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An Expertise-Oriented Training Framework for Robotics-Assisted Surgery †

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Abstract— **This paper proposes an expertise-oriented training platform for robotics-assisted minimally invasive surgery. The framework builds on previous work of the authors and makes use of dual-user teleoperation scenario, allowing the presence of an expert in the training loop. A Fuzzy-Logic (FL) methodology is proposed, which specifies the level/mode of the training required for the trainee according to his/her level of proficiency over the task. A major advantage of the proposed FL approach is that, having the expert in the loop, it can specify the trainee's proficiency level *relative* to that of the expert in real-time. Moreover, based on the relative skills assessment, the proposed FL approach decides if or to what extent the trainee should receive a haptic guidance force based on Virtual Fixtures or the environment force from the interaction between the surgical instrument and tissue at the slave side. In addition to the level/mode of the haptics-enabled training required for the trainee, the proposed FL framework specifies the authority level of the trainees over the operation in real-time, according to their proficiency levels over the task. Stability of the overall closed-loop teleoperated system is also investigated using the small-gain theorem, resulting in a sufficient condition to guarantee stability in the presence of constant communication delays. Finally, experimental results are given to evaluate the design and feasibility of the proposed framework.**

Indexing Terms: Dual-User System, Fuzzy Logic, Relative Skills Assessment, Surgical Training, Teleoperation.

I. INTRODUCTION

Robotics-Assisted Minimally invasive surgery (RAMIS) offers several benefits, including: faster recovery, reduced trauma and improved cosmesis for patients, as well as increased dexterity, stereovision capability, tremor filtering and motion scaling [1], [2]. While this form of surgery has significant advantages for patients, it could be challenging for novice surgeons and residents to perform. Achieving technical competence requires a well-planned learning strategy. For successful RAMIS, effective surgical training is necessary for novice surgeons to acquire appropriate psychomotor skills [3].

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In order to provide on-demand training to trainees for RAMIS, Intuitive Surgical Inc. has developed the *da Vinci Skills Simulator* [4] which is operated from the surgeon's console of the da Vinci. The Simulator incorporates a virtual reality (VR)-based simulation platform from Mimic [5] and provides the trainee with the look and feel of the da Vinci Surgical System. The latest addition to the da Vinci® product line, the dual-console *da Vinci Si* Surgical System [6], addresses questions that normally arise regarding fidelity of the simulation environment by providing a feature that enables a trainee to be involved in an actual surgical procedure. However, in this system the training is offered to the trainee based on a see-and-repeat approach, but without any haptic cues from the expert guiding the trainee along the proper path of the surgery.

In [7], the authors proposed a dual-user teleoperated surgical training approach incorporating Virtual Fixtures (VFs), that allows a trainee surgeon to receive training based on haptic cueing, while an expert performs a surgery. Using the dual-user teleoperation concept, both the trainee and the expert can be involved in the surgery, while the trainee's involvement level over the task can be adaptively adjusted in real-time based on his/her proficiency level over the operation. In addition, the presence of an expert in the loop through the dual-user framework allows online evaluation of the trainee's proficiency level *relative* to that of the expert. In contrast with the conventional skills-assessment approaches, the motions generated by the expert in the loop provide a suitable reference, to which the performance of the trainee could be compared and relatively assessed. This relative assessment allows for real-time evaluation of the trainee's performance, with no need for any *a priori* knowledge about the task trajectories for use as the evaluation reference.

Taking the advantage of the real-time relative skills-assessment approach proposed in [7], the authors take a further step by proposing a real-time expertise-oriented surgical training system. "Expertise-oriented" refers to providing the trainees with specialized training adaptively specified for them according to their level of proficiency. For example, novice trainees should receive haptic VF cueing on their hands, guiding them along the right path of the operation; while trainees with sufficient level of expertise do not need any VF cueing, but they can receive haptic force reflected back from the patient side which allows the trainees to get acquainted with the range of forces applied to the surgical instruments in the patient's body.

For this purpose, we propose a Fuzzy Logic (FL) methodology to specify expertise-oriented training appropriate for each trainee. In addition to the appropriate level of training, the proposed FL approach also specifies the appropriate authority of the trainee over the task according to his/her level of expertise.

FL is a powerful flexible tool, dealing with approximate reasoning; that enables vagueness, uncertainties, and subjectivity to be taken into account in the evaluation system [8], [9]. This flexibility makes FL appropriate for surgical skills evaluation criteria that might include somewhat subjective measures, such as relative comparisons between a trainee and an expert. FL has been used in several studies to assess a trainee's proficiency level [10-14]. However, none of them addresses the *relative* evaluation of the trainee's proficiency compared to that of an expert. In addition, the FL approaches introduced in the literature do not address the expertise-oriented mode of training.

II. Desired Objectives

A dual-user teleoperated system enables concurrent performance of a surgical operation by an expert, while training a novice [7]. To allow for this, master robot #1 is manipulated by the expert, while the trainee manipulates master robot #2. In order to give both the operators some authority over the slave robot, the desired position for the slave robot is defined as an authority-based combination of the trajectories generated by the two operators [15] as follows:

$$x_{sd}(t) = \alpha_{adp}(t)x_{m_1}(t) + \alpha_{adp-T}(t)x_{m_2}(t) \quad (1)$$

where x_γ refers to the end-effector positions of the master robots ($\gamma = m_1, m_2$) or slave robot ($\gamma = s$) and the subscript "d" refers to the desired value of the parameter. α_{adp} and α_{adp-T} corresponds to the dominance factors specifying the authority of operators #1 and #2 over the task, where $\alpha_{adp}(t) + \alpha_{adp-T}(\mathrm{t}) = 1$. The trainee's dominance factor is adaptively adjusted by the proposed FL scheme according to two main factors: 1) the expertise level of the trainee, 2) the maximum allowable level of the trainee's authority specified by the expert.

The expert, who will mainly be performing the procedure, receives haptic feedback indicating the forces reflected back from the patient's body. Therefore, the desired objective for operator #1, as in conventional teleoperation systems, can be defined as $F_{h_1d} = F_e$, where F_{h_1} and F_e correspond to operator #1's hand force and the environment force respectively. In [7], the desired objective for the trainee, operator #2, was defined as:

$$F_{h_2d} = F_{VF} \quad (2)$$

where F_{h_2} refers to operator #2's hand force and the subscript "d" refers to the desired value. In addition, F_{VF} corresponds to the force generated by a VF designed to guide the trainee along the right path of the surgery. The presence of an expert in the loop provides the opportunity to generate the VF according to the motions generated by the expert as the desired reference trajectory in an online fashion. For this purpose, the hand position of the expert, $x_{m_1}(t)$, at each time, can be used to create a spherical VF, inside which the trainee is able to move his/her freely. As soon as the trainee starts to go beyond the sphere surface, force F_{VF} is reflected to his/her hand by the VF modeled by impedance characteristics. The inner spherical free region, created at $x_{m_1}(t)$ with radius R_{VF}, allows the trainee's hand to moves freely as long as it has a magnitude position error of less than R_{VF} with hand position of the expert surgeon, $x_{m_1}(t)$, that is $F_{GVF} = 0$ if:

$$\left(x_{m_2,x} - x_{m_1,x}\right)^2 + \left(x_{m_2,y} - x_{m_1,y}\right)^2 + \left(x_{m_2,z} - x_{m_1,z}\right)^2 \leq R_{VF} \quad (3)$$

As soon as the condition given in (3) is violated, the VF applies $F_{GVF} = M_{VF}\ddot{E}_x + B_{VF}\dot{E}_x + K_{VF}E_x$ to the trainee's hand, where $E_x = x_{m_2} - x_{m_1}$; and M_{VF}, B_{VF} and K_{VF} correspond to the desired impedance characteristics of the VF. In addition, R_{VF}, the radius of the inner spherical free region, is used to adjust the VF's boundaries. The subscripts x, y and z in (3) represents the position elements along the *x*, *y* and *z* directions.

In this paper, we propose an expertise-oriented training for a trainee, rather than providing the pure VF haptic cueing F_{VF}. For this purpose, the definition of the desired objective for the trainee is proposed as follows:

$$F_{h_2d}(t) = \beta_{VF}F_{VF}(t) + \beta_e F_e(t) \quad (4)$$

where β_{VF} and β_e are parameters varying between 0 and 1, while at each time only one of them can take a non-zero value. β_{VF} and β_e will be adaptively adjusted by the proposed FL scheme in real-time according to the proficiency level of the trainee. For example, if the FL recognizes the trainee as a novice, then β_{VF}=1 and β_e=0; while if the trainee at some point is recognized as having attained expert status, then β_{VF}=0 and β_e=1.

III. The Fuzzy Interface Design

The proposed FL-based assessment will be used to specify the authority level of the trainee over the task, in addition to the appropriate level of training according to the trainee's expertise level. In order to quantify the trainee's expertise level, skills-assessment metrics from the literature are used: total path length, motion smoothness [16]-[17] and VF force effect metrics proposed by the authors in [7]. Having the advantage of an expert-in-the-loop through the dual-user framework, the quantified skills metrics calculated for both the trainee and the expert can be used to derive a relative measurement for the trainee's performance compared to that of the expert. For this purpose, a comparative measure introduced in [7] is used to derive the relative measure between the trainee's and the expert's performance as follows:

$$\rho_\Gamma(t) = 1 - \left|\frac{\Gamma_{m_2}(t) - \Gamma_{m_1}(t)}{\Gamma_{m_2}(t) + \Gamma_{m_1}(t)}\right| \quad (5)$$

where Γ_{m_1} and Γ_{m_2} refer to absolute skills-assessment metrics for the expert and the trainee, respectively. The absolute skills metrics, Γ, could be any of the gold-standard metrics used in the literature [16-21], three of which are used in this paper: total path length, motion smoothness and VF force effect metrics. The FL scheme will utilizes a combination of the three metrics to decide on the proficiency level of the trainee. Note that the structure of the proposed FL scheme allows for replacing/adding other metrics, if desired.

The proficiency level of a user is categorized into 4 divisions: 1) Beginner, 2) Intermediate, 3) Advanced, and 4) Skilled (BIAS). Moving from a beginner trainee to a skilled trainee, the FL scheme should increase the trainee's (operator #2's) authority level over the task, of course to a maximum level, $\alpha_{T_{max}}$, specified by the expert surgeon in the loop (operator #1). In addition, the FL scheme should provide a beginner trainee, compared to an intermediate/advanced trainee, with smaller VF boundaries, R_{VF}, to constrain the trainee's freedom and to guide him/her more firmly along the right path of the procedure. Moving more towards the upper bound of the proficiency level: "skilled", the FL scheme should provide a smaller amount of VF to the trainee, while a skilled trainee should receive, rather than the haptic guidance cueing F_{VF}, haptic feedback F_e applied by the patient's body to the instrument tool to train him/her on the range of forces at the slave side.

Therefore, the inputs for the FL scheme will be the quantified skills metrics normalized by (5) into the range [0,1] and the output will be the trainee's authority level and the appropriate training force level/mode for the trainee. In order to fulfill the desired requirements for the training system, the following fuzzy rules are proposed:

- *If the user is Beginner, then:*
  - Decrease his/her authority over the task significantly
  - Decrease the VF's boundaries significantly
- *If the user is Intermediate, then:*
  - Slightly increase his/her authority over the task
  - Slightly increase the VF's boundaries
- *If the user is Advanced, then:*
  - Increase his/her authority over the task considerably
  - Increase the VF's boundaries significantly, up to a level that does not interfere with his/her motions anymore.
- *If the user is Skilled, then:*
  - Increase his/her authority over the task significantly, up to the max allowable level, $\alpha_{T_{max}}$, specified by the expert surgeon in the loop
  - Provide him/her with the haptic feedback from the slave side

In order to design the FL scheme, the MATLAB Fuzzy Logic Toolbox is used. To fuzzify the relative measure for each of the three skills-assessment metrics, "generalized bell-shaped" and "Gaussian curve" membership functions are used. Note that using (5), the relative skills metrics will have the range [0-1], without regard to the values of the absolute skills metrics, total path length, motion smoothness and VF force effect. The Membership Function (MF) designed for the relative skills-assessment metrics is shown in Fig. 1. The FL uses the same MF for all three metrics. In addition, the "triangular-shaped" and "trapezoidal-shaped" membership functions are used for the purpose of defuzzification at the output. The resulting output surfaces corresponding to the inputs are shown in Fig. 2. It should be noted that, since the proposed Fuzzy Interface System (FIS) has three inputs, one of the inputs should be fixed for the purpose of 3D representation. Therefore, the output surfaces, shown in Fig. 2, are plotted with respect to two of the FIS inputs, while the third one is set to a fixed value.

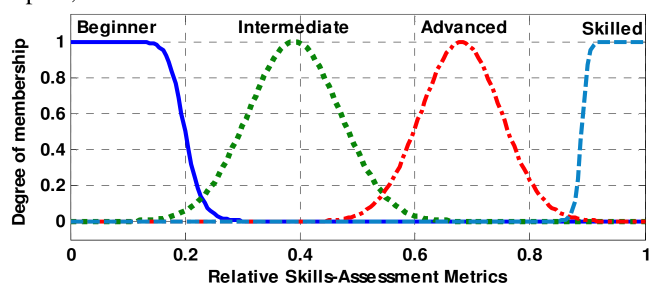

Fig. 1: Degree of membership with respect to the normalized skills metric for the trainee relative to that of the expert

The MFs pattern at both the inputs and the outputs could be even more precisely designed, by comparing/evaluating the skills metrics based on real data acquired from a number of subjects with a wide range of expertise levels. However, this requires an extensive users study to collect and analyze data from a wide range of subjects, which is beyond the scope of this paper and will be the focus of future work.

A major advantage of the proposed FIS is that, with an expert in the loop, it can specify the trainee's proficiency level relative to that of the expert in real-time, and decide on the appropriate level/mode of the training required according to the trainee's proficiency level. The relative skills assessment eliminates the need to have any a priori knowledge about the surgical path, to be used as the reference trajectory for the purpose of skills evaluation.

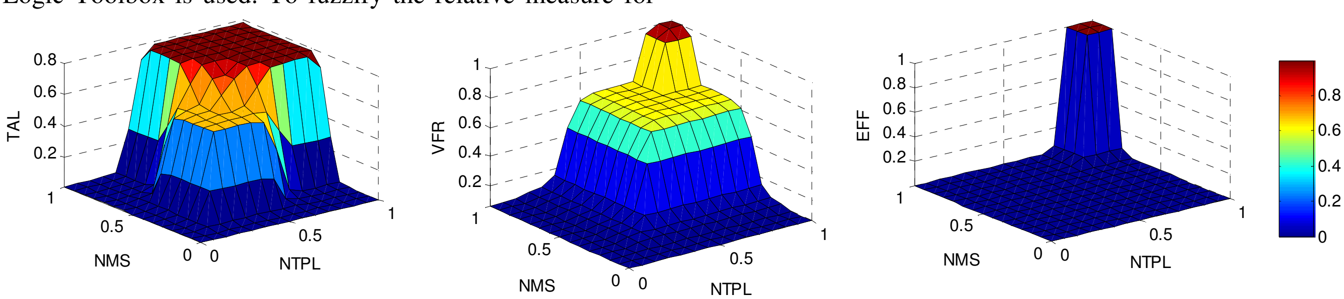

Fig. 2- the FIS output surfaces TAL, VFR, EFF with regards to the FIS inputs NMS, NTPL, while the NVFE is set to 0.5,1,1, respectively. Note that since the FIS receives 3 inputs, one input should be set to a fixed value for the purpose of 3D representation of the output surfaces with respect to the inputs. TAL: Trainee's Authority Level, VFR: Virtual Fixture Radius, EFF: Environment Force Factor, NMS: Normalized Motion Smoothness, NTPL: Normalized Total Path Length, NVFE: Normalize VF Force Effect.

IV. Control Methodology and Stability Analysis

To satisfy the desired objectives given by (1)-(4) for the system, an impedance controller is used [22]. We define three impedance surfaces as the desired closed-loop system as given in (6); and an impedance controller is used to satisfy these impedance surfaces.

$$\begin{cases} M_{1,d}\ddot{x}_{m_1} + B_{1,d}\dot{x}_{m_1} + K_{1,d}x_{m_1} = F_{h_1} - F_e \\ M_{2,d}\ddot{x}_{m_2} + B_{2,d}\dot{x}_{m_2} + K_{2,d}x_{m_2} = F_{h_2} - \beta_{VF}F_{VF} - \beta_e F_e \\ x_s = \alpha_{adp}x_{m_1} + \alpha_{adp-T}x_{m_2} \end{cases} \quad (6)$$

where the impedance equations represent the desired closed-loop system for master #1, #2 and the slave robot, respectively. $M_{i,d}$, $B_{i,d}$ and $K_{i,d}$ $(i = 1,2)$ denote the desired mass, damping and stiffness for each master robot. Modeling the operators and the environment by second-order linear time-invariant systems [23], F_{h_i} and F_e are as follows:

$$F_e = M_e\ddot{x}_e + B_e\dot{x}_e + K_e(x_e - x_{e0}) \quad (7)$$

$$F_{h_i} = F_{h_i}^* - M_{h_i}\ddot{x}_{h_i} - B_{h_i}\dot{x}_{h_i} - K_{h_i}(x_{h_i} - x_{h_i0}) \quad (8)$$

where M_γ, B_γ and K_γ $(\gamma = h_1, h_2, e)$ represent the mass, damping and stiffness, respectively and $F_{h_i}^*(i = 1,2,)$ correspond to the users exogenous forces. In addition, $x_{h_i}$and x_e refer to the positions of the operators' hands and the environment, which are in contact with the master robot $\#i$ and the slave robot, respectively, i.e. $x_e = x_s, x_{h_i} = x_{m_i}$.

To investigate the stability of closed-loop teleoperated system, the small-gain theorem is used. The system stability is analyzed for the case of a constant communication delays between the slave robot and the master robots. In this paper, it is assumed that the expert and the trainee are located at the same site, communicating via a delay-free network.

Theorem 1: The feedback system given in Fig. 3 is input-output stable if [24]:

$$u_1 \in L_\infty \;\&\; u_2 \in L_\infty \quad (9)$$

$$\Sigma_1 \in L_1 \;\&\; \Sigma_2 \in L_1 \quad (10)$$

$$\gamma_1.\gamma_2 \le 1 \;\; where \;\; \gamma_1 = \|\Sigma_1\|_{L_1}, \gamma_2 = \|\Sigma_2\|_{L_1} \quad (11)$$

T_1 and T_2 in Fig. 3 *refer to communication delays.*

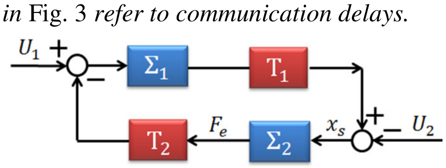

Fig. 3: General scheme of a feedback system with time-delays.

Using some algebraic manipulations, the closed-loop system can be transformed into the format given in Fig. 3, where:

$$\Sigma_2 = Z_e = M_e s^2 + B_e s + K_e \quad (12)$$

$$\Sigma_1 = \frac{1}{Z_{h_1} + Z_{1,d}} + \frac{\beta_e(Z_{h_1} + Z_{1,d}) + \beta_{VF}Z_{VF}}{(Z_{h_1} + Z_{1,d})(Z_{h_2} + Z_{2,d} + \beta_{VF}Z_{VF})} \quad (13)$$

$$U_1 = \frac{Z_{h_2} + Z_{2,d} + \beta_{VF}Z_{VF}}{Z_{h_2} + Z_{2,d} + \beta_e(Z_{h_1} + Z_{1,d}) + 2\beta_{VF}Z_{VF}}.F_{h_1}^* + \frac{\beta_e(Z_{h_1} + Z_{1,d}) + \beta_{VF}Z_{VF}}{Z_{h_2} + Z_{2,d} + \beta_e(Z_{h_1} + Z_{1,d}) + 2\beta_{VF}Z_{VF}}.F_{h_2}^* \quad (14)$$

$$U_2 = 0 \quad (15)$$

with $Z_{h_i} = M_{h_i}s^2 + B_{h_i}s + K_{h_i}$, $Z_{i,d} = M_{i,d}s^2 + B_{i,d}s + K_{i,d}$, and $Z_{VF} = M_{VF}s^2 + B_{VF}s + K_{VF}$ for $(i = 1,2)$.

$F_{h_i}^*(i = 1,2)$, the operators' hand exogenous forces belong to L_∞ [24]. In addition, Z_{h_i} and $Z_{i,d}(i = 1,2)$ correspond to the operators' hand dynamics and the desired closed-loop impedances, respectively, the dynamics coefficients of which are positive and bounded. Moreover, Z_{VF} corresponds to the impedance characteristic of the VF, which has positive and bounded coefficients. As a result, U_1 belongs to L_∞, and also $U_2 \in L_1$ that is, the first stability condition given by (9) is fulfilled. For the second stability condition given by (10), we have $\Sigma_1 \in L_1$. However, $\Sigma_2 = Z_e$ does not belong to L_1, since it has improper dynamics. In small-gain-based teleoperation systems, as elaborated in [25], to transform Σ_2 to a proper dynamics form, a low-pass filter $\Pi(s) = \frac{1}{\phi_1 s^2 + \phi_2 s + \phi_3}$ can be applied to the environment force, before sending it to the master robots. By applying the filter $\Pi(s)$, Σ_2 will be equal to $Z_e(s)\Pi(s)$ which belongs to L_1 space and consequently, the second stability condition given by (10) is also satisfied.

In order to investigate the third stability condition given by (11), according to the definition of the L_1-norm, we have:

$$\|\Sigma_1\|_{L_1} = \int_{-\infty}^{+\infty} \left| \frac{Z_{h_2} + Z_{2,d} + \beta_e(Z_{h_1} + Z_{1,d}) + 2\beta_{VF}Z_{VF}}{(Z_{h_1} + Z_{1,d})(Z_{h_2} + Z_{2,d} + \beta_{VF}Z_{VF})} \right| d\omega \quad (16)$$

$$\|\Sigma_2\|_{L_1} = \int_{-\infty}^{+\infty} \left| \frac{Z_e}{\phi_1 s^2 + \phi_2 s + \phi_3} \right| d\omega \quad (17)$$

Using (9) and (10), considering the fact that $\Pi(s)$ is a user-defined filter which can be designed in such a way that $\|\Pi(s)\|_{L1} \le 1$, a sufficient condition can be derived, to guarantee the third stability criterion given in (11) as follows:

$$\left| \frac{Z_{h_2} + Z_{2,d} + \beta_e(Z_{h_1} + Z_{1,d}) + 2\beta_{VF}Z_{VF}}{Z_{h_2} + Z_{2,d} + \beta_{VF}Z_{VF}} \right| \le \left| \frac{Z_{h_1} + Z_{1,d}}{Z_e} \right| \quad (18)$$

The derived stability condition can be easily satisfied by appropriate adjustment of the desired impedance parameters $M_{i,d}, B_{i,d}$ and $K_{i,d}$ (i = 1,2), as $Z_{i,d} = M_{i,d}s^2 + B_{i,d}s + K_{i,d}$.

V. Experiments

In order to evaluate the behavior of the proposed FL-based training framework, experiments were conducted. The experimental setup, shown in Fig. 4, consists of two customized Quanser Haptic Wands as the master robots, and one Mitsubishi PA10-7C robot with a da Vinci tool attached at the tip as the slave robot [26].

a

b

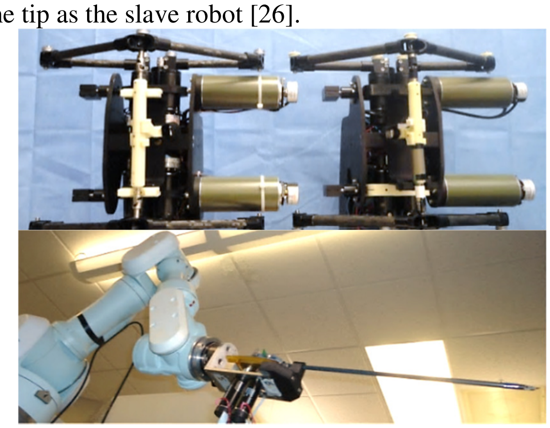

Fig. 4: The experimental setup [7], [26].
a: Quanser haptic wands, b: Mitsubishi PA10-7C robot and da Vinci tool.

The conducted experiment consists of three phases, each focusing on a different scenario, to investigate various aspects of the framework. The master robots were manipulated by two operators, one as an expert and the other as a trainee. In the first phase, between $t = 0s$ and $t = 45s$ sec, the expert, operator #1, was asked to execute a trajectory with his master robot. At the same time, in order to simulate a skillful performance for the trainee (operator #2), she was asked to replicate the hand trajectories generated by the expert. In the second phase of the experiment, between $t = 45s$ and $t = 100s$, while the expert was accomplishing his task, the trainee was asked to keep her master robot firmly at a fixed position, without regarding the trajectories generated by the expert as well as the forces exerted on her hand by the VF. This allows simulating unskilled behavior for the trainee, as her performance is very different from the desired reference trajectory. Finally, in the third phase occurring from $t = 100s$ to $t = 140s$, the trainee was asked to let the VF guide her hand through the desired trajectory generated in real-time by the expert in the loop, without giving her any knowledge about the desired path in advance.

In this experiment, the VF was characterized by a spring with the stiffness $40Nm^{-1}$. In addition, the maximum allowable authority level for the trainee, $\alpha_{T_{max}}$, was set to 1 by the expert, permitting the trainee to receive full authority over the task if she is recognized by the FIS as skillful. The results are given in Fig. 5-Fig. 8.

Fig. 5 shows the normalized skills metrics calculated for the trainee relative to those for the expert, where NTP: Normalized Total Path Length, NMS: Normalized Motions Smoothness, NVFE: Normalized VF Force Effect. As can be seen in this figure, all three metrics show a high level of expertise level for the trainee in the first phase of the experiment, where she behaved as a skilled trainee. In the second phase, as soon as the trainee started to deviate from the desired reference trajectory without paying any attention to the VF force cues provided to her, the skills metrics start to decrease and ultimately reach zero, referring to a fully unskilled trainee. In the third phase, where the trainee allows the VF to guide her along the desired reference trajectory, since the trainee is moving along a path with a similar profile to that of the expert, NTPL and NMS show an increase for the trainee's skills level. However, the interesting point is that, although the trainee's hand is travelling on the right path, NVFE does not show any improvement in her performance, compared to that in the second phase. The reason is that this metric evaluates the trainee's performance according to the VF force guiding the trainee. As long as the trainee is not capable of generating the right path on her own, which results in the VF cueing to guide her, this metric refers to an inadequate level of expertise for her. Therefore, this metric is suitable for distinguishing between two "on-the-right-path" trajectories generated by the trainee to decide if the right trajectory has been the result of high proficiency level of the trainee or of the effect of VF guidance cueing.

According to the normalized relative skills metrics, the FIS has specified the authority level of the trainee in real-time, as shown in Fig. 6. As can be seen, in the first phase of the experiment, the trainee was given the maximum authority level by the FIS, as she behaved as a skillful trainee. However, in both the second and the third phases, she was specified as a novice, resulting in zero authority level for her over the slave robot.

In addition to adjustment of the authority level for the trainee according to her level of expertise, the FIS also specifies the level/mode of the haptic-based training required for her. Fig. 7 shows, F_{h_2}, the training force exerted on the trainee's hand generated by the FIS; F_e, the environment force at the slave side; and F_{VF}, the VF guidance force. As can be seen, in the first phase of the experiment, the trainee feels the environment force on her hand, i.e. $F_{h_2} = F_e$, which resulted from the high level of expertise she showed. In the second and third phases, due to the inadequate proficiency level of the trainee, the VF cuing mode was activated. Therefore, the trainee was not able to feel the environment force anymore, but receiving the VF force on her hand to guide her along the right path. Comparing the VF force generated in the second and the third phases, an interesting point is the difference between the level of the VF forces. Although in both phases the trainee received the VF force, she received a considerable less amount of VF force on her hand in the third phase, compared to the second. The reason is that in the third phase she was letting the VF force guiding her, to generate less deviation from the desired trajectory, rather than resist the VF guidance as in the second phase.

Finally Fig. 8 shows the trajectories travelled by the expert, x_{m_1}; by the trainee, x_{m_2}; and by the slave robot, x_s. As can be seen, in phase II and III, the slave robot completely tracked the expert's trajectory without regard to the trainee's trajectory, as she was recognized by the system as a novice, setting her authority level to zero.

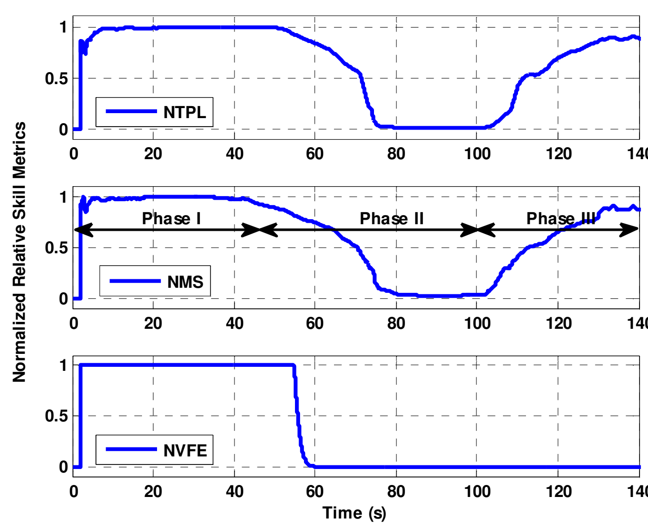

Fig. 5: Experimental results: normalized skills measures for the trainee relative to those of the expert.

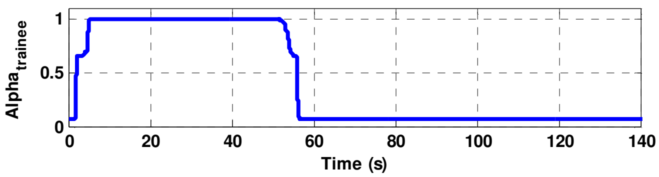

Fig. 6: Experimental results: the trainee's authority level α_{adp-T}

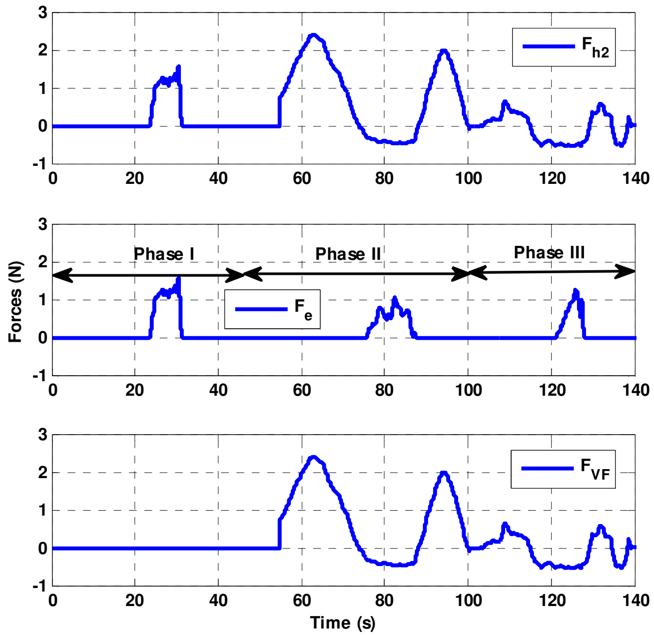

Fig. 7: Experimental results: forces exerted on the trainee's hand, the environment force and the VF force

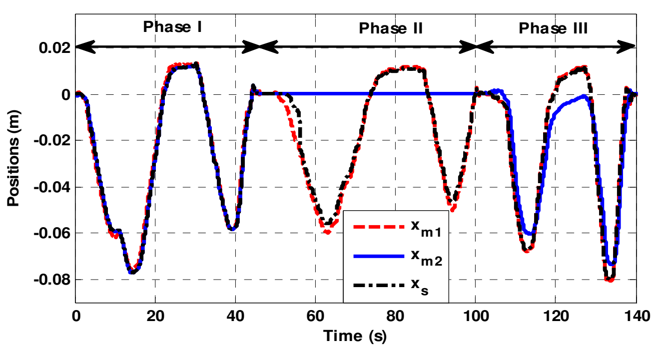

Fig. 8 Experimental results: end-effector positions

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