Predictive Communication Quality Control in Haptic Teleoperation with Time Delay and Packet Loss

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Abstract—Teleoperation in extreme environments may suffer from communication delay and packet loss during the transmission of command signals and sensory feedback. The present study investigates whether online control of communication time delay by using Quality of Service (QoS) techniques can improve operator task performance in a virtual teleoperated collision avoidance task. We first introduce the framework of predictive communication quality control based on a dynamic performance model of a human handling the teleoperation system. We then apply the framework to a virtual collision avoidance scenario, and evaluate it with two behavioral studies. Study 1 identifies that prolonging time delay significantly increases the frequency of collisions and completion time. We develop a model for predicting the probability of the operator causing collisions with the wall and fit its parameters with the experimental data. In Study 2 we compare the completion time and the number of collisions with and without the predictive QoS control. We find the predictive QoS control to reduce the number of collisions, but not affect task completion time. The prediction model and empirical validation provide a successful proof-of-concept for a human-centered system design, in which the dynamic model of the operator is the center of the control architecture.

Index Terms—User centered design, Communication systems, Haptic control, Human-Robot Interaction, Forecasting.

I. INTRODUCTION

TELEOPERATION systems enable a human operator to perform tasks in remote, dangerous, micro-scale, or otherwise inaccessible environments by controlling a human-system interface (HSI), which is coupled via a communication channel to a robotic teleoperator (TO). Teleoperation has been successfully applied to various applications, including search-and-rescue tasks, on-orbit servicing of satellites in space, and telesurgery [1].

Data transmission between the HSI and the TO over long distances can suffer from time delay and data loss [2], [3]. These effects are known to challenge the stability of a teleoperation system, when the global control loop with the remote environment is closed via the haptic modality. Appropriate stabilizing techniques for time-delayed teleoperation alter the mechanical environment's impedance and haptic events occurring on the remote side (e.g., impact situations) are less recognizable [4]–[6]. Besides the perceptual distortions, several studies have also found task performance to be degraded [7], [8] as a result of communication time delays.

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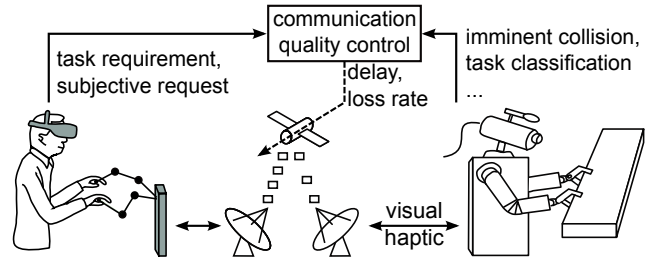

Fig. 1. Communication quality control in teleoperation can take into account various quality requests from the operator and teleoperator.

Packet loss in the communication channel can negatively affect operator task performance, given that the quality of haptic feedback depends on the environmental impedance, packet rate, and loss burst length [5]. It has been shown that an increase in the packet loss rate reduces the accuracy of temporal order judgments between visual and haptic events [9]. Movement time can also be impacted by packet loss that is caused by time-varying time delays [10]. In this paper, we investigate the relation between task performance, communication delay, and information loss in teleoperation systems with haptic feedback in greater depth.

Recent developments in communication protocols, such as the IPv6 protocol, include the ability to online-regulate the Quality-of-Service (QoS) in terms of transmission time delay, packet loss rate, traffic throughput, and jitter [11] (see Figure 1). QoS control can generally improve the performance of networked control systems [12], such as autonomous control of mobile robots [13]. For these applications, a specifically designed control algorithm computes appropriate control actions based on sensory feedback, the goal to be accomplished and the QoS strategy itself [13]. In teleoperation, the human operator acts as a controller, receiving sensory feedback from the remote site and sending commands in the form of actions to the TO, but his/her control strategy is largely unknown. Task-related empirical rules for QoS control can provide for an informed allocation of communication bandwidth during teleoperation [14]–[16], potentially boosting the operator's task performance. Current approaches, however, focus exclusively on control aspects, rather than explicitly considering the requirements of the human operator to accomplish the task at hand when allocating communication resources. The ecological interface design (EID) framework [17] can provide important insights into the components of a task that are crucial for efficiently accomplishing a given goal, and it has proven applicability to the design of efficient telerobotic

systems [18]. While it is essential to know the requirements for the technical system posed by the task, an understanding of the operator's task-dependent dynamic behavior may likewise be important for identifying key factors leading to improved task performance. Consequently, modeling human behavior under the influence of communication parameters such as time delay and packet loss would be crucial for realizing a QoS controller for the communication channel in teleoperation.

In this regard, the contribution of the present article is twofold: First, we introduce a framework of *dynamic* prediction models for human task performance in general; this is described in Section II. Such predictive models can be utilized by QoS control algorithms for online-regulating service quality to improve task performance; we develop one specific model for this purpose in Section III. Second, we explore online-control of time delay in the communication channel as a means for improving operators' performance in a collision avoidance task. Two behavioral experiments are reported as proof of concept for the proposed framework. We develop and parameterize a dynamic prediction model of task performance with regard to the number of (to-be-avoided) obstacle collisions, based on Experiment 1 described in Section IV. The model is then applied in Experiment 2 to online adjust the communication quality in terms of the time delay, which did yield a reduction of the number of collisions, as predicted. This experiment and the findings are presented and evaluated in Section V. The final Section VI summarizes the implications of the work presented.

II. Methods

Here, we describe methods for identifying models of human performance when performing teleoperation over a disturbed communication channel and how to include these models in a control algorithm. We assume that the communication network is capable of fulfilling every quality request, where high channel quality corresponds to low time delay, low packet loss rate, low jitter, and high bandwidth.

A. Model-Based Communication Quality Control

A high-quality communication channel can contribute to high task performance when interacting with a teleoperation system [7], [8], but comes at a high cost. Thus, high communication quality should be applied when it can significantly improve task performance (e.g., help avoid collisions), while keeping the costs low should be prioritized when operator task performance is not greatly affected by the channel's quality. For a quantitative network quality control law, the influence of communication quality parameters on human performance must be explicitly taken into account. The optimal way to derive the time-varying communication quality parameters $\theta_C^*(t)$ is to solve the multi-objective dynamic optimization problem

$$\underset{\theta_C(t) \in \Theta_C}{\arg\max} \begin{bmatrix} J_P(t) & -J_C(t) \end{bmatrix}^T, \quad (1)$$

where $J_P(t) \in \mathbb{R}$ governs the achievable task performance given the communication parameters over time t, and $J_C(t) \in \mathbb{R}$ is a function describing the network costs. The

communication quality parameters $\theta_C(t) \in \Theta_C$ are quantized into permissible quality levels.

Multiple approaches exist to solve the optimal control problem posed in (1) [19]. In theory, the global optimum $\theta_C^*(t)$ can be found via dynamic programming and value iteration. Because this method requires complete knowledge about the environment, the task, and human behavior, we consider model-predictive control (MPC) instead [20]. MPC algorithms repeatedly solve the dynamic optimization problem formulated in (1) in every time step, while considering only a limited prediction horizon. Thus, the approach is more robust to modelling uncertainties. Furthermore, MPC can handle higher-order system dynamics, whereas dynamic programming suffers from the "curse of dimensionality".

The communication cost $J_C(t)$ depends on the network architecture and other factors which can be determined explicitly (e.g., by using game theory [21]). Task performance models $J_P(t)$ always depend on the specific task and the goal to be achieved: Assembling and pick-and-place tasks typically need to be quick and accurate. For micro- or nanomanipulator tasks, precise positioning is required. Classical task performance measures, such as completion time or tracking accuracy, are *static* measures, meaning there is a one-to-one mapping of a specific task parameterization to one performance value and the actual performance value can be quantified only after completion of the task. Consequently, they cannot be used for performance predictions during task execution, which would be a requirement for online-adjustments of communication quality parameters. In the following section, we develop *dynamic* task performance prediction models, capable of serving in an online-control scheme for communication parameters.

B. Dynamic Performance and Cost Models

We model task performance $J_P(t)$ at a discrete time instance t as the output of a discrete-time state-space model as

$$J_P(t) = \phi_P(\theta_C(t), \theta_T(t), \mathbf{x}_P(t), \mathbf{u}(t), t),$$
$$\mathbf{x}_P(t+1) = \psi_P(\theta_C(t), \theta_T(t), \mathbf{x}_P(t), \mathbf{u}(t), t). \quad (2)$$

The dynamics are contained in $\psi_P(\cdot)$, while $\phi_P(\cdot)$ is a static mapping between the actual state $\mathbf{x}_P(t)$ and the task performance measure $J_P(t)$. The input vector $\mathbf{u}(t)$ contains the operator's action, e.g, the force applied.

Task-specific parameters $\theta_T(\theta_C(t), t)$ that impact the performance measure $J_P(t)$ can be separated into communication-independent $\theta_T^i(t)$ and communication-dependent $\theta_T^d(\theta_C(t), t)$ parameters. Here, $\theta_T^i(t)$ contains factors associated with the specific task itself, that is, they would influence performance even when the operator performed it directly, without using a teleoperation system (e.g., the path length in a navigation task or the number of items in a pick-and-place task). However, communication artifacts, such as time delay, can change the haptic properties of the task, which is reflected in $\theta_T^d(\theta_C(t), t)$: Imperfect communication quality can cause stability problems [5]–[7], [22]–[24] and change the mechanical properties of the task. In the simplest case where a stability analysis reveals large closed-loop stability margins, for example with a soft environment and manipulators with a limited force range,

time delay changes the phase characteristics of the haptic environment instead of causing instability [25]. Both, $\theta_T^i(\cdot)$ and $\theta_T^d(\cdot)$ can be time-varying in the case of a dynamically changing environment where moving obstacles interfere with the desired movement trajectory.

The state variable $\mathbf{x}_P(t)$ is used to describe dynamical processes defining $\phi_P(\cdot)$. Mechanical states of the teleoperation system, such as the end-effector position and velocity, may be included in $\mathbf{x}_P(t)$ as well as non-observable virtual states modelling the dynamic control behavior of the human operator.

Similar to the dynamic task performance model, a dynamic communication cost model using the state variable $\mathbf{x}_C(t)$ can be written as

$$J_C(t) = \phi_C(\theta_C(t), \mathbf{x}_C(t), t),$$
$$\mathbf{x}_C(t+1) = \psi_C(\theta_C(t), \mathbf{x}_C(t), t). \tag{3}$$

where $\phi_C(\cdot)$ is the algebraic output function in $\mathbf{x}_C(t)$, and $\psi_C(\cdot)$ contains dynamical processes. The state $\mathbf{x}_C(t)$ can account for cumulative processes (e.g., the overall cost spent on communication for full task execution). Time-varying network load or failure of network resources can add a time-varying component to $\phi_C(\cdot)$.

In general, determining $\phi_P(\cdot)$ and $\psi_P(\cdot)$ is challenging due to the complex, stochastic nature of human behavior, and the generally unknown and ambiguous tasks to be solved. Thus, model approximations that fit the human behavior sufficiently well have to be identified.

C. Illustrative Example

As an example illustrating the development of an MPC algorithm for optimal online-control of communication quality, we imagine a telepresent pick-and-place task with adjustable communication bandwidth $bw(t) \in \mathbb{R}^+$, directly affecting the resolution of the transmitted video stream. Without loss of generality, we constrain movements into one direction and denote the velocity as $v(t) \in \mathbb{R}$. The task performance measure $J_P(t)$ in this task is the positioning accuracy achieved during the placement component. As a communication cost criterion $J_C(t)$, we consider the transmission cost over one standardized time unit (e.g., one sample time period of the dynamic task performance model). Assume that the following characteristics of the communication system, task, and human operator are known:

- The cost $J_C(t)$ for reserving communication bandwidth $bw(t)$ for one time unit is $\gamma\, bw(t)$ where $\gamma \in \mathbb{R}^+$ is a constant determining the network's cost policy.
- The operator task performance $J_P(t)$ scales linearly with communication bandwidth.
- In the placing phase where it is important to achieve high task performance, the operator's absolute velocity $|v(t)|$ is low compared to the maximum speed v_{max}.
- Due to a large inertia of the object to be placed in comparison to the available actuator force, the velocity stays approximately constant within a prediction horizon of 100 time steps.

Based on experimental observations and considerations of network quality, performance and cost models can

be derived with communication bandwidth as the only communication quality parameter $\theta_C(t) = bw(t)$ where $bw(t) \in BW = [bw_{min}, bw_{max}]$.

$$J_P(t) = \phi_P(bw(t), v(t)) = (v_{max} - |v(t)|)\, bw(t),$$
$$v(t+1) = v(t).$$
$$J_C(t) = \phi_C(bw(t)) = \gamma\, bw(t).$$

Resolving the multi-objective optimization problem using a weighted sum with weighting factors $\lambda_1, \lambda_2 > 0$, an example MPC problem with a prediction horizon of 100 samples can be formulated as

$$\arg\max_{bw(t) \in BW} \sum_{j=0}^{100} \lambda_1 \phi_P(bw(t+j), v(t+j)) - \\ \sum_{j=0}^{100} \lambda_2 \phi_C(bw(t+j)). \tag{4}$$

Because of the system dynamics

$$v(t+1) = v(t+2) = \ldots = v(t+100) = v(t)$$

the solution to the MPC problem posed in (4) is the simple control law

$$bw(t) = \begin{cases} bw_{max} & \text{if } (\lambda_1(v_{max} - |v(t)|) - \lambda_2\gamma) > 0 \\ bw_{min} & \text{otherwise} \end{cases}$$

The choice of performance model is the most challenging part in the development of an optimal network quality control scheme. In this example, we implicitly assume that the operator acts only based on velocity and video quality, and ignores all other features. Any controller developed on the basis of a human model should be evaluated to test the validity of any assumption made and iteratively refined in subsequent experiments if necessary.

III. Dynamic Performance Prediction Model for Collisions

As an application for communication quality control in a teleoperation system, a specific task requiring speeded navigation through a course of obstacles was devised and investigated. Visual and haptic feedback was provided. For ease of experimentation, evaluation, and comparability of the results among the participants in our experiment, the teleoperation system was 'abstracted' by a virtual environment, representing the teleoperator's position by a circle moving on the screen. Furthermore, the operator's permissible motions were constrained to a plane by using a 2DoF haptic interface. The obstacle course was represented by a labyrinth with a unique path, similar to previous studies [26], [27]. Virtual environment and experimental setup are depicted in Figure 2. Because time-varying time delay $T_d(t)$ and packet loss are challenging problems for teleoperation systems operating over long distances [5], [7], [22]–[25], we consider $T_d(t)$ and the packet loss rate $p_l(t)$ in the communication quality parameters $\theta_C(t) = [T_d(t)\ \ p_l(t)]^T$. To guarantee stability in the case of contact with an obstacle, the exchange of haptic signals between the master device and the virtual environment
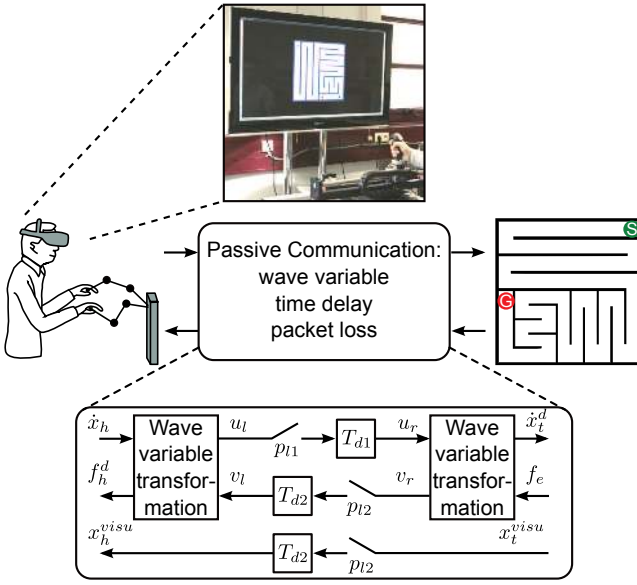
Fig. 2. The experimental setup consisted of a 2DoF haptic interface with monitor for visual feedback, and a virtual environment with emulated network characteristics, wave variable transformation, and a virtual labyrinth. The experimental task was to navigate through the labyrinth, as fast as possible, from the start point S to the goal location G, avoiding any collisions with the wall.

is mediated by the wave variable transformation, ensuring stability for arbitrary long time delays [1], [4], [5], [7]. The following two dependent variables are the performance metrics considered in $J_P(t)$ for the given task j [26]:

1) task completion time t_{com},
2) number of obstacle collisions N_{col} at time t_{com}.

This section focuses on the development of a dynamic task performance model for predicting (only) the number of obstacle collisions. The nature of $N_{col} \in \mathbb{N}$ to attain only discrete values is problematic for most optimization algorithms that rely on the gradient in the objective function, because gradient estimation on quantized functions is unreliable. Thus, the probability of colliding with an obstacle within a future time horizon $p_{col}([t, t_{+}t_p])$ is taken as an optimization variable. This measure returns quasi-continuous values, where a collision probability $p_{col}([t, t + t_p]) = 1$ is equivalent to an inevitable obstacle collision within t_p. Collision probabilities $0 < p_{col}([t, t + t_p]) < 1$ can be used to predict the amount of network quality that is needed to ensure safe task execution. The dynamic part $\psi_P(\cdot)$ and output function $\phi_P(\cdot)$ contained in equation (2) are derived in the following. We will consider the prediction model and the network cost model to exhibit no time-varying parameters.

A. Task Performance Dynamics $\dot{\mathbf{x}}_P(t) = \psi_P(\cdot)$

The state vector $\mathbf{x}_P(t)$ can contain mechanical states associated with the teleoperation system as well as states describing sensorimotor processes of the human operator. Given that the sensorimotor system is complex, we focus only on the modeling of mechanical processes. The dynamics of the human-system interface are often modeled as a mass-damper system [5]. Motions in one dimension are governed by the

dynamic equation

$$f_h = m\ddot{x} + d\dot{x} \tag{5}$$

where f_h is the operator's force exerted into a spatial direction x. For now, any influence of the remote (haptic) environment is not included, so the inertia m and the damping d to be moved are solely determined by the haptic device and the control algorithm, denoted as m_{HSI} and d_{HSI}, respectively. In favor of presentation clarity, we present the dynamical process for the continuous case and use an approximated time-discrete version with equal dynamic properties for computing the collision probability later on. For usage in a task performance model in the sense of equation (2), equation (5) is extended to two spatial dimensions x and y and formulated as a state-space system with the continuous state variable $\mathbf{x}_P(t) = \begin{bmatrix} x(t) & \dot{x}(t) & y(t) & \dot{y}(t) \end{bmatrix}^T$. We assume that the dynamics in x- and y-direction are independent from each other.

1) Environment Dynamics: The simple task considered in this paper has two distinct dynamics: Free-space motion with zero environment impedance in the case of pure navigation, and a hard contact in case of an impact. The walls are rendered as damped stiffness. Considering that the goal is to minimize the number of collisions, it is important to predict the collision probability *before* any impact occurs. Consequently, only the case of free-space motion with $Z_{env} = 0$ is considered as relevant for subsequent computations.

2) Communication-Sensitive Task Parameters $\theta_T^d(\theta_C(t))$: Communication parameters $\theta_C(t)$ can change properties of the task, reflected by $\theta_T^d(\theta_C(t), t)$, by means of stabilising techniques or other changes in the teleoperation system's haptic properties. We limit our considerations for determining $\theta_T^d(\theta_C)$ to the application of the wave-variable transformation [1], [4], [5], [7] for stable closed-loop control. Following this approach, linear combinations u and v are computed from the velocity $\dot{x}_{\{h,t\}}(t)$ and force $f_{\{h,e\}}(t)$ and transmitted over the time-delayed and 'lossy' communication channel. It can be shown [5] that in the case of free-space motion of the telerobot, a virtual inertia m_h^d is added to the impedance of the human-system interface that needs to be moved by the human operator on the local side. The magnitude of m_h^d that depends on the time delay can be computed as

$$m_h^d = \frac{bT_d}{2}. \tag{6}$$

The wave impedance $b > 0$ is a tuning factor [5].

While there is an analytic solution for the impedance displayed in the case of constant time delay, the effect of packet loss is non-deterministic, given that packet dropouts occur randomly. Furthermore, their influence on system transparency strongly depends on the reconstruction strategy for lost packets. Replacing a lost data packet containing wave variable information with zero values does preserve passivity and stability, but causes a significant position drift, as well as a drastically decreasing transparency [5]. Conversely, a hold-last-sample (HLS) technique that repeats the last transmitted value in case of missing information leads to better transparency, but induces active, thus potentially unstable behavior. Therefore, we reconstruct lost packets using

an energy-supervising algorithm [5], which ensures passivity while mostly preserving transparency. In this approach, the HLS reconstruction technique is used as long as the energy contained in the wave variable does not increase over bounds (passive behavior). In the case of an energy increase, a wave variable with zero values is to be sent.

Taking together the dynamic models of HSI, environment, and the additional communication-induced impedance, the actual dynamics that the human operator interacts with is of the form specified by equation (5) with the inertia and damping parameters

$$m = m_{HSI} + \frac{bT_d}{2}, \; d = d_{HSI}. \tag{7}$$

Remark 1. The (uncompensated) device inertia as part of equation (7) contributes to the felt impedance of the device. Impedance-type haptic interfaces (e.g., the Geomagic® Phantom® and Novint Falcon®) typically have lower inertial moments, but at the cost of a lower achievable force range. With a constant wave impedance b, the relative importance of the delay-dependent inertial component becomes more prominent with smaller m_{HSI}. It should be noted, however, that b is chosen in accordance with the device characteristics, and thus may be smaller with lower m_{HSI} [24].

B. Task Performance Output Function $J_p = \phi_P(\cdot)$

The output function $\phi_P(\cdot)$ relates the system state, communication and task parameters to the task performance measure $J_P(t)$, which is the probability to collide with an obstacle within the prediction horizon $[t, t + t_p]$,

$$J_P(t) = p_{col}([t, t + t_p]).$$

The algorithm for computing p_{col} is based on a number of assumptions with regard to the human operator:

- The operator is able to exert a (bounded) force in every direction in the x-y plane.
- The rate at which the human force changes has an upper bound [28].
- All forces are equally likely to be exerted within a prediction horizon t_p.

The latter assumption is made so as not to restrict to a specific strategy or forecast of human behavior in the context of a specific task. Given the present article focuses on the methodology of using a dynamic performance model and an experimental proof-of-concept, the complete formalism for computing p_{col} will not be described here. We refer readers to [29], [30] for an overview of methodological aspects associated with probabilistic reachable sets, and Appendix C in [31] for an application of this method to mass-damper systems. The collision probability is inferred in three major steps:

1) Determine the probability $p_i([t, t + t_p])$ of reaching a discrete system state X_i within a prediction horizon $[t, t+t_p]$. First, the time horizon is divided into N_p equally-sized intervals of length T, and we assume a constant exerted force within this time interval. $T = 100$ ms is chosen in agreement with observations in the literature that volitional
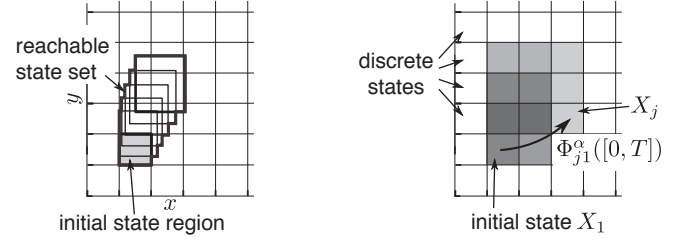

(a) 2D-projection of the reachable state set.

(b) Abstraction of the reachable set by a Markov chain.

Fig. 3. (a) A 2-dimensional projection of the 4D reachable set of states, developing from an initial state set under the influence of a bounded force. (b) A Markov chain with transition matrix Φ represents the probability of passing a discrete state X_j. Darker states are more probable to be reached from the initial state X_1.

bandwidth for human movements is between 3 and 10 Hz [28]. Next, the state space is discretized, and the probability of reaching a specific state X_i within a time horizon $[t, t+T]$ is computed using reachable sets and represented as a Markov chain. This procedure is illustrated in Figure 3. Predictions beyond $t + T$ are achieved iteratively by taking the reachable states at $t + T$ as initial values and weighting the predictions with the respective probability $p_i(t_T)$.

2) Determine the probability $q_i([t, t + t_p])$ if reaching X_i leads to a collision. The entries in q_i are either 1 or 0. In case X_i corresponds to a position coincident with an obstacle: $q_i([t, t + t_p]) = 1$, otherwise $q_i([t, t + t_p]) = 0$.

3) As a worst-case estimate, the collision probability $p_{col}([t, t+t_p])$ is defined as the maximum reaching probability in the set of discrete system states leading to a collision

$$p_{col}([t, t + t_p]) = \max_i p_i([t, t + t_p]) q_i([t, t + t_p]). \tag{8}$$

Projections to the $x - y$ plane of $p_i([t, t + t_p])$ are depicted in Figure 4 for different initial states. Evidently, $p_i([t, t + t_p])$ does not only depend on initial speed, but on the dynamic properties of the teleoperation system, specifically on m in (7) which depends on the communication channel's time delay. Qualitatively, when there is only a small inertia, it is easy for the operator to decelerate and avoid a collision during a rapid approach towards an obstacle. In case of a high inertia, the rapid approach is likely to lead to a collision. This means that a communication channel with a long time delay, resulting in high virtual inertia, would increase the probability of a collision.

Using collision probability as a performance criterion has the following benefits compared to other methods:

- Only the range of forces and the force bandwidth are required for predicting the collision probability, so the method is not bound to a specific architecture of the path.
- Only local knowledge of the labyrinth is required, that is, in the vicinity of the current position where $p_i([t, t + t_p]) \neq 0$. Given this, this method is in principle adaptable to real teleoperation systems equipped with obstacle detection sensors such as laser scanners.
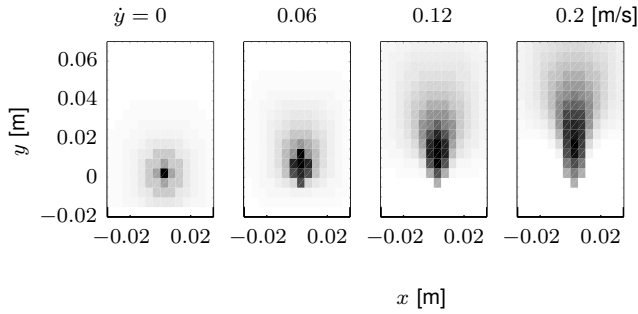- Knowledge about the human strategy could easily be taken into account [30], as well as more detailed task

Fig. 4. The probabilities $p_i([0, 500 \text{ ms}])$ of being in a specific discrete state X_i are projected onto the x/y-plane. Four initial states X_j with different initial velocities $\dot{x}_{h,y}(0)$ are depicted. Darker states are more likely to be reached.

knowledge, to improve the estimation of collision probability.

On the other hand, there are potential weaknesses in the approach, challenging its application in a model-based communication quality control algorithm:

- The computation of p_{col} is only based on human motor capabilities, without considering visual feedback.
- Any changes in communication quality could alter the control behavior of the human operator, which is not considered in the present model.

IV. MODEL EVALUATION

We conducted behavioral proof-of-concept experiments to evaluate the above prediction model. The experimental setup as depicted in Figure 2 was used for a collision avoidance task while moving through the course as fast as possible. In favor of a limited number of degrees-of-freedom in the experimental design, we kept the parameters of communication quality constant over each trial and consider only the impacts of time delay and packet loss rate $\theta_C = [T_d \, p_l]^T$.

A. Experimental Methods

1) Participants: Six university students (3 female, age range 20-26 years) participated in the experiment. One male participant dropped out prior to completion of the experiment and was excluded from the analysis. All were right-handed, had normal or corrected-to-normal vision, and were recruited through postings in the Technische Universität and Ludwig-Maximilians-Universität in Munich. They gave their written consent prior to their participation and were paid at a rate of 15 EUR/h.

2) Apparatus: The haptic feedback was rendered via a 2DoF haptic interface, consisting of a Thrusttube module 2504 (Copley Controls Corp.) mounted on top of a Thrusttube module 2510 at a right angle. Each actuator was equipped with an optical position encoder, with a precision of 1 μm. A 6DoF JR3 force-torque sensor attached to the handle measured interaction force. The haptic interface was controlled in real-time at a sampling rate of 1 kHz using a Quad-Core AMD Phenom desktop PC equipped with a Sensoray 626 DAQ card running Gentoo Linux with the RTAI kernel patch for

maximum timing reliability. Visual stimuli were presented on a 42-inch flat screen TV at a refresh rate of 60 Hz. The inherent time delay between visual and haptic stimuli was determined, using a luminance sensor, to be within one refresh cycle, thus varying between 0 and 16 ms. The inertia and damping of the admittance-controlled haptic interface were 9 kg and 8 Ns/m, respectively. The virtual walls were rendered as a spring-damper system with spring coefficient $k_{wall} = 7000$ N/m and damping $d_{wall} = 500$ Ns/m.

Network Model: The network used in the experiment was emulated to ensure maximum reliability of the experimental conditions. For simulating packet loss characteristics, either a Bernoulli process or the Gilbert-Elliot model [32], [33] are popular choices. We selected the latter for the current experiment, as the two-state Markov process of the Gilbert-Elliot model better characterizes the loss characteristics of packet-based networks such as the Internet [34]. Lost packets must be reconstructed on the receiving side of the teleoperation system: Visual feedback does not affect system stability, therefore we chose a hold-last-sample reconstruction for the visual data stream. This caused the image to freeze during loss bursts. For the haptic feedback, we applied the energy-supervised hold-last-sample algorithm as described in Section III-A2. The feel of this reconstruction method is ambiguous and hard to quantify as it strongly depends on the current situation (accelerating, decelerating etc.) and would be reportedly noticed as mostly a "disturbing effect", e.g. an momentary increase in system damping.

3) Experimental Design: A course of virtual obstacles was designed to allow movements only along a unique path 3 cm in width (see Figure 2). The straight length of the course was approximately 3.0 m, while the actually movement distance could vary across individual trials owing to deviations from the midline between the walls. Participants were instructed to move through the course without touching any wall, while being as fast as possible. They were also told that avoiding collisions should have a higher priority compared to mere speed. To minimize possible learning effects that may be attributable to a specific path through the labyrinth, 12 different variations of the course, depicted in Figure 2, were presented: The original configuration as shown in Figure 2 (1), path rotated by 90°, 180°, 270° (2-4), horizontally reflected original configuration (5), rotated by 90° and reflected horizontally (6), and starting point and goal point interchanged (7-12). All paths were counter-balanced and presented in a random order.

Three levels of round-trip time delay $T_d = \{0, 0.04, 0.1\}$ s and packet loss rates $p_l = \{0, 0.1, 0.2\}$ with a fixed mean burst length of 60 ms at a packet rate of 1000 packets/sec for the haptic modality, and 60 frames/sec for the visual modality were tested in an orthogonal experiment design. For reasons of simplicity, we set time delays and loss rates in the send- and receive-channel to $T_{d1} = T_{d2} = T_d/2$ and $p_{l1} = p_{l2} = p_l/2$, respectively. The wave impedance parameter b (compare equation (6)) was fixed to $b = 100$ as a trade-off between a high transparency in free-space and oscillations in impact situations. These parameters and the admittance control scheme for the control of the HSI resulted in an inertia felt by the human operator of $m = 9$ kg for

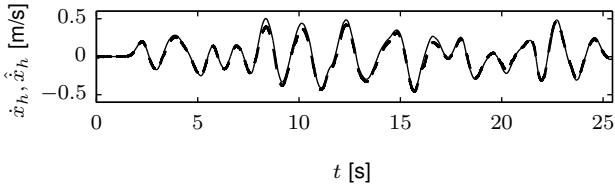Fig. 5. Predictions of human velocity $\hat{\dot{x}}_h$ from real force data and an identified mass-damper model (solid), compared to the actual velocity $\dot{x}_h$ (dashed) obtained with a packet loss rate of 20%.

$T_d = 0$ s, $m = 11$ kg for $T_d = 0.04$ s, and $m = 14$ kg for $T_d = 0.1$ s. On the virtual side, an ideal position controller was assumed for driving the abstracted "slave robot". All conditions were presented randomly to a human operator with 20 repetitions, yielding a total of 180 trials per participant. Each trial was completed within approximately 45 seconds. The experiment was split into two sessions, with 10 repetitions of each condition to avoid fatigue effects. Each session lasted for about one hour.

B. Results and Discussion

1) Influence of Communication Quality on Task Parameters: First, we validated the assumptions made about the effect of time delay and packet loss on task parameters $\theta_T(\theta_C)$, in our case the time-delay-dependent inertia $m_h^d(T_d)$. A system identification algorithm was used to parameterize the assumed mass-damper model in eq. (5), minimizing the error between the recorded velocity data and the model prediction. The goodness-of-fit for the identified model is quantified by

$$\xi = 1 - \sqrt{\frac{\int_0^{t_{com}} \dot{x}_h(t) - \hat{\dot{x}}_h(t)\mathrm{dt}}{\int_0^{t_{com}} \dot{x}_h(t) - \bar{\dot{x}}_h(t)\mathrm{dt}}}$$

where $\hat{\dot{x}}_h$ denotes a predicted handle velocity from the identified mass-damper system and $\bar{\dot{x}}_h$ is the mean handle velocity, calculated over data taken from a whole trial of the experimental procedure, respectively. A value of 1 for ξ stands for a perfect match between model predictions and actual data, while 0 means simulated behavior that was no better than simulating the mean value of all observations. Predictions from the model and real data with zero time delay and a packet loss rate of 20% are depicted in Figure 5. In the case of time delay only, the model fit with measured velocity and force data is $\xi \geq 0.98$ for every trial. The magnitude of identified damping and mass for the different delay conditions is consistent with the values of the admittance controller and the additional inertia due to time delay and the wave variable transformation as computed from equation (6). The identified models for the time delay conditions can also fit data from trials with 20% of packet loss, achieving a goodness-of-fit measure of $\xi \geq 0.80$. Deviations of measured from simulated handle velocity in (time) instances of packet loss bursts are attributable to a change of the mechanical impedance during lost packets, which are responsible for the lower consilience of model and data. The magnitude of this impedance change depends on burst length, and the force and velocity profiles during loss bursts.

A comparison indicates a <0.5% mismatch between the values of the identified model parameters and the predicted inertia and damping from equation (7). This result and the good agreement between model and experimental data qualifies the mass-damper model in equation (5) to be included in the computation of the collision probability.

2) Influence of Communication Quality on Collision Count and Completion Time: The influence of time delay and packet loss rate on the total number of obstacle collisions during task execution $N_{col}(t_{com})$ and the completion time t_{com} is depicted in Figure 6. Hartley's F_{max} tests applied to the collision and completion time data confirmed homogeneity of variance, and the Kolmogorov-Smirnov test failed to reveal a significant violation of the normality assumption. Thus, two 2-way repeated-measures ANOVAs with main effects packet loss rate and communication time delay were conducted for $N_{col}(t_{com})$ and t_{com}, respectively. The Greenhouse-Geisser correction was applied to correct for lack of sphericity. Note that due to the small number of participants, the interpretation of non-significant results must be treated carefully. Packet loss rate yielded no significant (main) effect on $N_{col}(t_{com})$ ($F(1.8, 7.1) = 2.8$, $p = 0.13$, $\eta^2 = 0.41$), while the effect of time delay was significant ($F(1.7, 6.8) = 17.03$, $p < 0.01$, $\eta^2 = 0.81$). The interaction between the two factors was not significant ($F(1.6, 6.63) = 0.94$, $p = 0.42$, $\eta^2 = 0.19$). Tukey HSD tests indicated that only the highest level of time delay $T_d = 0.1$ s resulted in a significantly increased rate of collisions, and the mean number of collisions increased about 1.6 on average from zero delay to 100 ms delay (see Figure 6a), while the number of collisions did not differ significantly between conditions $T_d = 0$ s and $T_d = 0.04$ s ($p = 0.13$). In contrast to collision frequency, completion time was impacted significantly by both packet loss rate and time delay ($F(1.1, 4.4) = 18.51$, $p < 0.05, \eta^2 = 0.82$ and $F(1.3, 5.3) = 48.25$, $p < 0.01$, $\eta^2 = 0.92$, respectively); the interaction between the two was not significant ($F(2.2, 8.7) = 0.037$, $p = 0.97$, $\eta^2 = 0.01$). The relation of completion time and the communication parameters T_d and p_l can be described by a linear regression within the investigated parameter range. The norm of residuals to the regression model was 0.18, indicating a good fit. The combined data suggest that participants attempted to maintain the same level of collision performance by trading off the completion time. This kind of trade-off strategy was manageable for all three packet-loss rates, but it failed for the longest time delay condition ($T_d = 0.1$ s).

These results confirm previous findings that time delay has a negative influence on performance, accuracy and completion time [7], [35], [36]. The negative influence of packet loss on task completion time, however, contrasts with a previous report that video game players were unaffected by information dropouts [37]. The inconsistent findings may partly be explained by differences in the loss burst lengths used in the different studies. In the present experiment, the loss burst length was relatively long, and loss rate was high, causing the visual feedback to freeze and the mechanical impedance to change in the instance of lost information. In the wired, local networks that were investigated in [37], dropout rates are usually within a few percent. The range of loss rates
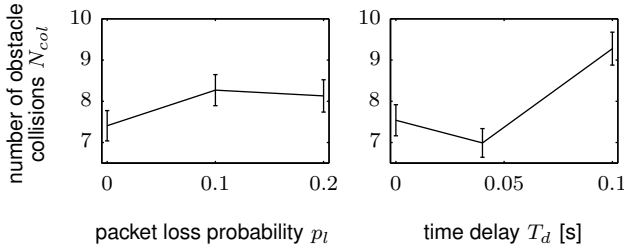
(a) The number of collisions with an obstacle N_{col} increased significantly with time delay.
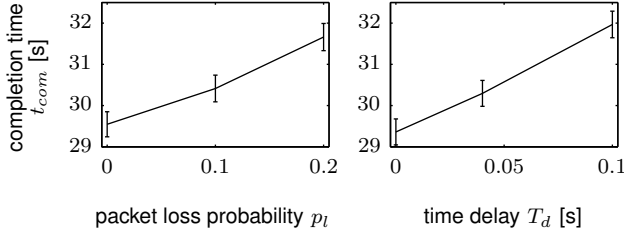
(b) The experimentally observed completion time t_{com} depends near-linearly on time delay T_d and packet loss rate p_l.

Fig. 6. Time delay had a significant influence on the number of collisions N_{col} and completion time t_{com}, whereas packet loss had a significant impact only on completion time.

Fig. 7. An example for the rise in collision probability $p_{col}([0, 100 \text{ ms}])$ before a collision occurs, indicated in gray.

investigated in the present study is close to the values found in wireless communication channels to space or underwater.

Humans are, in general, capable of adapting their control strategy to a technical system to maintain a constant level of task performance [38]–[40], though this does not necessarily hold for time-delayed sensory feedback [10], [41]. The degraded task performance observed here may well be attributable to the change in environmental impedance discussed in Section IV-B1: The time delay-dependent inertia that must be moved by the human operator in addition to the inertia and damping from the position-based admittance controlled haptic interface requires more effort during acceleration and deceleration. Considering humans' natural energy-saving behavior [42], the task completion time t_{com} achievable for a control strategy using similar energy levels is lower when accelerating the low compared to the high inertia. A similar argument can also explain the finding that the number of collisions is larger for high compared to low inertia, as the amount of energy needed for braking is higher with the former.

The effect of the packet loss rate p_l on task performance, in terms of the number of collisions and task completion time, cannot be explained by changes in the impedance, as p_l does not influence the mechanical properties; see Section IV-B1. Instead, we must consider both packet loss rate and time delay affecting visual feedback. Time delay in visual feedback has been found to consistently deteriorate task performance [7], [10], [41]. Corruption of sensory feedback due to packet dropouts is manifested in a stagnation of visual (perceived) motion, followed by a position jump and a variation in haptic impedance during loss bursts. As a consequence, the system behavior is less predictable for the operator, and the risk of collision increases when the speed is kept unchanged. Such unpredictable system behavior can affect operator's control strategy [43] in two possible ways: Operators either use a
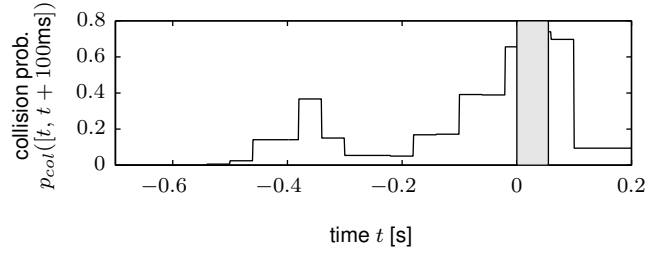
risk-averse control strategy by lowering their control gain, or they exhibit risk-seeking behavior by raising their gain with uncertainty in the sensory feedback. A risk-averse strategy was explicitly recommended by instructing our participants to focus more on the avoidance of collisions than on execution speed. A lower control gain lets the human operator, on average, react with smaller control inputs (e.g., smaller forces). This fact would lead to a lower speed during navigation and, thus, prolong completion time. Such a speed-accuracy trade-off could explain why the task completion time is significantly affected by the packet loss rate, while the number of collisions is not.

3) Influence of Communication Quality on Collision Probability: To serve as a key parameter in the dynamic task performance model, the predictive power of the collision probability p_{col} on the number of collisions N_{col} must be experimentally verified. First, the maximum force $f_{max} = 8$ N is identified as a boundary for the force range used in the task. Based upon the known device and environment dynamics and f_{max}, the time-course of the collision probability $p_{col}([t, t + 100 \text{ ms}])$ can be computed off-line for a trajectory recorded in the experiment. In the example depicted in Figure 7, the collision probability increases prior to the actual collision. This behavior is consistent for all occurring collisions. Note that p_{col} does not increase to 1 because estimation of the collision probability relies solely on the system dynamics, the operator's force range, and bandwidth. It is thus conceivable, though unlikely, that the collision might be avoided. The elevated value of $p_{col} \approx 0.7$ as compared to situations with no imminent collision is indicative of high predictive power for detecting a collision within the next time step. On this basis, we hypothesize that minimizing the collision probability by applying communication quality control would lead to a reduced number of collisions.

We also examined how time delay and packet loss rate influence the collision probability p_{col}, by computing the mean collision probability for different levels of time delay and packet loss. The difference in mean collision probability to the non-delayed baseline condition is depicted, as a function of time delay, in Figure 8. Curve fitting showed the collision probability to increase when the delay increases ($\Delta p_{col}([t, t + 100 \text{ ms}]) = 1 - 0.964 \exp(-3T_d)$, $r^2 = 0.96$). On the other hand, packet loss rate had no predictive power with regard to collision probability computed with our model. This is because we only consider the mechanically displayed impedance and assume a constant human force range and bandwidth across all levels of time delay (see Section IV-B1).
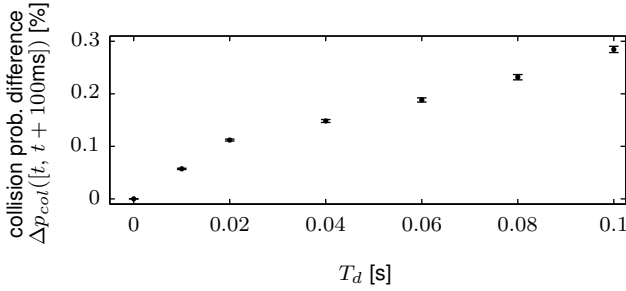
Fig. 8. The mean difference in collision probability for the next time step $\Delta p_{col}([t, t+100\text{ ms}]) = p_{col}([t, t+100\text{ ms}]) - p_{col}([t, t+100\text{ ms}])|_{T_d=0}$ is higher with longer time delays.

V. COMMUNICATION QUALITY CONTROL FOR IMPROVED COLLISION AVOIDANCE PERFORMANCE

Our aim is the minimization of collisions and communication costs by online-adjustments of the communication quality. For this purpose, we designed a model predictive controller (specified below), based on the dynamic performance model developed in Section III and a model for network costs. We did not consider the effect of packet loss in the MPC scheme, given that it had no significant influence on the number of obstacle collisions (see the results in Section IV-B2) and no predictive power in the performance model.

A. Model Predictive Control Algorithm

For deriving a MPC algorithm suitable for communication quality control, a multi-objective optimization problem in the sense of equation (1) has to be formulated. Given that our motivation is to minimize the number of obstacle collisions while saving communication costs, the equivalent to equation (1) is

$$\underset{\theta_C(t) \in \Theta_C}{\arg\min} \begin{bmatrix} N_{col}(t) & C_{net}(t) \end{bmatrix}^T . \quad (9)$$

The controlled communication quality parameter is the channel time delay $T_d \in \Gamma_d$, where Γ_d is a set of permissible time delay values. Following the considerations in Section III, a model predictive controller based on the collision probability p_{col} instead of the collision count N_{col} is preferred. Instead of solving the optimization problem (9) directly, the MPC repeatedly solves

$$\underset{T_d([t, t+t_p]) \in \Gamma_d}{\arg\min} \underbrace{\lambda_1 p_{col}([t, t+t_p]) + \lambda_2 J_C([t, t+t_p])}_{J_1(T_d(t))} \quad (10)$$

to determine the optimal time delay value $T_d^*([t, t+t_p])$. The relation between J_1 and T_d is in the probability distribution $p_i([t, t+t_p])$ in equation (8), as depicted in Figure 4.

B. Communication Cost Model $J_C = \phi_C(\cdot)$

The costs for guaranteeing a specific communication quality in terms of time delay is generally dynamic, see equation (3). There are several possibilities of defining network costs, for example the cost per packet and the overall cost at task completion. As the task and its completion time are usually unknowns in a teleoperation scenario, the overall cost cannot be considered. Instead, we use the cost per packet, making

the use of a state $\mathbf{x}_C(t)$ as in equation (3) unnecessary. The relation between network cost and time delay is usually defined to be monotonically decreasing with increasing time delay [21], [44], such as exponential or rational functions. We set the cost function to a first-order rational function, in line with [21],

$$\phi_C(T_d(t)) = c_{max} - \frac{c_{max}}{T_{d,max}} T_d(t) \quad (11)$$

such that a time delay $T_d = 0$ s corresponds to a maximum cost c_{max} and the highest possible time delay $T_{d,max}$ comes free of charge'. Without loss of generality, we set the maximum cost $c_{max} = 1$. For the experimental validation, we assume that sufficient network resources are available, such that every quality request can be fulfilled and dealt with immediately.

C. System Stability Considering Time-varying Time Delay

The online-control of time delay poses problems for guaranteeing stability. The wave variable transformation is known to provoke active, and thus potentially unstable, behavior of the communication channel if time delay is time-varying. To counteract this problem, a time-varying scaling factor

$$k(t) = \sqrt{1 - \dot{T}_d(t)/2}$$

is applied to into the communication channel [22], as shown in Figure 9. This factor depends on the temporal derivative of time delay and can fully prohibit communication in the case of a rapidly rising value of $T_d(t)$. To soften this effect, we constrain the rate of the variable time delay by inserting a first-order low-pass filter with cut-off-frequency of 5 Hz.

D. Experimental Validation

1) Participants: Five right-handed male students (age range 21-25 years) participated in this experiment; none of them had participated in Experiment 1. All had normal or corrected-to-normal vision and none reported any history of somatosensory disorder. They gave their written consent to participate in the study and were paid at a rate of 15 EUR/h.

2) Apparatus and Design: The same hardware setup as in Experiment 1 was used here. The network emulator described in Section IV-A2 was complemented with the ability to regulate the time delay online. Furthermore, a virtual environment with different obstacle positions as depicted in Figure 9 was considered. In contrast to the Experiment 1, there was no unique path for the human operator to follow; instead, an obstacle course was designed allowing different alternative routes of similar overall length and structure. Path width was 1cm at the most narrow gap between obstacles and included phases without any obstacle to avoid. We designed this scenario to require fine positioning within narrow bounds and dynamic braking in free-space – two extreme cases where the communication quality control mechanism would have to prove its effectiveness. The time delay was regulated at a rate of 25 Hz in 5 equal steps between 0 and 200 ms. We chose a wider range of time delays here since small values of T_d did not produce a significant effect on human task
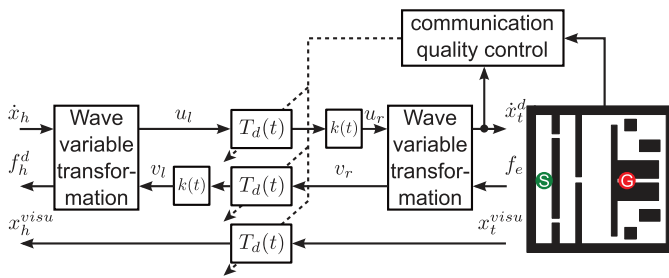
Fig. 9. The experimental setup is complemented with a communication quality control mechanism and a time-varying gain to ensure stability.
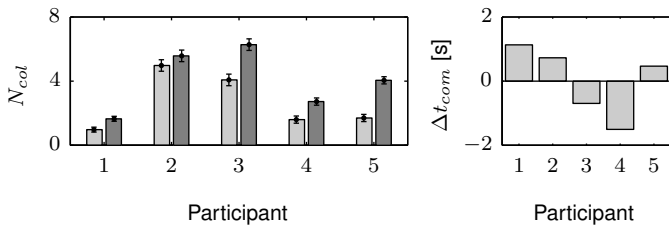

Fig. 10. The number of collisions with the walls was (across participants) consistently lower when time delay was controlled (QoS condition, light grey), compared to the control condition (no QoS, dark grey). The influence of communication quality control on completion time was not statistically significant.
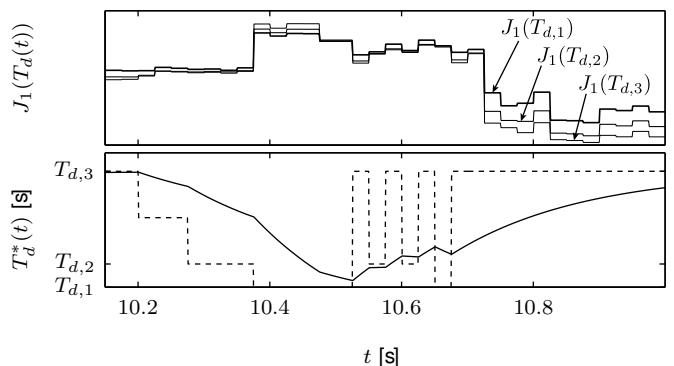

Fig. 11. The value of the cost function $J_1(T_d(t))$ is depicted for three (example) levels of time delay $T_{d,\{1,2,3\}}$. The optimal time delay $T_d^*(t)$ resulting from the optimization in equation (10) (dashed) was low-pass-filtered (solid) and applied to the communication channel.

performance in Experiment 1. The weighting factors λ_1 and λ_2 in the MPC algorithm resulting from equation (10) were set to weight collision probability higher than network costs. This means that the maximum latency was applied in non-critical situations, but the time delay was lowered in case of an imminent collision, where lower latencies reduce collision probability $p_{col}([0, t_p])$. A prediction horizon of 500 ms, which is well beyond the time delay, was chosen.

After being familiarized with the system and training of the task on at least five trials with quality-controlled time delay and five constant-delay trials, participant performed 40 trials with communication quality control using the cost function from equation (10) and 40 trials using a cost function without considering the collision probability, resulting in a constant time delay of $T_d = 0.2$ s.

All experimental conditions, with and without applying the communication quality control algorithm, were randomly shuffled to avoid adaptation effects. The time taken for a trial was less than 30 seconds, thus all 80 trials could be completed within one hour.

E. Results and Discussion

The same statistical analyses for homogeneity of variance and normality that were used in Experiment 1 were applied here and confirmed the applicability of ANOVA and t-tests. Paired t-tests revealed communication quality control to have a significant positive effect by reducing the number of obstacle collisions ($t(4) = 3.73$, $p < 0.05$, JZS Bayes Factor = 0.32, on average 2.67 (QoS) vs. 4.06 (no QoS) collisions per trial), as depicted in the left panel of Figure 10. However, completion time was not significantly influenced by QoS control ($t(4) = 0.052$, $p = 0.96$, JZS Bayes Factor = 2.34).

Figure 11 depicts a schematic of the online control of communication quality using the predictive controller model we developed. In cases where a better cost/task performance tradeoff could be achieved with a long delay, the channel's quality was switched accordingly (e.g., in the case of no imminent collision). The success of the communication quality control scheme can be explained by considering that in case of a rapid obstacle approach, the operator usually decelerates movement to avoid a collision. Lowering the inertia during this phase leads to a shorter breaking distance, thus helps the operator to perform the task.

Our experimental finding suggests that the proposed quality adjustment algorithm does improve operator's performance, rather than merely inducing a speed-accuracy trade-off, given that reducing collisions did not increase completion time with the proposed algorithm. Time-varying time delay causes packet loss [5] that could potentially increase task completion time, but in contrast to randomly varying time delay, we predictively lower the time delay when the operator approaches an obstacle. While lower time delay could potentially also speed up task completion, we found no such effect which may be explained by the operator normally decelerating in phases of low time delay. In these situations, a low delay-dependent inertia supports a fast braking action and helps avoid a collision, while not necessarily affecting task execution time.

VI. CONCLUSION AND FUTURE DIRECTIONS

In this paper, we introduced a framework for model-predictive control based on a dynamic task performance model, controlling the level of communication quality to improve human task performance. The approach was evaluated in two proof-of-concept behavioral studies using a virtual teleoperation scenario with visual and haptic feedback over a 'lossy' and time-delayed communication channel. Communication delay as well as packet loss hindered operators' task performance, as indicated by an increased number of obstacle collisions and a longer completion time when moving through a course of obstacles. The communication quality control algorithm based on a model for collision probability

demonstrated the usefulness of this approach for assisting collision avoidance.

All testing has so far been confined to a virtual reality setting with simulated networking conditions. Although we chose a network model that governs the characteristics of packet loss and time delay conditions well, the next step would be to evaluate communication quality control under real network conditions. One way to do this is to physically relocate the simulation of the remote environment to a different location and establish a quality-controlled communication link between the human-system interface and the remote virtual environment. This could be realised e.g. by using an acoustic modem for underwater communication that allows a variable transmission power to influence the amount of packet losses [45]. A controllable time delay could be achieved by using active queue management techniques. Future research should also include teleoperation in "real" remote environments instead of virtual reality.

It is noteworthy that there are several overlaps of the approach described here with the EID (ecological interface design) framework. For instance, the notion of an *affordance* according to the EID framework is essentially equivalent to our approach that considers the operator's physical ability in combination with the dynamics of the task [46]–[48]. Taking into account the task-relevant information for the human operator as well as the temporal requirements may enhance both the design of teleoperation systems and the EID framework in the future.

One important issue for future investigations, for improving task completion time in addition to collision avoidance, it would be important to consider multiple task performance prediction models in the predictive control scheme. Also, it may be interesting to compare and contrast different communication quality control algorithms in terms of the performance improvements they yield under equal-cost conditions (e.g., the current MPC algorithm could be compared with static quality assignment). The dynamic performance model developed in this paper was only based on a mechanical model with time delay-dependent inertia. More sophisticated models, taking into account the human control strategy and the role of the visual modality in time-delayed teleoperation, would arguably be needed to achieve a more accurate prediction of the operator's forthcoming behavior. Furthermore, the present approach assumes that every quality request on the communication channel can be fulfilled. However, this assumption is likely to be too strict for real-life situations. It is yet to be answered how the operator's task performance is affected if the optimal time delay determined by the communication quality controller is too small to be achieved. We presume that task performance is still higher than without QoS control. Finally, the generality of the present claims should be underpinned by evaluating the method in larger-scale studies using different tasks and apparatus.

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