A Trajectory Modification Method for Tool Operation Based on Human Demonstration Using MITATE Technique

Satonori DEMURA[1], YAQIANG Mo[1], Kotaro NAGAHAMA[1] and Kimitoshi YAMAZAKI[1]

***Abstract*— We propose a novel method for a daily assistive robot to learn a new task from its user who does not have technical knowledge. "MITATE," which is a human capacity to communicate a motion of a tool using a different tool and environment, provided inspiration to this system. The proposed system automatically estimates the mapping from the task space of the user's to the robot's. This enables the online teaching of a task by showing the target motion with a different tool and a different environment from the robot. We evaluated the proposed method with daily tasks experimentally, and the results proved that the proposed method is effective.**

I. Introduction

Many of the domestic daily tasks are burdensome for elderly people and handicapped people. Therefore daily assistive robots are expected to reduce the burden of such housework. These robots should be input the contents and the manners of the tasks which vary from family to family.

However, the users of the daily assistive robots do not necessarily have professional knowledge to program the robots. Therefore, a method to easily modify and expand the operation of the robot would be useful. The method is expected to be available by the users who do not have professional knowledge about robotics. As methods to teach a task for a robot without normal programming, simple programming software with GUI, direct teaching methods and "teaching by showing" technique have been proposed. Among them, teaching by showing is conceivable to be used by a wide range of people since it does not need large force to directly move a robot arm, and it is the same way as a person normally teaches a motions to another person.

In previous studies on teaching by showing [1], the methods to learn object manipulation [2] and tool manipulation [3] from visual observations were proposed. However, these studies assume that the teacher has the same work space and the same objects as the robot, or require multiple sensors for the recognition. There remains an unresolved issue that the teacher needs to prepare identical environments between the teacher and the robot for online observational learning. Moreover, the online modification of the motion of the robot while it is operating is not considered during the conventional teaching by showing process.

The purpose of this research is to construct a method with which a user can easily modify a robot's motion while the robot is operating. We propose a new observational learning method which is inspired by "MITATE" technique.

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Fig. 1: Various MITATE expressions used in Rakugo

"MITATE(-ru)" means to express a thing using another similar thing in Japanese. Especially, MITATE technique has been utilized by a person to express motions when a person cannot prepare the actual tool for the motions. A typical example of MITATE technique is seen in Rakugo, which is one of Japanese traditional verbal entertainments (Fig. 1). A Rakugo performer has only a fan during the performance, but he/she expresses the motion of slurping up noodles by using the fan as if it were chopsticks; he/she expresses the motion of pouring sake by tilting the opened fan in another situation. MITATE technique is not only a technique of Japanese culture and performing art, but has been utilized by human beings to communicate movements from person to person. If a robot becomes able to understand this technique, a person would be able to instruct intuitively the target manipulation online in detail, using an object that he/she has.

With proposed system which understands MITATE, the robot first recognizes the teacher's motion while the teacher is temporarily imitating the motion of the robot. When the teacher change the motion to the ideal one, the robot notices that the motion has changed and imitates the motion to acquire the new motion. It is not necessary for the teacher and the robot to use the same object and the same environment with this system.

The primary contributions of this paper are as follows.

- We propose a new observational learning method which is inspired by MITATE technique, implemented to daily assistive robots and evaluated with some periodic tasks such as wiping a table.
- We point out the necessity of the task condition space as a requirement for achieving MITATE and propose a method to estimate it.

This paper is organized as follows. The related studies are described in Section II. The outline of the proposed system

to modify the tool's trajectory based on the visual observation and MITATE implementation is written in Section III. Section IV describes the system to understand MITATE technique, which includes a method to recognize the hand and the surrounding area of a teacher, and a method to evaluate the similarity between the motion of the teacher and that of the robot itself. The proposed system is implemented to two daily assistive robots and evaluated by the experiments to teach mixing and wiping motion in Section V. Section VI concludes the paper.

II. Related work

There have been proposed two main methods to teach motions for robots intuitively. The first one is direct teaching and the second one is teaching by showing. Direct teaching is a method to teach motions for a robot by directly holding and moving the robot arm. Teaching by showing is a method with which the robot visually recognizes and learns the motion while a teacher demonstrates the target motion normally.

In the previous work on direct teaching, Kushida et al. [5] presented zero gravity control for the teaching process in which a person is holding and manipulating an industrial arm. Fukuda et al. [6] proposed a method to automatically generate the transition of the task constraints from a teacher's demonstration and achieved a simplified teaching. Sylvain et al. [7] analyzed the movements which are directly taught by a human teacher and proposed a method to optimize the orbit to imitate. With these methods a teacher can intuitively teach the movements to the robot. However, since these methods require a certain level of force to move directly the bodies of the robots, it is difficult for an elderly person or a handicapped person.

As a visual teaching method, Kuniyoshi et al. [2] proposed a method to recognize a human behavior sequence and to plan the motion sequence to achieve the goal. This was called "Learning by Watching" method and they achieved a block stacking task. Ikeuchi et al. constructed a system whose target is a pick & place task. Their system recognized not only the target object but also the movements of the teacher to recognize the type of the work. The contact states between multiple objects were classified based on the surface restraint conditions and assembly tasks were described by combining the changing states and the transition between the states of the target object. Ramirez-Amaro et al. [9] succeeded in classifiying the manipulations in domestic tasks. They combined features of hand motions and properties of multiple objects to extract the hierarchical meanings from the human activity. M. Pardowitz et al. [10] installed multiple sensors under the working environment to recognize the motion of the human hand, the upper body, the objects, and the states of grasping and non-grasping. They succeeded in classifying the kitchen tasks into "Transport Operations," "Device Handling" and "Tool Handling." Yezhou et al. [11] used CNN to recognize tools and objects and analyzed the behavior using Viterbi algorithm. They succeeded in clasifiying cooking actions, e.g., cutting and mixing. Martin et al. [12] extracted hand positions and upper body contours from color image and calculated the Motion Motor Map (MMM) using the LM algorithm. The MMM is a map to associate the joint angles of a human teacher and a learner robot. They succeeded in teaching some motions to ARMAR-IIIb humanoid robot. Sofiane et al. [13] proposed a method to teach movements through communication. The body movements of not only adults but also children of TD/ASD are correctly recognized by NAO humanoid robot. These studies have succeeded in teaching motions to robots safely and intuitively since the human teacher needs only to play tasks in front of the robots or sensors and does not need to touch the robot bodies. However, there are still severe preconditions that the teaching is not executed in online, the human teacher needs the same environment with the robot learner, and the methods needs various types of sensors.

The advantages of our method are: (1) the user can teach the target movements without great force because the user does not have to move the robot by hand directly since the method is based on the teaching-by-showing framework; (2) the proposed method does not need the same tool and the same environment as the robot has since the system understands and utilizes MITATE technique; (3) the proposed method uses the input from a single RGB-D sensor and it does not need large-scale sensors.

III. Acquisition of trajectory generation method for tool operation

A. Motion teaching based on "MITATE"

In this research, we assume that a teacher and a learner have different objects/tools and are located in different environments. This is a typical situation for the teacher to communicate movements of the tool using MITATE technique. For example, while a learner is stirring something with a cooking tool, a teacher teaches better manipulation with an object in the teacher's hand, as if the object were the tool in the learner's hand.

In this situation, the following processes are considered to exist for the teacher and the learner.

1) The teacher moves an object in the teacher's hand as if the object were the tool in the learner's hand (use of MITATE technique).
2) The learner understands how the teacher expresses the movements of the learner's tool (understanding of MITATE technique).
3) The teacher teaches a new movement to the learner.
4) The learner observes 3) and corrects their own tool operation trajectories.

During the process 2), the learner needs to understand what is the important difference to learn between the teacher and the learner. There are various types of differences: the surrounding environments, ranges of movements, objects in hands. A visual learning system needs to perceive such differences and decide where to learn. In this research, we make a robot learn the appropriate trajectories of the tool in the robot hand. Therefore we propose and use a method to abstract only a difference between the robot's trajectory and the human teacher's trajectory.

B. Task condition space

As mentioned in Section III-A, there are generally various differences between the conditions of the leaner and the teacher during the observational learning. Therefore the learner needs to find the proper correspondence between the conditions of the learner and the teacher to acquire only the appropriate tool manipulations. The proposed method finds the spatial conditions that define the constraints of the tool's trajectory. We describe the space in which such constraints are defined as "a task condition space" hereafter.

In the process 1) in Section III-A, the human teacher naturally acquires the task condition space of the learner and expresses the operational trajectories. Then the learner recognizes the task condition space of the teacher in the process 2). After both of the teacher and the learner acquire the opposite task condition space, sharing a new trajectory becomes possible in the process 3) and 4).

C. Task setting and approach

Based on the discussion in the previous section, we propose a visual motion teaching method for a robot learner and a human teacher. This research focuses on establishing an overall system for the robot to estimate the task condition space of the teacher and to acquire the new trajectory based on the estimation and MITATE technique. Therefore, we simplified the problem as follows.

- We assume that the tool operation is a periodic movement, e.g., moving the cloth back and forth or wiping the table.
- The robot knows how to grasp the tool in advance. The difference of the way to hold a tool between a robot learner and a human teacher is not taken into account in the system.
- The robot holds the tool in its initial state and has already started the operation.

In the teaching process, the teacher first imitates the movements of the robot to show that the teacher understands the task condition of the robot. After that, the teacher shows appropriate periodic trajectory for the robot, using their own task condition space. The teaching process is accomplished when the robot imitates the teacher's movements.

To imitate the teacher's movements properly, the robot needs to estimate the task condition space of the teacher. This procedure is shown in Fig. 2. First, the system checks whether the teacher is doing something which expresses the learner's movements. For this checking process, the system detects the teacher and tracks the movements of the working point of the teacher. Next the system estimates the task condition space of the teacher. The proposed system assumes the objective tool's trajectory can be defined using the work plane. Therefore the system calculates the pose of the work plane on which the teacher moves an object. After the work plane is detected, the system uses it as the task condition space of the teacher. The proposed system assumes that the movements of the teacher and the robot are the same except for the difference between the object's velocity and the direction on the work plane. Finally, when the teacher starts to move the object on a new periodic orbit, the robot transforms the movements of the teacher into the movements in its own task condition space and obtains a new operational trajectory.

For the above processing flow, a "visual processing module," a "similarity judgement module," and a "task condition space estimation module" are required for the proposed system. The details of each module are described in the following sections.

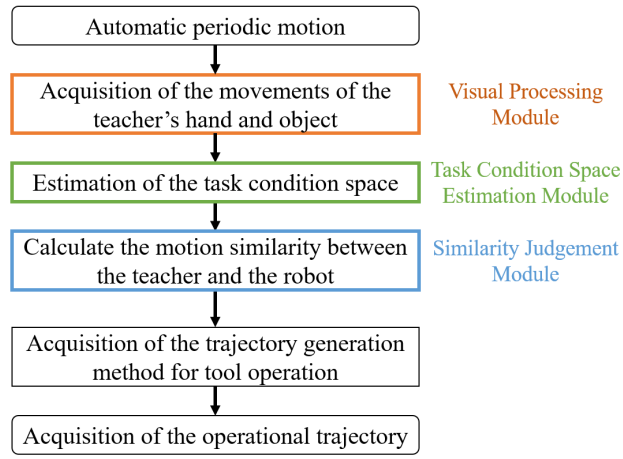


Fig. 2: System flow for the proposed MITATE system

IV. Modules for MITATE system

A. Working point estimation module

The proposed system first recognizes the body movements of the teacher. The inputs of the system are a color image and a depth image from an RGB-D sensor. Using the OpenPose method [14], the system acquires the two-dimensional position of each joint of the teacher in real time. Then the three-dimensional hands' positions are calculated using the result of the Openpose and the depth image. The proposed method sets the recognition area for the object in the teacher's hand using the teacher's working point calculated above, and finds the object and the work plane.

To estimate the velocity of the object in the teacher's hand, the proposed method uses Kanade-Lucas-Tomasi feature tracker [15] and calculates the optical flows. We assume that the region of the object is thought to move considerably, therefore the proposed method abstracts a region with a large optical flow as the position of the object in the teacher's hand. The position is treated as the "working point" of the teacher's arm hereafter.

B. Similarity judgement module

Using the teacher's working point obtained by the above-mentioned visual process, a motion similarity between the teacher and the robot is calculated. First, the movements of the working point during two subsequent frames is extracted and the velocity is calculated. Then the correlation coefficient r is calculated from teacher's hand velocity x[m/frame] and

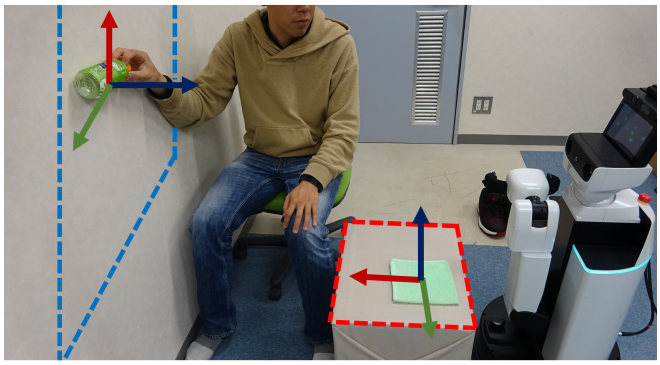


Fig. 3: Work planes during the teaching of table-wiping task. Blue dotted line shows the work plane of the teacher. Red dotted line shows the work plane of the robot

robot's hand velocity y[m/frame] as follows:

$$r = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}}. \quad (1)$$

If the correlation coefficient exceeds the pre-defined threshold, it is regarded as there is a relationship in the trajectory of the teacher and the robot. Once such a relationship has been detected, and after that the similarity decreases again, it is a trigger to start teaching because it means that the teacher changes his/her behavior.

C. Task condition space estimation module

First, a 3-D point cloud is obtained from a range image sensor mounted on the robot, and then a work plane is searched by a plane detection process. If there is an appropriate plane, e.g., in the case as shown in Fig. 3, then the normal vector of the plane is calculated. Then, an angle between the normal vector of the teacher's work plane and the other normal vector of the robot's work plane is calculated by means of inner product.

Next, the scale difference of the trajectory is calculated by estimating the difference of average velocities. In addition, the difference of motion orientation is also calculated from the velocities. These results are used to define a task condition space. This means that the transformation parameters to associate robot's work plane to teacher's work plane become clear. Transformation of the task condition space enables teaching even if the teacher does not face to the robot as shown in Fig. 4.

V. Experiments

A. Experimental settings

In order to evaluate the proposed method, experiments to obtain tool manipulation trajectories were performed. Two type of tasks, wiping a table and mixing a liquid in a pot, were targeted. To investigate the generality of the proposed method, we tested the system with a single arm mobile manipulator HSR [16] and a dual arm robot HIRO. As a tool for MITATE, plastic bottles or books with rich texture were used. One reason for choosing such daily objects is that the aim of this study is to equip the proposed method on daily assistive robots.

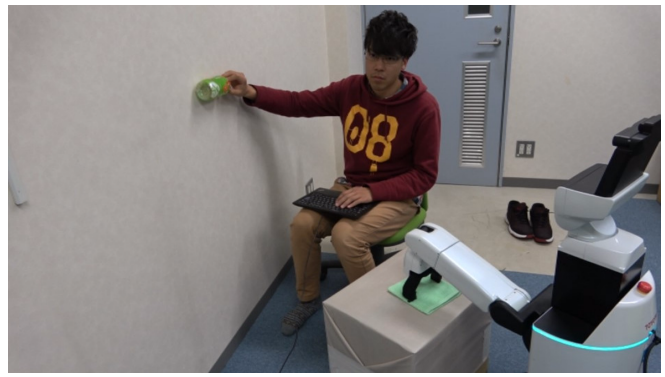


Fig. 4: Experiments to teach table-wiping task. The teacher uses the wall to communicate the proper trajectory while the robot is wiping a table

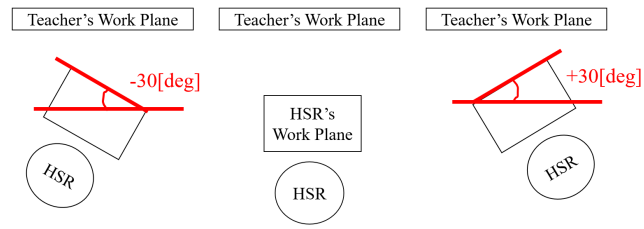


Fig. 5: Geometric relationship between the teacher's and the robot's work plane

In the wiping task, teaching was performed under the following conditions. A work plane was assumed to be a wall (Fig. 4) or a table. In the case of a wall, a work plane was inclined to left or right from the direction facing the teacher. As shown in Fig. 5, the inclination angle was randomly set within the range of plus or minus 30 degrees.

On the other hand, it was assumed that there was no work plane at mixing task. In that case, the teacher changed the position of the tool three-dimensionally. Only downward motions of the robot was limited to avoid collision with a pot, and other motions were targets for teaching.

B. Experimental results

The flow of the trajectory acquisition was as follows. First, the position of the hand and the working point of the teacher was detected, and then the plane detection process was performed in the vicinity of the hand position. When a

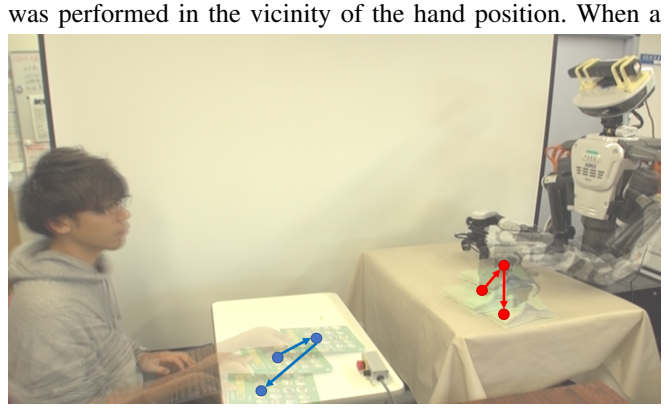
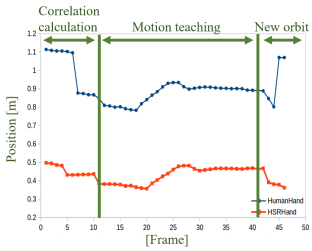
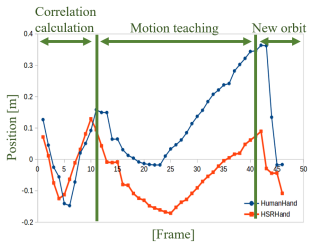


Fig. 6: Experimental result of teaching wiping task to HIRO humanoid robot

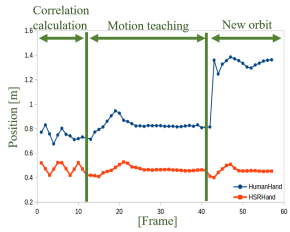


(a) Transition of the position of each working point (X axis)

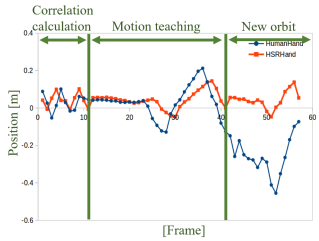


(b) Transition of the position of each working point (Y axis)

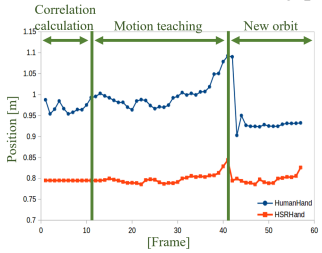
Fig. 7: Transition of the position of each working point during table-wiping task (HSR). Blue line: the teacher's working point, red line: the robot's hand



(a) Transition of the position of each working point (X axis)



(b) Transition of the position of each working point (Y axis)



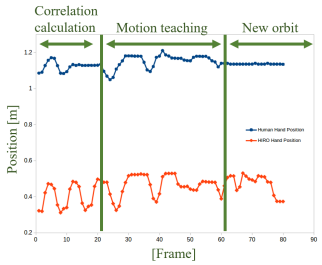
(c) Transition of the position of each working point (Z axis)

Fig. 8: Transition of the position of each working point during mixing task (HSR). Blue line: the teacher's working point, red line: the robot's hand

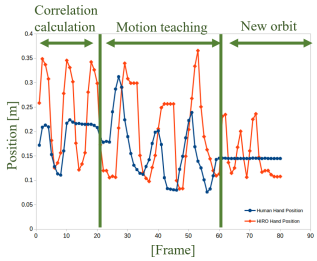
work plane was not detected, the working point of the teacher and that of the robot were converted to the world coordinate system. Thereafter, the respective working point speeds were calculated, and then the correlation value, the scale difference, and the difference of the working point velocity were calculated. After that, when the correlation coefficient once again falls below the pre-defined threshold, it was regarded that the teacher was showing a different trajectory. Then, the robot modified the manipulation trajectory with referring its task condition space, as shown in Fig. 6, and repeated the new manipulation trajectory.

On the other hand, when a work plane is found by the plane detection process, the following procedure was performed. The normal vector of each work planes for teacher's and robot's was calculated. Then, coordinates transformation was calculated using the angle formed by the vectors. After that, processes such as the correlation calculation etc. were performed.

Figures 7 to 10 show the transition of robot's hand position during the period from the detection of trajectory with high

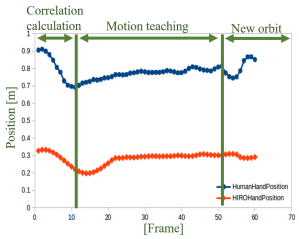


(a) Transition of the position of each working point (X axis)

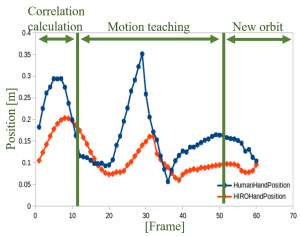


(b) Transition of the position of each working point (Y axis)

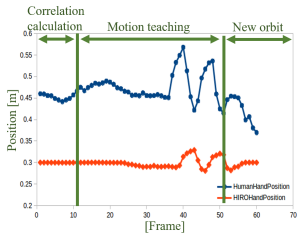
Fig. 9: Transition of the position of each working point during table-wiping task (HIRO). Blue line: the teacher's working point, red line: the robot's hand



(a) Transition of the position of each working point (X axis)



(b) Transition of the position of each working point (Y axis)



(c) Transition of the position of each working point (Z axis)

Fig. 10: Transition of the position of each working point during mixing task (HIRO). Blue line: the teacher's working point, red line: the robot's hand

similarity until the acquisition of the new trajectory. Each hand position is based on the world coordinate system of the robot. Figure 7 shows the transition of the hand position when HSR did a wiping task. In this experiment, the work plane of the teacher was not a table but a vertical wall. Figure 8 shows the case of a mixing task by HSR. There was no work plane for the teacher. Figure 9 shows the case of a wiping task by HIRO. The work plane was a horizontal table at this case as shown in Fig. 6. Figure 10 shows the case of mixing task by HIRO. There was no work plane as the same case as the experiment using HSR (Fig. 8).

VI. Discussion

Based on the experimental results, regardless of the presence of a work plane, the robot performed roughly the same motions with the human teacher. It can be said that a novel manipulation trajectory was appropriately acquired by the robot. From Figs. 9 and 10, it was shown that not only imitating the teacher's motion but also the scaling of the hand speed and the correspondence of the position relation

was enabled by estimating the task condition space. However, some problems were found at the experiments.

The first problem was the failure of estimating the position of the teacher's working point. When a feature point that moves larger than the hand position is detected, or the feature point moves due to the influence of the background, or the most moving point differs from frame to frame, the correct working point could not be detected with the optical flow. In order to cope with these problems, we added some screening processes; e.g. weighting to detected points, and limiting the length of optical flow. With these processes, outliers can be suppressed, and accordingly the false detection rate decreased.

The second factor is that the position of the teacher's hand deviated from the measurement range of the sensor. HSR has only four joints in its arm, therefore it needs to move the wheels when it reaches to the right or left. This caused the robot to face an unexpected direction in some cases. To cope with this problem, weighted inverse kinematics was introduced. However, the problem could not be completely solved. In the current experimental system, it is necessary to take a certain distance between the robot and the teacher. In other words, it is difficult to teach detailed trajectory if the sensor resolution is low.

VII. Conclusion

In this paper, we focused on MITATE technique that has been used to communicate a behavior from person to person, and proposed a method to implement it from an engineering point of view. The proposed method enables robots to obtain a novel tool manipulation by observing a behavior of a human demonstrator. Even if grasping tools and surrounding environments differ between the teacher and the robot, trajectory modification can be done by means of estimating the task condition space for each other.

One important issue to estimate the task condition space is how to calculate the similarity level of hand motions between the robot and the teacher. In the case that a tool trajectory is not constrained by surrounding environment, we used correlation coefficient of tool velocities for similarity calculation. By adjusting the scaling of the velocities, it was possible to convey fine movements and large movements to the robot without significantly changing the movement range of the teacher. Furthermore, in the case that a tool trajectory constrained to a work plane, not only the movement but also the constraint condition to the environment was possible to transmit using a plane detection result.

Future work is to generalize the framework using MITATE. In order to teach behavior more naturally using MITATE, it should be considered that the robot side needs a high recognition ability. For example, the task using a wiping cloth is normally table cleaning, and the task to use a whipper is normally mixing work. The knowledge about work types should be given according to the role of the tool. After that, a function to recognize what the teacher is doing and a function to estimate the role of the handled tool are needed. By introducing them, it seems that more natural teaching will be possible.

Acknowledgements

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