A Regression and Boundary-Crossing Based Model for the Perception of Delayed Stiffness

Ilana Nisky, Ferdinando A. Mussa-Ivaldi, *Member, IEEE*, and Amir Karniel, *Senior Member, IEEE*

Abstract——The stiffness of the environment with which we come in contact is the local derivative of a force field. The boundary of an elastic field is a singular region where local stiffness is ill-defined. We found that subjects interacting with delayed force fields tend to underestimate stiffness if they do not move across the boundary. In contrast, they tend to overestimate stiffness when they move across the elastic field boundary. We propose a unifying computational model of stiffness perception based on an active process that combines the concurrent operations of a force and of a position-control system.

Index Terms— Human factors, Human information processing, Telemanipulation, Control theory, Neuroscience, Perception and Psychophysics

1 INTRODUCTION

IDEALLY, in bilateral teleoperation, the operator holds a master robot that determines the motion of a remote slave robot and continuously receives instantaneous force feedback. Accurate feedback with negligible delay can considerably improve the performance [1]-[4]. However, due to the distance between master and slave and limits in information rate and propagation velocity, the force feedback incurs some unavoidable – and often significant – delays. The delay may cause instability and distortion in the perception of the mechanical properties of the manipulated object.

Stiffness perception and discrimination have been investigated under various conditions. Stiffness discrimination has been studied in human subjects by using a contralateral limb-matching procedure [5]. The discrimination thresholds for compliant objects have also been explored [6], [7]. Some studies have shown that vision [8] and arm configuration [9] can alter the perception of stiffness. Other studies have evaluated the effect of using rigid tools or constraining the manual exploration process by using probes on the perception of softness [10] and on haptic identification [11]. However, only recently has there been a realization of the importance of the effect of delay.

While stability and transparency of teleoperation systems have been studied extensively [1], [12], [13], human haptic perception of delayed environments has received relatively little attention. In a recent study, the just noticeable difference (JND) of time delay was determined [14], but the influence of the delay on the perception of stiffness was not addressed.

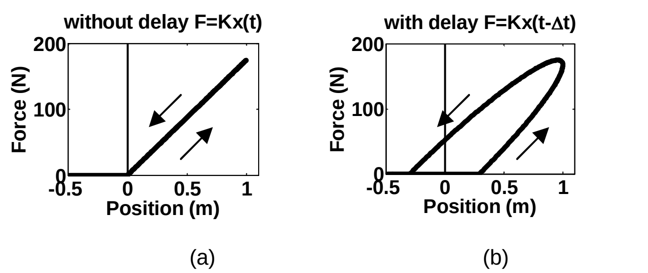

Fig. 1: Perception of delayed stiffness in a bilateral (force-reflecting) teleoperation – force position trajectory in contact with a spring-like field without (a) and with (b) delay. Arrows denote travel direction. In the case of a delayed spring-like field (b), the operator first penetrates the field without force feedback, and only after the delay does the force increase gradually. As the operator reverses the movement direction, the force continues to increase for the duration of the delay and then decreases. The horizontal line denotes the position of the boundary. In both trajectories, the probing movement begins and ends outside the field. We designate such movement as "probing a spring-like field with boundary crossing".

Fig. 1 illustrates the probing of a spring-like field in the force-position domain. A spring-like field (SLF) is a position-dependent force field, which has the mechanical properties of a one-sided spring, i.e., the applied force is proportional to the penetration into the field (Fig. 2b). The ratio between the applied force and penetration is the stiffness of such a field. In the non-delayed case, the trajectory is a straight line (Fig. 1a). Introducing delay into the system causes this trajectory to become elliptical (Fig. 1b), i.e., force is no longer a single-valued function of position. During this movement, the local stiffness is some times lower and at other times higher than the non-delayed stiffness. Therefore, without a detailed model of human stiffness perception, it is not possible to predict

- *Ilana Nisky is with the Department of Biomedical Engineering, Ben-Gurion University of the Negev, Beer-Sheva 84105, Israel E-mail: nisky@bgu.ac.il.*
- *Ferdinando A. Mussa-Ivaldi is with the Sensory Motor Performance Program, Rehabilitation Institute of Chicago, 345E. Superior Street, Chicago IL E-mail: sandro@northwestern.edu.*
- *Amir Karniel is with the Department of Biomedical Engineering, Ben-Gurion University of the Negev, Beer-Sheva 84105, Israel E-mail: akarniel@bgu.ac.il.*

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whether the perception of stiffness will change with delay and in which direction.

In a recent study Pressmann et al. [15], [16], [17] explored the perception of delayed stiffness when a subject interacts with virtual elastic force fields, emulated by a robotic manipulandum. In these studies, it was found that subjects overestimate delayed stiffness and that overestimation increases monotonically with increasing delay. Several candidate models were suggested to account for the subjects' answers, including models of global and local stiffness (i.e., global or local regression of force over position data), as well as models using force and position measurements at distinct time instances. In these studies, Pressmann et al. [16] ruled out the global regression of force over position model for a spring-like force field with a boundary. The subjects of their study overestimated delayed stiffness even if the delay was nonzero only on the way into or out of the force field; thus, local regression models based on partial information acquired on the way into or out of the force field were ruled out.

In the current study, we set out to explore the generality of the above results and extended the experiments to address the effect of boundary crossing. The boundary of a linear spring-like field, such as the one described in Fig. 1 and 2b is a region where stiffness is ill-defined, i.e., the derivative of the force/position relation exhibits a sudden transition from zero to a non-zero value, and at the transition point it has different values along different directions. The movements depicted in Fig. 1 both started and ended outside the spring-like field's boundary. We designate such movement as "probing a field with boundary crossing". Studying the perception of stiffness without such boundary is important theoretically and practically. Advanced analysis and design tools for teleoperation systems are based on linear system description tools. These techniques can be easily employed for developing a theory of teleoperation with linear boundaryless springs. To illustrate the practical notion of probing without boundary crossing, one can envision situations in telesurgery and telerehabilitation where the physician needs to probe a tissue or a limb while remaining inside the tissue or in contact with the limb. This could be the case, for example, in abdominal palpation performed by a doctor during physical examination, or spasticity examination while holding the limb and moving it back and fourth. To the best of our knowledge, there have been no studies to date on the perception of delayed stiffness without access to the boundary.

Surprisingly, we found that the absence of access to such boundary consistently reversed the perception of stiffness in the presence of force feedback delays. i.e., delayed elastic stiffness tends to be underestimated. We show here that this apparently irregular effect of a boundary can be accounted for by computational models that consider stiffness estimation as a regression process in the context of a control system that regulates (i) the force at the transition between free space and an elastic field and (ii) the position when estimating stiffness within a homogenous field. In the first case, the estimation is based on the regression of position as a dependent variable (the output of admittance). In contrast, when the boundary is not present, stiffness appears to be estimated by a regression process in which force is the dependent variable (the output of impedance). A simple convex combination of these two processes successfully captures the subjects' performances in a variety of probing and force-delay conditions.

The rest of this paper is organized as follows: in the next section the experimental setup, apparatus and data analysis techniques are described. Then the experimental results are reported along with ranking of computational models by their ability to predict the subjects' responses. Finally, the possible interpretations and implications of these results are discussed in the last section.

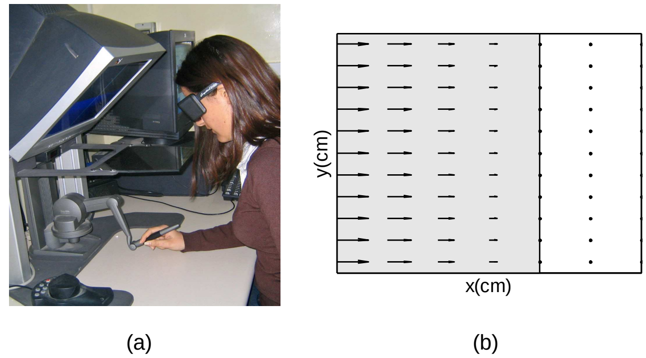


Fig.2: Experimental setup: (a) The subject and the virtual reality system. (b) The emulated spring-like field (SLF) – a position-dependent force field which has the mechanical properties of a one-sided spring, i.e., the applied force is proportional to the penetration into the field. Shaded area represents the SLF, and arrows represent the force field vectors. The force field is independent of the z coordinate.

2 METHODS

2.1 Subjects, Apparatus and Protocol

Thirty subjects participated in the experiments after signing the informed consent form as stipulated by the local Helsinki Committee. A seated subject held, with his/her dominant hand, the handle of PHANTOM® Desktop™ haptic device, with the wrist resting on the table. The subject looked at a projection glass of a Reachin® virtual reality system, placed horizontally above the hand (Fig. 2a), on which was displayed, in full-screen width, a virtual SLF as blue or red square. An opaque screen was fixed under the glass to prevent visual information about hand position. Hand position was sampled through digital encoders in the haptic device at 100 Hz, and this information was used online to calculate the force feedback, which was interpolated and rendered at 1 KHz.

To investigate subjective stiffness perception, a forced-choice paradigm was used: in each trial, subjects were presented with two virtual SLFs and were asked to choose which one of them was stiffer by probing both fields without time limits. One of the fields - the "reference field" - had always a stiffness of 175 N/m, and its force feedback was never delayed. The other – the "stimulus field" – had stiffness varying in the different trials between 10 different equally spaced stiffness levels in the range of 85-265 N/m. The force feedback of the stimulus field was delayed by 50 ms in half of the trials. We chose this delay because it represents "median" delay [13], i.e., large enough to be significant at typical probing velocities, and therefore to allow clearly observable distortion effects, but small enough to maintain the perception of the SLF. Each pair of reference and stimulus fields was considered as a "single trial". The subjects performed 20 training trials and 200 test trials. Only the test trials were analyzed. Subjects were never provided with feedback about their answers. Subjects received only partial visual feedback of the probing hand location: the position of the handle in the y,z plane was indicated by a white line, perpendicular to the SLF boundary. Thus, there was no visual feedback along the x axis direction - the probing direction. To limit the variability of arm and hand posture while probing different fields, subjects were instructed to make probing movements while maintaining the white line in a fixed position. Subjects were free to switch between the fields as often as they wished and to probe each SLF for as long as they wished. To switch between the two SLFs, subjects had to press a virtual button located below the working area, at $x = x_i$. Once they felt ready, they were asked to state which field was stiffer by pressing an appropriate button with the free non-probing hand.

Subjects were instructed to make rapid probing movements and to keep the hand in motion while inside the SLF. To avoid force saturation, subjects were asked to generate only short movements into the field, and an auditory cue was sounded at the maximum allowed level of penetration (2.5 cm). After a short practice (during training trials), subjects learned to make short movements and to avoid this (intentionally annoying) auditory cue in most of the trials.

Experiment 1 - Delayed stiffness without access to the SLF boundary: Ten subjects participated in this experiment. One subject did not complete the experiment due to technical reasons, and one subject was excluded from the analysis since he had less than 70% success in non-delayed trials. We calculated the force feedback exerted by the haptic device with the aim to emulate a spring-like field according to $F(t) = -K(x(t-\Delta t) - x_{0n})$, where K is the stiffness level, Δt is the delay, and x_{0n} is the field's boundary, always unreachable, i.e., $x(t) > x_{0n}\ \forall t$. This ensured that the subject's hand remained inside the SLF and away from the boundary during the entire probing session in both delayed and non-delayed force fields. Accordingly, subjects always felt some nonzero force. This experimental setup is equivalent to probing stiffness while always maintaining contact with the probed object, similarly to abdominal palpation performed by a doctor during physical examination. To prevent discontinuity in the exerted force at the point of switching, the locations of the boundaries, x_{0n}, were calculated such that $-K(x_i - x_{0n}) = F_i = -1.06N$. Subjects switched between the SLFs by pressing a virtual button located at x_i; therefore, they remained at the point of switching for more than 50 ms and felt a force of 1.06 N, regardless of the stiffness level or the delay of the SLF.

Experiment 2 - Delayed stiffness with access to the SLF boundary: Twenty subjects participated in this experiment. Four subjects were excluded from the analysis: two, who had less than 70% success at the non-delayed trials, one, who reported a change in the interpretation of stiffness, and one who did not follow the instructions and reported that due to the strange nature of some objects she made very slow probing movements, thereby eliminating the influence of delay. We calculated the force feedback exerted by the haptic device according to $F(t) = -K(x(t-\Delta t) - x_0)$ when $x < x_0$, and 0 otherwise, where x_0 is the SLF boundary. The SLF boundary was accessible in this experiment in both delayed and non-delayed force fields; subjects were free to probe the SLF with or without crossing the field's boundary according to their preferred probing strategy.

2.2 Data Analysis

Psychometric curve

The psychometric curve is a common method of quantifying a subject's performance in a psychophysical task. It relates an observer's performance to an independent variable, usually quantifying some physical property of a stimulus [18]. The general form of the psychometric function is:

$$\psi(x,\alpha,\beta,\gamma,\lambda) = \gamma + (1-\gamma-\lambda)F(x,\alpha,\beta) \qquad (1)$$

where x is the physical property of the stimulus. The shape of the curve is determined by the parameters [α, β, λ, γ] and the choice of a two-parameter function F, typically a sigmoid function. We used the psignifit toolbox version 2.5.6 for Matlab [18] to fit the psychometric curves, and found confidence intervals by the bias-corrected and accelerated (BC_a) bootstrap method described in [19].

We derived the psychometric function by estimating the subject's probability to answer "stimulus is stiffer" as a function of the actual difference $\Delta K = K_{stim} - K_{ref}$, where K_{stim} is the stiffness of the stimulus field and K_{ref} is the stiffness of the reference field. This probability was calculated from the subject's answers according to:

$$P(\Delta K) = \frac{\sum_{n=1}^{N(\Delta K)} A[n]}{N(\Delta K)}; \qquad A[n] = \begin{cases} 1 & \textit{stimulus stiffer} \\ 0 & \textit{reference stiffer} \end{cases} \qquad (2)$$

where $A[n]$ is a binary representation of the subject's answer, and $N(\Delta K)$ is the total number of trials with the given stiffness difference ΔK.

Point of Subjective Equality and Just Noticeable Difference

After fitting the psychometric curve, we used the 0.5 threshold value to find the point of subjective equality (PSE), indicating the stiffness difference that was perceived to be zero. When the subject could not discriminate between the fields, the probability to answer that the stimulus has higher level of stiffness is 0.5. Following [18] and assuming that F describes the psychological mechanism of decision, and λ, γ are stimulus-independent error rates, we used $F^{-1}(0.5)$ to estimate the PSE. Our expectation was to observe zero PSE values for the curves derived from non-delayed trials. For delayed trials, the whole curve was expected to shift. A positive PSE value implies underestimation of delayed stiffness, since the delayed and non-delayed fields were perceived equal when the actual difference between their stiffness levels was positive. Similarly, negative PSE value implies overestimation of delayed stiffness (see below).

We used the 0.75 and 0.25 threshold values to calculate the JND for each subject according to:

$$JND = \frac{F^{-1}(0.75) - F^{-1}(0.25)}{2} \tag{3}$$

(as in [20], [21]) and used these values to compare the effect of delay between different subjects.

Stiffness perception models

The data collected comprise the trajectories in the force-position plane, i.e., each subject's hand position and force exerted by the haptic device. We considered three computational models that use this information to estimate the stiffness of SLFs, and assessed their ability to predict subjects' answer to the question: "Which SLF is stiffer?" We calculated each model's prediction of the subject's answer according to the sign of the difference between estimations of reference and stimulus stiffness levels, $\hat{K}_{ref}[n]$ and $\hat{K}_{stim}[n]$ respectively, and calculated the total score according to:

$$S = \frac{\sum_{n=1}^{N_{delayed}} S[n]}{N_{delayed}}; \qquad S[n] = \begin{cases} 1 & \hat{A}[n] = A[n] \\ 0 & \hat{A}[n] \neq A[n] \end{cases} \tag{4}$$

$$\hat{A}[n] = \begin{cases} 1 & \hat{K}_{stim}[n] - \hat{K}_{ref}[n] > 0 \\ 0 & \hat{K}_{stim}[n] - \hat{K}_{ref}[n] < 0 \end{cases}$$

where $N_{delayed}$ is the total number of delayed trials, $A[n]$ is the subject's answer in trial n (see (2)). This score represents the model's probability to agree with the subject's answers. Since all three models yielded correct estimation of non-delayed stiffness, we used trials with delayed stimulus to calculate the models' scores for each subject and experiment.

In addition to this score, we used $\hat{A}[n]$ to fit psychometric curves representing each model's predictions. Based on these psychometric curves, we calculated PSE values of the models' prediction (PSE_m) and compared these values to the PSE values of the subjects' answers (PSE_s) by calculating linear regression parameters for the regression of PSE_m over PSE_s. A model that perfectly predicts subjects' PSE is expected to yield a regression line with slope of one and zero intersection.

We interpolated the trajectories in the force-position plane and fitted a regression line. Then, we used the slope of the fitted line as an estimate of stiffness. The outcome of this estimation strongly depends on the choice of dependent and independent variables (Fig. 3). These two estimation strategies are identical when the measured points all fall on a straight line, see e.g. [22], [23]. In the case of delayed SLF, the predicted estimations according to these two models are different (Fig. 3).

We tested the following models:

Model 1 (Force Over Position - FOP): The parameters of $F = bx$ were fitted to the force/position data and then the slope was used as an estimate of stiffness $\hat{K}_{FP} = b$.

Model 2 (Position Over Force - POF): The parameters of $x = bF$ were fitted and then the inverse of the slope was used as an estimate of stiffness $\hat{K}_{PF} = 1/b$.

Model 3 (Combined): The proportion of movements with boundary crossing α was calculated for each trial and used to derive the combined estimation

$$\hat{K}_{comb} = (1-\alpha)\hat{K}_{FP} + \alpha \hat{K}_{PF} \tag{5}$$

Note that the parameter α is not fitted, but obtained directly from the boundary crossing ratio. We calculated the boundary crossing ratio, α, as the fraction of probing movements completed outside the force field. Fig. 4c illustrates four consecutive probing movements of a subject from experiment 2; two probing movements were completed outside the force field, and two inside; therefore, α is exactly 0.5. We first identified each probing movement according to local maxima of the trajectory (reversal points - blue circles in Fig. 4c). A probing movement was designated as "completed outside" if the subject left the force field at least once before the next reversal point.

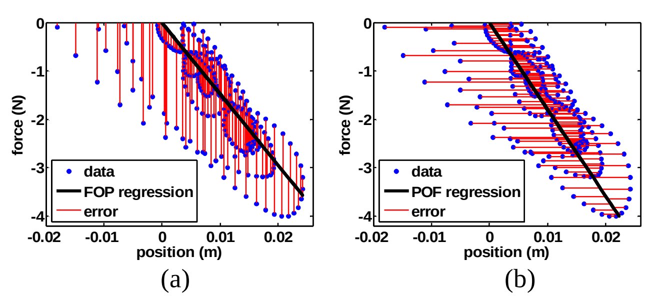


Fig. 3: Regression line fitted to a force-position trajectory of a subject from experiment 2. (a) The position is the independent variable, and force is the dependent variable. The regression line is fitted by minimizing the sum of the square force errors. (b) The force is the independent variable, and position is the dependent variable. The regression line is fitted by minimizing the sum of the square position errors.

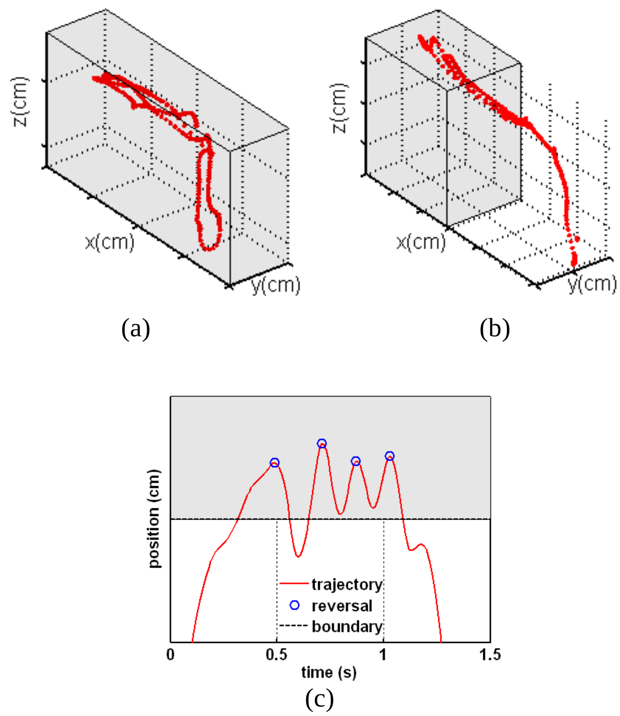


Fig. 4: Examples of subjects' trajectories in 3D from (a) experiment 1 and (b) experiment 2. The shaded volume represents the elastic field. In both cases, subjects made several probing movements along the x axis, and one movement along z axis, intended to press a virtual button (not shown) to switch between reference and stimulus fields. Subjects probed the field with approximately one-dimensional movements along the x axis, as were requested. In (a) the boundary is unreachable, and all movements, including the switching movements, are inside the field. In (b) the subject made probing movements with a boundary crossing, and therefore part of the movement is outside the elastic field (i.e., outside the shaded area). Nevertheless, the length of the penetration into the field is similar for these two subjects (the grid is 1 cm in all planes). In (c) an example of four consecutive probing movements of subject from experiment 2 is depicted as a function of time. Probing movements were identified according to reversal points (blue circles).

Then α was calculated according to

$$\alpha = N_{completed\_outside} / N_{probing\_movements} \qquad (6)$$

The reason for selecting this model and its possible meaning are further discussed in the following sections. Two additional models were tested and yielded inferior results; therefore, we defer their description to Appendix A, in which they are compared to the three models described above.

3 Results

All subjects reported that they felt confident about their answers in most of the trials. A detailed examination of the position trajectories revealed that all subjects made movements with similar penetration into the spring-like field, i.e., 1.3±0.5 cm (mean ± standard deviation), which is sufficient for collecting information and making decisions about stiffness (Fig. 4). From the psychometric curves fitted to subjects' responses, we found JND for stiffness discrimination in our experiment to be 18±11 N/m and 23±12 N/m (mean ± standard deviation) for the non-delayed and delayed trials, respectively. The delayed JNDs were statistically significantly higher than non-delayed JNDs (paired t-test $t_{23} = 3.3$, $p = 0.003$); however, the increase was not large (27%). The PSE in delayed trials of all subjects that demonstrated significant change in the perception of delayed stiffness (20 out of 24 subjects) was larger in magnitude than the mean non-delayed JND. For 18 out of these 20 subjects the PSE was larger than the subject's individual non-delayed JND. Therefore, the effect of delay, when such was observed, was above the discrimination threshold. See Appendix B for more details regarding the JND analysis.

3.1 Underestimation of delayed stiffness without boundary

In experiment 1, we found that all subjects underestimated delayed stiffness when probing fields without access to the fields' boundary (Fig. 5a&c). This finding was rather surprising, as it seems to contradict previous studies in which delayed stiffness was overestimated [15], [16], [17]. In experiment 2, seven subjects overestimated the delayed stiffness, five subjects underestimated it, and four subjects showed no significant change in the perception of delayed stiffness (Fig. 5b&d). As described in the next section, we believe that the non-consistent results of experiment 2 were due to the fraction of movements with boundary crossing.

3.2 Proportion of movements with boundary crossing influences subjects' perception of delayed stiffness

Fig. 6a depicts the trajectories in a trial of experiment 2, in which subject underestimated the delayed stiffness. This subject spent most of the probing time inside the field, and his trajectory resembles the trajectory of a subject from experiment 1, depicted in Fig. 6b. Therefore, he had little information about the boundary of the field. This observation is in contrast with a trajectory of a subject from experiment 2, who overestimated delayed stiffness, depicted in Fig. 6c. This subject probed the SLF with a boundary crossing at every probing movement. We found that subjects who underestimated the delayed stiffness spent most of the probing time *inside* the field, and almost never crossed the boundary. This observation led us to hypothesize that subjects who obtained little information about the boundary used the same estimation strategy as subjects in experiment 1 where the boundary was not reachable. To test the hypothesis that underestimation of delayed stiffness is consistent with a low fraction of movements with boundary crossing, we calculated this fraction, trial by trial, for each subject. All subjects (from both experiments) were assigned to three groups according to their perception of delayed SLF: underestimation, no change in perception, or overestimation of delayed stiffness. The difference in probing strategy

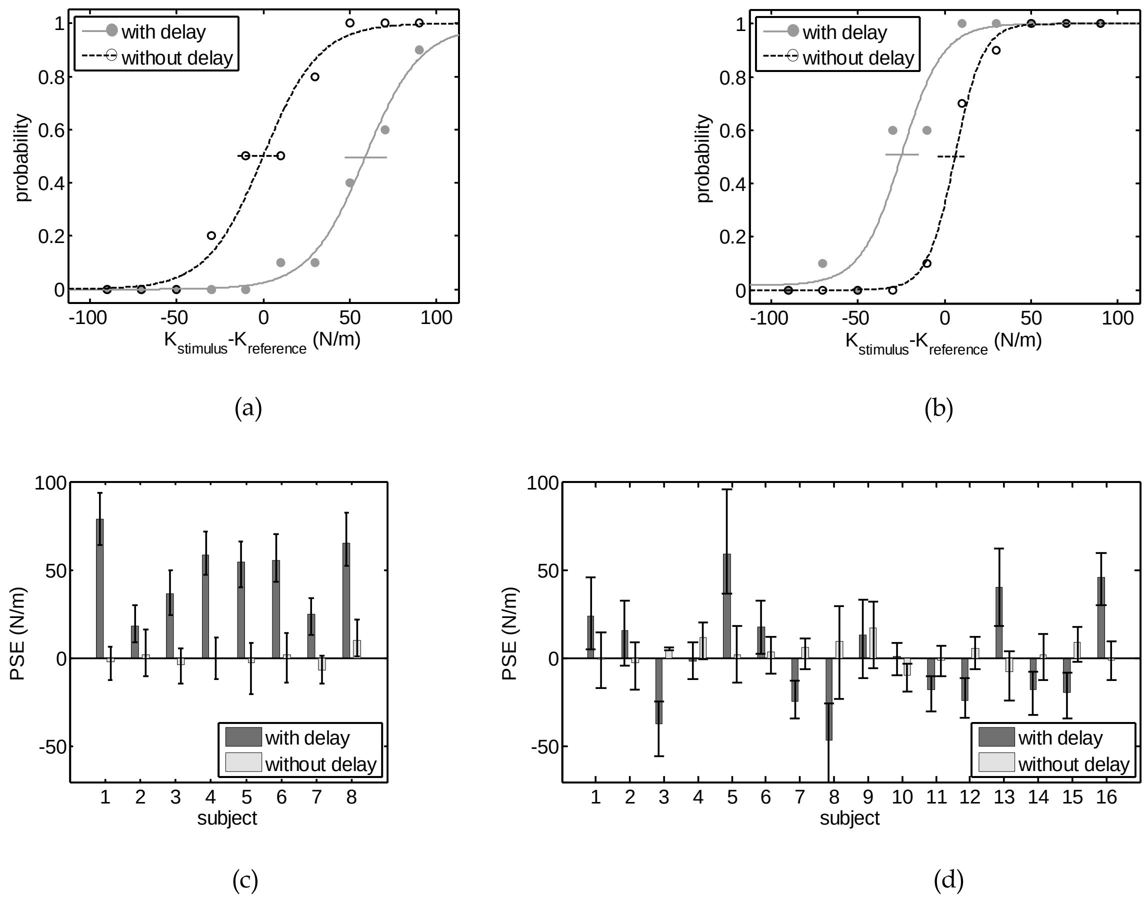


Fig. 5: (a&b) Psychometric curves of typical subjects: the curve fitted to trials with delay is shifted to the right (a), depicting underestimation of the stiffness of delayed SLF without boundary crossing in the first experiment, whereas the curve fitted to trials with delay is shifted to the left (b), depicting overestimation of the stiffness of delayed SLF with boundary crossing in the second experiment. The horizontal bar shows 95% confidence interval for the point of subjective equality (PSE). Positive PSE indicates underestimation, negative PSE indicates overestimation, and PSE value not significantly different from zero indicates correct estimation of stiffness (see text for further details). (c&d) PSE values (bars) and 95% confidence intervals (error bars) of PSE estimation from psychometric curves fitted to subjects' answers from experiments 1 - delayed stiffness with unreachable boundary (c) and 2 - delayed stiffness with a boundary that can be reached (d). Overestimation and underestimation were observed, since not all subjects in experiment 2 crossed the boundary, See text section 3.2 for detailed explanation of our claim about boundary crossing.

between these three groups was significant (one-way ANOVA $F = 900$, $p<0.0001$), as depicted in Fig. 6d. When we repeated this analysis solely with subjects from experiment 2, we observed a similar effect, and the difference was significant (one-way ANOVA $F = 135$, $p<0.0001$). According to this analysis, subjects can be classified as subjects who did or did not cross the fields' boundary, and therefore overestimated or underestimated delayed stiffness, respectively.

3.3 Evaluation of models for human perception of delayed stiffness

All three candidate linear regression models yielded correct estimation of the stiffness of non-delayed spring-like fields. In the case of delayed stiffness, the POF and FOP models yielded different estimations of the stiffness, either overestimation or underestimation, respectively. Fig. 7 depicts the regression lines that were fitted to a force-position trajectory from experiment 2, and the nominal stiffness line. It is clear that estimating the stiffness according to either FOP or POF model leads to underestimation or overestimation, depending on the choice of the independent variable. Naturally, the combined model can yield estimation over the entire range between the red and the black lines. Examples of psychometric curves fitted to the predictions of a subject's answers according to the combined model are presented in Fig. 8, together with the psychometric curves fitted to the subject's answers. The combined model predicted underestimation (Fig. 8a) or overestimation (Fig. 8b) of delayed stiffness according to the boundary crossing ratio of the subjects.

The mean scores of models are depicted in Fig. 9. In experiment 1, the FOP model (regression of force over position) model is significantly better than the POF model (Student's t-test, $p<0.001$). In experiment 2, the POF model (regression of position over force) model predicts the subject's response with higher success than the FOP model (Student's t-test, $p<0.001$). The performance of the combined model is at least as good as the best model for each experiment, without suffering from over-fitting: α is

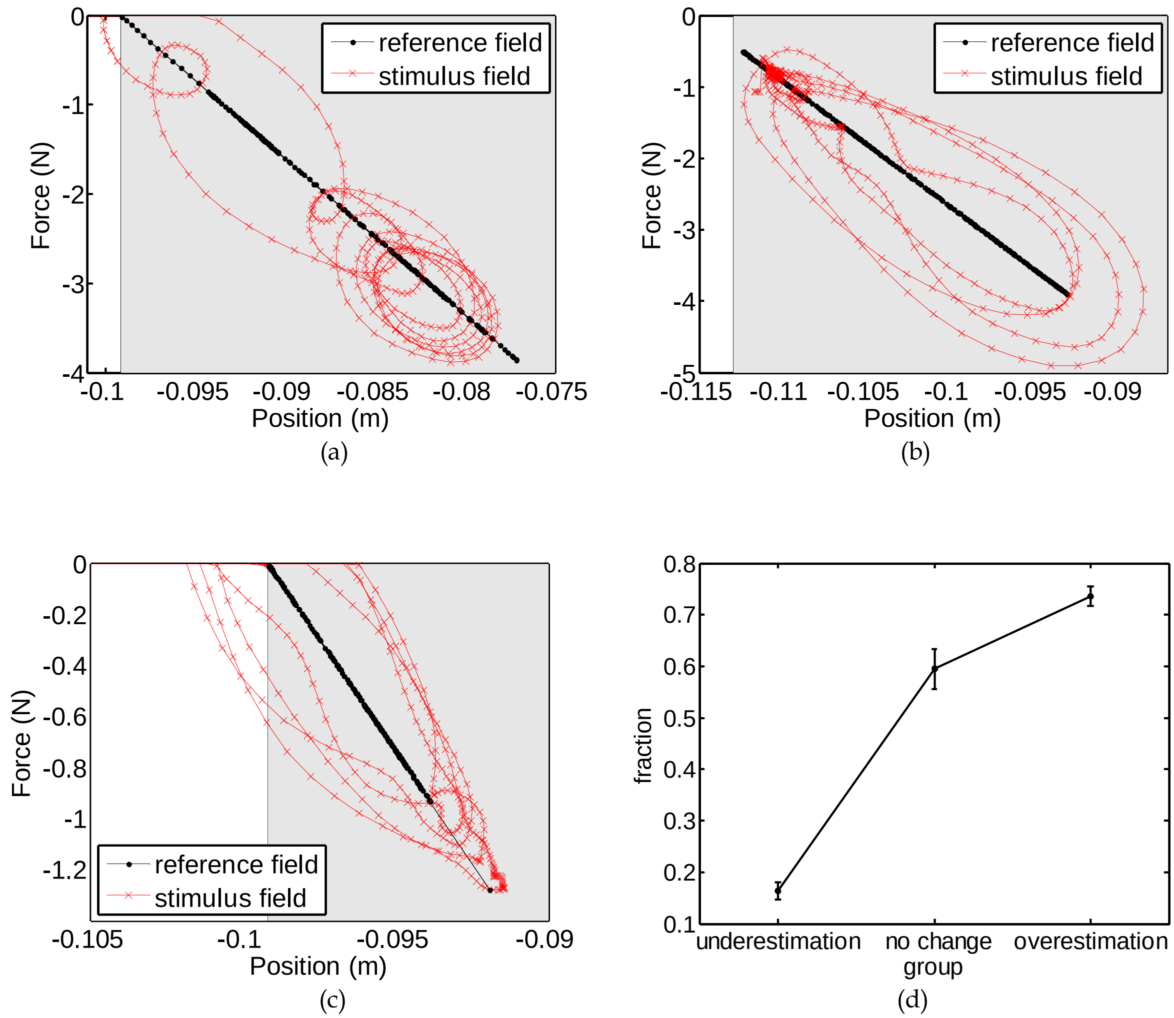


Fig. 6: (a-c) Force-position trajectories of typical subjects. Shaded area represents the SLF. (a) A trajectory of a trial in experiment 2, where the stiffness was underestimated. All probing movements in this trial were inside the SLF, with only one boundary crossing, after the subject had finished probing the field. (b) A trajectory of a trial in experiment 1, in which all probing movements were completed inside the field, since the boundary was unreachable. The stiffness of this SLF was underestimated. (c) A trajectory of a trial from experiment 2, where the stiffness was overestimated. Each probing movement in this trial included a boundary crossing. (d) Fraction of movements with a boundary crossing of subjects from all experiments. Each dot is the mean fraction of the group, trial by trial, and the bars represent 95% confidence intervals for the estimation of the mean of fractions (see text for details of statistics).

not fitted, but directly obtained from subject's trajectories according to (6).

The second evaluation method provided similar results. The slope and intersection pairs of the regression lines fitted to the FOP, POF, and combined models were {-0.42, 60}, {0.35, -32}, and {0.54, -8} respectively, indicating that the combined model was better than the POF and FOP models.

4 Discussion

In this study, we explored the influence of delay on human perception of stiffness. In earlier studies [15], [16], [17], we observed overestimation of positively delayed stiffness (force lags behind position), and underestimation of negatively delayed stiffness (force leads position). Here we examined the role of boundary crossing only for positively delayed stiffness. In this study, in apparent contrast to earlier observations [15], [16], [17], we found that subjects tend to underestimate the stiffness of spring-like fields without a boundary crossing when the force feedback is delayed (i.e., lags behind penetration). However, consistently with previous studies [15], [16], [17], subjects overestimated the stiffness of a spring-like field when probing it with sufficient boundary crossing when the force feedback was delayed. We found that after interacting with spring-like fields, subjects tend to underestimate delayed stiffness if most of probing movements took place inside the spring-like field, without crossing its boundary. A model based on a convex combination between regression of FOP and POF according to the relative fraction of probing movements completed outside and inside the field best predicts the behavioral results (Model 3).

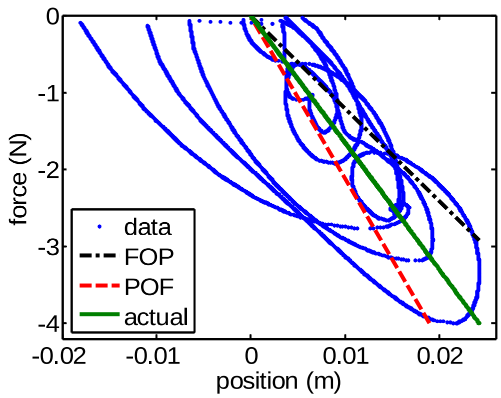


Fig. 7: Example of a trajectory with a delayed SLF and the corresponding regression lines. It is clear that estimating the stiffness according to either model 1 or 2 leads to underestimation or overestimation, depending on the choice of the independent variable. Naturally the combined model can yield estimation in the entire range between the red and the black lines).

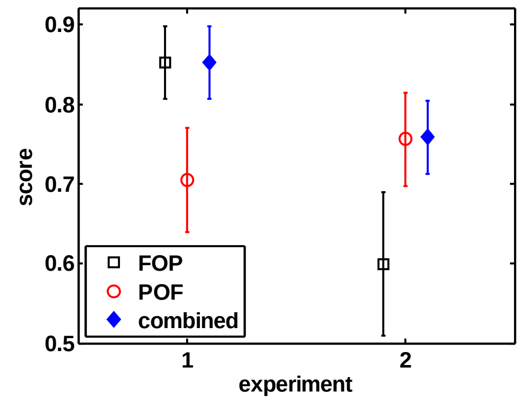
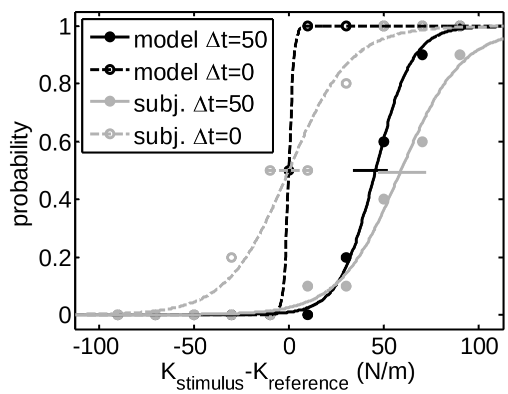


Fig. 9: Ranking of models: the symbol represents the mean of the score, and the error bars represent 95% confidence intervals for the mean, estimated using a t-distribution. Clearly, the combined model is as good as the best model (FOP and POF) in both experiments.



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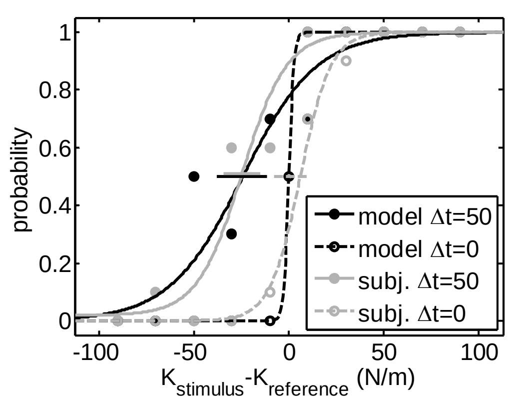

(b)

Fig. 8: Psychometric curves fitted to a subject's answers (gray) and to predictions of the subject's answers according to the combined model (black) under delayed (solid) and non-delayed (dashed) conditions for (a) underestimating subject from experiment 1 and (b) overestimating subject from experiment 2. The model yields perfect discrimination in non-delayed trials (unlike subjects) and a shift in the psychometric curve in delayed trials.

A speculative interpretation of these findings suggests that the estimation process is directly related to the control policy that guides the hand. This premise is illustrated schematically in Fig. 10. When the hand moves in homogeneous space, e.g., inside an elastic field, the appropriate control causality is implemented by a state controller that attempts to enforce a trajectory of the hand. The environment is seen as impedance, delivering a force in response to an imposed motion. In this case, the SLF stiffness is estimated by regressing sensed force over imposed position. Conversely, if the hand encounters a boundary, the appropriate control causality is implemented by a force controller that attempts to regulate the interface force. This approach is particularly safe in the presence of rigid objects. In this case, the environment is seen as admittance, setting a motion in response to an imposed force. The corresponding stiffness estimation strategy is a local regression of position over force. This model is consistent with the existence of a hybrid control system that combines force and position control policies according to the demands of the contact with the environment. The idea of combining independent force and position control was recently explored by Chib et al. [24] where the errors in combined motion and force task were predicted by a sum of the errors in separate force and motion tasks. More recently, it was suggested that the nervous system switches between motion and force control in transition from downward tapping to vertical force production [25]

Stability is an issue of great concern in studies of delayed teleoperation [1], [12], [13], [26] and delayed haptic displays [27], [28]. In our experiments there is a potentially unstable point near the boundary; however, subjects naturally stabilized the system by their movements and hand impedance, in a manner that was sufficient for the purpose of answering which SLF is stiffer. Therefore, since we did not observe any signs of instability, we could concentrate on the perceptual effect of delay.

Decisions are often thought of as a form of statistical inference [29]. The state of the world is estimated on the

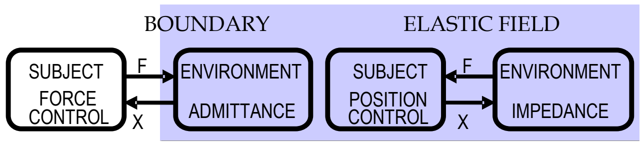

Fig. 10: Proposed conceptual model of active stiffness perception. When the hand moves inside a homogeneous elastic field (right), position control is used, and the stiffness is estimated by force over position regression. When the hand crosses a boundary (left) force control is used, and the stiffness is estimated by regression of position over force.

basis of a combination of prior information with sensory inflow [29], [30], and on information integration from different sources [31],[32]. A number of studies have suggested maximum likelihood estimation (MLE) to describe integration within [31] and between [32] modalities. According to the MLE, the brain combines all available cues for a certain property in a statistically optimal fashion, namely, the percept is a convex combination of different estimates, and the weights are determined according to the reliability of each estimate, e.g., the inverse of its variance [31], [32]. In Bayesian inference, priors and evidence are combined in a similar manner, according to their reliability [30]. However, most of the above studies dealt with combining cues about a single property, such as height [32] or curvature [31], and not with the integration of several variables into a single perception, such as in the case of stiffness, which requires a combination of force and position cues. Two studies have explored the integration of visual and haptic information for perception of compliance [33], [34] and found evidence for violation of the MLE principle or the independency assumption when visual and haptic information are combined. However, in our study, we explored perception through the haptic modality without visual feedback, and therefore these results do not necessarily apply. Our combined model can be interpreted in terms of MLE: two estimations of stiffness - according to both regression models - form a convex combination according to their reliability, and the reliability is determined by the variance of the appropriate estimation, which is affected by the weight of the corresponding control module in the control of probing movement. Consider a discrete description of the control modules in a single trial, namely, each probing either includes or does not include boundary crossing, and therefore is controlled either with a force or with a position control module. If, in a certain trial, the subject probed the force field n times, and k of these probing movements included a boundary crossing, the boundary crossing ratio is $\alpha = k/n$. We assume that the noise in both estimations $\hat{K}_{PF}, \hat{K}_{FP}$ is similar, that the variance of both estimations after a single probing is σ^2, and that estimation after several probing movements is the mean of estimations obtained from each probing movement. Thus, the variance of stiffness estimation based on k probing movements is σ^2/k. Therefore, the combined estimation according to MLE [31], [32], is:

$$\hat{K}_{comb} = \frac{\frac{n-k}{\sigma^2}}{\frac{k}{\sigma^2}+\frac{n-k}{\sigma^2}}\hat{K}_{FP} + \frac{\frac{k}{\sigma^2}}{\frac{k}{\sigma^2}+\frac{n-k}{\sigma^2}}\hat{K}_{PF} = \frac{n-k}{n}\hat{K}_{FP} + \frac{k}{n}\hat{K}_{PF} \tag{7}$$

which is exactly our combined estimation from (5). Further studies are required to test this formulation experimentally and to account for the possible physiological mechanism facilitating switching between impedance and admittance control and the appropriate estimation mechanism in real time.

In this study, we explained the difference in perception of delayed stiffness between the experiments and between subjects according to the boundary crossing ratio. We also examined the mean forces experienced and the velocity of probing movements as candidate explanatory variables for subjects’ answers (see Appendix A), but these were not as good as the regression-based model in predicting subjects’ answers. However, there were other discrepancies between the experiments. For example, to enable access to the boundary in the second experiment the force field was located further away from the subject in the second experiment than in the first experiment, and therefore the configuration of the hand was not identical in the two experiments. It has been shown that arm configuration [9] and haptic device location [34] can alter perception. Further studies are required to explore the influence of arm configuration. Indeed, even our best model does not explain variance in the subjects' answers, and there are many other factors to consider in future studies. Nevertheless, among all the tested first-order models (first order in the sense of fitting one parameter to the data) described in this paper and in Appendix A, the proposed combined model best accounts for the subjects' answers.

Understanding the effect of delay on perception is expected to contribute to building better teleoperation systems, in general, and to promote telesurgery and telerehabilitation, in particular. The fact that the probing method (with or without crossing the boundary) can completely alter the perception of delayed stiffness must be considered in building the successful teleoperation systems of the future.

APPENDIX A

In this paper, we presented only regression based models for the perception of stiffness and suggested that the boundary crossing ratio can be successfully used to weigh between FOP and POF regression models, which predict underestimation and overestimation of delayed stiffness, respectively, to yield a combined model that accounts for subjects' answers. However, additional factors in subjects' movements are correlated with the boundary crossing ratio and could therefore be potential explanatory variables for subjects' decisions. Therefore, we built additional models that can account for the results and compared their ability to predict subjects' answers with the ability of the regression-based models. In particular, we searched for physical variables that were correlated with the extent of behavioral effect, namely, with the PSE in delayed trials, and constructed the following two models.

Model A1 (mean-F): The mean experienced force during SLF probing is a proxy for stiffness level, i.e. a force field with a higher level of stiffness will yield a higher mean experienced force.

Model A2 (RMS-V): The root mean square (RMS) of velocity (V) during SLF probing as a proxy for stiffness level.

Mean models' scores are depicted in Fig. 11. The RMS-V model score was around chance level in both experiments. The mean-F model had scores well above chance level, but worse than our combined model. One can see that the combined model reported in this paper is also superior compared to these additional two models.

APPENDIX B

In section 3, Fig. 5, we showed the effect of delay on the perception of delayed stiffness by presenting the PSE of the psychometric curve fitted to subjects' responses together with confidence intervals for PSE estimation. While this is statistically correct presentation of parameters estimated from experimental data, it can be misleading in the sense that larger confidence intervals might be interpreted as lower discrimination ability of the subject. However, the confidence intervals represent the goodness of fit of the psychometric curve, namely, our uncertainty about the estimated parameters. While the discrimination ability of the subject affects uncertainty about estimation of the parameters, it is not the only factor that increases uncertainty. When the effect of delay is large, there are not enough stimuli levels on one of the sides of the PSE value, and therefore, the confidence interval for the estimation of PSE is inflated. This issue is discussed thoroughly in [19]. We wish to verify that subjects were asked

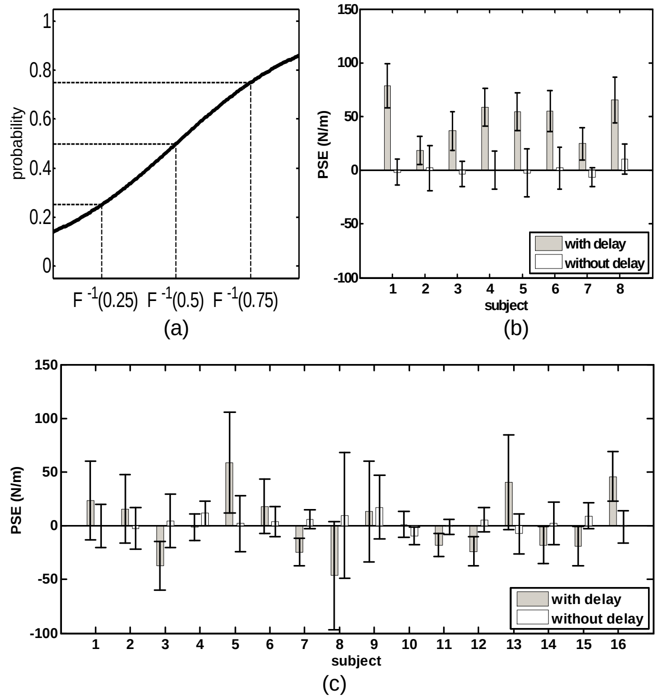

Fig. 12: (a) Close-up of the transition region of a typical psychometric curve depicting the procedure of extracting the PSE [$F^{-1}(0.5)$] and the error bars in planes (b) and (c): the lower bar represents $F^{-1}(0.25)$ and the upper bar represents $F^{-1}(0.75)$. (b&c) PSE values (bars) and ±JND (error bars) extracted from psychometric curves fitted to answers of subjects from experiments 1 - delayed stiffness with an unreachable boundary (c) and 2 - delayed stiffness with a boundary that can be reached (d).

to compare comparable force fields; the JND statistic provides better assessment of subjects' uncertainty and therefore is better for that purpose. The same information is presented in Fig. 12 b&c and in Fig. 5 c&d as in Fig. 12, but the error bars in Fig. 12 are $F^{-1}(0.25)$ and $F^{-1}(0.75)$ [see (1) for definition of F]; namely, the error bars are PSE±JND. We clearly see that although there is a general increase in the JND in the delayed trials, the increase is not large. For example, subject 8 from experiment 2 (compare Fig. 5d with 12c), who had the largest confidence interval in Fig. 5 and the largest JND in delayed trials, also had the largest JND in non-delayed trials. Our main conclusion from this analysis is that the task of comparing delayed to non-delayed force fields' stiffness was indeed reasonable, and subjects' discrimination ability was not substantially affected.

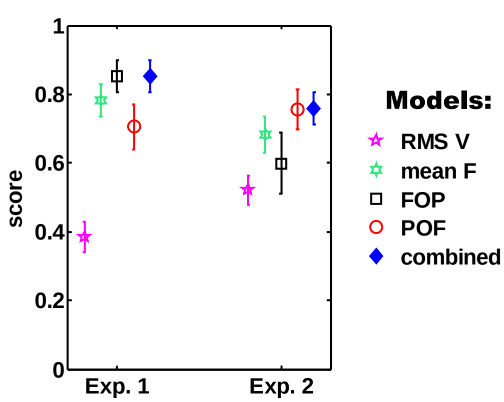

Fig. 11: Ranking of models: the symbol represents the mean of the score, and the error bars represent 95% confidence intervals for the mean, estimated using a t-distribution. Clearly the combined model is better than the other four presented models in both experiments.

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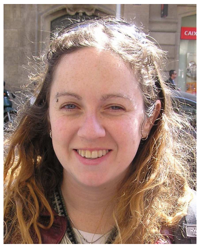
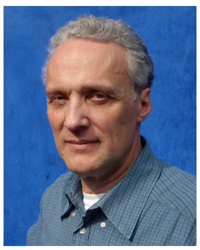


Ilana Nisky was born in Russia, in 1981. She received her B.Sc. degree (summa cum laude) from the Department of Biomedical Engineering, Ben-Gurion University of the Negev, Israel, in 2006, and is currently studying towards a Ph.D. (direct track) in biomedical engineering. Ms. Nisky received the Wolf Foundation scholarship for undergraduate students, and she is currently a Kreitman Foundation fellow. Her research interests include motor control, robotics, human and machine learning, teleoperation, and human-machine interfaces. She is a member of the Society for the Neural Control of Movement, and the Society for Neuroscience.



Ferdinando A. Mussa-Ivaldi was born in Torino (Italy) in 1953. He is a member of the IEEE. He holds a degree (Laurea) in physics from the University of Torino (1978) and a PhD in biomedical engineering from the Politecnico of Milano (1987). He is Professor of Physiology, Physical medicine and Rehabilitation and Biomedical Engineering at Northwestern University. Dr. Mussa-Ivaldi is Senior Research Scientist at the Rehabilitation Institute of Chicago, where he founded and directs the Robotics Laboratory. His areas of interest and expertise include robotics, neurobiology of the sensory-motor system and computational neuroscience. Among Dr. Mussa-Ivaldi's achievements are the first measurement of human arm multi-joint impedance, the development of a technique for investigating the mechanisms of motor learning through the application of deterministic force fields, the discovery of a family of integrable generalized inverses for redundant kinematic chains, the discovery of functional modules within the spinal cord that generate a discrete family of force-fields, the development of a theoretical framework for the representation, generation and learning of limb movements, and the development of the first neurorobotic system in which the brainstem of a lamprey controls the behavior of a mobile-robot through a closed-loop interaction. Dr. Mussa-Ivaldi has 110 full-length publications and 85 abstracts. He serves on the editorial boards of the Journal of Neural Engineering and The Journal of Motor Behavior and is member of the Society for Neuroscience and of the Society for the Neural Control of Movement.

Amir Karniel was born in Jerusalem (Israel) in 1967. He received the B.Sc., M.Sc. and PhD. degrees in 1993, 1996 and 2000, respectively, all in Electrical Engineering from the Technion-Israel Institute of Technology, Haifa, Israel. He served for four years in the Israel Navy as an electronics technician and worked during his undergraduate studies at Intel Corporation, Haifa, Israel. Dr. Karniel received the E. I. Jury award for excellent students in the area of systems theory, and the Wolf Scholarship award for excellent research students. He spent two years as a post doctoral fellow at the Department of Physiology, Northwestern University Medical School and the Robotics Laboratory of the Rehabilitation Institute of Chicago. In 2003, he joined the Department of Biomedical Engineering at Ben-Gurion University of the Negev, where he serves as the head of the computational motor control laboratory and the organizer of the annual international computational motor control workshop. His research interests include Brain Theory, Neural Networks, Haptics, Motor Control and Motor Learning.