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Shared Decision Making in a Collaborative Task with Reciprocal Haptic Feedback - an Efficiency-Analysis

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***Abstract*— When robots leave industrial settings, they have to be designed allowing intuitive communication with the humans they interact with. The current paper focuses on collaboration in kinesthetic tasks. Herein, we investigate decision situations. This way, the need of communication between partners can be addressed. The current paper introduces for the first time an experimental paradigm which allows studying the effect of decision making in haptic collaboration. Because reciprocal haptic feedback is challenging to provide, we analyze its efficiency in human-human collaboration to understand when it is worth to invest in this additional modality. A one degree of tracking experiment with two human partners revealed that the additional physical effort accompanying reciprocal haptic feedback is directly transformed into higher performance (compared to a control condition without reciprocal haptic feedback). Thus, the presented results motivate further research on the nature of the haptic negotiation between human partners to achieve the same performance benefits in kinesthetic collaboration with robotic partners.**

I. INTRODUCTION

When two humans physically interact with each other in joint kinesthetic tasks such as object manipulation (e.g. carrying and placing heavy objects) or guidance (e.g. rehabilitation, training) reciprocal haptic feedback between partners is inevitably present. This, however, is not necessarily the case when physical interaction occurs in technology mediated systems like virtual or remote environments. Then, depending on the used human-system interface, collaboration is influenced by the type, number, and quality of the provided feedback channels. Similarly, reciprocal haptic feedback can vary when interacting with autonomous assistant robots, e.g. the full capacity of the haptic communication channel may not be addressed when the robot behaves only as passive follower [14].

The current paper strives to understand the benefits of haptic feedback as communication channel in collaborative interaction tasks. We investigate the overall-hypothesis that the partners not only *interact* via haptic signals (the bilateral exchange of force and position signals) but that *collaboration* takes place. Collaboration implies that intention recognition between partners is made possible [6]. Intentions consist of goals and action plans to achieve them [19]. To investigate the role of haptic feedback in the negotiation of action plans, we study human-human collaboration (HHC) as a reference with the aim of obtaining design guidelines for multi-user

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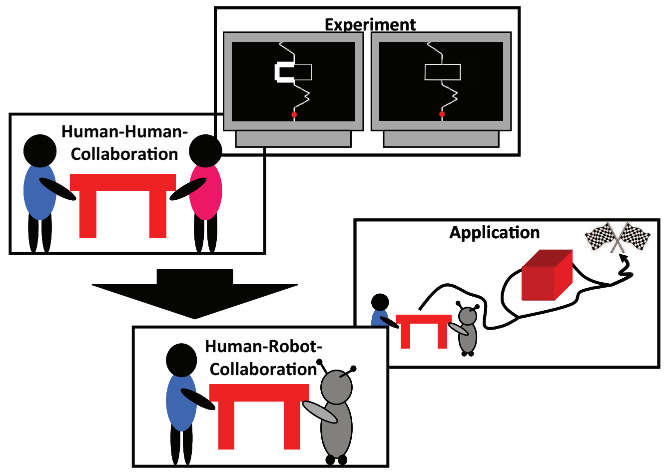

Fig. 1: One approach to design intuitive technical partners in kinesthetic tasks is to substitute one human partner of the interacting dyad. The knowledge gained on HHC in controlled experiments (here: shared decision making) can enhance HRC in practical applications (here: obstacle avoidance).

telepresence systems, collaborative virtual environments, and the interaction with autonomous robots. This approach, see Figure 1, is in line with recent investigations in this field [4], [5], [7], [8], [15], [17], [18].

A. Haptic Shared Decision Making

Whenever the environment or capabilities of interacting partners (whether humans or robots) offer several action plans to achieve a shared goal, shared decision making plays a key-role. *Decision making* is generally defined as the act of choosing one available option out of several possibilities which have different trade-offs between benefits and costs. Some researchers refer to decision as the ”forming of intentions before acting” [10] whereas others define the exact time-point as decision [11]. In *shared decision making* two partners have to agree on a solution. Even though, they may prefer different action plans due to different information bases or perceived options. Shared decision making is the interactive process to negotiate action plans to reach the shared goal. Thus, shared decision making is one form of collaboration and allows to study intention recognition between partners i.e. the building a mental model of the partner’s decision state. For a general overview on shared decision making see [3]. In kinesthetic tasks *haptic shared decision making* (HSDM) may be required. Therein, joint decisions on the shared trajectory of the interaction point (or manipulated object) need to consider individual workspace restrictions or other physical constraints. A typical scenario of binary HSDM is obstacle avoidance (compare Figure 1). In the context of HRC, the information which varies between the human and robotic partner can be diverse. Generally the human planned trajectory may be more adaptable to environmental changes whereas the robot is more accurate in trajectory repeatability and may be faster in calculating optimal solutions. In [10] it is proposed that robots should generally be able of decision making. We transfer this claim to human-robot interaction and suggest enhancing haptic collaboration by technical partners able of HSDM.

B. Efficiency in Haptic Collaboration

Taking into account the challenges to implement mutual haptic feedback (e.g. instabilities in systems involving bilateral energy exchange [1], [12]) it is of high advantage to be able to judge if intentions can be communicated via the haptic channel, leading to higher overall performance in a given task.

We introduced an *efficiency measure* for haptic interaction *relating performance to physical effort* [8]. Based on this measure, decisions of when to provide mutual haptic feedback in the three scenarios described above can be taken: the possible disturbances for the individual dealing with the partner's applied forces (effort) are related to the dyadic performance benefits. In our previous study [8] we found that mutual haptic feedback leads to lower efficiency compared with a control condition without such feedback in a 1 DoF (degree of freedom) tracking task. This was due to the fact that performance was equal in both conditions but interaction forces between partners (as one of the investigated effort components) were increased with haptic feedback. We explain the inefficiency of haptic feedback with the low task complexity which reduces the necessity of communication between partners. Hence, the advantages of an additional channel for information exchange (haptic interaction) did not become clear.

The current paper investigates efficiency of mutual haptic feedback in kinesthetic binary shared decision making between two humans, which requires action plan negotiation between partners. Therefore, we propose that shared decision making in kinesthetic tasks will profit from the haptic communication channel in addition to indirect information exchange based on visual signals only.

To our best knowledge shared decision making has not yet been directly addressed in haptic interaction research. Hence, this paper is the first introducing a paradigm which allows experimental control of the complexity, respectively the need for negotiation, in a haptic interaction task.

II. Hypotheses

In an interactive tracking task, executed by two human partners, including binary shared decision situations, we investigate the effect of mutual haptic feedback by comparing it to a vision-only feedback control condition. We contrast three different types of decision: 1) decisions where the experimentally instructed preferences of the two human partners on the two options are equivalent 2) decision types where only one partner has a preference whereas the other is undetermined 3) decisions where the preferences of the two partners are opposite. We consider the need for negotiation between partners increasing in the order of the presented decision types (details see Section III-A).

We raise the following hypotheses:

H1: **Performance** decreases with the need for negotiation in the *decision* situations, representing an upward trend in task complexity. In addition, haptic *feedback* should lead to higher performance (especially in decision type 3 where the task is most challenging) because of the additional communication channel.

H2: **Effort** (measured as energy) is higher when *decision* preferences between partners are less compatible, expressing the negotiation activities. Furthermore, haptic *feedback* is assumed to cost generally higher effort in accordance with our previous study [8].

H3: **Efficiency**, meaning the relation (within the given sample of participants) between performance and physical effort, is higher for *decision* types with low need of negotiation (type 1 and 2) than in decision type 3. This is expected because task execution should be easier and no effort necessary to communicate. The relation of the assumed performance benefit of haptic *feedback* compared to the effort costs cannot be predicted due to missing previous knowledge. Thus, we formulate the effect of haptic feedback on efficiency as open research question.

III. EXPERIMENT

We consider haptic interaction as a negotiation regarding the trajectory of an interaction point or the jointly carried object. In contrast to the *measurable* object trajectory resulting from negotiation between partners, planned individual (desired) trajectories are *latent* cognitive constructs which are not accessible for measurement. A key feature of the tracking task paradigm is that it externalizes these latent desired trajectories by means of the tracking paths. The path serves to instruct the participants about the desired trajectories (compare Figure 1), so the deviation from the desired and the actual shared trajectory can be objectively defined and studied.

A. Experimental Setup

In the present experiment, participants were asked to move a virtual mass, visually presented by a red cursor, along given reference paths which partly involved binary shared decision situations as introduced in Section III-B. Each participant saw an individual path on a separate screen and the cursor which was jointly controlled, see Figure 2. The paths were displayed as a white line on black screens and scrolled down in z-direction with a constant velocity of 15 mm/s. One trial took 190 s. Participants had to follow the reference tracks with the cursor they jointly manipulated. The cursor renders the horizontal position of the two haptic interfaces.

These interfaces have 1 DoF and allow movements along

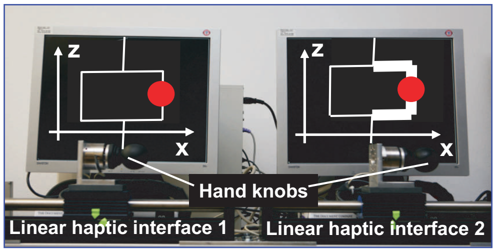

Fig. 2: The experimental setup consists of two screens and two haptic interfaces which allow linear movements. The picture shows a decision situation of type 2 (graphic on screens is not original size; motion of path in negative z-direction). In the experiment a wall was placed between the two devices / monitors.

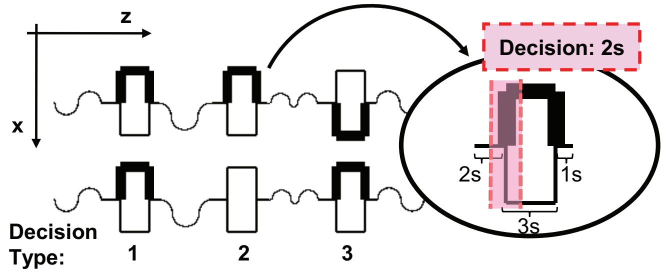

Fig. 3: Exemplary paired reference tracks which scroll down the negative z-axis, see also Figure 2. The instructed individual preferences (thickness of the path) are varied between partners to make action plan negotiation necessary. The enlarged section depicts which part of the decision is analyzed (2s). This is identical for all three decision types.

the x-axis. Each interface uses a linear actuator (Thrusttube) equipped with a force sensor (burster load cell 8542-E) and a hand knob. Their control is implemented in Matlab/Simulink and executed on the Linux Real Time Application Interface RTAI. The graphical representations of the paths run on two other computers and communication is realized by an UDP connection in a local area network, so time delay is negligible. The position-based admittance control of the haptic interfaces is designed to model a jointly carried virtual object, with the dynamics

$$f_{sum}(t) = f_1(t) + f_2(t) = m\ddot{x}_{vo}(t) \qquad (1)$$

where f_{sum} is the sum of the forces applied by the participant which can be measured separately (f_1 and f_2), m is a virtual mass and $\ddot{x}_{vo}$ is the acceleration of the virtual object (for details please refer to our previous work [5]).

We provided two different conditions regarding the feedback between partners:
1) Vision-haptic condition (VH): The partners get visual feedback of the tracking scenario and are also connected via the haptic channel. In addition to feeling the mass of the virtual object ($m = 20$ kg), they also feel the forces applied to the object by the partner. This is achieved by introducing a virtual rigid, very stiff connection between the interacting partners, i.e. $x_{vo}(t) = x_1(t) = x_2(t)$.
2) Vision condition (V): Again, visual feedback is provided. The mass ($m = 20$ kg) of the cursor is divided into two parts, such that each partner has to carry 10 kg, which presents an equal sharing of workload. The participants feel the mass, but not the forces applied by their partner. The cursor position is defined as the mean of the two individual device positions: $x_{vo}(t) = (x_1(t) + x_2(t))/2$. Each partner can only infer what the other is doing from inconsistencies between his or her own movements and the resulting cursor position (for further research on these inconsistencies see [9]).

To standardize the test situation we undertook the following arrangements: a wall was placed between the two participants so they did not gain visual information about the partner's movements and individual path (details in Section III-B); participants used their right hand to perform the task (all of the participants are right-handed); participants were not allowed to speak to each other during the experiment; white noise was played on headphones worn by participants, such that the noise of the moving haptic interfaces would not distract; the position (left or right seat) was randomized with the order of experimental condition.

B. Experimental Design

To embed shared decision making to the tracking task paradigm introduced in [8], it is necessary to fork the track to offer available options in decision situations. Separated by intermediate no-decision track sections the decision sections are introduced in the form of squares, see Figure 3, leading to binary decision situations.

Part of the definition of shared decision making is intention recognition or in other words the building of mental models from the partner's preferences. When approaching the decision, participants do not know the partner's intentions in terms of the preferred path and thus, negotiation of the shared trajectory is required. However, there are two challenges in the experimental design of such situations: A) the dyad could agree on one of the two options (either left or right track) at the beginning of the trial, stick with this solution and thus make no decisions in the remaining trials. B) one of the partners could behave passively in decision situations - then we would no longer study shared decision making.

To overcome these challenges, we externally introduce preferences to the decision situation. Hence, partners do not receive the same visual representation of the path. Although, the general form is the same, the thickness in the analyzed decision types varied: a track segment could be depicted in normal path thickness or in forty times the normal path thickness. In Figure 3 one paired path is shown as an example. The variation of the path thickness introduces individual preferences into the tracking task because the path was easier to track when thicker. These preferences are equivalent to different information between partners in real scenarios. We had to make sure that participants were motivated to consider the shared performance to be the goal with the highest priority. Thus, we informed participants beforehand that they would be paid performance-related. This, however, was not true; all participants gained the same amount.

We differentiate three decision types (compare Figure 3):

Decision type 1 requires no negotiation of action plans as both partners prefer the same option (instructed via the individual path thickness). In *decision type 2* a preference is instructed to only one partner. Negotiation of action plans may be necessary because it is unpredictable how the partner, who has no instructed preferences, may individually prefer to accomplish the task to stay on the track. In *decision type 3* the negotiation of the executed trajectory is inevitable because we instruct opposite preferences. To answer a possible side bias in decision situations, each decision type was presented in all possible left / right combinations. That leads to 8 analyzed decision situations (2 (decision type 1) + 4 (decision type 2) + 2 (decision type 3)).

Summarizing, our experiment allows investigating two factors which may have an effect on the efficiency of interacting dyads in kinesthetic tasks: A) the three decision types, representing the need for trajectory negotiation and B) the presence of reciprocal haptic feedback. This results in a 3x2 experimental design which we conducted as repeated-measurement study, meaning that all participants provided data for each of the six conditions. Whereas the decision types varied within one trial, the feedback conditions were investigated in different trials. Each trial was executed with one of 8 different tracks. The tracks varied in relation to the presented order of the path sections including the 8 analyzed decision types. In this way we prevented learning-effects through track repetition. In addition, we randomized the sequence in which the feedback conditions were presented to the participants.

C. Procedure and Participants

Participants were informed about the feedback condition beforehand. Furthermore, they knew that the first curve of the tracking path was for practice and would be excluded from the analysis. Participants had an extended test run where they could view both screens and, thus, gathered information on the different types of shared decision situations. Therefore, they knew that they had to recognize the partner's intentions. The tracking task was conducted by 32 participants forming eight groups of four persons each. All participants were randomly assigned to a group. During the experiment each participant interacted with the three partners of the group and also conducted an alone-condition of the described experiment. The alone-condition is mentioned for the sake of completeness and not part of the here reported analysis. In the results presented here only independent dyads were considered due to the independent error assumptions in inference statistical analyses [13]. Thus, in this analysis, 32 participants (age mean: 25.38, std. deviation: 3.845) forming 18 independent mixed-gender dyads are involved. We consider the task intuitive enough so pre-knowledge on haptic devices is not influencing the task.

D. Data Analysis

The results of this experiment are based on performance, physical effort and a resulting efficiency measure which we used in our previous work [8].

To allow a standardized data analysis, an interval of two seconds around the parting of the track into two parallel track segments to the left and right is defined as decision situation independent of the decision type. The influence of the decision types is analyzed using the mean values in effort, performance and the resulting efficiency across the left/right variations of preferences within each type. For each of the three decision types the analyzed time interval requires a step response of the cursor. Therefore, if the task is performed perfectly the task execution alone requires the same effort in all conditions. Differences in measures between the three decision types, therefore, are causally determined by the decision factor.

We define the involved performance and physical effort for an interacting dyad as follows:

Performance was defined as a transformed (so high values mean good performance) root mean square error (*RMS*) based on the horizontal displacement between the desired position and the actual position:

$$B = 1 - \frac{RMS}{RMS_{max}} \tag{2}$$

where $RMS_{max} = 0.0312$ m is the maximum *RMS* found in the given data set. The path thickness was not accounted for.

Physical effort was expressed in mean absolute power, which results in the following measure for dyads:

$$MAP = \frac{1}{N}\sum_{k=1}^{N}|P_{1,k}| + \sum_{k=1}^{N}|P_{2,k}| \tag{3}$$

where $P_{1,k}$ and $P_{2,k}$ is the power at the respective interfaces at a given time step k ($k = 1 \dots N$) which is defined as $P_i = f_i\ \dot{x}_i$ with f_i representing the applied force by partner i and $\dot{x}_i$ the velocity of his/her haptic interface.

Efficiency, as defined here, was first presented in [2], [16]. In the results section Figure 5 depicts the z-standardized (sample mean = 0, standard deviation = 1) performance and effort values as well as a reference line. Efficiency is calculated as the Euclidean distance between a data-point and the reference line and data points above this line represent efficient values, below inefficient ones.

$$\Lambda = \frac{Z(B) - Z(MAP)}{\sqrt{2}} \tag{4}$$

The z-standardization, $Z(B)$ and $Z(MAP)$, takes place over all six experimental conditions. Note, that this efficiency measure is relative, thus, only allowing comparisons within a given data set: The dyadic values are related to the overall z-standardized means (= 0) in the data set, see horizontal and vertical lines in Figure 5.

Repeated measurement ANOVAs (analysis of variance) for all three measures were separately conducted, results are reported for a significance level of 5%.

IV. RESULTS & DISCUSSION

In Figure 4 performance and effort for the six experimental conditions are shown:

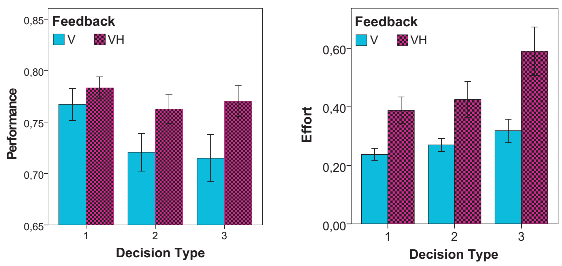

Fig. 4: Mean and standard error of performance (left) and effort values (right) contrasting the two feedback and three decision conditions: Increased decision complexity leads to lower performance but higher effort. With reciprocal haptic feedback performance is higher but effort increased compared to the control condition without such feedback.

Performance is significantly influenced by the provided feedback between partners (F(1, 15) = 6.761; p = 0.020; partial η^2 = 0.331): The positive performance measure (transformed root mean square error) is higher when reciprocal haptic feedback is provided. In addition, the decision type significantly affects performance (F(2, 30) = 3.421; p = 0.046; partial η^2 = 0.186): The mean performance across both feedback conditions is lower with higher complexity in decision types (However, only the difference between decision type 1 and 3 reach significance as tested with Bonferroni adjusted pairwise comparisons). Thus, the need to negotiate a decision with a partner negatively influences performance. Hypothesis 1 is strengthened. Descriptively performance decreases less when decision complexity increases and haptic feedback between partners is provided compared to the control condition without such feedback. However, the interaction between the two factors did not reach significance. Judging from the effect size (partial η^2), feedback has a higher influence on performance than the decision type.

Effort is significantly affected by the feedback factor (F(1, 15) = 11.446; p = 0.004; partial η^2 = 0.433) as with haptic feedback the energy (*MAP*) used by the dyad to perform the task is higher. Furthermore, the effort significantly increases when the involved preferences in the decision types are opposite, meaning that the effort in decision type 3 is significantly higher than in the other two decision types (F(2, 30) = 10.676; p $>$ 0.000; partial η^2 = 0.416; Bonferroni adjusted pairwise comparisons are significant for differences between decision type 1 vs. 3 and 2 vs. 3). The effect of these two factors on effort is similar as can be seen from effect size. Hypothesis 2 can be accepted. Again, interaction between the feedback and the decision type factor does not reach significance. As the necessary effort to execute the task is equal in all six conditions, any additional effort is related to interaction between partners. Thus, the haptic communication channel is actually used when provided, and the effort is increasing with the need to communicate intentions related to the decision types.

Efficiency values more than 4 standard deviations away from the mean in one condition were excluded from analysis. Therefore, the following results are based on data from 15

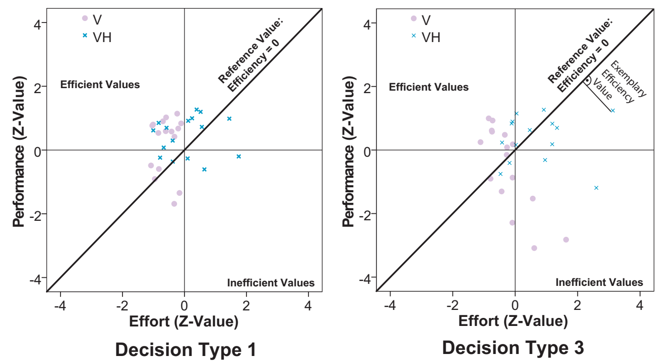

Fig. 5: Scatter plots showing z-standardized performance and effort of 15 dyads for both feedback conditions, separately for decision type 1 (left) and 3 (right). The zero-line of each axis represents the mean of the z-standardized values across all six conditions. Efficiency is calculated as distance from the reference line which represents an efficiency value of 0. Positive/negative efficiency values describe efficient/inefficient behavior.

dyads only (instead of 16). Figure 5 shows scatter plots visualizing the calculation of dyadic efficiency values based on the z-standardized performance and effort values. Results are depicted separately for decision type 1 (left side) and decision type 3 (right side). The zero line of each axis presents the mean of the z-standardized values across all conditions. Whereas in decision type 1 (equal preferences) the majority of values is above the reference line, for the third decision type (opposite preferences) the distance to the reference line is increased towards the area below the reference line, illustrating inefficient behavior.

In Figure 6 we report the mean of these efficiency values per condition. The value of zero efficiency is depicted as reference line. Inference statistic tests (ANOVA) revealed that we could not find evidence that the feedback factor is influencing efficiency (answering the research question associated with hypothesis 3): By the same relative amount that reciprocal haptic feedback leads to a higher effort (compared to the control condition), performance is also increased. Efficiency values are affected by decision type (F(2,28) = 6.752; p = 0.000; partial η^2 = 0.325). Bonferroni adjusted pairwise comparisons show that decision type 1 leads to significantly more efficient values than the other two decision types, between which we cannot detect any difference. This can be explained by the fact that in this decision type performance is high due to low decision complexity and no effort is, hence, needed for negotiation.

V. CONCLUSION

The presented tracking task experiment introduces shared decision making in haptic interaction research to investigate the role of reciprocal haptic feedback for intention recognition between partners.

We introduced three different types of decisions in relation to the congruence of preferences between partners for either one of the two presented options. It was shown that with opposite preferences the amount of physical effort is increased, which is interpreted as additional negotiation effort. Performance decreases when executing this decision type.

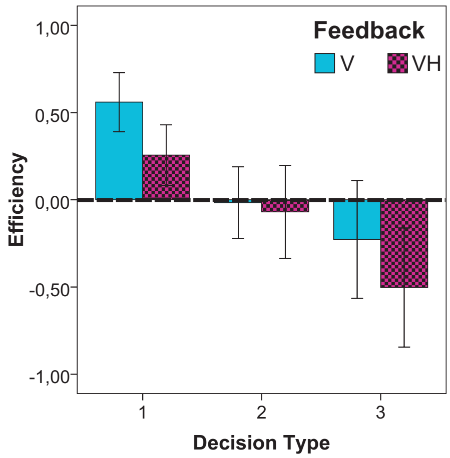

Fig. 6: Efficieny measure in dependence of the feedback and decision type factors (Mean and standard error): Only the decision factor had significant influence on efficiency: With the same preferences between partners (type 1), efficiency was higher than in the other two decision conditions.

Overall, opposite preferences in decision situations lead to an inefficient behavior compared to decision types of identical preferences. We conclude that the task challenges related to the negotiation of different individual preferences cannot be compensated fully with negotiation effort in neither feedback condition.

Compared to the visual only feedback condition, task execution with haptic feedback evokes higher physical effort. However, performance increases comparably, relatively to the overall group mean. As a result, the efficiency of haptic feedback is comparable to the efficiency of task execution with visual feedback only, where effort was lower, but even so performance. Hence, the additional effort related to reciprocal haptic feedback pays off with better performance. This is contrasting our previous work [8] on efficiency of haptic feedback in no-decision tasks. There, effort was also increased in the haptic feedback condition, but no positive effect on task performance could be found. Thus, for interaction between human partners in teleoperation systems and virtual reality, and for human-robot interaction, the here presented results implicate that in (binary) decision situations the technical challenges in providing reciprocal haptic feedback are worth to face - they pay off in better performance when different individual action plans have to be negotiated.

Though, in the current study the investigation of haptic shared decision making is limited to binary decisions and one degree of freedom movements, relevant results on the benefits of haptic feedback could be found. These findings encourage further experiments on the negotiation of intentions in haptic human-robot shared decision making. Future studies will strive to generalize the findings to tasks involving more degrees of freedom movements and larger objects. We assume that with further increased task complexity the advantages of the additional communication channel due to haptic feedback between partners will become even more evident.

VI. ACKNOWLEDGMENTS

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