Analytical and Psychophysical Comparison of Bilateral Teleoperators for Enhanced Perceptual Performance

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***Abstract*—This paper focuses on the human perception capabilities for haptic interaction with remote environments. The perception capabilities are compared for two well-known control methods with two kinds of haptic cues. Analytical and psychophysical methods are used to analyze the performance. The first control method aims at maximizing the transparency of the remote interactions (i.e., *transparency-based method*), whereas the second one aims at maximizing the detection and discrimination abilities of the human operator (i.e., *perception-based method*). For each of these two control methods, two kinds of haptic cues are studied, which use position and force cues from remote environments. Hybrid matrix formulation is employed, and it is analyzed in the frequency domain for these studies. Psychophysical experiments are then conducted for human-centered evaluation and comparison of the control methods. Analytical and experimental results clearly show that the perception-based method, when compared with the transparency-based method, enhances the human operator's perceptual capabilities of remote environments irrespective of force cues. For each of the two control methods, the force cues always contribute more to the increase in perceptual sensitivity when compared with the case of position cues.**

***Index Terms*—Kinesthesia, medical robotics, perception, psychophysics, remote haptic interaction.**

I. Introduction

HAPTIC perception is an essential requirement in many day-to-day applications. Haptic cues from the environment can be in the forms of force, stiffness, viscosity, or impedance. This becomes more important for cases where a human has to interact with an environment located at a remote location (i.e., bilateral teleoperation [1]). This is because the sensations and cues are transmitted via mechanical devices and the human operator is physically separated from the environment. Since human operator is actively involved in teleoperation systems (i.e., human-in-the-loop systems), perceptual characteristics of the human operator (e.g., threshold and sensitivity of haptic stimulus) should be considered for better enhancement of the teleoperator's performance. From the same perspective, the evaluation of system performance needs to be conducted from the human operator's perspective. We call the first paradigm as *human-centered design*, whereas the latter is known as *human-centered evaluation*.

In this paper, several standard controllers of bilateral teleoperation systems are analyzed by considering human operator properties. Note that these controllers are developed based on similar motivations and have been already published. We also employ psychophysical methods for human-centered evaluation of the perception capabilities of controllers. Specifically, we focus on remote surgical applications because enhanced perception is very important in these cases due to the involvement of human lives.

A. Related Work

There have been numerous studies to discuss the fundamental characteristics in human perception of haptic cues. Jones and Hunter analyzed the stiffness and viscosity feedbacks from a perception point of view. They claimed that although human subjects can perceive stiffness and viscosity over a wide range, intra-individual variations exist in the perception [2], [3]. Tan *et al.* conducted psychophysical experiments to evaluate the role of force cues in the manual discrimination of compliance using active pinch grasps and found out that subjects rely on force cues for compliance discrimination tasks [4]. Interactions with haptic virtual surfaces were dealt in [5] wherein it is claimed that human subjects maintain a constant penetration force during their interaction, which can sometimes lead to perception distortion. This result could be used to simulate complex virtual environments for teleoperation applications by applying appropriate haptic compensation techniques to minimize the distortion. Cholewiak *et al.* discussed the aspect of channel capacity required to transmit information through stiffness or force magnitudes in [6]. The effects of active and passive touch for the perception of simulated virtual shapes were also studied in [7] wherein it was shown that passive

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touch can detect the stimulus but cannot identify the shape as concave or convex. This shows the importance of motor command feedback during tactile exploration.

Haptic feedback in teleoperation systems also has been extensively studied. Various bilateral control schemes have been developed to transmit the haptic or force cues from the remote environment to the human operator [8], [9]. One of the most widely accepted schemes is by Lawrence [8], which says that mechanical impedance can exhibit the dynamics of interactions and hence, for an effective remote operation, the haptic cues are transmitted such that the impedance of environment is equal to the transmitted impedance to the human operator (i.e., transparency). From this perspective, a *transparency-based method* was proposed and rigorously studied in [8] and [9], respectively. Recently, Slama *et al.* developed a bilateral predictive controller for teleoperation systems, which takes into account slave force feedback. Their method can exhibit robust performances in spite of variable communication time delays and packet losses [10]. An H_∞ optimization-based gain-scheduling controller is also proposed to enhance transparency in the absence of force signal [11]. Several methods can be also found in the literature to consider haptic perception in multi-robot teleoperation systems. Son *et al.* proposed a method to improve operator's perceptual sensitivity to control of multiple mobile robots [12]. Franchi *et al.* also addressed that the proper design of haptic feedback is essential to improve the overall performance in multiple mobile robot teleoperation systems [13].

Since the bilateral controllers are applied to human-in-the-loop systems, human involvement in experiments and their feedback are important to judge the practical usability of the controllers. Hence, the human-centered evaluation (e.g., psychophysical studies) is conducted to judge the effectiveness of the controllers. Psychophysical experiments were used by Botturi *et al.* who suggested that perception can be enhanced by suitable scaling in different directions [14]. It was shown that the inclusion of nonlinear and linear time-invariant filter mappings between the master/slave position and force signals enhances stiffness discrimination thresholds by Malysz and Sirouspour in [15]. Son *et al.* discussed the effect of impedance shaping on the remote perception of soft tissues for applications with macro–micro-interactions. They included an impedance-shaping compensator in the generalized teleoperation architecture and conducted psychophysical experiments. They claim that the kinesthetic perception of a teleoperation controller with force cues from the environment is higher than that of only position-information-based teleoperation controller [16].

In our previous studies [17], [18], we argued that haptic cues should be transmitted using a modified framework based on the enhancement of the perceptual sensitivity of the human operator. This framework followed the human-centered design paradigm and was different from the traditional transparency-based scheme. We named this the *perception-based method* for haptic teleoperation systems [18]. Psychophysical experiments were conducted in [18] to evaluate the proposed perception-based method with the previous perception oriented methods, such as the ones by Cavusoglu *et al.* [19] and by Malysz and Sirouspour [15]. However, there has not been any analytical comparison of fundamental performance and any rigorous human-centered comparison studies between the most widely used conventional method (i.e., transparency-based method) and the perception-based method. To achieve this, this paper extended the previous study [17] by presenting in-depth analyses and discussions regarding a teleoperator's fundamental perceptual performance with the perception- and transparency-based methods.

B. *Objective and Organization*

In this paper, we rigorously compare the perception-based method with the transparency-based method. We evaluate the performance of the control methods using theoretical analysis tools and psychophysical experiments. In addition to the two control methods, the contribution of two haptic cues (positions and forces) from the remote environments on the human operator's perceptual sensitivity is also evaluated [20]. In the analytical study, hybrid matrix formulation [21] is adopted to model the control methods. The transmitted impedance and its sensitivity functions are derived from the hybrid matrix and are used for an in-depth frequency-domain analysis. Psychophysical experiments are then employed to evaluate the designed controllers based on the control methods with two haptic cues.

The structure of this paper is as follows. In Section II, we review the bilateral teleoperation control, including the transparency- and perception-based methods, and present a controller design based on these methods. Following this, a theoretical analysis of the designed controllers is presented in Section III. Then, in Section IV, a psychophysical study using human-centered evaluation and comparison of the controllers is presented. Finally, this paper ends with conclusion and future direction.

II. Bilateral Controller Design

A. *Generalized 4C Control Architecture*

The control architectures of bilateral teleoperation systems are classified based on the exchanged information (e.g., position and force) between master device and slave robot. The generalized four-channel (4C) control architecture is widely used to represent the teleoperator's control architecture, which is presented in Fig. 1.

1) Control Method and Haptic Cue: The haptic teleoperation system shown in Fig. 1 consists of the operator (Z_h), the master (Z_m), the slave (Z_s), the environment (Z_e), and the bilateral controller. There are four bilateral controllers, including two position controllers (i.e., C_1 and C_4) and two force controllers (i.e., C_2 and C_3). Additionally, there are local feedback controllers C_m and C_s for the master and the slave, respectively, and local feedforward controllers of the master and the slave, which are denoted as C_6 and C_5, respectively. The exogenous control inputs generated by the human operator are denoted as f_h^*. In addition, $\dot{x}_m, f_m \in \Re^3$ and $\dot{x}_s, f_s \in \Re^3$ represent velocities and forces of the master and the slave, respectively.

Note that a proportional–derivative (PD) controller is generally employed for the position controllers because in practice, acceleration signals are too noisy. The bilateral controllers are given by $C_i = K_i^D + K_i^P/s, i = m, s, 1, 4$, where $K_i^D, K_i^P \in$

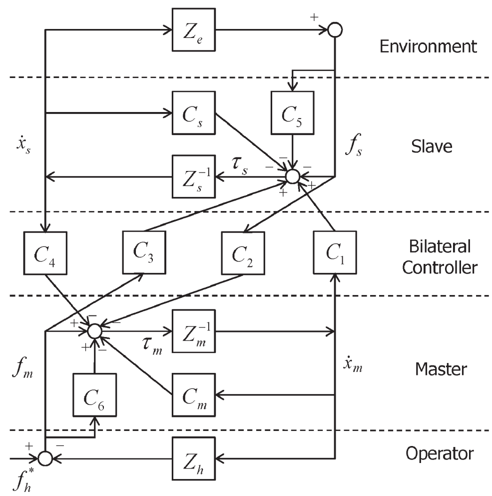

Fig. 1. Generalized 4C control architecture.

$\Re^{3\times3}$ are the positive definite/symmetric derivative and proportional gain matrices. A symmetric scalar gain matrix $K_f \in \Re^{3\times3}$ is defined for the force controllers such as C_2, C_3, C_5, and C_6. Finally, the control inputs to the master and slave, i.e., τ_m and τ_s, respectively, are determined as a function of the bilateral controller and the local controller.

In this paper, methods for the design of bilateral controllers (i.e., *design of control parameters* for C_1, C_2, C_3, and C_4) are referred to as *control methods*, whereas cues for the selection of information channels for bilateral controllers (i.e., *selection of controllers* among C_1, C_2, C_3, and C_4) are named as *haptic cues*. Generally, force information from the master is not transmitted in order to maintain high performance (e.g., low inertia) of the haptic device and to keep low cost [9], [22]. Motivated by this practical perspective, we evaluate two kinds of haptic cues in this paper, viz.: the position–position (PP where $C_2 = C_3 = 0$) and the force–position (FP where $C_4 = C_5 = 0$) control architectures. Although these two control architectures show inferior performance than the 4C control architecture [22], those architectures are still widely accepted in many practical cases, including [23], [24], and [25]. Moreover, those two control architectures have their unique characteristics in terms of stability robustness and haptic sensitivity from each other, and this is why it is very interesting to compare two different control architectures.

2) Hybrid Matrix Representation: It is well known that a two-port network theory is a useful tool for analyzing the system performance and stability of the teleoperation systems [21]. By using the two-port network approach, it is possible to analyze the teleoperation systems without any consideration of human operator and environment. This helps in the analysis because human-operator and environment dynamics are very difficult to model accurately due to their high-nonlinearity and time-varying characteristics.

Definition 1: The input–output relation of the bilateral teleoperation system shown in Fig. 1 is represented using *hybrid matrix* formulation, as given by

$$\begin{bmatrix} f_m \\ -\dot{x}_s \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \begin{bmatrix} \dot{x}_m \\ f_s \end{bmatrix}. \tag{1}$$

Each component in the hybrid matrix is defined as $h_{11} = (f_m/\dot{x}_m)|_{f_s=0}$, $h_{12} = (f_m/f_s)|_{\dot{x}_m=0}$, $h_{21} = -(\dot{x}_s/\dot{x}_m)|_{f_s=0}$, and $h_{22} = (-\dot{x}_s/f_s)|_{\dot{x}_m=0}$. Therefore, h_{11} and h_{21} represent the teleoperator's performance in free motion (i.e., the slave is not in contact with the environment), whereas h_{12} and h_{22} represent the performance in constrained motion (i.e., the master device is fixed). Finally, the transmitted impedance to the operator Z_{to}, through the bilateral controllers, is obtained in the form of the hybrid matrix as

$$\begin{aligned} Z_{\mathrm{to}} &= \frac{f_m}{\dot{x}_m} \\ &= \frac{h_{11} + (h_{11}h_{22} - h_{12}h_{21})Z_e}{1 + h_{22}Z_e}. \end{aligned} \tag{2}$$

B. Control Methods

We selected two most relevant control methods, i.e., the transparency-based method [8], [9], which is the most conventional controller in bilateral teleoperation, and the perception-based method [18], which was proposed by the authors to enhance the teleoperator's perceptual performance from the human-centered design perspective. Hereafter, we briefly review these control methods and refer the reader to [8], [9], and [18] for further details.

1) Transparency-Based Method: Transparency is considered as a fundamental goal of teleoperation systems. It is generally defined as $Z_{\mathrm{to}} = Z_e$ for perfect transparency, where Z_{to} represents the transmitted impedance to the operator via bilateral controllers. If perfect transparency is achieved, the operator can perceive the environment impedance accurately.

Definition 2: Transparency-optimized control law is defined as in (3) for bilateral teleoperation systems [8], [9]

$$\begin{cases} C_1 = Z_s + C_s \\ C_2 = 1 + C_6 \neq 0 \\ C_3 = 1 + C_5 \neq 0 \\ C_4 = -Z_m - C_m. \end{cases} \tag{3}$$

Theorem 1: Perfect transparency is achieved using the transparency-optimized control law, if time delay between the master and the slave is negligible.

Proof: Please refer to [8]. ■

Remark 1: Force measurements from the master and slave sides (i.e., the use of C_3 and C_2, respectively) are essential to achieve perfect transparency. Practically, it is very difficult to implement (3) because accurate dynamic models of the master and the slave (i.e., Z_m and Z_s) are needed to design C_4 and C_1, respectively.

2) Perception-Based Method: In psychophysics [26], human's perceptual sensitivity is quantitatively defined using the absolute threshold (AL) and the difference threshold (DL) metrics, which represent the smallest amount of stimulus to produce a sensation in a detection task and the smallest amount of stimulus change required to produce a change in sensation in a discrimination task, respectively. The just-noticeable difference

(JND) is defined as the linear relationship between the DL and the stimulus intensity, defined in

$$JND = \frac{DL}{\phi_0} \tag{4}$$

where ϕ_0 is the initial intensity of the stimulus. Note that lower AL and DL or JND values represent easier detection and discrimination, respectively.

Based on the AL and JND concepts, the perception-based method was proposed as follows. The perception-based method is designed by maximizing the performance index for kinesthetic perception defined in Definition 3.

Definition 3: Kinesthetic perception index is defined as follows, which quantifies detection and discrimination abilities of a human operator in bilateral teleoperation systems [17], [18]

$$PI_{\text{perception}} := \left(1 - \frac{1}{1+M_{\text{det}}}\right)\left(1 - \frac{1}{1+M_{\text{dis}}}\right)$$
$$\text{where} \begin{cases} M_{\text{det}} := \left\| W_{\text{perception}} \frac{Z_{\text{to}}}{Z_e} \Big|_{Z_e = \widetilde{Z}_e} \right\|_2 \\ M_{\text{dis}} := \left\| W_{\text{perception}} \frac{\Delta Z_{\text{to}}/Z_{\text{to}}}{\Delta Z_e/Z_e} \Big|_{Z_e = \widetilde{Z}_e} \right\|_2 \end{cases} \tag{5}$$

where $W_{\text{perception}}$ is a low-pass weighting function, and $\widetilde{Z}_e$ is a nominal environmental impedance value.

$PI_{\text{perception}}$ measures both the ratio of the transmitted impedance to the environmental impedance and the sensitivity of the relative change of the transmitted impedance to relative changes in the environmental impedance via M_{det} and M_{dis}. Please note that the metric of the detection ability M_{det} is based on the concept of AL to represent how much impedance the operator can perceive. In addition, M_{dis}, which is the metric for the discrimination ability, is based on the concept of JND to represent how much relative change of impedance the operator can perceive. The performance index for the kinesthetic perception $PI_{\text{perception}}$ is a nonlinear combination of M_{det} and M_{dis}. This index becomes zero as $M_{\text{det}} \to 0$ or $M_{\text{dis}} \to 0$, whereas it becomes unity as $M_{\text{det}} \to \infty$ and $M_{\text{dis}} \to \infty$.

There are two constraints in the perception-based method for the optimization of $PI_{\text{perception}}$. These constraints are defined to guarantee good position tracking and system stability. The position tracking constraint is given in the form of hybrid matrix, as defined in Definition 4. Conditions for system stability are derived using Llewellyn's absolute stability criteria [9], [21] for a teleoperation system with $Z_m = M_m s$, $Z_s = M_s s$, $C_m = K_m^D + K_m^P/s$, and $C_s = K_s^D + K_s^P/s$, where $M_m, M_s \in \Re^{3\times 3}$ are the positive-definitive/symmetric inertia matrices of the master and the slave, respectively.

Definition 4: Position tracking index is defined as

$$PI_{\text{tracking}} := \left\| W_{\text{tracking}} \frac{1}{h_{11}} (1 - h_{21}) \right\|_2 \tag{6}$$

where W_{tracking} is a low-pass weighting function.

Lemma 1: Let us assume that $C_5 = C_6 = 0$ with no time delay between the master and the slave. The PP control architecture for the teleoperation system is absolutely stable for all frequency ranges if $K_m^D \geq 0$, $K_s^D \geq 0$, and $K_m^P K_s^D - K_s^P K_m^D = 0$ with $C_1 = C_s$ and $C_4 = -C_m$.

Proof: Please refer to [18]. ■

Lemma 2: Let us assume that $C_5 = C_6 = 0$ with no time delay between the master and the slave. The force–position control architecture for the teleoperation system is absolutely stable for all frequency ranges if $K_s^P \leq 0$, $K_m^D \geq 0$, and $K_s^D = 0$ with $C_1 = C_s$ and $C_2 = 1$.

Proof: Please refer to [18]. Please note that any negative controller gain signifies that the controller is a reverse-acting controller. In other words, if the error in the measured variable is large, the control input is lowered. These kinds of reverse-acting controllers are used in many practical applications. ■

The control scheme is, finally, formulated as a multiconstrained optimization problem where the objective is to maximize the performance index for the control objective while minimizing position tracking error and guaranteeing stability conditions as defined in Definition 5.

Definition 5: Perception-optimized control law is defined as (7) with the position tracking index defined in (4) and the stability conditions presented in Lemmas 1 and 2

$$\begin{array}{lll} \underset{C_i, i=1,\ldots,6}{arg\max} & PI_{\text{perception}} & \\ \text{subject to} & \text{minimize} & PI_{\text{tracking}} \\ & \text{satisfying} & \text{stability conditions.} \end{array} \tag{7}$$

Remark 2: The optimization problem to maximize $PI_{\text{perception}}$ is nonconvex in nature, and hence, convergence to the global optimum is not guaranteed. However, proper selection of models and criteria and a varied range of model parameters with repetitive simulations can make the local optimum very close to the global optimum, and the results so obtained can be satisfactory for our cases [18], [19]. For any basic optimization or search procedure, whenever the algorithm gets stuck in local minima/maxima, it is a general technique to restart the optimization procedure using a different set of random points. In our case, these points are the model parameters. The basic idea is that repeated simulations with a varied range of parameters can help the algorithm to converge to a global optimum due to different model parameters as starting points. We try to make this repeated search process more intelligent by choosing proper selection of criteria and model parameters instead of just randomizing it. This is possible due to our prior knowledge of the domain.

Remark 3: The selection of the cutoff frequency ω_c for $W_{\text{perception}}$ and W_{tracking} depends on the specific application of scaled teleoperation systems. In the case of tactile feedback, ω_c for W_{tracking} should be more than 1 kHz. However, it is enough to obtain about 20–100 Hz for kinesthetic force feedback [27], [28]. Note that ω_c for $W_{\text{perception}}$ was recommended as about 40 Hz in [27] based on psychophysical studies. On the other hand, as the normal tremor of a human hand occurs at 8–12 Hz [28], the cutoff frequency for W_{tracking} is recommended to be less than 8 Hz. In addition, 2 Hz is sometimes considered as reasonable in surgical applications because, in general, surgeons carry out surgeries with very slow and carefully controlled movements [29].

Remark 4: In this paper, a nominal environmental impedance model $\widetilde{Z}_e$ was used for the optimization of the perception-based method, as shown in (5). Therefore, a more accurate

TABLE I
SUMMARY OF DESIGNED BILATERAL CONTROLLERS

Control Method	C_m	C_s	C_1	C_2	C_3	C_4
Transparency-based PP	$2.5 + 50/s$	$15 + 330/s$	$15 + 330/s$	0	0	$-2.5 - 50/s$
Perception-based PP	$3.46 + 91.47/s$	$10 + 264.44/s$	$10 + 264.44/s$	0	0	$-3.46 - 91.47/s$
Transparency-based FP	$2.5 + 50/s$	$15 + 330/s$	$15 + 330/s$	1	0	0
Perception-based FP	$3.73 + 100/s$	$18.42 + 332.13/s$	$10 + 264.44/s$	1	0	0

knowledge of environmental impedance could enhance the performance of the perception-based method. In addition, the perception-based method might not work adaptively with sudden and significant changes in the environment impedance. An online estimation of environmental impedance and its application to the perception-based method should be investigated for a better performance. Please refer to [11] in this regard.

C. Controller Design

The control parameters of the two control methods, which include the PP and FP control architectures, are designed in this section. For this, the master device impedance is modeled as $Z_m = 0.072s$, which is estimated from the PHANToM haptic device because we used the PHANToM as the master in both the analysis and the experiment. It is assumed that a PHANToM device with a small surgical tool (300 g) is used as the slave manipulator, whose impedance is given by $Z_s = 0.372s$.

A fair design of controllers for both the transparency-based method and the perception-based method is required for their mutual comparison purposes. First, we designed the local position controllers in master and slave C_m and C_s, based on the dynamics of the haptic device and the slave manipulator, respectively. The bilateral controllers are then designed based on C_m and C_s by using the transparency-optimized control law in (3) and the perception-optimized control law in (7). The initial values of the master and slave local position controllers are chosen the same for the transparency-based method and for the optimization of the control parameters of the perception-based method. We designed the local force controllers (i.e., C_5 and C_6) as zero in either case.

For the transparency-based method, the initial values of the master and slave local position controllers are chosen in proportion to the values proposed in [9]. The parameters are then tuned by a grid search for all possible controller combinations that offer the required position tracking and analytical stability to get the values before optimization. The tuned parameters of the local position controllers were therefore obtained as $C_m = 2.5 + 50/s$ and $C_s = 15 + 330/s$. The bilateral controllers (i.e., C_1, C_2, C_3, and C_4) were then designed using (3).

The control parameters for the perception-based method were, however, obtained after optimization using (7) as the multiconstrained optimization problem. The stability conditions are applied to run the optimization problem, which are presented in Lemmas 1 and 2. A steepest descent algorithm [30] has been used to optimize the control parameters. As a summary, the designed controllers are presented in Table I. Note that the cutoff frequencies of $W_{\text{perception}}$ and W_{tracking} are selected as 40 and 8 Hz, respectively, according to Remark 3. In addition, the effect of the cutoff frequencies on $PI_{\text{perception}}$ and PI_{tracking} was presented in Section III-B.

III. Analytical Study of Bilateral Controllers

In this section, we analyze theoretical performance of the transparency-based method and the perception-based method using hybrid matrix formulation. Although we can analyze the performance of the controllers using hybrid matrix (i.e., in the time domain), it is still necessary to analyze the hybrid matrix in the frequency domain because perceptual sensitivity of a human is highly related to it. Moreover, it is difficult to compare the performance of perception-based control with that of transparency-based control without a numerical analysis method because they practically differ only in the values of control gains.

A numerical simulation is therefore performed for frequency-domain analysis of the designed controllers designed in Section II-C. In the simulation, the human operator and the environment are modeled as $Z_h = 1.67s + 11.72 + 196.56/s$ and $Z_e = 1 + 500/s$, respectively, based on [31] and [32].

A. Hybrid Matrix Analysis

Hybrid matrices for the PP and FP control architectures are derived from the teleoperator in Fig. 1 using (1). The derived hybrid matrices are

$$H^{\text{PP}} = \begin{bmatrix} h_{11}^{\text{PP}} & h_{12}^{\text{PP}} \\ h_{12}^{\text{PP}} & h_{22}^{\text{PP}} \end{bmatrix} := \begin{bmatrix} \frac{Z_{\text{cm}} Z_{\text{cs}} + C_1 C_4}{Z_{\text{cs}}(1+C_6)} & \frac{-C_4(1+C_5)}{Z_{\text{cs}}(1+C_6)} \\ \frac{-C_1}{Z_{\text{cs}}} & \frac{1+C_5}{Z_{\text{cs}}} \end{bmatrix} \tag{8}$$

$$H^{\text{FP}} = \begin{bmatrix} h_{11}^{\text{FP}} & h_{12}^{\text{FP}} \\ h_{12}^{\text{FP}} & h_{22}^{\text{FP}} \end{bmatrix} := \begin{bmatrix} \frac{Z_{\text{cm}}}{1+C_6} & \frac{C_2}{1+C_6} \\ -\frac{C_1}{Z_{\text{cs}}} & \frac{1+C_5}{Z_{\text{cs}}} \end{bmatrix} \tag{9}$$

where $Z_{\text{cm}} = Z_m + C_m$ and $Z_{\text{cs}} = Z_s + C_s$, for the PP and FP control architectures, respectively.

The bode plots of the hybrid matrices in (8) and (9) with the controllers in Table I are presented in Fig. 2 for the transparency- and perception-based PP and FP controllers. Detailed analysis of the bode plots is presented in the following sections.

1) h_{11}: Theoretically, h_{11} means the impedance applied by a human operator when he/she manipulates an unconstrained environment. The smaller h_{11} is, the better is the performance of the teleoperator in free motion. For the PP control, h_{11}^{PP} goes to zero if we can implement the transparency-optimized law in (3) accurately. However, it is not zero because we designed the bilateral control as the PD-type controller. It becomes Z_{cm} for FP control. It is easy to notice that $h_{11}^{\text{FP}} > h_{11}^{\text{PP}}$, which means that theoretically, the FP control shows worse performance than the PP for free-motion impedance.

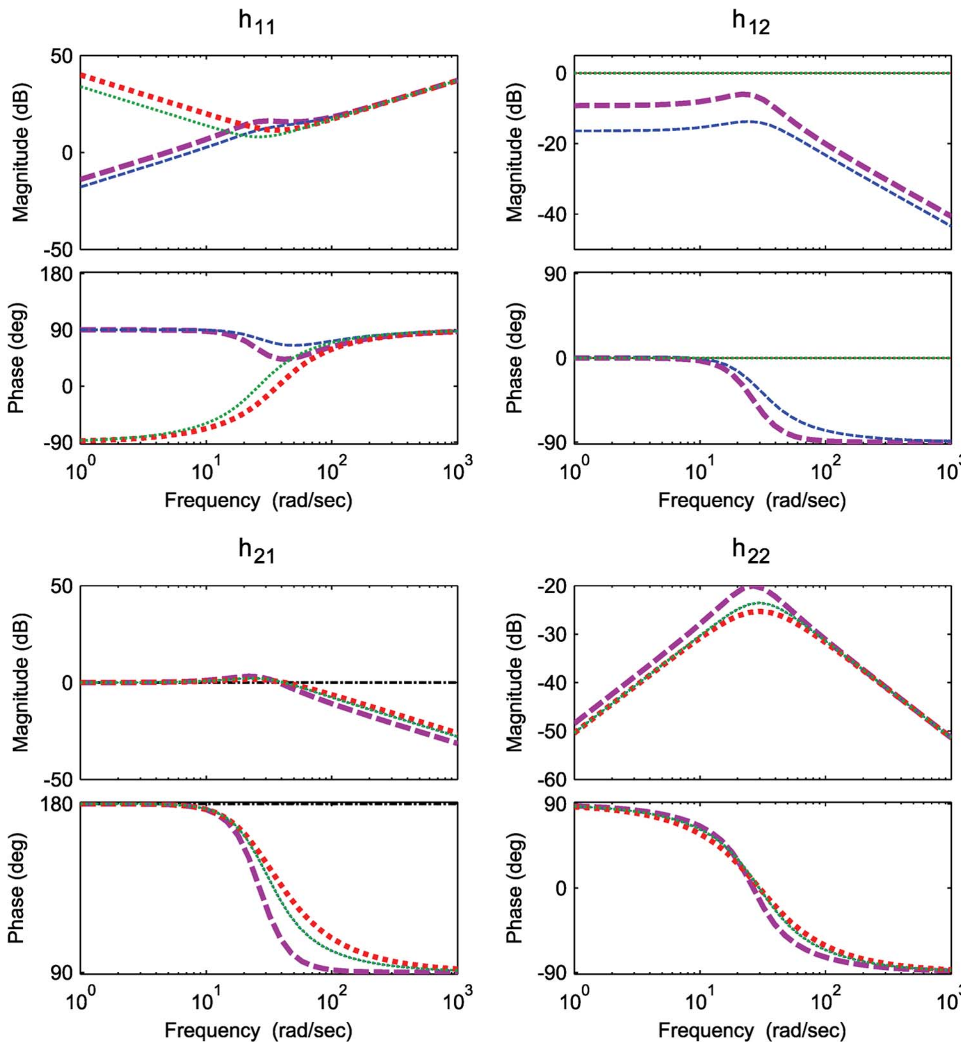

Fig. 2. Bode plot of hybrid matrix for transparency-based [(blue dash line) PP control; (green dot line) FP control] and perception-based [(magenta bold dash line) PP control; (red bold dot line) FP control] control methods. The ideal values (i.e., $h_{11} = h_{22} = 0$ and $h_{12} = -h_{21} = 1$ for perfect transparency case) were plotted in black dash-dot line. Note that h_{12}^{FP} of the transparency- and perception-based methods are the same and $h_{21}^{\mathrm{PP}} = h_{21}^{\mathrm{FP}}, h_{22}^{\mathrm{PP}} = h_{22}^{\mathrm{FP}}$ for the transparency-based method.

This is evident also from the simulation result shown in Fig. 2, which shows that h_{11}^{FP} has higher impedance than h_{11}^{PP}, particularly in low frequencies. It is noticeable that h_{11} of the perception-based method shows higher impedance level than that of the transparency-based method in both PP and FP cases. This could be considered as a performance tradeoff between the easiness in manipulation and the higher force perception.

2) h_{12}: For the both transparency- and perception-based FP controls, h_{12}^{FP} becomes one, whereas it becomes $-C_4/Z_{\mathrm{cs}}$ for both the PP ones. Therefore, it is $h_{12}^{\mathrm{FP}} > h_{21}^{\mathrm{PP}}$ regardless of the control method, and it results in a better perception of the remote environments because, theoretically, h_{12} represents the teleoperator's force tracking performance in contact tasks. This signifies that higher h_{12} makes the change of master force more sensitive to the change of the slave one.

The simulation study also shows the same result like $h_{12}^{\mathrm{FP}} > h_{12}^{\mathrm{PP}}$ for all frequency ranges, as shown in Fig. 2. In addition to this, as we aimed in the design of the perception-based method, the perception-based PP control shows higher sensitivity than the transparency-based one.

3) h_{21}: The velocity tracking ability in free motion (i.e., unconstrained motion) could be evaluated using h_{21}. Theoretically, $h_{21}^{\mathrm{PP}} = h_{21}^{\mathrm{FP}}$, as shown in (8) and (9).

It is also shown that $h_{21}^{\mathrm{PP}} \simeq h_{11}^{\mathrm{FP}} \simeq 1$ in low frequencies under 30 rad/s for the transparency- and perception-based methods from the simulation study shown in Fig. 2. This means that all controllers provide good velocity tracking performance. This is because both control methods are optimized under velocity tracking constraints. The difference in h_{21} between the transparency-based method and the perception-based method is not significant.

4) h_{22}: Finally, h_{22} is interpreted as an admittance of the slave when the master holds its position. The small magnitude of h_{22} is therefore better for providing higher impedance in terms of back-drivability. Similar to h_{21}, theoretically, it is $h_{22}^{\mathrm{PP}} = h_{22}^{\mathrm{FP}}$. However, practically, the perception-based method shows better performance than the transparency-based method regardless of the haptic cue as represented in Fig. 2.

In summary, the perception-based method shows better performance in contact (i.e., constrained) motion than the

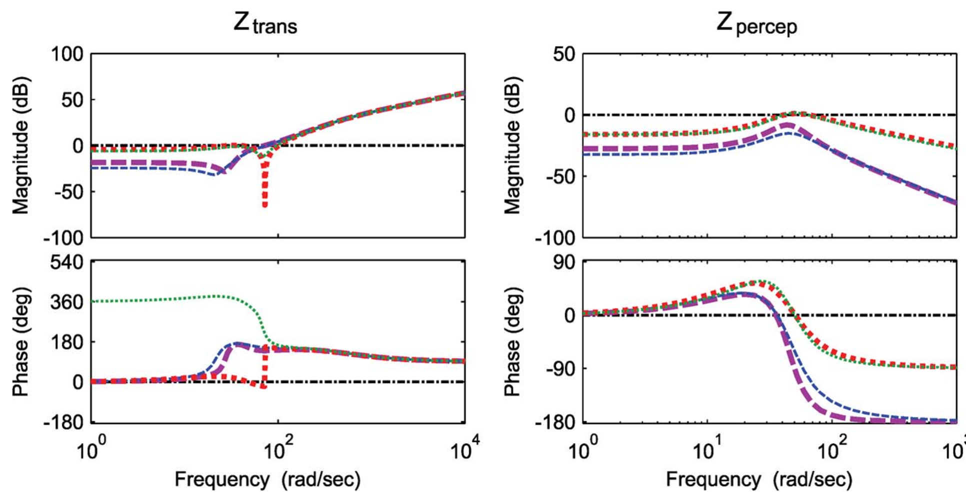

Fig. 3. Bode plot of transparency and perception performances for transparency-based [(blue dashed line) PP control; (green dot line) FP control] and perception-based [(magenta bold dashed line) PP control; (red bold dot line) FP control] control methods. The ideal values (i.e., $Z_{\text{trans}} = Z_{\text{percep}} = 1$ for perfect transparency case) were plotted in black dash-dot line.

transparency-based method, and it shows the opposite result in free-motion case. In the same manner, the FP control has better performance in contact motion than the PP control. From this analytical study, we can conclude that the teleoperation systems using the perception-based method shows better perception of the remote environments. In addition, the force cues contribute to better perception.

Remark 5: There is a tradeoff in performance between contact motion and free motion. The teleoperator's perception performance is more important in contact motion. Hence, for perception-based method, it could compensate its lower performance for free motion by a better perception performance in contact motion.

B. Transparency and Perception Analysis

The transparency performance is formulated using (2) as follows:

$$\begin{aligned} Z_{\text{trans}} &:= \frac{Z_{\text{to}}}{Z_e} \\ &= \left[\frac{h_{11} + (h_{11}h_{22} - h_{12}h_{21})Z_e}{1 + h_{22}Z_e}\right] Z_e^{-1} \\ &= \frac{h_{11}h_{22} - h_{12}h_{21} + h_{11}Z_e^{-1}}{(1 + h_{22}Z_e)Z_e}. \end{aligned} \tag{10}$$

For the derivation of the perception performance, we assumed that $\Delta Z_{\text{to}}/\Delta Z_e \cong dZ_{\text{to}}/dZ_e$ because $\Delta Z_e \rightarrow 0$ with high sampling rate. Therefore, the detailed derivation, based on (2) and (5), is given in the following equations using the hybrid matrix:

$$\begin{aligned} Z_{\text{percep}} &:= \frac{\Delta Z_{\text{to}}}{\Delta Z_e} \\ &\cong \frac{dZ_{\text{to}}}{dZ_e} \\ &= \frac{-h_{12}h_{21}}{(1 + h_{22}Z_e)^2}. \end{aligned} \tag{11}$$

Then, Z_{trans} and Z_{percep} for the PP and FP controls are represented as (12) and (13) by applying (8) and (9) to (10) and (11), respectively. Please note that, theoretically, Z_{trans} and Z_{percep} become unity for the perfect transparency case (i.e., $Z_{\text{to}} = Z_e$)

$$\begin{cases} Z_{\text{trans}}^{\text{PP}} := \frac{Z_{\text{cm}}Z_{\text{cs}} + C_1C_4 + (1+C_5)Z_{\text{cm}}Z_e}{(1+C_6)[Z_{\text{cs}} + (1+C_5)Z_e]Z_e^2} \\ Z_{\text{trans}}^{\text{FP}} := \frac{Z_{\text{cm}}Z_{\text{cs}} + [C_1C_2 + (1+C_5)Z_{\text{cm}}]Z_e}{(1+C_6)[Z_{\text{cs}} + (1+C_5)Z_e]Z_e^2} \end{cases} \tag{12}$$

$$\begin{cases} Z_{\text{percep}}^{\text{PP}} := \frac{-C_1C_4(1+C_5)}{(1+C_6)[Z_{\text{cs}} + (1+C_5)Z_e]^2} \\ Z_{\text{percep}}^{\text{FP}} := \frac{C_1C_2Z_{\text{cs}}}{(1+C_6)[Z_{\text{cs}} + (1+C_5)Z_e]^2}. \end{cases} \tag{13}$$

Theoretically, it is shown in (10) that smaller h_{11} and h_{22} values are needed for better transparency. The perception-based method therefore shows worse performance for transparency, but it is expected to provide higher feedback of environmental impedance. FP control behaves in a similar way. However, in case of perception performance, higher h_{12} and h_{21} will result in better performance, and therefore, the perception-based method has better perception performance than the transparency-based one. This is also true for the FP and PP control schemes.

These analyses are also verified using simulation studies. Simulation results of the transparency and perception performances (i.e., Z_{trans} and Z_{percep}) using the derived formulations in (12) and (13) are presented in Fig. 3.

As shown in Fig. 3, Z_{trans} of the FP control architecture is greater than that of the PP control architecture. In addition, the perception-based method generates the higher impedance than the transparency-based method, as we analyzed previously. In Fig. 3, it is noticeable that the perception-based method enhances the perceptual sensitivity more when compared with the transparency-based method, particularly for the PP control case. In addition, in the FP control architecture, the perception-based method has better perception performance than the transparency-based method. The magnitude difference in Z_{percep} of the perception- and transparency-based PP controls is about 5 dB (i.e., means 80% enhancement). Therefore, we can expect better perception enhancement for the FP control architecture.

As noted in Remark 3, the selection of the cutoff frequencies for $W_{\text{perception}}$ and W_{tracking} could affect the perception and

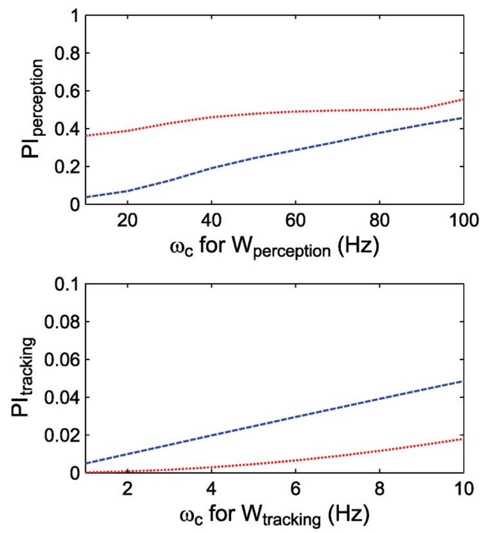

Fig. 4. Perception and tracking performance of perception-based (blue dashed line) PP and (red dot line) FP control methods with various cutoff frequencies for $W_{\text{perception}}$ and W_{tracking}.

tracking performances, respectively. We simulated $PI_{\text{perception}}$ and PI_{tracking} of the perception-based PP and FP controls in Table I with various ω_c (i.e., 10–100 Hz and 1–10 Hz for $W_{\text{perception}}$ and W_{tracking}, respectively) to study the effect of ω_c. The results are presented in Fig. 4. As expected, both $PI_{\text{perception}}$ and PI_{tracking} were increased with increasing ω_c. Therefore, the cutoff frequency should be increased for better perception and decreased for tracking performance. There will be high-frequency noises (e.g., the force information that a human cannot perceive) if high ω_c is selected for $PI_{\text{perception}}$. In the case of PI_{tracking}, tracking performance will be less robust to high-frequency motions if low ω_c is selected for better tracking performance. In summary, ω_c for $W_{\text{perception}}$ and W_{tracking} should be designed and selected according to the application of teleoperation control.

IV. Psychophysical Study of Bilateral Controllers

In this section, psychophysical experiments are conducted for the human-centered evaluation of control methods and haptic cues.

A. Participants

For the psychophysical experiment (i.e., the perceptual sensitivity test), six subjects of different backgrounds and gender, falling under the age group of 21 to 29 years, are chosen to maintain the generality of the experiment. All of the subjects were right-handed by self-report. The experiment was conducted in accordance with the requirements of the Helsinki Declaration.

B. Apparatus

The experimental setup of the perceptual sensitivity test is shown in Fig. 5. The human subject manipulates the stylus-type PHANToM Premium used as a haptic master device in the experiment. The virtual slave manipulator is interacting with virtual walls as the environment. The haptic update rate has been fixed at 1 kHz for the PHANToM haptic device. In the experiment, the transparency- and perception-based methods designed in Section II-C (i.e., Table I) are implemented.

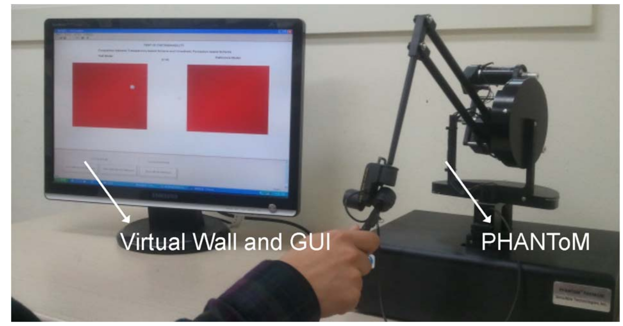

Fig. 5. Setup for psychophysical experiment showing a human operator manipulating a haptic device to interact with a remote environment consisting of virtual walls.

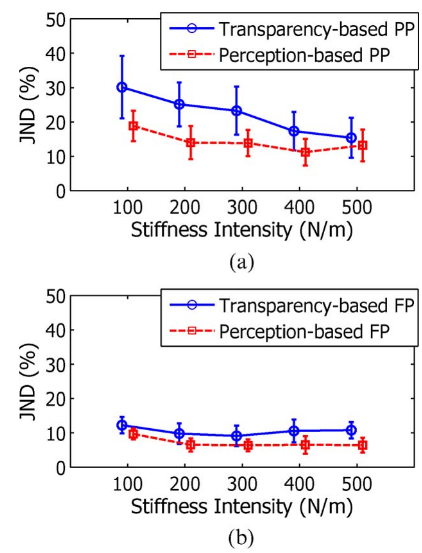

Fig. 6. Variation of JND with control method and architecture. This figure is illustrated using the data of Table. The perception-based method with force cues from the environment shows the best performance in the perceptual sensitivity for all references. (a) PP control architecture. (b) FP control architecture.

C. Method

The experiment is designed based on the *method of limits* [26]. There are two virtual walls, as shown in Fig. 5, one of which is called the test model and the other is named as the reference model. Each subject is asked to respond if he or she can discriminate between the test model and the reference model. Five reference models are chosen uniformly among the impedance models such as $1 + 100/s$, $1 + 200/s$, $1 + 300/s$, $1 + 400/s$, and $1 + 500/s$ (i.e., stiffness is the stimulus).

In detail, each subject has to perform the experiments for five different cases where each case is divided into two series such as ascending series and descending series, which are generally defined in the method of limits. The five cases differ according to the different lower limits for the ascending series and different upper limits for the descending series. The step size is varied from case to case to rule out any possibility of intelligent guesses. In addition, the cases and the series are all randomized to minimize the human response bias (e.g., learning effect).

TABLE II
QUANTITATIVE EVALUATION OF THE EFFECT OF CONTROL METHOD ON PERCEPTUAL SENSITIVITY

Controller	Enhancement Ratio R	Statistical Analysis	
		$F_{1,58}$	p-value
Transparency-based PP vs. Perception-based PP	36.14%	5.11	< 0.05
Transparency-based FP vs. Perception-based FP	32.38%	5.29	< 0.001

All the ten trials (i.e., five cases multiplied by two series) are repeated for the transparency-based method and the perception-based method for fair comparison. These are repeated for two kinds of teleoperation control architectures (i.e., the PP and FP controllers). Therefore, each subject has to perform 40 trials (i.e., 10 trials $\times$ 2 control methods $\times$ 2 control architectures) in the experiment.

The subjects were given a detailed tutorial about the experiment in the beginning and were provided a small training session with the PHANToM to get them familiarized with that. Please refer to [18] for more details because, in this paper, we used the same experimental design and method with [18].

D. Data Analysis

The DL of each reference was taken as half of the difference between the mean of the lower limens and the mean of the upper limens. The JND was then computed from diving DL by the intensity of the reference stiffness. The JND is expressed as percentage in this paper.

The two-way analysis of variance test (ANOVA) was used to check whether the difference of DL and JND among controllers was significant. The tests were performed with a confidence level of 95%. In other words, a p-value, which is the probability of obtaining the test statistic, of less than 0.05 was considered to be significant. Before running the two-way ANOVA tests, the Kolmogorov–Smirnov test was performed to check if the experimental data followed a standard normal distribution. When the two-way ANOVA demonstrated statistical significance for the control methods or control architectures, we employed the one-way ANOVA test (within-subject design) followed by a post hoc Tukey's test of honestly significant difference to further investigate this significance.

E. Result and Discussion

Six subjects completed the perceptual sensitivity test using the PHANToM while interacting with the virtual wall. The JND is calculated using the experimental results of the DL and the impedance intensity of references. The calculated experimental results are expressed in the form of JND and are shown in Fig. 6. Please note that the experimental results show similar results with previous studies about the JND for human's stiffness perception (i.e., 8%–22%) [2], [33].

To compare the perceptual sensitivity of each control method, the ANOVA tests have been performed at the confidence level of 95%. Experimental data for all the four controllers passed the Kolmogorov–Smirnov test as $p < 0.0001$ for JND. We can therefore perform the ANOVA test.

First, a two-way ANOVA test is conducted to formally determine if there were statistically significant differences between the perceptual sensitivities for the two types of control methods and haptic cues. The results indicate that both the chosen control methods and obtained haptic cues were statistically significant factors for the perceptual sensitivity as $p < 0.001$ $(F_{1,116} = 23.97)$ and $p < 0.005$ $(F_{1,116} = 21.18)$, respectively. Then, one-way ANOVA tests are performed to analyze the difference between the controllers statistically, the results of which are given in Table II.

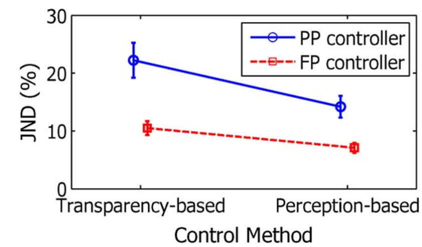

Fig. 7. Summary of experimental results in the form of JND. The perceptual sensitivity is enhanced with the perception-based control by decreasing the JND for both the PP and the FP control architectures.

1) Effect of Control Method: Fig. 6 shows the variation of the JND with increasing environment stiffness. As the environment stiffness increases, the JND decreases, as shown in Fig. 6. The decrease is more for the PP architecture than that for FP. In any particular architecture, the transparency-based control method shows steeper decrease, as compared to that of the perception-based one. The JND for all stiffness intensities is summarized in Fig. 7 to get an overall behavior of the various control methods, which show the efficacy of the perception-based method in increasing the perceptual sensitivity (in the form of the JND) of human beings.

This finding is also statistically analyzed as given below. Quantitatively, there is a 36.14% enhancement in the perception ability for the PP control architecture and 32.38% enhancement for the FP control architecture, as shown in Table II, when the difference is expressed in terms of JND. However, the quantitative enhancement is sensitive to the initial controller values chosen. It is also be shown that the p-value for the enhancement of perceptual sensitivity for PP control architecture is $p < 0.05$ $(F_{1,58} = 5.11)$, whereas the p-value for the enhancement in FP controller is $p < 0.001$ $(F_{1,58} = 5.29)$, which shows that the enhancement of the perceptual sensitivity is highly significant.

2) Effect of Haptic Cue: It can be noticed that irrespective of control methods chosen, the FP control architecture always shows better perceptual sensitivity than that of PP in Fig. 7. In addition, for each of these control architectures, the perception-based method always enhances the perceptual sensitivity by lowering the JND, as compared to that of the transparency-based method.

We can see that there is a 52.81% enhancement of the perceptual sensitivity if the force cues are present due to the FP control architecture when compared to the scenario when the force cues are absent as for the PP control architecture for the transparency-based method as summarized in Table III. However, for the perception-based method, the enhancement of the perceptual sensitivity is 50.03% when force cues are present, as

TABLE III
QUANTITATIVE EVALUATION OF THE EFFECT OF HAPTIC CUE ON PERCEPTUAL SENSITIVITY

Controller	Enhancement Ratio R	Statistical Analysis $F_{1,58}$	Statistical Analysis p-value
Transparency-based PP vs. Transparency-based FP	52.81%	12.99	< 0.001
Perception-based PP vs. Perception-based FP	50.03%	12.01	< 0.001

compared to when force cues are absent. The p-value for the enhancement with force cues for the transparency-based method is $p < 0.001$ ($F_{1,58} = 12.99$), and it is $p < 0.001$ ($F_{1,58} = 12.01$) for the perception-based method, which are quite significant.

We can finally say that force cues play an important role in enhancing the perception even for remote operations. It can be concluded from Fig. 7 that force cues from the environment definitely help to discriminate between two environments in a better way as the JND values are smaller. These results reiterate the claim made in previous studies [9], [18], [19], [34].

V. CONCLUSION

This paper has aimed at analyzing the haptic perception capabilities of human subjects for remote operations. Two control methods have been considered for transferring information from a remote environment to a human operator. The first method is based on transparency optimization, whereas the second method is based on perception optimization. For each of these methods, two haptic cues, i.e., position and force cues, are presented. First, we have rigorously analyzed the various performances of the control methods and haptic cues via frequency-domain analysis using the hybrid matrix formulation. Psychophysical experiments are then conducted for the human-centered evaluation of the control methods and haptic cues from the perspective of human subjects' perceptual sensitivity.

In applications such as telesurgery, when the robot is interacting with soft environments, appropriate haptic feedback would be crucial to determine the operations of a doctor. This paper addresses its importance to optimize the controller in accordance to the operator's perceptual sensitivity rather than the transparency. Analytical and psychophysical comparison results clearly show that the perception-based method enhances the perceptual sensitivity of human operators. In addition, it can be noticed that force cues are indeed important for an enhanced perception of remote environments irrespective of the methods used.

These results serve as guidelines to choose a task-specific control method based on the importance of perception, as compared with transparency for a specific application. For some applications with macro–macro interactions, transparency-optimized control might be useful to perceive the environment without any distortion or perceived scaling. Hence, we will also focus on implementing a switching control scheme between the two control methods such that our method can be generalized across different cases. Furthermore, we would like to perform detailed experiments with more number of subjects to identify such cases where such a switching control scheme might be helpful. A concrete design of the simulation environment with dynamic haptic interactions across multiple degrees of freedom, instead of a simple unilateral constraint such as a virtual wall, will help us to generalize across more realistic experimental conditions.

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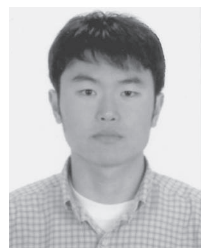

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