angles and angular velocities of the torso and the body tends to be out from the range of the learned state space. This happens especially in early learning stage of classification of observed body image. Therefore, simple extrapolation of state value from the learned state to inexperienced state is introduced. Concretely, the state value in an inexperienced state is extrapolated as discounted value with γ of the average of the state values on the adjoining learned states. The example of two-dimension state space is shown in Fig. 6. If the center state is inexperienced and has no state value, discounted value of the average of the state values in adjacent states is calculated as the extrapolated state value of the center state.

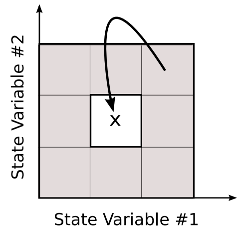


Fig. 6. Fill state value

III. Experiment with Inverted Pendulum Robot

In the experimental environment, there are two inverted pendulum mobile robots. Each robot acquired throwing behavior through trial and error based on reinforcement learning. One of them becomes a performer and the other becomes the observer. The observer has a single camera and it captures a sequence of images as shown in left side of Fig.7. It extracts the region of the performer on the image called silhouette as shown in right side of Fig.7. The range

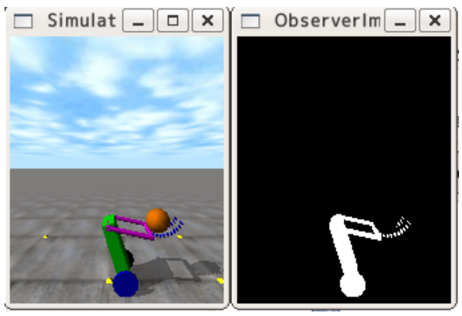


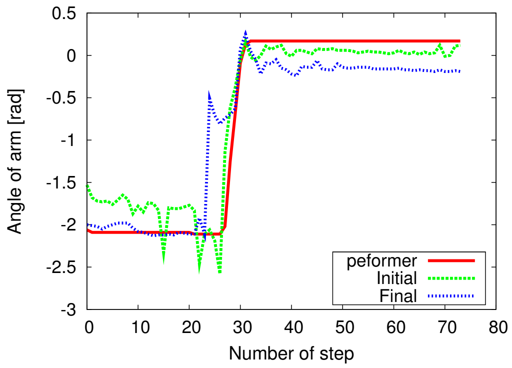
Fig. 7. View of observation

of the arm angle is limited to $-0.84\pi < \theta_a < 0.84\pi$[rad] so that the arm of the robot doesn't collide with the torso. The range in the torso angle is limited to $-0.5\pi < \theta_t < 0.5\pi$ [rad] so that the torso doesn't collide with the ground, as well.

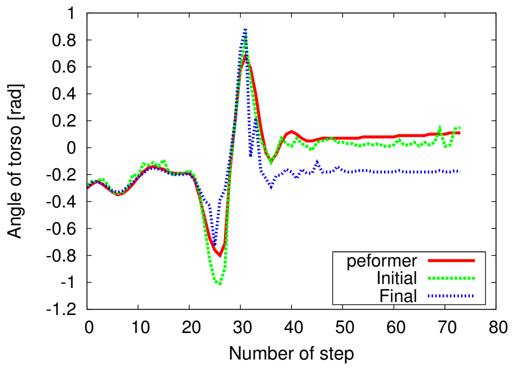
A. Experiment: Identical Structure and Constraints

The performer has the same physical structure and constraints with the observer. This experiment is carried out in order to confirm how the body segmentation converges with different initial clustering (body segmentation) parameters. The performer shows exactly same throwing motion with the observer.

1) Condition 1: In Condition 1, the observer initializes the clustering parameters as the upper 3/4 area of the extracted region is clustered into the arm and the rest into the body. Then, it updated the clustering parameters according the procedure described in the last section until the TD error converged. Fig.8 shows estimated and ground-truth



(a) Arm



(b) Torso

Fig. 8. Posture trajectory in Condition 1

trajectories of the arm and torso posture during the throwing motion before and after the update of clustering parameters. Fig.9(a),(b) shows the sequence of the body segmentation before and after the update of the clustering parameters. The arm and the torso are recognized as blue and green regions, respectively. The upper 3/4 area of the extracted silhouette region is clustered into the arm and the rest into the body as it initialized before the update. After the update, at some points, half of the area is clustered into the arm and the rest into the body. Interestingly, even though the posture trajectory is estimated reasonably as shown in Fig.8, the clustered regions of the arm and the torso are somewhat different from an expected result. For example, the torso is recognized with smaller region and the arm is bigger than the actual one. In order to understand this result correctly, Fig.9(c),(d) shows the sequence of its own body image with the sequence of the recognized posture parameters of the performer. There is no big difference in Fig. 9(c) and (d). However, the angel of arm at the early stage of the throwing motion is estimated well. This can be confirmed with Fig.8 (a). This motion, the arm stay folding to the body, is necessary for keeping the ball to throw. The inclination of the arm from number 1 to 2 of Fig. 9(c) is shallower than the ground-truth. On the other hand, the inclination of the arm from number 1 to 2 of Fig. 9(d) is close to its own throwing. Moreover, the oscillation of the arm at the early stage is improved after the update of clustering parameters. Therefore, the clustering into the arm and the body is appropriately converged so that the clustering results can explain the observed motion with its own throwing motion deeply.

2) Conditon 2: In Condition 2, the observer initializes the clustering parameters as the upper 1/2 area of the extracted region is clustered into the arm and the rest into the body. There is no big difference in Fig. 11(c),(d). In Fig. 10, the estimated posture trajectory is almost the same as the performer's posture trajectory before the update. After the update, it isn't so. This is thought by the difference between learning experience of performer and the observer. However, the body part matching after the update is similar to that in condition 1. Therefore, the body part matching between oneself and others is appropriately done in this initial clustering parameter.

B. Experiment: Recognition of Body Parts of Throwing Human

In this experiment, a human performer shows throwing motion to the robot. Obviously, the robot does not have the same physical structure and constraints of the performer. The observer initialized the clustering parameters as the upper 3/4 area of the extracted region is clustered into the arm and the rest into the body. Then, it updated the clustering parameters until the TD error converged.

Fig.12 shows estimated and trajectories of the arm and torso posture during the throwing motion before and after the update of clustering parameters. There is no ground-truth trajectory because the human body angle trajectory does not have any sense for the observing robot and the observer just recognize the human's throwing motion based on its own throwing motion.

Fig.9(a),(b) shows the sequence of the body segmentation before and after the update of the clustering parameters. The arm and the torso are recognized as blue and green regions, respectively. Fig.9(c),(d) shows the sequence of the body image reproduced by own body before and after the update of the clustering parameters. During the throwing motion of the observer, the torso is inclined ahead and then the arm is raised greatly. The inclining the torso ahead means the torso angle becomes less than 0[rad] in Fig.12(b). In Fig.9(c),(d), the arm(before/after update the clustering parameters) is raised from number 2 to number 4. With the initial clustering parameters, the torso isn't inclined ahead (the torso angle is always larger than 0) from Fig.12(c). After the update of the clustering parameters, the torso inclines ahead once during the throwing motion. This posture trajectory estimation and clustering results indicates that the observer successfully segments the silhouette of the throwing human on the image and maps each of them to its own torso and arm reasonably.

IV. Conclusions

This paper proposed a method for segmentation of performer's body for the imitation of the observed behavior based on a value system from which values can be obtained by reinforcement learning. The parameters of the segmentation are updated based on the temporal difference error, analogous to the way such that the parameters of the state value of the behavior are updated based on the TD error. The proposed method can be easily combined with a behavior imitation method based on reinforcement learning, especially value function based learning. The validity of the proposed method is investigated by applying it to a imitation of a dynamic throwing motion of an inverted pendulum robot. The experimental results showed that the method successfully updates clustering parameters for estimation of the posture trajectory of the performer, however, the sizes and shapes of the clustered regions is different from the ones expected by human. As future work, we are planning to improve the method by adding some constraints on the shapes and sizes of the body parts.

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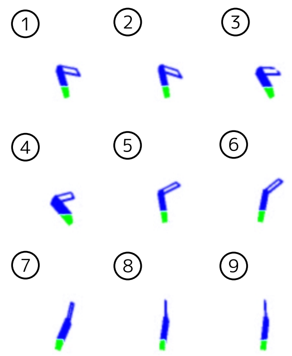
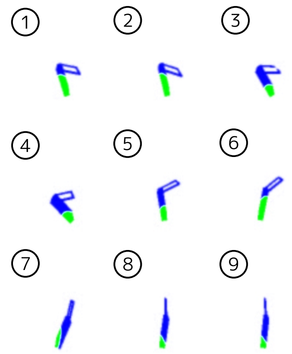
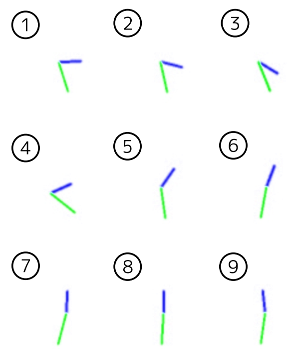


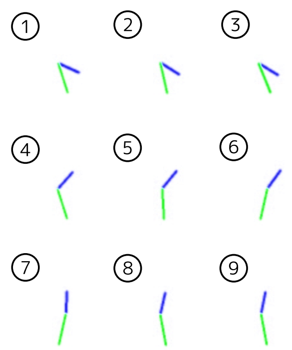
(a) before the update(segmentation)



(b) after the update(segmentation)

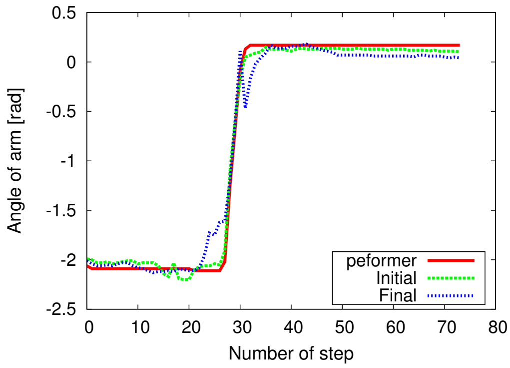


(c) before the update(image)

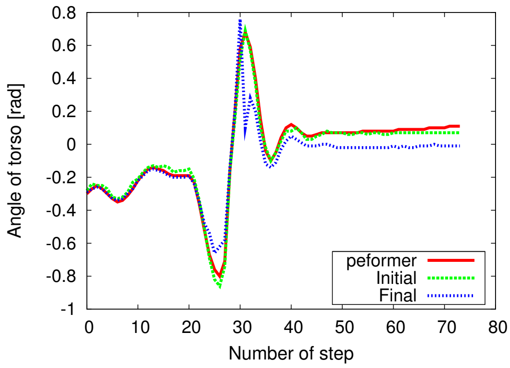


(d) after the update(image)

Fig. 9. Body segmentation and image before/after update of clustering parameters in Condition 1

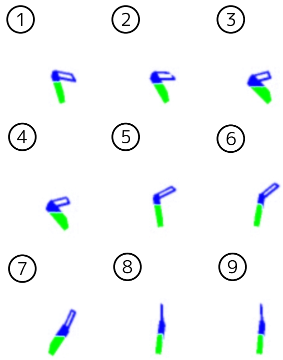


(a) Arm

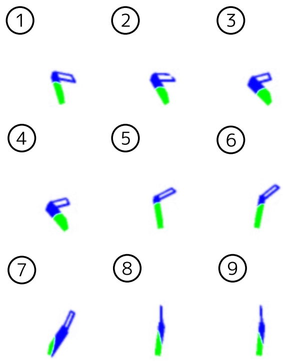


(b) Torso

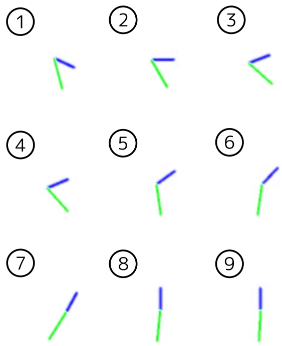
Fig. 10. Posture trajectory in Condition 2



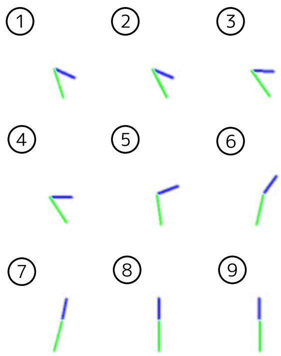
(a) before the update(segmentation)



(b) after the update(segmentation)

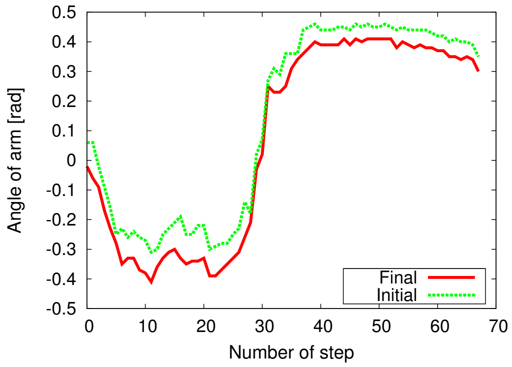


(c) before the update(image)

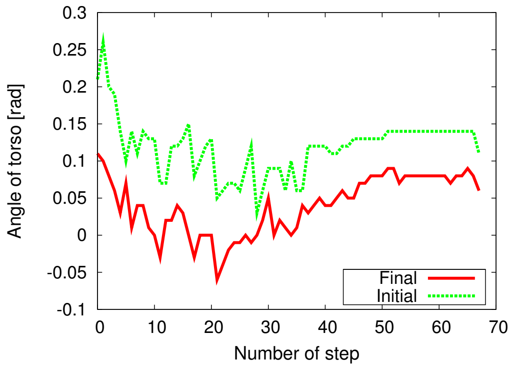


(d) after the update(image)

Fig. 11. Body segmentation and image before/after update of clustering parameters in Condition 2

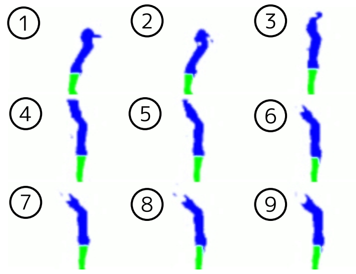


(a) Arm

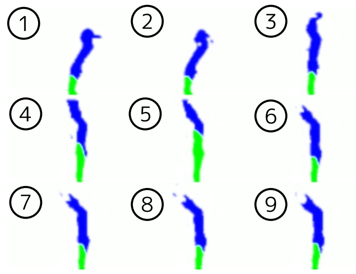


(b) Torso

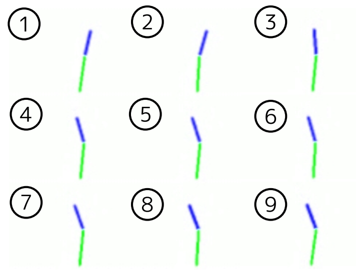
Fig. 12. Posture trajectory in experiment of recognition of human throwing motion



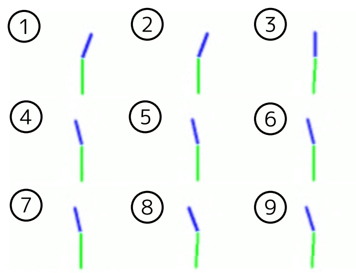
(a) before the update(segmentation)



(b) after the update(segmentation)



(c) before the update(reproduction)



(d) after the update(reproduction)

Fig. 13. Body segmentation and reproduction before/after update of clustering parameters for human throwing motion recognition