Control-theoretic Model of Haptic Human-Human Interaction in a Pursuit Tracking Task

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***Abstract*— Achieving natural and intuitive interaction is one of the main challenges in physical human-robot interaction. We approach this challenge by modeling haptic human-human interaction with the final goal of transferring found relationships to human-robot interaction. The focus of this paper is on two human operators performing collaboratively a joint object manipulation, i.e. a pursuit tracking task. McRuer's crossover model is a well established method to describe the behavior of *one* human operator performing such a task. In this paper, we extent McRuer's approach to *two* human operators performing the task collaboratively. Results based on experimetally gained data show that the interacting partners adapt their behavior to each other and to the task in such a way that the crossover model can still be applied to the interacting dyad. It is also shown that the individual's behavior changes when interacting with a partner in contrast to performing the task alone.**

I. INTRODUCTION

While the analysis of human-robot interaction via speech and gestures is rather advanced, the topic of haptic human-robot interaction is still largely underrepresented. Haptic interaction describes the bidirectional exchange of force and position signals between two physically connected partners. Interaction can hereby occur either directly, e.g. when holding hands, or indirectly via an object. Depending on the involved partners we distinguish between human-human interaction (HHI) and human-robot interaction (HRI).

There are several scenarios of HRI which are recently enhanced by physical interaction: In the field of service robotics direct contact of humans and robots is often desirable. Also in virtual reality applications the haptic modality is added, which makes physical interaction with an avatar possible. Both applications require the implementation of appropriate robotic partners that are able to interact with a human in a natural manner. On the other hand, in multi-user teleoperation scenarios haptic interaction between two human operators is of interest if the task exceeds the capabilities of a single person. In this context, the interaction with an assistance function that is implemented to simplify the task execution might also be considered.

Early attempts to realize physical HRI were focused on passively moving robots whereby the human acted as leader and the robot as follower [1], [2]. Another approach is based on capturing human behavior in a HHI task and replaying recorded signals [3]. Both approaches have in common that no real interaction takes place. As found by [4], such unilateral information exchange is not suitable for haptic interaction. Therefore, the challenge in haptic HRI interaction is to construct more intuitively behaving, interactive robotic partners. For this undertaking models of interacting partners have to be derived, which act as human-like as possible.

In social sciences, dynamic interaction models in form of differential equations are formulated to describe the influence of one partner's behavior on the other [5], [6]. Furthermore, in [7] an information-theoretic model of three-way relationship is presented. It describes the dependencies between human, robot and their environment and the knowledge of each party by evaluating entropy and mutual information. Probabilistic approaches like Hidden Markov Models (HMM) are widely used in robotics to recognize and generate motions, gestures etc. Interconnected HMMs are hereby used to model interacting systems [8]. In the context of a (haptic) hand-shaking scenario [9] introduces a HMM approach that allows to adapt the parameters of a robot to the behavior of its human partner. [10] presents control laws to enable haptic human-robot interaction. Both of these approaches aim for interactive robotic partners, but their motivation is not to understand HHI and transferring the results to HRI. In [11] a control-theoretic feedback structure to model the interaction between a human operator and an extender that assists the human in a manipulation task is introduced. In contrast, the focus of our work is not on implementing an assistance function, but on modeling natural HHI.

To simplify the complexity of haptic interaction, we investigate two humans carrying an object along a reference trajectory. The trajectory tracking allows to study differences between desired (= reference path) and actual (= object position) behavior. This scenario of a pursuit tracking task (definition with reference to [12]) is used widely in aviation research to analyze pilot's behavior [13], [14], [15]. The task offers the advantage that models for *single* user behavior are already well established. A survey of relevant control-theoretic methods on this matter is provided in [12]. Therein, human behavior is modeled as a combination of feedforward and feedback control structures, whereby highly trained operators behave mainly like a feedforward controller. As we focus on untrained persons with no task knowledge, we concentrate on feedback structures in this paper. In [13] the crossover model, a linear feedback model with the human acting as controller is introduced. This approach is based on the idea that the human adapts his behavior to the plant's

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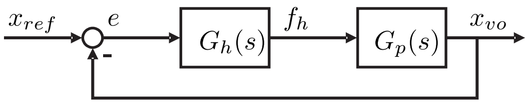

Fig. 1. Human behavior as feedback control in a pursuit tracking task

characteristics. Optimal control is also a way to model human behavior in pursuit and compensatory tracking tasks [14]. However, only little is known about the optimization criteria to be used. More complex, non-linear models are introduced in [15], [16]. In this paper we try to gain control-theoretic knowledge about haptically interacting partners by applying the crossover model, which seems to be the best established model in the context of tracking tasks.

The transfer to dyadic haptic interaction, however, provides challenges: Based on experimentally gained data and descriptive measures, [4] has already showed that human behavior differs in partner conditions compared to single conditions. Thus, we assume, that models of individuals acting alone or within a dyad are not exchangeable. However, the motivation to find such a model is high as the usage of an interactive model instead of pre-recorded signals allows to realize an artificial partner with real bilateral information exchange.

Based on experimentally gained data we aim for answering the following research questions:

1) Can we verify that the crossover model explains the behavior of a *single* person (control condition)? (RQ1)
2) Is the crossover model also appropriate to model the behavior of a haptically interacting *dyad*? (RQ2)
3) Is there any difference between the individual behavior of *one partner within an interacting dyad* and a single person's behavior? (RQ3)

In the following section II Mc Ruer's crossover model is introduced for a single person. Next, its extension to haptically collaborating couples is presented and discussed. A 1 DOF tracking task experiment was performed to obtain measurement data for model identification, see section IV. The model identification and validation procedure is described in section V. Section VI presents the results and discusses them in the context of the above mentioned research questions. Finally, the main results are summarized and directions for future research are formulated.

II. McRuer's Crossover Model

The crossover model [13] assumes a linear feedback structure as shown in Fig. 1. The principle idea is that *the human operator adapts her/his behavior to the plant characteristics* and behaves like a 'good servo' in the region of the crossover frequency ω_c. This results in a *constant overall (open-loop) transfer function* of the system

$$G_0(s \approx j\omega_c) = G_h(s) \cdot G_p(s) = \frac{K_c e^{-\tau_c s}}{s}. \qquad (1)$$

where $G_h(s)$ is the transfer function modeling the human behavior as a linear feedback controller and $G_p(s)$ is the plant transfer function, which is (supposed to be) known.

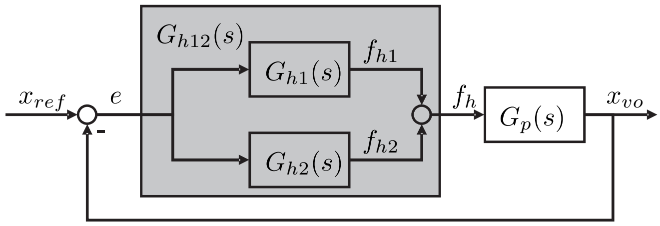

Fig. 2. Block diagramm of two human operators in haptic interaction

This approach assumes that the human actions are only a reaction on the current position error $e = x_{ref} - x_{vo}$. In the context of this paper the plant is a stiff object with a certain mass m. Thus, the plant dynamics are given by the following second-order system (more details follow in section IV)

$$G_p(s) = G_{vo}(s) = \frac{1}{ms^2}. \qquad (2)$$

According to [13] this leads to a human control model of

$$G_h(s) = \frac{F_h(s)}{E(s)} = \underbrace{\frac{e^{-\tau s}}{(1+T_p s)}}_{\text{perception-action loop}} [K(1+T_z s)] \qquad (3)$$

where τ is the time-delay caused by the human perception-action loop and T_p is the lag due to the limited bandwidth of the human motor control system. K and T_z are the parameters of the actual human control actions. $G_0(s)$ in the crossover region ((1)) is obtained by a low frequency approximation assuming $T_z\omega_c >> 1$. In order to ensure stability $T_z > \tau_c$ is a necessary condition, with $\tau_c = \tau + T_p$ (for more details please refer to [13]).

III. Crossover Model in Haptic Interaction

The block diagram for the haptic interacting dyad in a joint object manipulation task is introduced in Fig. 2. The humans are assumed to be rigidly connected to the object. Hence, their individual transfer functions G_{h1} and G_{h2} are in parallel and their outputs, i.e. their applied forces, are summed. $G_{h12} = G_{h1} + G_{h2}$ describes the resulting behavior of the two human partners. It is still an open question if the interaction partners are capable to adapt their behavior to the plant and, in addition, to each other in such a way that the resulting behavior is consistent with the idea of a constant overall transfer function $G_0(s)$ as predicted by the crossover model. To approach this question we examine the resulting behavior of the overall interacting dyad as well as the behavior of each of the interacting partners within the dyad.

A. Model of Overall Interacting Dyad

If humans are able to adapt their behavior to each other in such a way that the crossover model approach is not only valid for one human performing a pursuit tracking task, but also for two haptic interacting partners, their resulting behavior could by described by

$$G_{h12}(s) = \frac{F_h(s)}{E(s)} = \frac{e^{-\tau s}}{(1+T_p s)}[K(1+T_z s)]. \qquad (4)$$

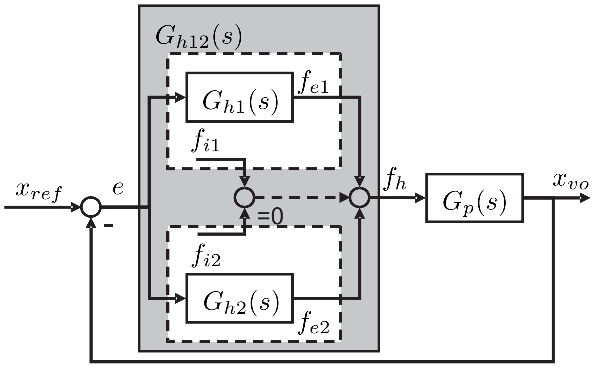

Fig. 3. Block diagramm of two human operators in haptic interaction with internal and external forces

The validation of this approach is a first, important step towards the understanding and modeling of haptic human-human interaction. A behavior model of the dyad would provide information required to derive a model of the individual's behavior.

B. Model of Interacting Partners

In haptic interaction, the forces applied by each partner can be split up into *external* and *interactive* forces f_e, f_i

$$f_h = f_e + f_i. \tag{5}$$

Therein, the external forces lead to a motion of the object

$$f_h = f_{h1} + f_{h2} = f_{e1} + f_{e2} \tag{6}$$

whereas the interactive forces

$$f_{i1} \equiv -f_{i2}. \tag{7}$$

describe the interaction between partners and indicate whether they pull away from of push against each other. These interactive forces are determined by

$$f_{i1} = \begin{cases} 0 & \text{if } sgn(f_{h1}) = sgn(f_{h2}) \\ f_{h1} & \text{if } sgn(f_{h1}) \neq sgn(f_{h2}) \wedge |f_{h1}| \leq |f_{h2}| \\ -f_{h2} & \text{if } sgn(f_{h1}) \neq sgn(f_{h2}) \wedge |f_{h1}| > |f_{h2}| \end{cases} \tag{8}$$

and the external forces by inserting the internal forces in (5).

As the pursuit tracking task is the same for the single person and the dyad, one could assume that the external forces causing the object motion remain the same. Only interactive forces would be added in the haptic interaction condition (see Fig. 3).

The crossover model receives the tracking error as the model's input and the force to correct the error as the model's output. Its focus is on minimizing the tracking error and, hence, on the object motion. For this reason, we do not apply the crossover model on the applied operator forces but only on the external forces.

Please note, if only one person performs the task, there are no interactive forces ($f_i = 0$) and the external force is the same as the force applied by the person ($f_{h2} = 0$, $f_h = f_{h1}$).

IV. Experiment

A 1 DOF pursuit tracking experiment was conducted to validate McRuer's model approach in haptic human-human interaction. The following section introduces details on the task, the experimental setup and the experimental description including participants, design and procedure. In this experiment participants had to perform a pursuit tracking task either on their own or as an interacting dyad. In the latter case the two partners were linked by a virtual object and exchanged haptic signals. The 'alone' trials serve as control conditions to examine how well the crossover model fits our scenario.

A. Experimental Setup

The experimental setup consists of two 1 DOF linear haptic interfaces (Thrusttube) each equipped with force sensors (burster tension-pressure load cell 8524-E), hand knobs and linear actuators as shown in Fig. 4. Measurement data is sampled with a frequency of 1 kHz.

The graphical representation of the pursuit tracking task is implemented in C++. In order to keep the overall path length constant, the path is build of a random sequence of predefined components (triangles, curves, straight lines, jumps) which are repeated 3 times. The path is visualized as a white line on a screen and participants are asked to follow this path as accurately as possible with a red cursor representing a virtual object ($G_p(s)$). There are no extra avatars visualizing the interaction partners. But, participants were instructed such that they know that they manipulate the virtual object collaboratively.

The path is scrolling down the screen with a constant velocity of $v_z = 15$ mm/s. The haptic interfaces are moved along the x-direction. Because of the z-motion of the path and its amplitude in x-direction, velocities of up to 80 mm/s are required by the participants to sucessfully perform the task. Only the current part of the reference track is visualized to prevent a prediction of the path. This prediction would enable the participants to plan their actions which could have an impact on their behavior. Due to the structure of the crossover model, with the current tracking error as input, it is applicable only to describe human behavior without prediction.

One trial takes 161 s. Depending on the condition the horizontal position of the red ball renders the position of either a single or both haptic interfaces.

The control of the linear haptic interfaces is implemented in Matlab/Simulink and executed on the Linux Real-Time Application Interface RTAI. The graphical representation of the path runs on another computer and communication is realized by an UDP connection in a local area network.

The control takes into account the mechanical coupling of the participants over a virtual rigid object. We assumed indefinite stiffness and no friction for the virtual object. Thus, the dynamics of the virtual object can be modelled according to Newton's law

$$f_h(t) = f_{h1}(t) + f_{h2}(t) = m\ddot{x}_{vo}(t) \tag{9}$$

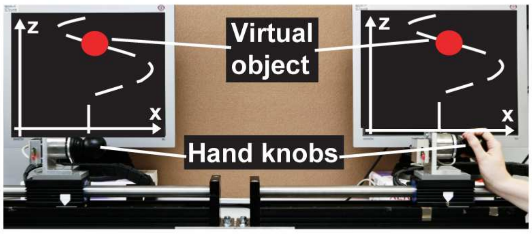

Fig. 4. Experimental setup consisting of two linear haptic interfaces (linked by the virtual object) and two screens with the graphical representation of the tracking path

where f_h is the sum of the forces applied by the participant/s, m is the virtual mass and $\ddot{x}_{vo}$ is the desired acceleration of the virtual object and, hence, of the linear haptic interfaces. The transfer function in the Laplace domain of the virtual model

$$G_{vo}(s) = \frac{X_{vo}(s)}{F_h(s)} = \frac{1}{ms^2} \tag{10}$$

is realized by a position-based admittance control. Due to the high-gain inner control loop we can further assume

$$x_{vo}(t) = x_{h1}(t) = x_{h2}(t). \tag{11}$$

For more details on this please refer to our previous work [17], where a similar experiment was conducted.

In the alone condition participants performed the tracking task on their own by interacting with a single haptic interface ($f_{h2} = 0$).

B. Participants, Design & Procedure

In the presented experiment 12 participants (10 male, 2 female) took part. The participants were assigned randomly to 6 independent pairs of 2.

We introduced three levels for the factor interaction:
1) condition 'alone with half mass' (*ah*),
2) condition 'alone with full mass' (*af*), and
3) condition 'with partner' (*p*)
where the full mass was chosen to be $m = 20$ kg and half the mass $m = 10$ kg. The two different masses in the single trials were introduced for the following reason: Participants in partner trials might perform better, because they share the physical workload. Hence, an increased task performance would be obtained due to a lower workload and not because of haptic interaction. On the other hand, in terms of applied forces the mass of the object plays an important role and should be the same whether two or one person handle it, to keep the conditions comparable.

For each participant two single trials (*af* and *ah*) and one partner trial were recorded. We balanced the order of conditions to control for sequence effects. To standardize the test situation further we undertook the following arrangements: participants not taking part in the on-going trial had to wait outside the laboratory; a wall was placed between the two participants so they gained visual information about their partners' movements only via the virtual reality; the position (left or right seat) was randomized with the order of experimental condition and participants; 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 the headphones worn by participants, so the noise of the moving haptic interfaces would not distract. Due to the simplicity of the task, there is no oral communication necessary in order to accomplish the task successfully. Hence, we consider it eligible to suppress any oral communication in order to standardize our experiment.

Following general instructions, the participants had a test-curve at the beginning of each trail. This curve was not part of the analysis.

Using the measurement data obtained by this experiment models of haptic interaction based on McRuer's crossover model are identified and validated.

V. Model Identification and Validation

First, we check if McRuer's crossover model is applicable to our experimental scenario at all. Therefore, we identify the transfer function G_h according to (3) for both single conditions (*af*, *ah*). Next, we identify and validate the model of the overall interacting dyad G_{h12} (in (4)) based on measurement data of the partner condition (*p*) to determine if the crossover model approach can be applied to haptic human-human interaction. Finally, a model of the behavior of each of the interacting partners is identified.

All models are identified and validated by adopting the following procedure: Taking into account that the pursuit tracking path was repeated 3 times by each participant, the first trial was used for system identification and the two repetitions for system validation.

A. Identification

The transfer functions of the single person $G_h(s)$, the overall interacting dyad $G_{h12}(s)$, and the individuals within the dyad $G_{h1}(s)$, $G_{h2}(s)$ are assumed to have the same crossover model structure defined by (3). Their (time-constant) parameters K, T_z, T_p, and τ are determined by using the respective measurement data. The parameter set is estimated for each transfer function separately.

For the identification of the crossover models the horizontal error between x_{ref} and x_{vo}

$$e(t) = x_{ref}(t) - x_{vo}(t) \tag{12}$$

is the input and the force $f_h(t)$ applied by the human/s is the output (see Fig. 1).

Relatively high delay times τ have to be expected, because the human perception-action process takes approximately 100 ms $- 200$ ms [13]. As large time delays cause a high computational load in the identification procedure we determine τ first by heuristics. The best fitting results were obtained for a time delay of $\tau = 120$ ms± 10 ms. Hence, we assume τ to be constant for all identified models. Then, using the Matlab Identification Toolbox an iterative prediction-estimation algorithm (`pem`) is applied on the shifted measurement data $[e(t) f(t+\tau)]$ to identify K, T_z and T_p.

TABLE I

MEAN VALUES AND STANDARD DEVIATIONS OF THE PARAMETERS OF THE DIFFERENT CROSSOVER MODELING APPROACHES (LEFT HALF) AND EVALUATION OF MODEL QUALITY (RIGHT HALF)

	$\overline{K}$ $[N/m]$	σ_K $[N/m]$	$\overline{T}_z$ $[s]$	σ_{Tz} $[s]$	$\overline{T}_p$ $[s]$	σ_{Tp} $[s]$	$\overline{\text{NMSE}}$	σ_{NMSE}
G_{af}	31.68	27.10	3.47	4.73	0.165	0.053	0.61	0.08
G_{ah}	18.88	13.00	4.75	5.71	0.12	0.030	0.65	0.08
G_{h12}	109.7	19.9	0.86	0.09	0.096	0.019	0.62	0.06
G_{h1}, G_{h2}	43.73	51.64	0.91	1.29	0.34	25.60	0.98	0.27

B. *Validation*

The quality of the identified models is evaluated by the normalized mean square error

$$\text{NMSE} = \frac{\sum_{i=1}^{N} |f_{m,i} - f_{h,i}|^2}{\sum_{i=1}^{N} |f_{h,i}|^2} \tag{13}$$

which is determined for each data set (N: length of measurement vector). Therein, the index ”m” indicates model data and the index ”h” human measurement data.

VI. RESULTS

A. *Single Person*

The models of the single person G_{af} and G_{ah} are identified and validated according to the procedure introduced in the previous section. The means of the estimated parameters and their standard deviations σ, averaged over all 12 identified parameter sets, are presented in Table I. In the *af* condition double the mass has to be moved compared to the *ah* condition. For this reason, the forces that have to be applied at a given tracking error are higher. This explains the increased K. Furthermore, the different masses have only minor influence on T_z and T_p.
The high standard deviation σ within each condition can be explained by the fact, that human behavior is modeled. Human behavior is subject to high variability because of the participant’s interpersonal perception, motor system, physical state or concentration on the task.

The mean NMSE of all 12 data sets $\overline{\text{NMSE}}$ is reported in Table I, too. The model describes the main characteristics of the human behavior. Forces and positions generated by the model (in simulation) are similar to the simulation results of the interacting dyad, which are presented in the next section and illustrated by Fig. 5. This validation shows, that the model fits the data in the *af* as good as in the *ah* condition. We conclude that the crossover model approach describes the behavior of a single person in our scenario even if different masses are presented to the participants. Hence, if the individual’s behavior in haptic interaction was different to a single person’s behavior, this would not be due to the lower necessary forces each partner has to apply to move the mass.

B. *Interacting Dyad*

The results of the parameter identification of G_{h12} (mean and standard deviation) are presented in Table I. To illustrate the quality of the models Fig. 5 shows exemplarily one dyad’s measurement data in comparison to data generated by the respective model G_{h12}. The model data is obtained by a closed-loop simulation according to Fig. 2. The parameters K, T_z and T_p of G_{h12} differ from those of the single conditions (G_{af}, G_{ah}). In particular, the higher K shows, that higher external forces are applied by the interacting couple than by the single person to compensate for the same tracking error. This indicates that haptic interaction has an effect on the behavior of the interacting partners.

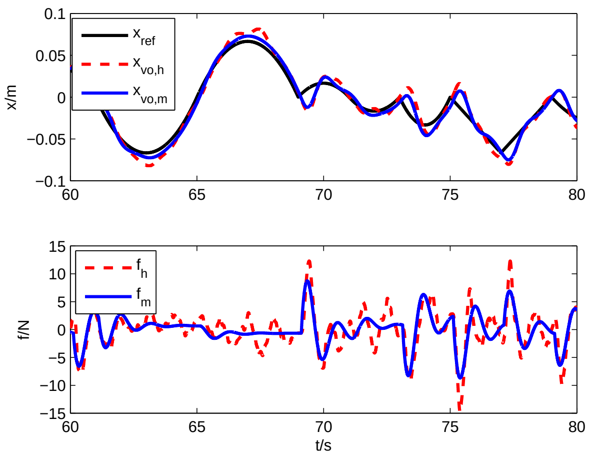

Fig. 5. Comparison of one dyad’s measurement data and the respective model simulation (G_{h12})

The model evaluation reveals that the $\overline{\text{NMSE}}$ of all 6 dyads G_{h12} is the same as in the single conditions. Hence, *the application of the crossover model approach to the overall transfer function of haptic interacting humans (i.e. their resulting behavior) is as appropriate as for a single human*. More insight in the individual’s behavior within the dyad is gained by the identification of the respective models G_{h1}, G_{h2}.

C. *Individual Person in Dyad*

The results of the individual models within a dyad are presented in Table I. As the order of the participants was randomly assigned, the parameters of G_{h1} and G_{h2} are exchangeable and, for this reason, merged. Based the high $\overline{\text{NMSE}}$ it is obvious that haptic interaction has a high impact on the individuals’ external forces and that the behavior of each of the interaction partners cannot be described by (3). These results show that *in haptic human-human interaction not only interactive forces are added but the individual’s* *behavior changes also with respect to the external forces.* Please note: In this paper we analyze only external forces; interested readers are referred to our preceding work [18] for details on interactive forces. There, we show, that interactive forces occur in the haptic condition and that their magnitude is even larger than the magnitude of the external forces.

VII. Conclusion

This paper extends McRuer's crossover model approach, originally describing the behavior of a single person in a pursuit tracking task to haptic interaction of two partners. A 1 DOF pursuit tracking experiment was conducted to gain experimental data. Based on this measurement data, first, the crossover model was identified and validated for a single person performing the task as control condition. Results show that the main characteristics of the measured forces are reproduced by the model. We conclude that the crossover model approach is applicable to our pursuit tracking task scenario (RQ1).

Next, the identification and validation of the transfer function G_{h12} for the behavior of the overall interacting dyad revealed that *the crossover approach is as appropriate for the resulting behavior of the interacting dyad as for the behavior of a single person*. In haptic interaction, the partners adapt their behavior to each other and to the plant in such a way that the overall behavior, i.e. the overall transfer function remains constant as formulated by McRuer [13] (RQ2). Due to this, robotic partners have to be enabled to support this adaptation in HRI. In future, key features of this adaptation process have to be found.

The identification of the individual's model within a dyad revealed that in haptic interaction not only interactive forces are added but that human behavior changes also with respect to the external forces (RQ3). Furthermore, the difference in behavior is not caused by the fact that lower individual physical workload is required in the interaction condition as the comparison with the 'halved-mass'-condition (*ah*) showed. *Hence, with respect to the crossover model it is not sufficient to model a single person's behavior and apply the obtained model in haptic interaction.* Instead, haptic interaction has to be incorporated explicitely in the process of modeling human interaction. By adopting this procedure, the results obtained in HHI can be finally transfered to HRI.

In this paper, time-constant model parameters were defined for one specific task (constant path velocity, mass of the virtual object). If the task parameters are changed, new model parameters have to be identified. Although the here-presented model with time-constant parameters describes human behavior well, we assume that models with time-variant models are an appropriate way to achieve more realistic and feasible interaction models. In our future work, we will particularly focus on time-variant parameters of human behavior models. Furthermore, we aim at defining models of each of the interaction partners within a dyad. Thus, we approach different strategies in human behavior with the final goal of defining new models that are based on them.

VIII. Acknowledgments

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