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HMM-based Error Recovery of Dance Step Selection for Dance Partner Robot

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***Abstract*— A dance partner robot has been developed as an example of platforms for realizing the effective human-robot coordination with physical interactions. This robot could dance together with a human by estimating the next step intended by the human. If the robot would mistake the step estimation, the human-robot coordination could not be continued. In this paper, an error recovery method for step selections, which changes robot's behavior according to human's behavior, is designed using Hidden Markov Models. Experimental results illustrate the validity of the proposed method.**

***Index Terms*— Human-Robot Cooperation, Ballroom Dances, Mobile Robot, Error Recovery of Dance Step Selection.**

I. Introduction

Robots are expected to be used in human environments in cooperation with a human or humans against the background of the coming of aging society. The human-robot coordination problems for executing tasks have been studied by several researchers. In most of the human-robot coordination systems, robots have been controlled so as to move passively according to force/moment applied by a human to the robots [1]-[3] $^{etc.}$. These systems are effective to execute simple tasks such as handling an object. On the other hand, some researchers have proposed pet robots [4] [5] $^{etc.}$ for entertainment or human mental healing, which move actively based on information such as sound, light and simple interactions with touch sensors, etc. If robots could move not only passively but also actively based on human intentions, environments, knowledge of tasks, etc., we could realize a more effective human-robot coordination system than the conventional ones. Considering the case of coordination among humans, each human would move not only passively but also actively based on such information. In this research, human-robot coordination with physical interaction between a human and a robot is discussed to execute tasks more effectively, in which the robot moves not only passively but also actively based on such information.

As an example of human-robot coordination with physical interactions, a dance partner robot is focused, which realizes ballroom dances with a human. In the previous research [6], the concept of the dance partner robot has been proposed, and the robot referred to as "MS DanceR (Mobile Smart Dance Robot)" shown in Fig.1 and its control architecture referred to as "CAST (Control Architecture based-on Step Transition)" have been developed. CAST is composed of three modules, i.e. "Knowledge", "Step Estimator", and "Motion Generator". Knowledge stores the information on dancing such as basic trajectories and transition rules of dance steps. Step Estimator estimates the next step based on the rules and human intention. Motion Generator generates actual motions of the robot based on the trajectories and the coordination with a human. In [7], Step Estimator, i.e. the estimation module for the next dance step, has been improved by considering time series data of interactive force/moment applied between the human and the robot, and has made the step estimations more successful. Success rates of the step estimations, however, could not reach 100 [%] with the Step Estimator, e.g. a success rate for one subject is 98.88 [%]. The reason why the success rates could not reach 100 [%] would be that modeling human intentions and estimating it completely would be very difficult problems.

Fig. 1. Dance Partner Robot -MS DanceR-

Considering the case of coordination among humans, however, they could not always estimate partner's intention correctly. The more important issues for continuing the coordination would be detecting mistakes as soon as possible and changing his/her behavior to a correct behavior by perceiving his/her partner's behavior rather than completing the estimation of his/her partner's intention. Therefore addressing the issues would be one of the keys to the effective human-robot coordination. A human error recovery problem for human-robot collaborative parts conveyance tasks [8] have been studied by Y. Yamada et al., in which a robot behaves passively according to force applied by a human. In the error recovery process, the robot informs the human of error occurrences by alarm signals, and urges the human to change his/her behavior. Their error recovery could work

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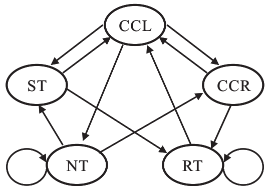


Fig. 2. Step Transition of Waltz

successfully on the assumptions that the robot would behave passively according to force applied by the human, and that robot's trajectory is the same as human's.

The more effective human-robot coordination system could be realized if error recovery problems for the coordination system could be solved, in which a robot behaves passively and actively according to human intention and it is not assumed that robot's trajectory is the same as human's. In the error recovery problems for such an active coordination system, human's motion and robot's have to be considered independently for detecting a mismatch between human's behavior and robot's differently from the passive-type human-robot coordination system because both of the human and the robot behave actively and human's motion and robot's motion are affected each other due to physical interactions. Such an error recovery problem could be applied to various human-machine systems with physical interactions, e.g. human-robot collaborative tasks, welfare systems and so on, in which the machine behaves not only passively but also actively based on human intention.

In the case of ballroom dancing, the error recovery issues would correspond to problems that he/she detects errors of step selections as soon as possible and that he/she changes his/her step motion to his/her partner's. In order to solve the problems for the dance partner robot, the robot has to execute error detections of step selections and has to change robot's own step motion according to human's motion with keeping physical interactions even if the robot starts executing another step motion. In [9], the error detection method for dance step selections has been proposed, which completely detects selection errors. This paper proposes the error recovery method for dance step selections, which changes robot's step to human's step after the error detections.

This paper is organized as follows. In the next section, error recovery problems of dance step selections for the dance partner robot are explained. In Section III, a step reestimation model, which is a part of the error recovery method, is designed using Hidden Markov Models (HMMs) [10]. And experiments on the error recovery are performed and discussions on the results are described in Section IV. Finally, Section V contains a conclusion of this paper and a description of future works.

II. Error Recovery of Dance Step Selection

In this paper, the error recovery of dance step selections is realized by two processes, i.e. reestimation of human's step

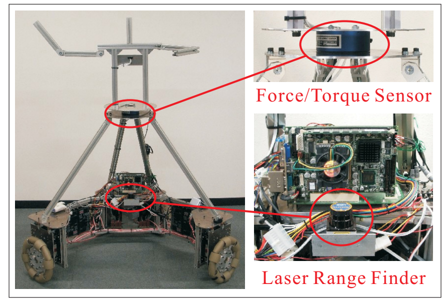


Fig. 3. Robot Structure

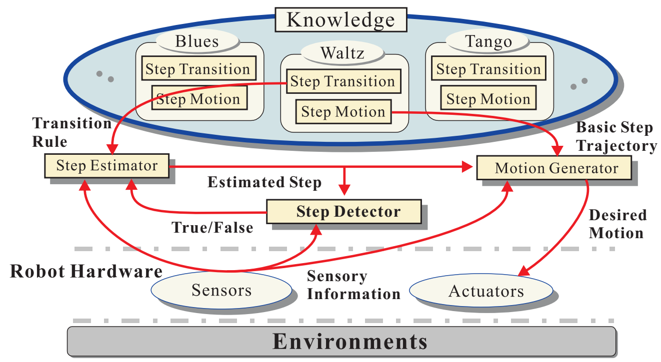


Fig. 4. Control Architecture -CAST-

and modification of robot's trajectory. In this section, first of all, review of the previous research is described. Next, the step reestimation and the modification are explained.

A. *Review of Previous Research*

In ballroom dancing, a male dancer selects his own next step from selectable steps limited by transition rules of dance steps. A male dancer leads a female dancer, and she executes a step motion actively by estimating a step intended by him. MS DanceR acts as a female dancer, and dances with a human. Therefore the robot has to estimate the next step intended by the human before the robot starts executing the step motion. In this paper, a waltz is selected as an example of ballroom dances. For the simplicity of modeling the waltz, five basic steps in the waltz are used, i.e. Closed Change Left (CCL), Closed Change Right (CCR), Natural Turn (NT), Reverse Turn (RT) and Square Turn (ST). Transition rules for these steps referred to as "Step Transition" in CAST are shown in Fig.2. According to male dancer's lead and the transition rules shown in Fig.2, the robot selects the next step from selectable steps.

The step estimation problem has been addressed in [7]. Step Estimator outputs the estimated next step at a transition from the current step to the next step. The robot estimates the next step intended by a human according to lead applied by the human, which is mainly communicated to the robot by interactive force/moment measured by a force/torque sensor installed between the upper body and the lower body of the robot (Fig.3). Although the estimation method could work successfully, success rates of the estimations could not reach

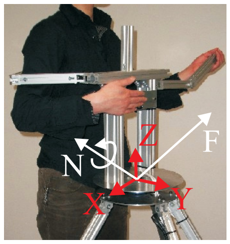
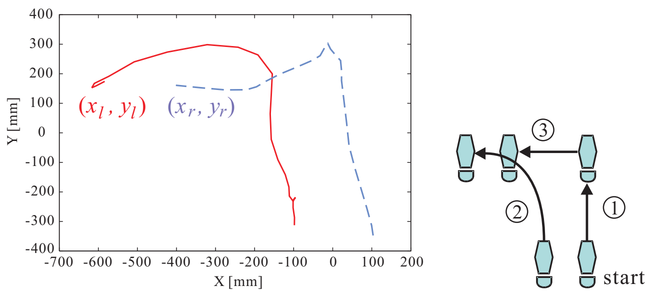


Fig. 5. Physical Interaction with Human in Dancing



(a) Observed Data (b) Step Pattern

Fig. 6. Feature Extraction of Human Step Motion [9]

100 [%]. And the case that the estimation is failed is not considered in the method.

In [9], an error detection problem for dance step selections has been addressed. A new module "Step Detector" has been added to CAST (Fig.4), which detects errors of dance step selections by observing human motions in dancing. In the error detection method, the human motions have been modeled stochastically. The error detection method has detected the step selection errors completely using the human motion models. Although the human motion models would be expected to realize not only the error detections but also reestimations of a correct step selected by the human, the models could not achieve high success rates of the reestimations. The reason is described in section II-B.

B. Description of Step Reestimation

The human motion models have been designed using human legs' motion trajectories (Fig.6), which are observed by a laser range finder installed at the robot (Fig.3) when the robot estimates human's step correctly and dances the same step as human's. The human motion models, however, could not include human motions affected by robot motions, which would arise from a mismatch between human step motion and robot step motion when the robot mistakes the step estimation. The mismatch arises from the facts that the robot moves actively based on the estimated step, and that the human and the robot dances with keeping physical contacts (Fig.5). Therefore the reliability of the human motion models is not enough to reestimate a correct step when the robot mistakes the step selection.

Paying attention to the step estimation, the physical interaction, i.e. force/moment applied by the human, would include not only information on the most possible step

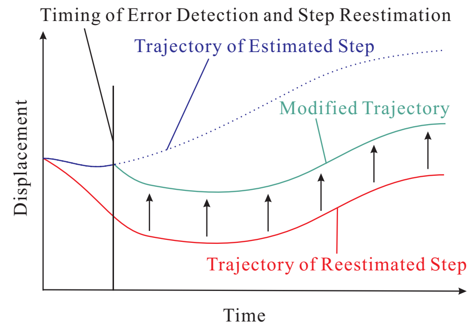


Fig. 7. Modification of Step Motion Trajectory

but also information on the second possible step when the estimation is failed. Therefore the interactive force/moment is useful information on the step reestimation if the most possible step selected by the robot in the step estimation is removed from selectable steps in case of the step estimation failure. However the reliability of the physical interaction would not be enough to reestimate a correct step because the first step estimation is failed due to the physical interaction.

In the error recovery method, both of the physical interactions and the human motions are utilized in order to increase the reliability of data used for the reestimation. And the physical interactions and the human motions are integrated into HMM [10]. HMM models time series data with human uncertainty, which arises from the fact that a human can not always apply the same force/moment and move along the same trajectory.

C. Description of Modifying Step Motion Trajectory

Although there would exist many kinds of methods for modifying robot's trajectories, a modification method illustrated in Fig.7 is used as an example of them. According to the error detection method [9], time required for the error detections is short if the difference between human step motion expected by the robot and actual human motion is quite large. And the time is long if those two motions are similar. Therefore the modification method could work enough for the robot not to affect human's dancing terribly.

III. Step Reestimation Model

A. Time Series Data used for Step Reestimation

Three processes, i.e. the step estimation [7], the error detection [9], and the step reestimation, are executed for step selections. Fig.8 illustrates time series data used for the processes. Data used for the step estimation are time series of force/moment applied by the human, which are observed before a transition of step. In the error detection, the human legs' motion trajectories are used, which are observed after the transition. In order to use both of the force/moment and the trajectories effectively, time series data observed before and after the transition are modeled in the step reestimation. Therefore each step reestimation model is designed for each step transition.

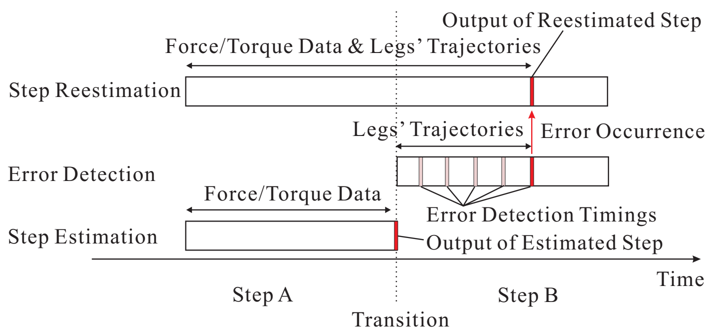


Fig. 8. Time Series Data used for Step Estimation, Error Detection and Step Reestimation

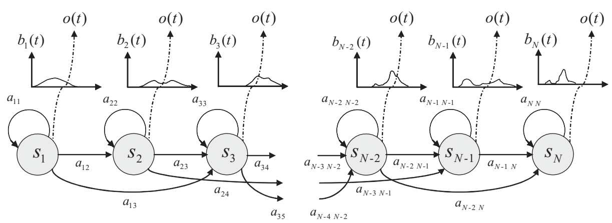
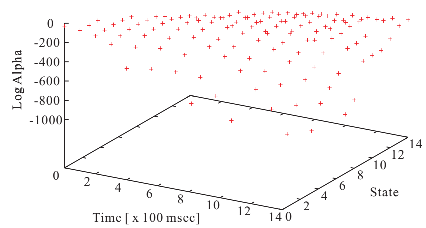
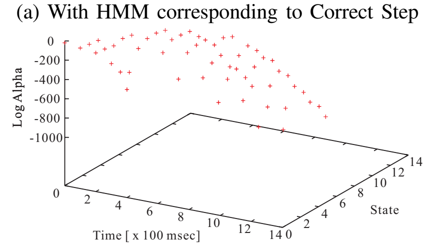


Fig. 9. Left-to-Right Continuous Hidden Markov Models



(a) With HMM corresponding to Correct Step



(b) With HMM corresponding to Incorrect Step

Fig. 10. Simulation Results for Forward Variables

The error detection method was designed so as to execute the error detection in each time segment because the step estimation failures should be detected as soon as possible for the active coordination in dancing and a timing of the error occurrence is unknown. For the same reason, the reestimation method should be designed so as to output the reestimated step at the timing of the error occurrence.

B. Designing HMM-based Step Reestimation Model

In this paper, the force/moment applied by the human and the human step motions are modeled by left to right continuous HMM [10] shown in Fig.9, which is composed of states $s_1, s_2, ..., s_N$. A set of HMM parameters is expressed by $\lambda = (\Pi, A, B)$, where Π is the probability distribution for the initial state, A is the probability distribution for state transitions, and B is the probability distribution for observed data. Concerning left to right type HMM, Π is obviously expressed as $\Pi = \{\pi_1 = 1, \pi_i = 0 (i = 2, 3, .., N)\}$. The detail of setting parameters A and B is described in [9]. Each HMM corresponds to each step transition, and input to the HMM is a set of observed data $O = \{o(t)|t = 1, 2, ..., T\}$, i.e. time series of the force/moment and the human legs' motion trajectories measured in dancing the previous step and the current step. In this paper, discrete time is expressed as $time = t \times \Delta t$, where t is a time index and Δt is the sampling rate [sec].

A forward variable $\alpha_i(t)$ [10] expressed in eq.(1) is focused in the step reestimation, which evaluates the validity of observed data $o(1), o(2), ..., o(t)$ and the possibility that a state at $time = t \times \Delta t$, i.e. $q(t)$, exists at state s_i.

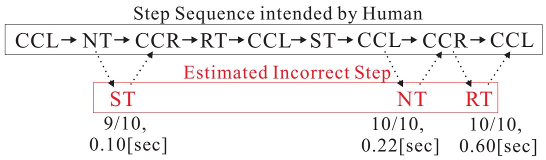
$$\alpha_i(t) = P(o(1), o(2), ..., o(t), q(t) = s_i|\lambda) \tag{1}$$

The HMM is designed so that a forward variable has a characteristic as shown in Fig.10. Fig.10(a) is a simulation result for forward variables when observed data in dancing a step are inputted to HMM corresponding to the step. And Fig.10(b) is a simulation result for forward variables when the observed data are inputted to HMM that does not correspond to the step. According to Fig.10, $\alpha_i(t)$ would be high in the case that a state index i is close to a time index t if the robot selects the same step as human's, and would be low if robot's step is incorrect.

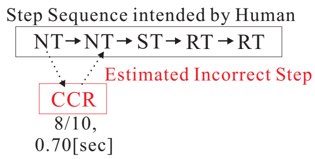
In order to evaluate forward variables $\alpha_i(t)$, reference likelihood $L(t)$ in eq.(2) is introduced, which is the sum of $\alpha_{t-\Delta}(t), \alpha_{t-\Delta+1}(t), ..., \alpha_{t+\Delta-1}(t), \alpha_{t+\Delta}(t)$.

$$L(t) = \sum_{i=t-\Delta}^{t+\Delta} \alpha_i(t) \tag{2}$$

The reference likelihood $L(t)$ evaluates $\alpha_i(t)$ effectively, whose state index i is close to a time index t. A step is selected as a result of the step reestimation, whose reference likelihood $L(t_{detect})$ is the largest, where t_{detect} is a time index corresponding to the timing of the error occurrence.



(a) Step Sequence 1



(b) Step Sequence 2

Fig. 11. Experimental Results

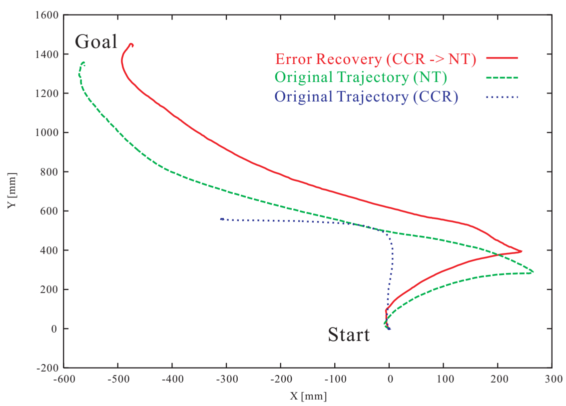
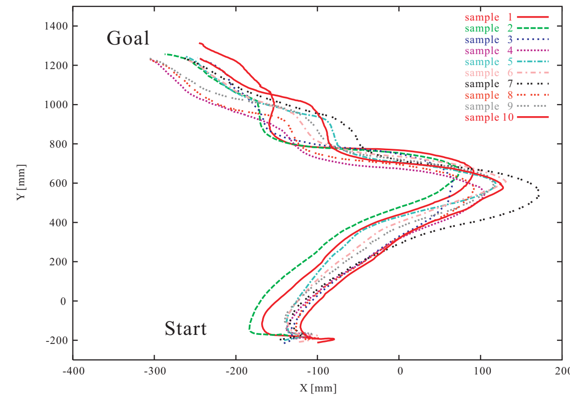
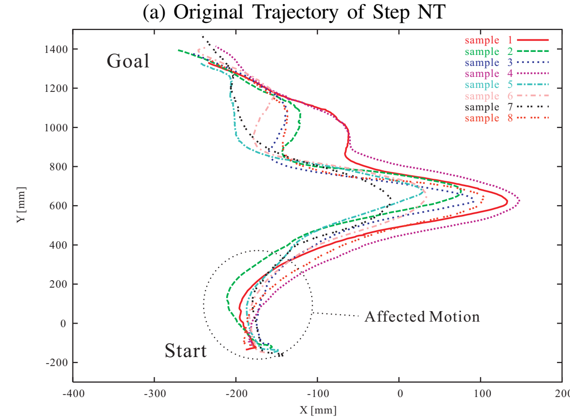


Fig. 12. Robot Trajectory measured by Motion Capture System



(a) Original Trajectory of Step NT



(b) Trajectory Affected by Robot's Motion

Fig. 13. Human Step Motion Trajectory measured by Motion Capture System

IV. EXPERIMENT

Experiments on error recovery of dance step selections are performed in order to illustrate the validity of the proposed method. In the experiments, the robot reestimates human's step and modifies own motion according to the step when the robot mistakes the step estimation.

A. Condition

The step estimation method proposed in [7] works successfully when the robot dances with a subject using step estimation parameters of that subject. Therefore step estimation failures rarely occurred. In order to evaluate the step reestimation method effectively, the experiments are performed on the condition that the failures will occur. This condition is implemented in the experiment, where subject A uses step estimation parameters of another subject B. In this experiment, subject A, for whom the success rate of the step estimations is 98.88[%], has performed the experiment with the step estimation parameters of another subject B, for whom the success rate of the step estimations is 89.29[%].

In the experiments, a subject intends to select the following two step sequences.

Step Sequence 1 :

$$\mathrm{CCL} \Rightarrow \mathrm{NT} \Rightarrow \mathrm{CCR} \Rightarrow \mathrm{RT} \Rightarrow \mathrm{CCL} \Rightarrow \mathrm{ST} \Rightarrow \mathrm{CCL} \Rightarrow \mathrm{CCR} \Rightarrow \mathrm{CCL}$$

Step Sequence 2 :

$$\mathrm{NT} \Rightarrow \mathrm{NT} \Rightarrow \mathrm{ST} \Rightarrow \mathrm{RT} \Rightarrow \mathrm{RT}$$

All step transitions are executed by dancing the sequences. Ten trials are repeated in each experiment.

The real time OS QNX is utilized to control the robot, whose control frequency is 1 kHz. The laser range finder (Fig.3) sends data to QNX on 10 Hz. Whole time of all steps is fixed at 2.5 [sec], and the sampling rate for the reestimation is $\Delta t = 0.1$ [sec].

B. Results

The error recovery method completely selects a correct step selected by the subject and modifies robot's trajectory successfully according to the step. Fig.11 illustrates results of the step reestimations. In Fig.11(a), for example, step ST was selected as the third step in the step estimation, which was an incorrect step. After the human and the robot started moving, the error detection method judged that the step estimation was failed, and the reestimation method selected a correct step CCR. "9/10" and "0.10 [sec]" denoted at the lower part of the "ST" in Fig.11(a) mean that an incorrect step ST is selected nine times in ten trials and a correct step CCR is selected once in ten trials, and that the average of time required for the error detection in the nine trials is 0.10 [sec] respectively.

The longest average time is 0.70 [sec] at the second step in Fig.11(b), i.e. error recovery from step CCR to step NT, which is the average of the required time in eight trials. In order to evaluate the modification method for step motion trajectories, robot's trajectory in the error recovery from step CCR to step NT are shown in Fig.12, which are measured by motion capture system. Human motions are also measured by motion capture system in order to investigate human motions affected by the robot motions in the error recovery. Fig.13(a) shows human trajectories when the human and the robot dance the same step. And Fig.13(b) shows human trajectories when the robot executes the error recovery from step CCR to step NT.

C. Discussion

Experimental results on the step reestimations illustrate the validity of the step reestimation method. This success would be achieved by using both of the physical interactions and the human motions. Paying attention to likelihoods for the step estimations and the step reestimations, the above hypothesis could be ensured. At a transition NT $\rightarrow$ NT in Step Sequence 2, for example, log likelihoods for the step estimation are -189.6 for CCR and -224.3 for NT, and an incorrect step CCR is selected consequently. On the other hand, log likelihoods for the step reestimation are -1027.0 for CCR, which is removed from selectable steps in the error detection before the reestimation, and -483.3 for NT. The difference between likelihoods for CCR and NT in the step reestimation, i.e. -1027.0 and -483.3, is much larger than the difference between likelihoods for CCR and NT in the step estimation, i.e. -189.6 and -224.3. This fact explains that only force/moment is not enough for a correct step selection to increase success rate of step selection, and that a complete step selection is achieved by taking both of the physical interactions and the human motions into consideration.

Concerning the modification method, Fig.12 shows that the robot modifies own trajectory according to a reestimated step, which is selected by the subject. In order to investigate human motions affected by the robot's motions, human motions are measured by motion capture system. Compared with Fig.13(a), it is observed from Fig.13(b) that human motions are affected by robot's motions at the beginning of the step because the robot dances different step from subject's with keeping physical contact with the subject. After the error detection and the step reestimation, however, human motions in Fig.13(b) are similar to ones in Fig.13(a). Although the modification method would be simple, it could work successfully enough to continue dancing and not to disturb human motions terribly. These successes are obtained by the facts that the error detection method [9] judges the step estimation failures quickly, and that the step reestimation method selects correct steps completely.

V. Conclusions and Future Works

A. Conclusions

In this research, human-robot coordination with physical interaction was discussed. As an example of the effective human-robot coordination, ballroom dances were focused. A dance partner robot referred to as MS DanceR and its control architecture referred to as CAST were introduced. Although the step estimation system in CAST worked successfully, it could not achieve complete step estimations because modeling human intention and estimating it completely were very difficult problems. It would be considered that the more important issues for realizing the coordination were detecting estimation failures and changing the robot's behavior according to human's behavior. This paper addressed error recovery of step selections for the dance partner robot in order to continue dancing even if the robot could not estimate human's step. In order to realize the error recovery, the error recovery method was designed using HMM that models both of the physical interactions and the human motions. The experimental results illustrated the validity of the proposed method.

B. Future Works

In this paper, experiments are performed by one subject. In order to inspect the proposed method more strictly, the same experiments will be performed by multiple subjects in future works.

VI. Acknowledgments

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