The 2010 IEEE/RSJ International Conference on
Intelligent Robots and Systems
October 18-22, 2010, Taipei, Taiwan

Incorporating Human Haptic Interaction Models into Teleoperation Systems

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Abstract— **A classification of model-mediated teleoperation systems according to the model type and its application is introduced. While models of the human operator estimating position trajectories have been already applied in teleoperation, in the present paper, we propose the incorporation of force-based human haptic interaction models. This new approach allows to transfer the strength of advanced model-mediated teleoperation, i.e. increased stability and fidelity, to scenarios where forces applied to the remote environment are of importance. As an application example we present a tele-rehabilitation scenario which was implemented on a 1 DoF teleoperation system. Position and force fusion algorithms integrating human haptic interaction models are defined for time delay and packet loss compensation. The results demonstrate clearly the benefit of incorporating force-based human haptic interaction models into teleoperation systems.**

I. Introduction

In a teleoperation system a human operator interacts with a remote environment via a technical system consisting of a human-system interface, a communication channel and a robot, the so-called teleoperator. Teleoperation systems allow a human operator to be present in otherwise inaccessible environments, like e.g. space or disaster areas. Furthermore, experts can act in remote locations without the necessity of traveling. A specialist for a certain surgical intervention is, for example, enabled to operate in a remote hospital or a therapist can coach her/his rehabilitation patients in their home environment. This allows a reduction of travel time and costs.

In order to increase task performance, stability and usability of the system, advanced teleoperation systems integrate knowledge about the *e*nvironment, the human *o*perator or the *t*ask in the system. A good overview of such *EOT*-adapted controllers is given in [1]. We consider *model-mediated teleoperation*, a special case of EOT-adapted controllers, and classify it according to the type of model applied and its usage. Either a model of the remote environment is rendered on master side (Fig. 1) or a model of the human operator is rendered on slave side (Fig. 2). Further, either model parameters are estimated, exchanged, and master/slave control is based completely on the estimated model (Fig. 1a and Fig. 2a), or measurement data is fused with model data (Fig. 1b and Fig. 2b). By estimating and exchanging model parameters, the communication channel is by-passed and the bandwidth of the overall system is increased. The signal fusion is introduced to achieve an increased signal quality by compensating time delays and packet loss or to provide user-adapted assistance by defining shared-control strategies. A combination of these four types of control architectures is possible, e.g. a model of the remote environment and of the human operator is rendered, or the parameters of the model used in signal fusion are estimated and updated on-line.

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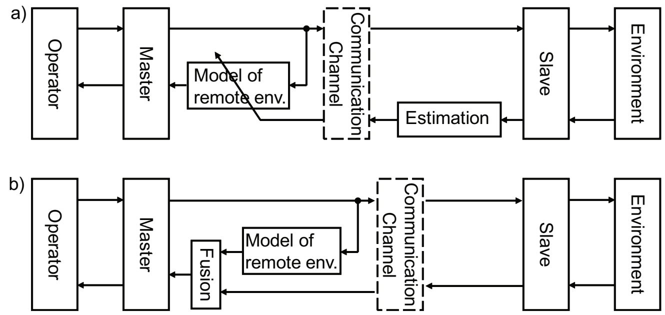


Fig. 1. Model-mediated teleoperation with model of remote environment used for a) model estimation and b) signal fusion

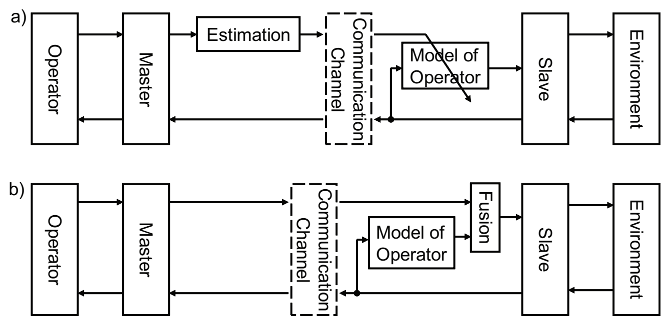


Fig. 2. Model-mediated teleoperation with model of human operator used for a) model estimation and b) signal fusion

In this paper we propose the integration of *force-based haptic interaction models* into a teleoperation system to allow for increased stability, usability and task performance. To demonstrate the validity of our approach, a 1 DoF tele-rehabilitation system is realized that compensates variable time delays and packet loss by using a model replicating human haptic interaction behavior.

II. Related work

In the introduction we identified different classes of model-mediated teleoperation architectures. To embed our present work in this classification and into the state of the art, in the following, we discuss recent literature related to the four types of model-mediated teleoperation. Furthermore, because we aim for the integration of force-based human models in teleoperation systems, we also present a short overview on existing studies and models on human haptic interaction behavior.

A. Model-mediated teleoperation

The state of the art on the four types of model-mediated teleoperation is presented according to the order of the diagrams in Fig. 1 and Fig. 2.

Model of remote environment on master side:

Model estimation: In [2], [3], [4], [5] knowledge about the remote environment is integrated into the teleoperation system. The remote environment is rendered as a virtual environment on master side. A model of the remote environment is estimated on slave side and, then, the estimated model parameters and not the sensor signals (forces/motion) are sent to the master side to update the model (Fig. 1a). Hence, the communication channel is by-passed and the bandwidth of the system is increased. Undelayed haptic interaction takes place on master side. However, the signals that are sent to the remote environment are still delayed, which results in a delayed task execution.

Signal fusion: In [4] a model of the remote environment is used (Fig. 1b) to compensate time delay by model-based prediction. Therefore, model and measurement data are fused on master side. The authors of [6], [7] aim at compensating packet loss which is characteristic to internet-based data transmission by estimating lost data.

Model of human operator on slave side:

Model estimation: Currently no approaches are known from literature that send parameters of a human behavior model to the slave side (Fig. 2a). If operator models are estimated, their output is fused with measurement data as presented in the next paragraph. In general, we distinguish two ways of exchanging estimated parameters of operator models in a teleoperation systems: Either the slave acts according to a model which parameters are adapted on-line to a particular situation/task, or the model of the human operator is estimated beforehand. Then, the slave performs specific (sub-)tasks in complete autonomy, which means a skill transfer took place.

Signal fusion: Measurement signals and model output of the human operator are fused in [5], [8], [9] (Fig. 2b). In [5] the model parameters are estimated on master side and sent to the slave side to introduce a shared-control strategy that assists the operator in task execution. The position trajectory generated by the human motion model is based on the widely-known minimum-jerk criterion [10] which applies for *free-space* point-to-point movements. The same minimum-jerk approach was applied by [8], [9] to predict human motion in order to compensate time delays and achieve a non-delayed task execution. Again, only free-space motions are possible. One difference to [5] is, that signal fusion is not conducted on slave but on master side, because the time delay is assumed to be known. As only free-space motions are considered, no information about the remote environment is required for prediction.

In summary, it can be stated that up to now operator models which have been integrated in teleoperation systems consider characteristics of human *free-space motion* [8], [5], [9], but not of *haptic interaction behavior*. However, we consider the integration of a force-based model of haptic interaction behavior essential, if there is physical contact with another human in the remote environment. In particular, this is crucial in tasks with a close physical coupling like tele-rehabilitation [11]. The success of the patient's rehabilitation process depends largely on the mutual haptic adaptation of therapist and patient.

B. Human haptic interaction models

In order to realize model-mediated teleoperation by integrating models of the human operator, a careful definition of appropriate human haptic interaction behavior models is important. Their definition is challenging, because they generally depend on the task, the interaction partner's as well as one's own, individual characteristics and abilities. Existing haptic interaction models are mostly task-specific and/or consider different roles of the interaction partners.
Haptic interaction tasks are generally divided into tasks with direct and indirect physical contact of the interaction partners. Haptic interaction models with direct physical contact are relevant e.g. for guidance like in handshaking [12] or dancing [13]. Tasks with indirect haptic interaction refer primarily to joint manipulation tasks, e.g. rotating [14] or carrying [15] objects.

In [14] the roles of accelerator and decelarator were identified for an object moving task and respective characteristic force profiles were presented. In [16] it was experimentally shown that dominance is distributed unequally between two human partners in a haptic collaboration task. Finally, [12] distinguishes between active and passive partners in a human-robot handshaking scenario.

The only known application of a model of human haptic interaction behavior in teleoperation is [17]. They apply a feedback model to represent human behavior in simulation to increase the accuracy of the results. However, this approach was not verified within a real experimental setup.

III. METHOD

A. Scenario

We chose a 1 DoF tele-rehabilitation scenario similar to the one proposed by [11] as an exemplary task to demonstrate the effectiveness of integrating force-based haptic interaction models in a teleoperation system. The success of rehabilitation is highly dependent on the guidance provided by the therapist, and, hence, the mutual adaptation of therapist and patient. This restricts the broad introduction of fully

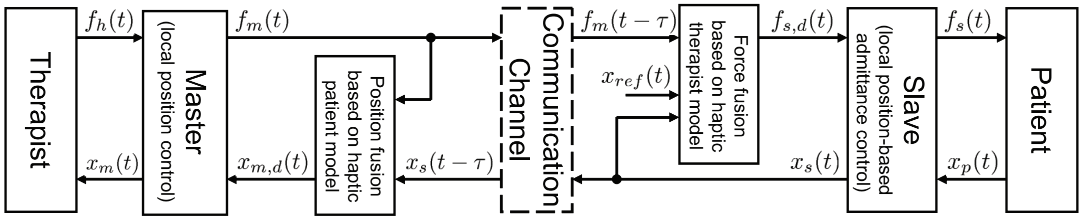


Fig. 3. Control architecture of tele-rehabilitation system

autonomous rehabilitation devices. Human performed rehabilitation allows this close interaction and adaptation to the patient's individual needs, while tele-rehabiliation allows the therapist to instruct the patients in their home environment such that travel time and costs can be decreased.

In tele-rehabilitation therapist and patient communicate and interact via the internet which exhibits packet loss and time-variant time delay. To compensate these disturbances and enable stable and transparent teleoperation, we fuse the measurement data with predicted data obtained by haptic interaction models of therapist and patient on the respective other side. The structure of the resulting overall control system is depicted in Fig. 3. We selected a classic force-position architecture, where forces are sent from master to slave and positions from slave to master [18]. As local controllers a PD-position control on master side and a position-based admittance control on slave side are realized. A non-ideal communication channel introducing a time-variant, but bounded time delay and packet loss is considered. Force data is sent to the remote environment and fused on slave side with predicted data provided by a force-based human haptic interaction model of the therapist. A model of the remote 'environment', i.e. the patient, is required on master side to compensate time delay and packet loss of the position data received from the slave side. Hence, a force fusion on slave side and a position fusion on master side based on Kalman filters is implemented.

Because of the close haptic interaction between therapist and patient, we prefer model-mediated teleoperation over passivity-based approaches which are commonly applied in situations where time delay and packet loss are present. Passivity-based approaches change the system dynamics in order to guarantee stability. This results in a reduced fidelity [19].

B. Signal fusion with modified Kalman filter

The general Kalman filter is based on a linear, time-discrete process model (here the model is time-invariant):

$$\begin{aligned} \mathbf{x}_{i+1} &= \mathbf{A}\mathbf{x}_i + \mathbf{B}\mathbf{u}_i + \mathbf{w}_i \\ \mathbf{y}_i &= \mathbf{C}\mathbf{x}_i + \mathbf{v}_i \end{aligned} \tag{1}$$

where $\mathbf{x}_i$ is the state vector at time step i, $\mathbf{A}$, $\mathbf{B}$ and $\mathbf{C}$ are the system matrices, $\mathbf{w}_i$ is the process noise and $\mathbf{v}_i$ is the observation noise. Process as well as observation noise are assumed to be drawn from a Gaussian distribution with covariances $\mathbf{Q}_i$ and $\mathbf{R}_i$. $\mathbf{Q}_i$ and $\mathbf{R}_i$ describe the reliability of process model and measurement data, respectively. Their exact values are often unknown and can be used as tuning parameters. The applied Kalman filter equations are:

$$\textit{prediction:} \quad \begin{aligned} \mathbf{x}^\star_{i+1} &= \mathbf{A}\hat{\mathbf{x}}_i + \mathbf{B}\mathbf{u}_i \\ \mathbf{P}^\star_{i+1} &= \mathbf{A}\hat{\mathbf{P}}_i\mathbf{A}^T + \mathbf{Q}_i \end{aligned} \tag{2}$$

$$\textit{update:} \quad \begin{aligned} \hat{\mathbf{x}}_{i+1} &= \mathbf{x}^\star_{i+1} + \mathbf{K}_{i+1}(\mathbf{y}_{i+1} - \mathbf{C}\mathbf{x}^\star_{i+1}) \\ \hat{\mathbf{P}}_{i+1} &= (\mathbf{I} + \mathbf{K}_{i+1}\mathbf{C})\mathbf{P}^\star(k+1) \\ \mathbf{K}_{i+1} &= \mathbf{P}^\star_{i+1}\mathbf{C}^T(\mathbf{C}\mathbf{P}^\star_{i+1}\mathbf{C}^T + \mathbf{R}_{i+1})^{-1} \end{aligned} \tag{3}$$

where $\mathbf{I}$ is the identity matrix, $\mathbf{P}_i$ is the error covariance matrix, $\mathbf{K}_i$ is the Kalman filter gain, $\mathbf{x}^\star$ denotes predicted values, and $\hat{\mathbf{x}}$ updated values, see [20].

In order to compensate time-variant time delays and packet loss, we realize a modified version of this classic Kalman filter based on [21]: We assume that measurement data arrives with a time-variant time delay, with an upper bound of T_{max} and is time-stamped such that the exact capture time is known. These measured data points $\mathbf{y}_i$ are stored chronologically in a vector for the last time window T_{max} together with the estimated values of $\hat{\mathbf{x}}_i$ and the covariance matrices $\hat{\mathbf{P}}_i$.

If at time k a new measurement data of time $j+p$ (until then $\mathbf{y}_j$ was the most recent measurement point, $j < k$, $p > 0$, $j + p \leq k$) arrives, the following procedure is applied: The state of the system $\mathbf{x}^\star_{j+p}$ and the covariance matrix $\mathbf{P}^\star_{j+p}$ is predicted starting from $\hat{\mathbf{x}}_j$, $\hat{\mathbf{P}}_j$ based on (2). Then, the new measurement data is integrated by using update equations (3) and obtaining $\hat{\mathbf{x}}_{j+p}$ and $\hat{\mathbf{P}}_{j+p}$. Finally, $\mathbf{x}^\star_k$ is determined by applying the prediction again.

If, however, an older measurement data $j-p$ arrives, we use this additional information and virtually jump back to the estimated state of the system at time step $j-p$ and update it. Afterwards, the prediction/update equations are evaluated from $j-p$ to k integrating every data point that was measured inbetween.

C. Haptic model of therapist and force fusion

For force fusion a haptic interaction model of the therapist is integrated into a Kalman filter as introduced in the preceding paragraph. The following task-specific haptic interaction model is used to describe the behavior of the therapist: The therapist guides the patient along the desired motion trajectory x_{ref} by controlling the error between the desired trajectory and the current position of the patient, see Fig. 4. The desired motion trajectory x_{ref} describes a certain rehabilitation task. The feedback control law is based on the crossover model which was originally introduced by [22].

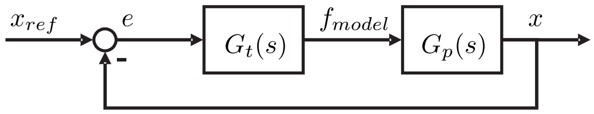


Fig. 4. Human haptic interaction model in a pursuit tracking task

It describes the behavior of a human operator in a pursuit tracking task, if a mass is moved along a desired reference trajectory,

$$G_t(s) = \frac{F_{model}(s)}{E(s)} = \underbrace{\frac{e^{-\tau_h s}}{(1+T_p s)}}_{\text{perception-action loop}} [K(1+T_z s)] \quad (4)$$

where τ_h 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 system. K and T_z are the parameters of the actual human control action (for more details please refer to the original work).

For the present system we assume that the task trajectory is known and the behavioural parameters are estimated beforehand and kept constant during task execution. Of course, different tasks, reference trajectories and models of the therapist's haptic interaction behavior or force profiles can be stored on slave side, to generalize our approach. In such a case, an intention recognition module would be required to decide on the currently active task/model.

For application in the Kalman filter the time-continuous transfer function $G_t(s)$ is transformed into a time-discrete state-space representation like (1), by a zero-order hold discretization with sampling time T:

$$\begin{aligned} f_{h,i+1} &= \left[(1-\frac{T}{T_p})\right] f_{h,i} + \left[\frac{KT}{T_p} \;\; \frac{KT_zT}{T_p}\right] \begin{bmatrix} e_i \\ \dot{e}_i \end{bmatrix} \\ y_i &= [1] f_{h,i} \end{aligned} \quad (5)$$

Therein, the time delay τ_h is neglected, because the therapist does not have to react to a certain change in the trajectory but is practiced in its execution and, hence, can plan her/his actions in advance.

D. Haptic model of patient and position fusion

For the position fusion on master side, we assume that the patient shows passive behavior and behaves like a mass only

$$G_p = \frac{F_s(s)}{X_p(s)} = \frac{1}{ms^2} \quad (6)$$

where m is the mass of the patient's arm. Hence, we assume that the patient does not apply forces actively to perform the rehabilitation task, but relies purely on the guidance of the therapist. Again, the model is transformed into a time-discrete state-space model according to (1)

$$\begin{bmatrix} x_{p,i+1} \\ \dot{x}_{p,i+1} \end{bmatrix} = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_{p,i} \\ \dot{x}_{p,i} \end{bmatrix} + \begin{bmatrix} 0 \\ T/m \end{bmatrix} f_{s,i} \quad (7)$$

which is implemented in a Kalman filter following the same procedure as presented before.

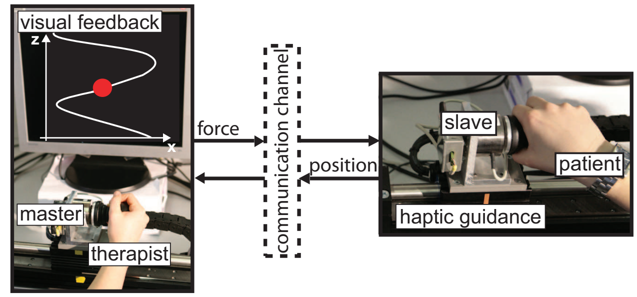


Fig. 5. Experimental setup: The therapist receives visual feedback about the patient's position (red ball) and the task's reference trajectory (white line). The patient is haptically guided only and receives no visual feedback.

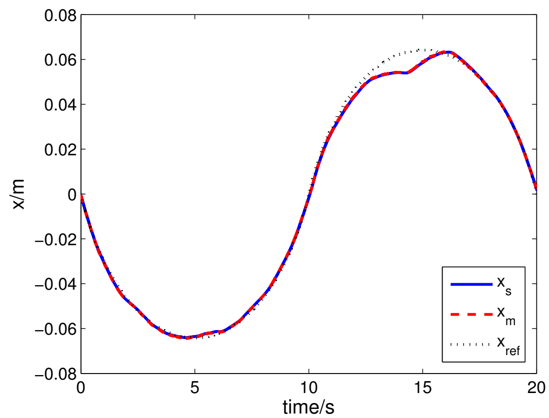
IV. EXPERIMENT

A. Task & Experimental setup

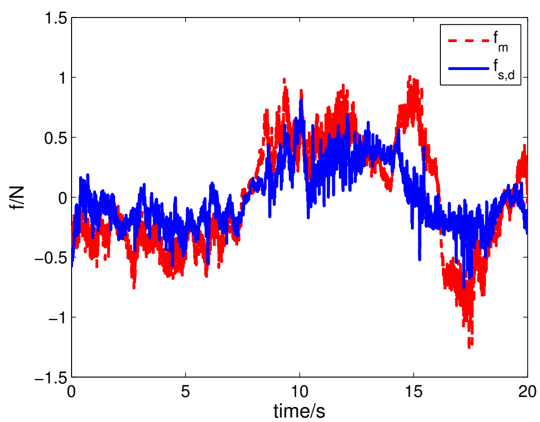
The experimental setup consists of two 1 DoF linear haptic devices each equipped with force sensors (burster tension-pressure load cell 8524-E) and linear actuators (Thrusttube). One is serving as haptic human-system interface (master) and the other as teleoperator (slave). The master as well as the slave device is equipped with a hand knob. The therapist is connected to the master and the patient to the slave as shown in Fig. 5. The control of the linear haptic devices is implemented in Matlab/Simulink and executed on the Linux Real Time Application Interface RTAI with a sampling time of $T = 1$ ms. The time-variant time delay of the communication channel is simulated and drawn from a Gaussian distribution with mean $\overline{T}_d = 100$ ms and a standard deviation of $\sigma_{Td} = 5$ ms. Further, a packet loss of 10% is simulated. If a packet is lost, the last received data is hold.

We chose an oscillating motion in x-direction as an exemplary task, because rehabilitation tasks are typically smooth, cyclic motions with no abrupt changes. On master side, this oscillating trajectory and the current position of the patient are visualized. The desired motion trajectory is displayed as a white line which is scrolling down a screen in negative z-direction with a constant velocity of 7 mm/s. The output of the position fusion module (in the ideal case this equals the patient's position) is displayed as a red ball in a simple virtual environment which is implemented in C++, see Fig. 5. The patient is only haptically guided by the therapist and receives no visual feedback. In this experiment instructed subjects instead of real patients took part.

In [15] we identified the mean parameters of the human haptic interaction model (4) in a 1 DoF pursuit tracking task, where a mass of $m = 10$ kg was to be moved: $K = 18.88$, $T_z = 4.75$, and $T_p = 0.12$. The mass of $m = m_a + m_c = 10$ kg is made up by the mass of the patient's forearm and hand ($m_a = 2$ kg) and the mass of the virtual admittance of the position-based admittance control ($m_c = 8$ kg). This model is integrated in the force fusion Kalman filter. We further assume an upper bound for the time delay of $T_{max} = 500$ ms. The covariance matrices of the force and position fusion Kalman filters are



(a) Position tracking



(b) Force tracking

Fig. 6. Prediction and tracking capabilities of the fusion algorithms, based on Kalman filters. In the experiment, the therapist guides the patient along a reference task trajectory. To adapt the task execution to the patient's needs, the motion trajectory can be altered from the reference trajectory (exemplarily at $t \approx 14$ s). x_s: slave position, x_m: master position ($\hat{=}$ output of position fusion), x_{ref}: task trajectory, f_m: force applied by therapist, $f_{s,d}$: force generated by slave ($\hat{=}$ output of force fusion)

determined heuristically to $\mathbf{Q}_i = 10e15$ and $\mathbf{R}_i = 0.1$, and $\mathbf{Q}_i = \begin{bmatrix} 10 & 0 \\ 0 & 10 \end{bmatrix}$ and $\mathbf{R}_i = 0.1$, respectively.

B. Results & Discussion

Fig. 6 shows the tracking and prediction capabilities of the force and position fusion algorithms, based on Kalman filters. In the presented scenario, the therapist would not be able to compensate the instabilites caused by the time-variant time delay (Gaussian distribution $\overline{T}_d = 100$ ms, $\sigma_{Td} = 5$ ms) and packet loss of 10% without the model-based prediction algorithms. Hence, our results demonstrate the improved stability of the controlled teleoperation system due to the integration of haptic interaction models.

In order to achieve a high accordance between the motion of the therapist and the patient, the objective of the position fusion algorithm (generating the desired master position $x_{m,d}$) is to track the slave position, and not the reference trajectory. As shown in Fig. 6(a), where the therapist guides the patient along the task trajectory, the position tracking is very good. The force fusion algorithm tracks the forces applied by the therapist, see Fig. 6(b). Due to the good position and force tracking, a high fidelity is achieved, and the interactiveness of the rehabilitation process is maintained in our experiment. These results demonstrate clearly the effectiveness of introducing force-based haptic interaction models in teleoperation systems.

Since we fuse human model and measurement data, the therapist can easily leave the reference trajectory by applying the respective forces as displayed in Fig. 6 at $t \approx 14$ s. Hence, the motion trajectory can be modified, and task execution can be adapted to the patient's needs. The position tracking is still very accurate. However, there are deviations between the force applied on master side and the force generated by the slave. This is explained by differences between the therapist's real behavior and the haptic interaction behavior modeled in the Kalman filter.

The human haptic interaction models of the therapist and the patient are basic and we tested them only in pursuit tracking tasks. Like in all model-mediated approaches, the system performance depends highly on how well the models describe the real behavior. One of the limitations of the applied operator model is that we assume that the therapist applies forces to track the reference trajectory. Hence, if she/he intends to leave the reference trajectoy, this causes an error between model and real behavior and the tracking performance of the Kalman filter realized for force fusion is decreased, see Fig. 6(b) at $t \approx 14$ s. Another limitation is that we assume that the patient is strictly passive and behaves like a mass only. In the experiment, we instructed the patient to behave passively. But, in real rehabilitation, patients commonly show the whole range of behavior, from fully passive to completely active depending on their level of rehabilitation.

V. Conclusion & Future Work

In the present paper we introduced a classification of model-mediated teleoperation according to the type (environment or human operator) and the usage of the model (model estimation or signal fusion). Unlike the state of the art, where free-space models of the human operator providing position trajectories were applied for model-mediated teleoperation, we suggest the usage of force-based human haptic interaction models. This new approach allows to transfer the strength of advanced model-mediated teleoperation, i.e. increased stability and fidelity, to scenarios where the forces applied on the remote environment are of importance. This is e.g. the case if excessive forces need to be avoided or if two human operators interact haptically via a teleoperation system.

In the presented experiment, we applied modified Kalman filters in a 1 DoF tele-rehabilitation scenario to fuse measurement data with the output of human haptic interaction models to compensate time delay and packet loss introduced by the communication channel. Results show a good position and force tracking of master and slave device. Hence, the stability and fidelity of the system is increased by applying model-based fusion and prediction, and the interactiveness of the rehabilitation process can be maintained. These results demonstrate clearly the effectiveness of incorporating force-based human haptic interaction models into teleoperation systems.

For a more profound evaluation, a control-theoretic analysis with respect to stability and transparency has to be conducted. In particular, a comparison with passivity-based control approaches is required to obtain quantitative results and allow more detailed conclusions about the benefits of integrating force-based haptic interaction models in teleoperation systems to compensate time delay and packet loss.

One approach to further improve and generalize our results is to progress from constant to user-adapted model parameters which are estimated on-line. Additionally, the performance of the tele-rehabilitation system can be improved by learning modifications of the tasks. The introduction of more advanced models describing the behavior of an individual within a haptically interacting dyad and intention recognition allows application of our approach to e.g. active patients and other scenarios like joint object manipulation tasks. As the definition and identification of human haptic interaction models is currently in the focus of research [14], [12], [13], we expect appropriate models to be established in the near future.

VI. ACKNOWLEDGMENTS

This work is supported in part by the German Research Foundation (DFG) within the collaborative research center SFB453 "High-Fidelity Telepresence and Teleaction".
We acknowledge the valuable discussions with Thomas Schauss about the design of the Kalman filter.

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