Imitation Learning for Human-robot Cooperation
Using Bilateral Control

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Abstract—Robots are required to operate autonomously in response to changing situations. Previously, imitation learning using 4ch-bilateral control was demonstrated to be suitable for imitation of object manipulation. However, cooperative work between humans and robots has not yet been verified in these studies. In this study, the task was expanded by cooperative work between a human and a robot. 4ch-bilateral control was used to collect training data for training robot motion. We focused on serving salad as a task in the home. The task was executed with a spoon and a fork fixed to robots. Adjustment of force was indispensable in manipulating indefinitely shaped objects such as salad. Results confirmed the effectiveness of the proposed method as demonstrated by the success of the task.

I. INTRODUCTION

Robots are expected to operate in the real environments where humans live. To perform tasks in such environments, robots are required to flexibly respond to environmental changes and adapt to unknown objects and situations. However, it is difficult to do that because conventional robots aim to track a targeted trajectory designed by humans. Hence, humans must design the trajectory considering the situation around the robot. However, designing them all manually is difficult as there are countless situations in the real environments. Many studies have been reported to solve this problem by improving the hardware. For example, research on object gripping attempted to adapt to various objects by using flexible or suction hands [1] [2]. Unfortunately, in these methods, operating objects that are not suitable for the hand’s shape is difficult.

Therefore, robots are desired to improve adaptability to various objects by improving the software. However, designing robotic motion is difficult because robots determine actions based on various information. Therefore, as methods to solve these problems, considerable research on robot motion planning by machine learning has been reported [3] [4]. Levine et al. succeeded in grasping various objects using reinforcement learning based on end-to-end learning [5]. However, this study is not practical because it requires 800,000 trials with real machines. Recently, methods called “imitation learning” or “learning from demonstration” have been reported to greatly reduce the number of trials for imitating object manipulation [6] [7]. Most of these studies generated robotic trajectories based on position information [8]. However, they have not been able to demonstrate high performance because each motion was described as a combination of position and force controllers [9]. Thus, although there were studies to estimate the gripping position of objects using high-accuracy image recognition [10] [11], it is often difficult to grasp indefinite shapes or unknown objects without force information.

Paccchierotti et al. showed that in peg-in-hole tasks using a remote-control system, operability was improved by feeding back force information to an operator, and pointed out the importance of force feedback [12]. Therefore, in imitation learning for object manipulation, it is desirable to consider force information in addition to position information. Some studies on imitation learning using force information have been reported [13]–[15]. However, tasks with fast motion have not yet been verified in these studies. These studies used different control systems during the training data collection and autonomous operation phases. Therefore, different control delays are caused during these phases. For this reason, only motions that are slow enough to prevent control delay have been verified. The reason these methods were used was that measuring action and reaction force independently were difficult. Action force is caused by the operator’s action, while the reaction force is caused by contact between robots and environments. In conventional research on direct teaching, these two forces are canceled out. In contrast, Yokokura et al. demonstrated that action and reaction force can be measured separately using bilateral control [16]. Bilateral control is a remote-control technology using a master robot and a slave robot [17] [18]. The master robot measures the action force from the operator, and the slave robot measures the reaction force from the environment. However, this method [16] is limited in its capacity to reproduce the operation and does not take into consideration environment changes.

Therefore, Adachi et al. have established a method of imitation learning for object manipulation that implements position and force control using bilateral control [19]. Thanks to force control, this method has high generalization ability. The neural network model was able to learn appropriate force adjustment in the motion of drawing a line with a ruler; it achieved an adaptive behavior with an untrained inclination.

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Fig. 1. System Overview of This Paper Method

and an untrained object (a protractor). The salient point here is that it succeeded with only 15 training data. Another notable point of this method is that robots can move as fast as humans. In the method using bilateral control, the same control system can be used during training data collection and autonomous operation phases. Therefore, control delay during these phases was the same. As a result, robot motions including control delay, could be trained, and tasks with fast motions could be performed. This research dealt with short-term motion tasks. On the other hand, Fujimoto et al. succeeded in inferring to write the written character “A,” which was long-term motion including multiple motions by using the position long-term (PLT) method [20]. Both of these studies demonstrated tasks performed with 3-degrees-of-freedom (DoF) robots, and did not implement general human tasks. Robots are required to perform common tasks in cooperative work with humans, considering that robots replace human labor in factories, farms, homes, etc. Thanks to cooperative work, robots can perform various tasks.

Therefore, this paper proposes a method for imitating human-robot cooperation using 4ch-bilateral control. Cooperative work with robots or humans is difficult for robots and several methods have been proposed for this [21]–[23]. However, this paper demonstrated that cooperative work could be performed by using the same framework as conventional imitation learning using 4ch-bilateral control [19] [20]. Using this same framework makes a great contribution to simplifying robot motion design. A system overview of this proposed method is as shown Fig. 1. Training data was collected using 4ch-bilateral control, and robotic motion was trained using a deep learning model. In this paper, practical tasks were performed in cooperative work between a human and two sets of 3-DoF robots. Effectiveness of the proposed method was verified through experimental tasks showing that force control was important. We focused on cooking as an important task in the home. Robots performed to serve a salad on a plate using a spoon and a fork.

This paper is organized as follows. Section II explains the control system including 4ch-bilateral control. Section III introduces the proposed method of imitation learning. This section describes the data collection method using 4ch-bilateral control, learning method, and task execution. Section IV describes the experiments and shows the results. Section V concludes this study and discusses future works.

II. CONTROL SYSTEM

A. Manipulator

We used two Geomagic Touch and two Touch USB haptic devices manufactured by 3D Systems as manipulators (Fig. 2). Both types of devices had the same mechanism. In this study, as shown in the upper left figure in Fig. 1, these robots were used as a bilateral system with dual-arm. Joint angles of the manipulator were as shown in the upper left figure in Fig. 2. Joint angles, angular velocity, and robot torque, respectively. The superscripts res, ref, and cmd indicate response, reference, and command values, respectively. The controller was composed of a combination of position and force controllers, with the position controller consisting of proportional and derivative controllers, and the force controller consisting of a proportional controller. These manipulators measured the angle \( \theta_{res} \) of each joint. Angular velocity \( \dot{\theta}_{res} \) was calculated using a pseudo-derivative, and disturbance torque \( \tau_{dis} \) was estimated by a disturbance observer (DOB) [24]. In addition, the reaction force \( \tau_{re} \) was calculated by a reaction force observer (RFOB) [25]. In this paper, robots were operated with a 1 msec control cycle.

B. 4ch-bilateral control

In this research, 4ch-bilateral control was used for training data collection. This method used a remote control system...
that used two robots and was suitable for teaching object manipulation. This is because the position is synchronized between the two robots and force information is fed back to both. As shown in (1) and (2), the control target of 4ch-bilateral control is to synchronize the master robot’s and the slave robot’s position, and the law of action and reaction force is established between a master robot and a slave robot [17].

\[
\begin{align*}
\theta^r_m - \theta^s_s & = 0 \quad (1) \\
\tau^m_r + \tau^s_s & = 0. \quad (2)
\end{align*}
\]

Superscripts \( m \) and \( s \) indicate master robot and slave robot, respectively. A block diagram of 4ch-bilateral control that satisfies (1) and (2) is shown in Fig. 4. Torque reference values to the master and slave are expressed by the following equations, respectively:

\[
\begin{align*}
\tau^r_m & = \frac{J_s}{2}(K_p + K_v s)(\theta^r_m - \theta^s) - \frac{1}{2}K_f(\tau^r_s + \tau^s_s) \\
\tau^r_s & = \frac{J_m}{2}(K_p + K_v s)(\theta^r_s - \theta^s_m) - \frac{1}{2}K_f(\tau^r_s + \tau^s_s)
\end{align*}
\]

Here, \( K_p, K_d, K_f, \) and \( J \) indicate proportional feedback gain, a differential feedback gain, a force feedback gain, and the identified inertia, respectively. Each value is shown in Table I. The values of feedback gain were determined by trial and error to have high operability of robots.

C. Control system tuning

In our system, the disturbance torque \( \tau^d \) was estimated by DOB. Reaction torques of each joint were calculated by the following formulas.

\[
\begin{align*}
\tau^r_1 & = \tau^d_1 - D\dot{\theta}_1 \\
\tau^r_2 & = \tau^d_2 - M_1 \cos\theta_2 - M_2 \sin\theta_3 \\
\tau^r_3 & = \tau^d_3 - M_3 \sin\theta_3.
\end{align*}
\]

Here, parameters \( D \) and \( M \) represent the friction and gravity coefficients, respectively. The parameters were determined using the system identification method of Yamazaki et al. [26]. Identified parameter values are shown in Table II. Here, the names of the robots in the table represent four robots. Details are given in Section IV.

III. SYSTEM FOR IMITATION LEARNING USING 4CH-BILATERAL CONTROL

This section explains the approach. In this paper, the goal was for a human and a robot to perform tasks through cooperative work. A robot autonomously performed cooperative work with a human by learning object manipulation. The proposed imitation learning was carried out in the following phases:

1) Data collection phase
2) Training deep learning model phase
3) Task execution phase.

The details of each phase are described below.

A. Data Collection Phase

Training dataset was collected using 4ch-bilateral control. 4ch-bilateral control was implemented in master robot 1 and slave robot 1, and in master robot 2 and slave robot 2 as pairs. A human operated master robot 1 with the right hand, and master robot 2 with the left hand. At the same time, slave robots performed tasks in the workspace. Here, recorded motion data values were angle, angular velocity, and torque response of all robots. Note that many conventional imitation learning collect responses of robots. On the other hand, control designers actually want to collect commands of robots because there are control delays between responses and commands. Thus, the conventional methods are effective only in very slow motion such that the control delays are negligible. On the contrary, in the proposed method, the responses of the master robots are equivalent to the commands of the slave robots. Because the operator can recognize the control delays of the slave robots, the operator can modify
Fig. 5. Construction of proposed deep learning model. Input to LSTM is the angle, angular velocity, and torque response value of slave robot 1. The total number of inputs is 9-dimensions because slave robot 1 is 3-DoF. Similarly, output is 9-dimensions of the response value of the master robot. LSTM model infers the state of the master robot 1 after 20 msec from the input.

| Layer            | Input | Output | Activation Function |
|------------------|-------|--------|---------------------|
| 1st layer (LSTM) | 9     | 50     | tanh (LSTM)         |
| 2nd layer (LSTM) | 50    | 50     | tanh                |
| 3rd layer        | 50    | 9      | identity mapping(Linear) |

The commands of the master robots to compensate the control delays. In other words, in the proposed method, skills of humans to adapt for the control delays can be also extracted.

B. Training Deep Learning Model Phase

The deep learning model we proposed is shown in the Fig. 5. Training data collected by 4ch-bilateral control was used to train the model. In this research, robot motion was trained by end-to-end learning. Data measured by the robots’ sensors was input to the deep learning model, and command signals to the robot of the next step were output.

In the proposed method, recurrent neural network (RNN) was adopted for the neural network that generated robotic motion. RNN was suitable for inference of the sequence data. It has demonstrated high performance in speech recognition and caption generation [27] [28]. It was desirable to use RNN because robot motion generation is also an inference-considering time series. Recently, research on robot motion generation using RNN has been reported [29]. In this paper, Long Short-Term Memory (LSTM), which is a type of RNN, was used. LSTM is a neural network that can handle a long time series [30]. LSTM structure used in this study is shown in the Table II. The input-output of LSTM is shown in Fig. 5.

The inputs of the LSTM were 9-dimensions, involving angle, angular velocity, and torque for each joint of slave robot 1, and the outputs were also angle, angular velocity, and torque for each joint of the master robot 1. The output inferred the states of the master robot 20 msec after input. Input-output data was normalized as preprocessing for learning in the same way as the conventional method [19] because the scales of angle, angular velocity, and torque were different. In the proposed model, the parameters of LSTM were updated according to the output error. The loss function was the mean square error.

Because the proposed method just infers the responses of the master robot, which are equivalent to the commands of the slave robot, there is no difference of controller structures between the data collection and task execution phases. It also contributes very fast motion of robots. Otherwise, the collected human skills for compensation of the control delays will lose meanings.

C. Task Execution Phase

The trained model was used for the robot to perform tasks autonomously. A block diagram of the robotic moves using the trained model is shown in Fig. 6. The robot measured sensor information in real-time and generated robotic motion using the trained model. In this phase, note that the robot performed tasks in cooperation with a human. Slave robot 2 was operated by a human using 4ch-bilateral control, and slave robot 1 worked by deep learning inference. While the robot was moving, angle, angular velocity, and torque of slave robot 1 were input to the LSTM model every 20 msec. LSTM output angle, angular velocity, and torque were the command values for the robot’s next motion. Just as in training, LSTM outputs were obtained at 20 msec intervals.

IV. EXPERIMENT

The experimental setup is shown in Fig. 7. We used four haptic devices. A fork was affixed to slave robot 1. Similarly, a spoon was affixed to slave robot 2. The task was serving
a salad on a plate. The salad on the plate was picked up through the cooperation of the two robots and served to the next plate. Note that the position of the two plates was fixed on the desk.

A. Data Collection

Training data was generated using 4ch-bilateral control. Conditions during collection of training data are shown in Fig. 7. An operator manipulated the master robots, and the slave robots served the salad. Snapshots of the slave robot’s motion while collecting training data are shown in Fig. 8. Angle, angular velocity, and torque responses of the slave robots and master robots were recorded every 1 msec. Trial time for a task was 10 seconds. 170 trials were performed.

B. Training Deep Learning Model

Motion data of the dataset was saved every 1 msec, so each trial contained 10,000 pairs of input-output data. The deep learning model of Fig. 5 was learned using these training data. Learning parameters were as follows: Optimization function: Adam [31]; Batch size: 100; Epoch: 1000. Learning took approximately 30 min with GPU calculation. In this paper, the computer used for this process had an Intel Core i9 CPU 64 GB memory, and a NVIDIA RTX 2080 Ti GPU.

C. Task Execution

Using the trained model, task execution of the robot was verified. Conditions during task execution are shown in Fig. 9. Slave robot 2 was operated by a human with 4ch-bilateral control, and a spoon was fixed to slave robot 2, while slave robot 1 was operated autonomously with an affixed fork using the trained model. The cooperative work between the robot and human was verified.

D. Experimental Result

Experimental results of the robot-human cooperation work is shown. We defined success as the case where a robot scoops salad and puts it on the next plate with a human. Specifically, the task was considered successful if more than 8 g of salad was served. This amount was about the same as the training data. Verification experiments were conducted 20 times with a success rate of 85%. The salad was an indefinitely shaped object and the amount changed randomly. The robot moved robustly against the changes in shape and quantity of objects. On the other hand, in some cases, the robot only scooped the top of the salad and could only scoop a small amount of salad, or stopped in the middle of transportation. Response values of slave robot 1 during the data collection and task execution phases were shown in Fig. 10. In both phases, tasks were completed in 10 seconds. This result also showed that robots can perform as fast as humans. Furthermore, focusing on torque responses, robots manipulated the salad with approximately the same but different force during training data collection and task execution phases. Hence, we can summarize that high adaptability against indefinitely shaped objects and fast motion were obtained at the same time. Note that the proposed method does not require any models of humans, special controllers for cooperation, and so on. And, human-robot
cooperation was realized only by imitation learning. Because our approach, imitation learning using 4ch-bilateral control, explicitly handles control delays, there is no need for special treatments.

V. CONCLUSION

In this paper, we verified task execution in the cooperation between a human and a robot. To demonstrate the effectiveness of our proposed method, we experimented with the serving of a salad. Results of our experiment had a high success rate of 85%. Owing to imitating force information, manipulating the indefinitely shaped object was achieved.

Cooperative work was succeeded using the same framework as the conventional method because robot motion as fast as humans can be realized owing to 4ch-bilateral control. Because there is no difference of controllers between those in training and inference, control designers do not suffer from the parameter tuning. In summary, the proposed method has great potential for realizing general manipulation. We believe that every task that can be realized by 4ch-bilateral control can be realized by the proposed method. In the future, our method can be applied to other tasks. Furthermore, by using visual information, we aimed to expand the task and improve the success rate.

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