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Bidirectional Operation Prediction for Body Integration System*

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Abstract— **The body integration system in which multiple users co-operate a single-robot avatar improves operability. However, collaboration among users is essential for smooth operation. In this study, we proposed bidirectional operation predictions for the actions of each operator with their partner in the body integration system. The robot arm and gripper are controlled by two operators. At the same time, based on each operator's actions, the system predicts the operations 0.3 seconds ahead using machine learning, and the prediction results are visually presented to the other operator. To confirm the operability of the system and its effect on cooperation between operators, we conducted pick-and-place experiments under conditions with and without bidirectional prediction. The results of the subjective evaluation and operation performance suggested that the subjective rating in smooth cooperation was significantly improved, and using the prediction could improve the similarity in the operations of two users who provided a small mental workload and shortened psychological distance.**

I. INTRODUCTION

Teleoperated robots can operate independently of time and space constraints, allowing them to perform tasks in environments that are inaccessible to humans, such as disaster areas [1] or outer space [2]. Additionally, integrating gain adjustment [3] or semiautonomous control [4] into a system can enable a wider range of tasks that surpass standard human performance. In such situations, reflecting human operations is desirable for adapting flexibly to the environment.

Human-robot collaboration technologies are also promising for assisting and augmenting human abilities [5]. Appropriate robot operation based on human intentions can reduce human workload. For example, by accurately recognizing what a human operator is trying to grasp, a robot can provide the appropriate part, leading to smoother task execution [6]. In addition, reciprocal awareness obtained through shared haptic perception, combined with an explicit strategy from the operator, can enhance task stability [7]. Additionally, displaying the robot's motion-path plans appropriately to humans can facilitate smoother collaboration [8].

Furthermore, studies on body integration, in which people cooperate with each other to operate a single virtual avatar [9] or teleoperation robot [10], have been conducted in the VR and robotics research fields. Collaborative operations by multiple operators allow greater stability of movements [11] and smooth execution of tasks that would be difficult for a single individual [12]. Additionally, if operators effectively coordinate and adapt their roles flexibly to the situation and environment, smoother operation and reduced workload may be achieved.

Understanding the movement and intention of a partner is crucial in such cases. Tanaka et al. explored vibrotactile feedback [13] that was amplitude-modulated according to the velocity of the partner's movement for sharing sensorimotor control and confirmed that recognizing the other operator's movements facilitated coordination among operators. In this study, information from one operator was provided as feedback during the operation, and the operator had to estimate the subsequent movement trajectory based on the partner's movement speed. If the movements of the operators can be predicted and displayed in advance, it is anticipated that operations will proceed more smoothly. In the fields of autonomous driving and motion analysis, the prediction of motion patterns can be conducted using model-based [14] or machine-learning-based [15] methods, and is also applied in semi-autonomous control [16]. Preliminarily, we are investigating the effects of predicting the movement information of a single user in the body integration of two operators with a single robotic arm [17]. Application of bidirectional feedback between operators could further enhance coordination and facilitate role assignment between the two operators according to the situation.

Thus, this study aims to develop a system that provides bidirectional visual feedback on operation predictions to help users understand each other's actions in a body integration system in which two users cooperate with a single robot avatar. Two users cooperate with the robot arm, and the predicted movements of each user are presented to each other in real time using Long Short-Term Memory (LSTM) based machine learning. We conduct cooperation experiments using the proposed system and evaluate its operability and effects on collaborative operation.

II. SYSTEM DESIGN

A. Robotic Arm and Gripper Cooperation Control

Fig.1 presents the system configuration and images obtained via a head mounted display (HMD). The system was controlled using Python (3.9.13) and operated at a sampling frequency of 100 Hz. A 7 DoF robotic arm (xArm7, UFACTORY) was used as the right arm. A small stereo depth camera (ZED Mini, STEREOLABS) was installed above the robot arm, which allowed the operators to view the stereo

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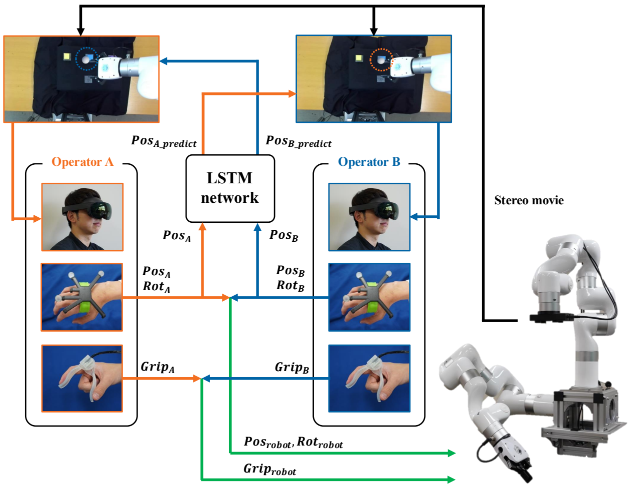

Fig. 1. Body integration system involving bidirectional operation prediction. A 7-DoF robotic arm with a gripper is controlled by two operators based on a control ratio. The LSTM network predicts the operators' movements.

view through an HMD (Meta Quest Pro, Meta). The robot arm was operated based on (1), (2), and (3):

$$Pos_{robot} = Pos_A * w + Pos_B * (1 - w), \tag{1}$$

$$Rot_{robot} = Rot_A * w + Rot_B * (1 - w), \tag{2}$$

$$Grip_{robot} = Grip_A * w + Grip_B * (1 - w), \tag{3}$$

where Pos denotes the position in Cartesian coordinates ($x, y, z \in \mathbb{R}^3$), Rot denotes the rotation in Euler angles ($roll, pitch, yaw \in \mathbb{R}^3$), and $Grip$ ($\in R$) denotes the width between the two fingers of the gripper. Coefficient w denotes the control ratio and can be adjusted within a range from 0.5 to 1. The subscript robot indicates the robot arm, and the subscripts A and B indicate each operator, respectively.

For the position and rotation inputs, a motion capture system (OptiTrack Prime 13, Acuity) and processing software (Motive 3.0.0) were used. Reflection markers were attached to the back of the right hand of each operator (A and B) to obtain their hand movements. The grip values were obtained by the opening and closing finger movements of Operators A and B using an interface assembled using a potentiometer and torsion spring, which was improved from a previous study [13].

The robot arm equipped with a camera was fixed at a position where it could view the target space so that both operators could view the same perspective. To account for changes in each operator's head position and posture, individual cameras for each operator or a 360-degree camera could be used. However, for this experiment, which aimed to investigate the effects of prediction, the head positions were fixed. The participants were instructed to maintain their heads in the same position as the robot and not move them during the experiment.

B. Bidirectional Operation Prediction

1) LSTM Network for Operation Prediction: An LSTM network was used to predict the operation. LSTM networks

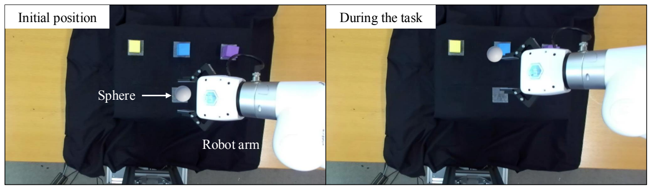

Fig. 2. Visualization of operation predictions within the workspace. The sphere moves according to the predicted movement of the partner's operation. In this study, workspace view was fixed.

have been applied to speech recognition and synthesis, and they are also used for time-series forecasting. For example, they have been used to predict stock price [18] and weather patterns [19]. In this research, the position of each operator 0.3 seconds into the future was predicted. The prediction time was determined based on preliminary experiments, which referred to the time required for humans to perceive visual stimuli [20].

The model was trained using Python (3.12.3) and PyTorch (2.3.0) frameworks on an NVIDIA GeForce RTX 4090. The prediction network consisted of a single LSTM layer (input size of 3 and hidden layer size of 7) and a fully connected layer (output size of 3). The dataset used for training comprised 30,000 frames of position data (x, y, z) recorded at 100 Hz, where a single experimenter randomly operated the robot arm, and the rigid body positions were captured. Data slicing was performed using an input sequence length of 50 frames (past 0.5 seconds) with the target labels set 30 frames ahead (0.3 seconds later). The mean squared error (MSE) was used as the loss function during model training. The Adam optimizer was employed with a learning rate of 0.001, and a scheduler was applied to reduce the learning rate by a factor of 0.5 every 50 epochs. Gradient clipping was also implemented with the maximum norm set to 2.0. Training was conducted with a batch size of 20 for 1000 epochs.

The LSTM model was built using the data from a single experimenter. Preliminary experiments showed that even an LSTM created by one person worked effectively in predicting the operations of others. Therefore, in this study, the developed LSTM model was applied to all participants in the experiment.

2) Visual Feedback of Prediction Results: Using a trained LSTM network model, the position data of operators A and B from the past 0.5 seconds were used as input, and the position data for 0.3 seconds later was predicted in real time. The obtained prediction results were visually presented using Unity (2020.3.42f1) and an HMD, as shown in Fig.2. A sphere with a diameter of 5 cm was displayed at the end of the robot arm in an image captured by a stereo depth camera. In the HMD of Operator A, the sphere moved in response to the operation prediction of Operator B. Similarly, in the HMD of Operator B, the sphere also moved in response to the operation prediction of Operator A. This allows operators to see the robot arm and the predicted partner's operation simultaneously.

III. EXPERIMENT

A pick-and-place task was adopted to evaluate improvements in body integration using the operation prediction system. Two conditions (with and without prediction display) were compared in terms of the subjective evaluation and operation features.

A. Method

Two experimental conditions were prepared for comparison, as follows.

- With prediction
- Without prediction

In the Without prediction condition, the sphere representing the prediction results was removed. Participants performed the task with the aboved-mentioned body integration in each condition. The order in conditions was determined by considering the counterbalance. Half of all participants started the experiment under the with prediction condition, while the other half started under the without prediction condition.

Six pairs of two people (nine males and three females, 23.1 $\pm$ 0.8 years old (22 to 24)) participated in the experiment and informed consent was obtained prior to the experiments. Based on Coren's test [21], eleven participants were strongly right-handed, and one was moderately right-handed. They used their right hand for the operation, which was consistent with the robotic hand. All pairs were familiar with one another.

Prior to the main test, each participant practiced operating the robot arm individually. In the practice session, the participants wearing the HMDs without prediction display operated the robot arm and gripper alone ($w = 1$). To prevent collisions between the table and robot arm, restrictions were applied to posture control, and the posture was fixed throughout the experiment, as shown in Fig.3.

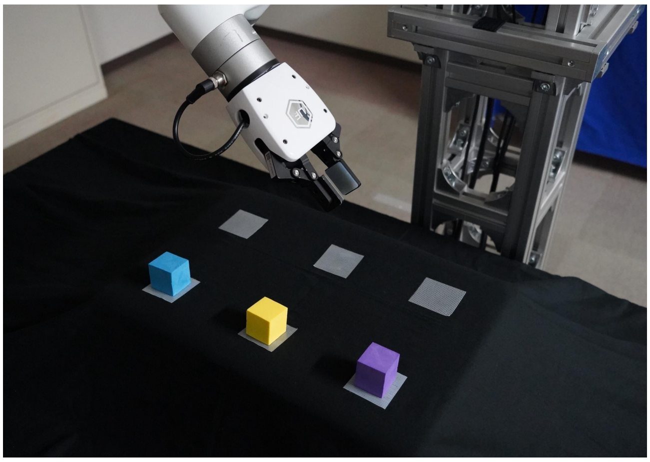

Fig. 3. Configuration of the robotic arm's end-effector, with the posture fixed to avoid collisions between the table and the robot arm during operation.

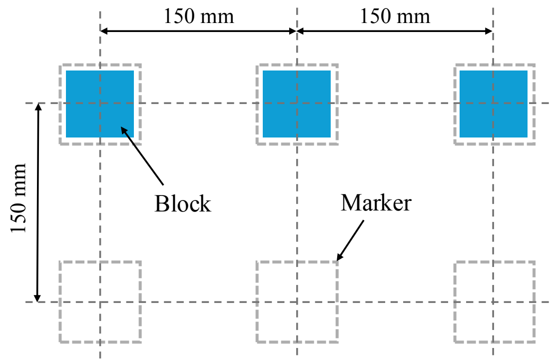

Fig. 4. The task used in th practice session. Operators performed a pick-and-place task as quickly as possible for one minute.

Fig.4 presents the tasks used in the practice sessions. Six markers (50 $\times$ 50 mm) and three blocks (35 $\times$ 35 $\times$ 35 mm) were prepared, and a pick-and-place task was performed as quickly as possible for one minute. Each pair of participants was allowed to decide on where to place each block based on the markers. Each participant repeated the practice task twice. To avoid influencing the participants' behavior during the experiment by knowing their partner's skill level, the participants were not allowed to watch the partner's practice session.

After both participants completed their practice sessions, the test sessions were conducted. The experimental setup is shown in Fig.5. In the experiment, two operators operate collaboratively through the body integration ($w = 0.5$).

Fig.6 presents the task used in the test session. Three blocks were placed on each of the three markers positioned in front of the robot arm. Additionally, an empty goal marker was placed under the initial position of the robot arm. Immediately after a sound indicating the start of the task was played, the participants selected one of the three blocks, picked it up, moved it to the goal marker, and placed it as quickly as possible. Throughout the experiment, participants were prohibited from discussing which blocks to pick up from among themselves.

The test task was conducted 15 times for each condition. Participants were required to continue their operation until the task was completed, even if they were unable to grasp a block or if it was dropped. The position trajectory data for each operator ware recorded and the task completion time was measured. After completing 15 trials, participants were required to complete a questionnaire for subjective evaluation.

B. Analysis

The experiment was evaluated based on questionnaires and operational data recorded during the test session. At this time, the first five tasks under each condition were excluded from the analysis because they were intended for participants to become accustomed to the operation. Thus, analysis was conducted for the last ten tasks. The leader ratio, which indicates the ratio of the trials when the operator appeared to serve as a leader, and the operational similarity between the two operators were calculated.

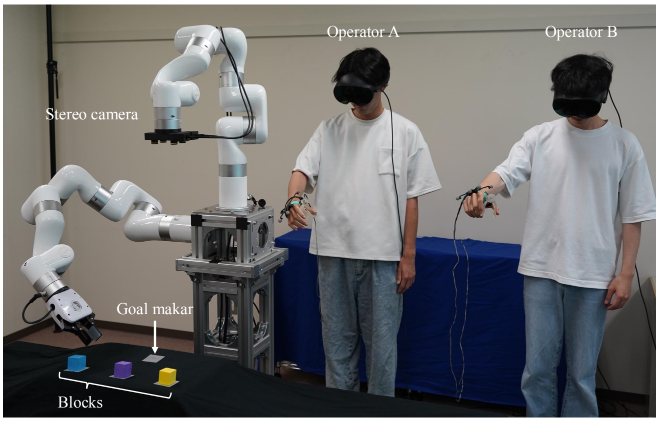

Fig. 5. Experimental setup for main test session.

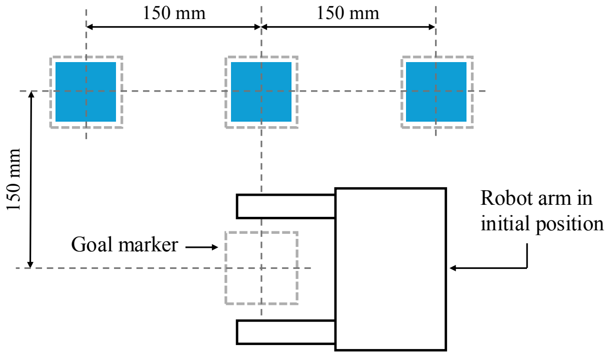

Fig. 6. The task used in main test. Operators picked one block from three blocks placed in front of the robot arm, and place it on the goal marker located beneath the robot arm's initial position, as quickly as possible.

1) Questionnaires: A questionnaire was used to subjectively evaluate operability. The questions were as follows.

- Smoothness: Was the task performed smoothly?
- Ease of coordination: Were you able to cooperate with your partner?
- Workload: Did you experience a high workload?
- Sense of being reflected: Did you feel that your actions were reflected in the robot arm?
- Sense of determination: Did you feel that you were determining the arm's movements?
- IOS [22]

The IOS was evaluated by selecting from the options shown in Fig.7, while the other questions were rated on a 7-point Likert scale ranging from Strongly Disagree (1) to Strongly Agree (7).

2) Task completion time: To evaluate task performance, the time required to complete the task was measured for each trial. The task completion time was defined as the interval from when the sound began until the block was grasped.

3) Leader ratio: To evaluate the effects on collaborative operation, it was estimated which operator led the operation in each task based on the timing of each operator's start of movement. It was assumed that the operator followed the operator who moved in advance because they conducted the task collaboratively and shared a goal.

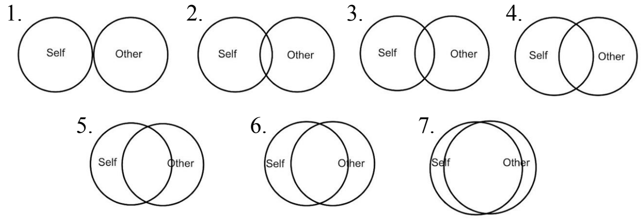

Fig. 7. IOS scale options for evaluating interpersonal closeness between participants. Participants selected the option that best represented their relationship with their partner.

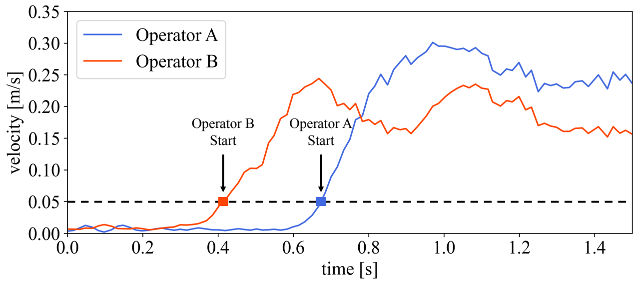

Fig. 8. Example of timings when operators started to move. In this case, Operator B was considered as the leader because moved in advance.

The timing at which the operator started to move was defined as the interval from when the sound began until the operating speed first exceeded 0.05 m/s, as shown in Fig.8. For each task, the operator who began moving first was considered as the leader. Additionally, the ratio of tasks in which each operator served as the leader during the last ten tasks (referred to as the 'leader ratio' in subsequent discussions.) was calculated separately for each operator.

4) Operation similarity: To evaluate operational similarity, the Dynamic Time-Domain Warping (DDTW) [23] score of the operation trajectory vectors ($x, y, z \in \mathbb{R}^3$) was used. The calculation interval was defined as the time from 10 frames before the leader started moving until the block was grasped, with a lower score indicating greater similarity between users' operations. In this study, owing to computational cost constraints, a FastDTW method [24] was adopted for the DDTW calculation process.

IV. RESULTS

Fig.9 shows the subjective rating results for each condition. Statistical analysis of the subjective rating results was conducted to evaluate the differences in operability between the conditions. A Wilcoxon signed-rank test was conducted on each of the questionnaire items, and a significant difference was revealed between the conditions for the "smoothness" ($V = 0$, $p = 0.0156$). This result indicated that the prediction significantly improved the smoothness of the operation. Additionally, a significant tendency of difference was observed for the "Workload" ($V = 32$, $p = 0.0547$), indicating that the prediction tends to reduce the workload. On the other hand, no significant differences were observed for other items.

The average task completion time was 3.30 ± 0.63 sec

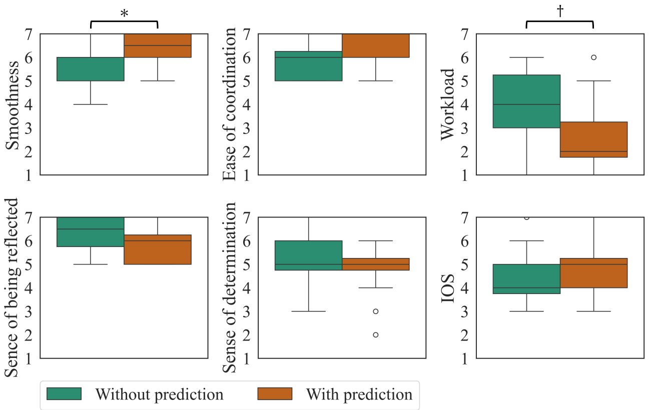

Fig. 9. Results of questionnaires used to subjectively evaluate operability. Each color indicates the condition with or without prediction. †, and * denotes $p < 0.1$, and $p < 0.05$, respectively.

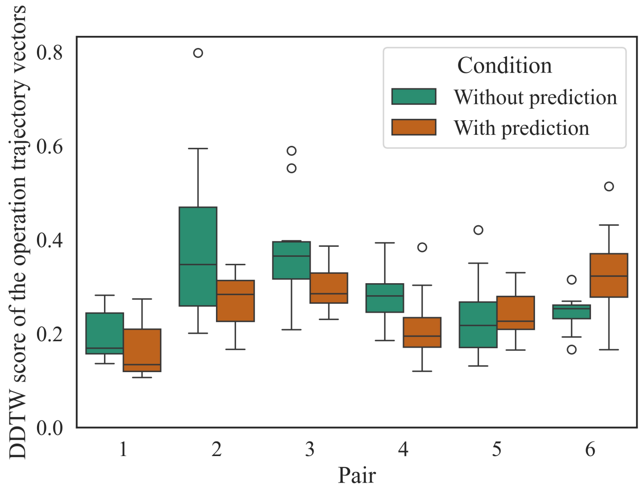

Fig. 10. Results of DDTW score of the operation trajectory vectors. Each color shows the condition with or without prediction.

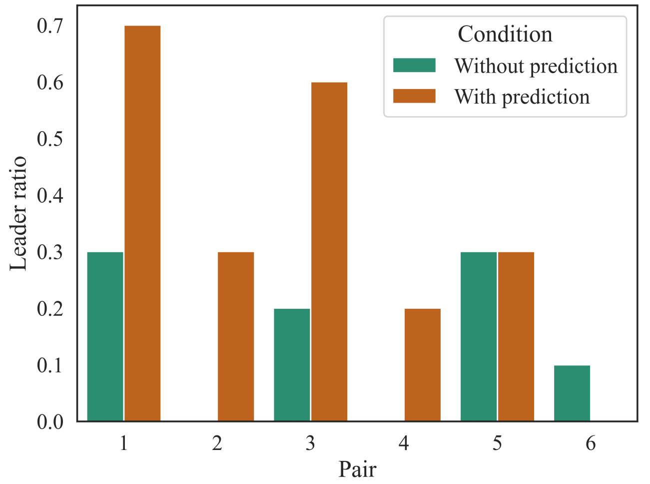

Fig. 11. Results of leader ratio for the operator with a lower leader ratio among each pair during the Without prediction condition. Each color shows the condition with or without prediction.

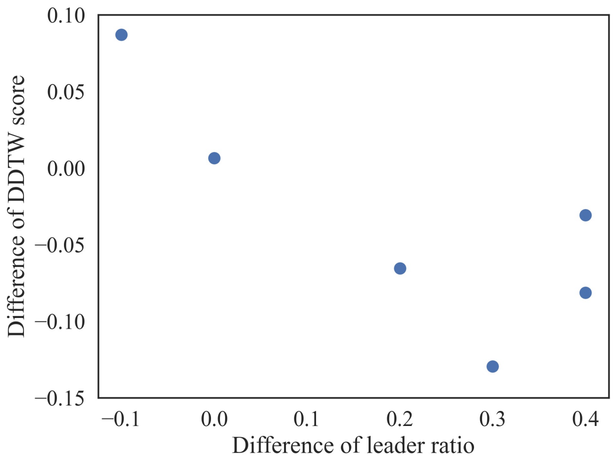

Fig. 12. Scatter plot showing the relationship between the change in leader ratio and the change in DDTW scores across conditions.

for the With prediction condition and 3.46 ± 2.12 sec for the Without prediction condition. The Shapiro-Wilk test was conducted to assess the normality of task completion time, and the results rejected normality, indicating a deviation from normal distribution. Then, a Wilcoxon signed-rank test was conducted and no significant differences were observed, indicating that the performance did not differ between the conditions.

Fig.10 shows the DDTW scores for each pair. For pairs 1-4, the DDTW score appeared to decrease under the With prediction condition. Additionally, Fig.11 presents the leader ratio under both conditions for the operator who had a lower leader ratio within each pair under the Without prediction condition. For pairs 1-4, the operators who tended to be followes (Leader ratio < 0.5) under the Without prediction condition showed an increase in their leader ratio under the With prediction condition. Conversely, no change in the leader ratio was observed for pair 5, and a slight decrease was observed for pair 6.

Fig.12 shows a scatter plot of the relationship between the change in the leader ratio under the With prediction condition compared to the Without prediction condition for users who were followers under the Without prediction condition (horizontal axis) and the change in the DDTW score for the With prediction condition compared to the Without prediction condition (vertical axis). In all pairs where the operators who were followers under the Without prediction condition showed an increase in their leader ratio under the With prediction condition, the DDTW score for the trajectory decreased.

Fig.13 presents the questionnaire results for Smoothness, IOS, and Workload relative to the DDTW score. The Spearman's rank correlation coefficient was calculated for each question, revealing a strong correlation between Smoothness and the DDTW score ($\rho = -0.722$, $p = 6.92 \times 10^{-5}$) and a moderate correlation between IOS and the DDTW score ($\rho = -0.504$, $p = 0.0121$). Additionally, a trend towards a weak correlation was observed between Workload and the DDTW score ($\rho = 0.354$, $p = 0.0897$).

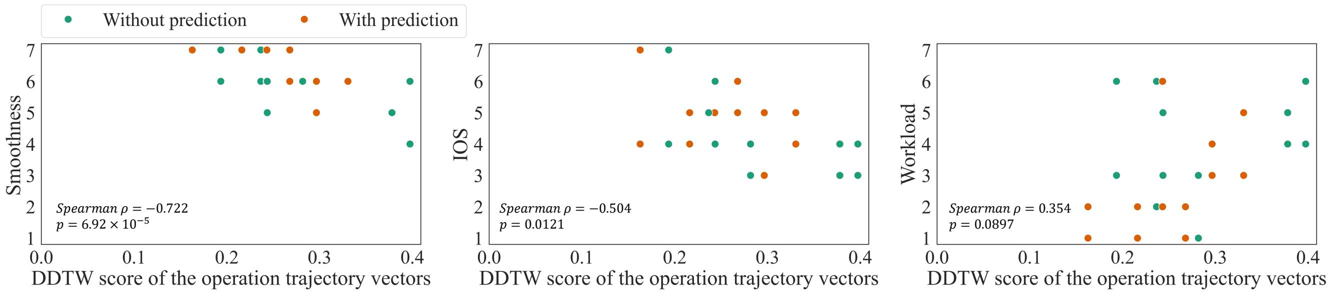

Fig. 13. Scatter plot showing the relationship between the change in the DDTW score across conditions and questionnaire results. Each color indicates the condition with or without prediction.

V. DISCUSSION

A. Effects of Operation Prediction

The questionnaire results revealed that the subjective smoothness of the operation significantly improved under the With prediction condition compared to the Without prediction condition. Therefore, it appears that the operation prediction helps operators cooperate with each other.

The DDTW scores of pairs 1-4 tended to decrease under the With prediction condition, suggesting that the similarity of operations improved. In contrast, no decreasing trend was observed for pairs 5 and 6. For pairs with decreased DDTW scores, operators who tended to be followers under the Without prediction condition tended to lead more under the With prediction condition.

Regarding the relationship between the DDTW score and the questionnaire results, it was revealed that as the DDTW score decreased, the two operators felt that the operation became easier. This trend was consistent with the results of the previous research on body integration [11]. The change in the leader ratio implied that both operators used the prediction. Taking into account the result that the similarity of the movement was significantly enhanced with the prediction condition, it might be suggested that the utilization of prediction among a pair promotes coordination and cooperation.

B. Limitations and Future Works

In this study, a single condition in the duration and prediction time for the operation prediction was used. However, the optimal prediction time may vary depending on the operator's visual reaction speed, which can affect operability. Additionally, differences in visual reaction speeds between pairs might influence the determination of the leader and follower roles. The prediction duration also affects the accuracy of the predictionby interacting with the prediction time. Therefore, appropriate prediction time and duration should be investigated in future research.

The participants were limited to university students, and their age range was not large. To deeply evaluate the effectiveness of the system, it would be desirable to have a more diverse group of participants. Furthermore, the personalities and relationships of the participants may affect collaborative operations. This study did not collect information on the participants' personalities and limited the participants to those who were familiar with each other. Thus, additional comparisons that consider the characteristics of operators are required to clarify their impact on collaborative operations.

In the experiment, each participants' motions were combined with a 50% overlap. However, varying the control ratio or employing a role-based operation could also affect the effectiveness of predictions and cooperation. Therefore, it is necessary to examine the effects of predictions using different body integration methods.

No significant difference in task completion time was observed in the current experiment, whereas the task used was a simple pick-and-place task. In cases requiring more decisions, coordination between operators may influence task performance. The proposed operation prediction should be evaluated in more complex tasks in future works.

VI. CONCLUSIONS

In this study, we developed a body integration system that involves bidirectional operation prediction. In the system, two operators control a single robot avatar by observing the predictions of each other's operation obtained through an LSTM network, which is applied in time series prediction. We conducted pick-and-place experiments under two conditions, with and without prediction. The results of the subjective evaluation and the operational analysis suggested that the similarity of operations between operators could be improved by using the prediction appropriately, and the subjective feeling of operation could be also improved as well. In the future, an appropriate prediction time and duration will be investigated, and the proposed system will be improved for practical use.

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