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Deep Neural Skill Assessment and Transfer: Application to Robotic Surgery Training

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Abstract— **Due to the high sensitivity and complexity of robotic surgery tasks, acquiring appropriate skill levels by trainee surgeons through an effective training process is very important and affects the patient's safety and the quality of surgical outcomes. With the advanced deep learning technology and the recent availability of surgical procedures data, intelligent methods can be deployed to assess and transfer the skills of an experienced surgeon (mentor) to a novice surgeon (trainee). In this paper, we introduce a novel deep-learning-based skill transfer scheme consisting of a deep convolutional model, *SkillNet*, and a skill transfer algorithm for robotic surgery training. The proposed SkillNet extracts skill-related features of the mentor from different layers of the network. Then, trainee's maneuver is enhanced by the proposed skill transfer algorithm while minimizing deviations from the trainee's original intended trajectory. For validation, the JIGSAWS dataset and also our own experimental data were used to prove the generalizability of SkillNet in capturing skill-related features. The capability of the skill transfer algorithm in enhancing trainee trajectories in terms of predictability, hand tremor reduction, and noise cancellation were investigated separately. The obtained results indicate that this approach can be used as a high-performance filter that makes minor corrections to the input trajectory and improves the skill level of the trainee's trajectory in practice.**

I. INTRODUCTION

In state-of-the-art robotic surgery systems, there is the opportunity for an expert surgeon (mentor) to apply guidance forces to the hands of a novice surgeon (trainee) to correct his/her motion for training purposes. There is a rich body of literature including papers from our research group in the haptics and telerobotics domain that deals with the mentor-trainee relationship in terms of expert-in-the-loop and haptics-enabled training [1]–[3]. For instance, [4] incorporated a trilateral dual-user shared control architecture for surgical skills training. The framework consists of one patient-side robot mutually controlled by two surgeon-side robots, one for the mentor and one for the trainee with a dominance factor that determines the authority level of the trainee relative to that of the mentor. These methods require the continuous presence of an expert surgeon during the training program. To have increased opportunities for surgical trainees to practice surgery while receiving haptic cues from a mentor, there is a motivation to use an automated deep-learning-based method for robotic surgery training.

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Incorporating skill-related knowledge through deep learning into collaborative robots in surgical training platforms not only improves the opportunities for training but also does not require the presence of an expert surgeon throughout the training procedure. In this context, Artificial Intelligence (AI) can contribute to enhancing the quality of Human-Robot Interaction (HRI) and transferring the skills of a mentor to a trainee through a smart collaboration with the robot in a training program. This intelligent supervision is very important in complex tasks (i.e., tasks that require more than one training session to be mastered [5]).

Inspired by the advantages of AI-enabled surgical training, Ershad et al. proposed a framework that detects the trainee's stylistic behavioral deficiencies and then produced near real-time haptic cues to inform the trainee about his/her motional mistakes [6]. However, the study does not provide guidance for the trainee about how to improve his/her action.

Tan et al. in [7] developed a robot-assisted laparoscopy training system that incorporates demonstrations from both human experts and reinforcement learning to teach the surgical tool manipulation task to the trainee. Various joint position trajectories of an expert are locally stored in FPGA resources to be replayed and regenerated by a generative adversarial imitation learning agent. In the teaching phase, the trainee can simply hold the device-handle and learn the skillful position, velocity, and force patterns required for performing the task. The limitation of this approach is that it cannot adapt to new trajectories that the trainee may want to implement.

Zahedi et. al in [8] presents a machine learning-based guidance method for a virtual kinesthetic teaching environment that aims to transfer the skills of mentor to trainees. Expert demonstrations develop a stiffness variation map of different bone layers in the training phase. The motion similarity estimator block measures the similarity of the drilling motion pattern of the trainee to that of the mentor in different bone layers. Based on the level of similarity and the position error of the trainee relative to the recorded expert trajectory, a resisting or assisting force will be applied to the hand of the trainee to correct the novice behaviors in the operational motions. In this work, the training obtained from this specific task is not generalizable to other tasks. Similar to [8], [9] developed a platform for training novice residents in the orthopedic surgical drilling task by using a deep learning method. In this paper, a recurrent neural network (RNN) with a long short-term memory (LSTM) architecture has been

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designed to extract the model of expert surgical behaviors as a reference trajectory using the captured data.

Inspired by the above-mentioned limitations and recent advancements in deep learning, we have developed an intelligent framework that extracts the skill-related features of a mentor and injects those features into the activity of a trainee. In this context, HRI will be controlled in such a way that the resultant collaboration between the robot and the trainee shows more skillful behavior and a higher level of expertise compared to when the proposed method is not used. The mentor's extracted skill-related features are continuously referenced by the AI algorithm and the trainee's trajectories are continuously improved accordingly. In this approach, there is no limitation on the type of trainee's activity and there is no requirement for prior knowledge about the task, environment, or human user. These features make our approach appropriate for skill transfer across different robotic platforms and applications.

Note that the concept of transfer learning (i.e., using the latent knowledge acquired from one AI model as the starting point for developing another model on a different task) has been adopted as skill transfer in HRI work [10]–[12]. Some of this research is based on data gathered from an easy-to-control robot in order to control another robot with a different structure. Others take advantage of the dataset gathered from a robotic simulation environment for real deployable robotic applications. These papers are not transferring any skill between human users of a robotic system to help the trainee to gain the skillful behavior of the mentor.

The main contributions of this paper are:

- We propose *SkillNet* that extracts the skill-related features from the kinematics data of a robot. The main advantage of this network compared to prior research in skill assessment that used all of the kinematics data in the Hopkins University (JHU)-Intuitive Surgical Inc. (ISI) Gesture and Skill Assessment Working Set (JIGSAWS) dataset [13]–[16] is that we only use Cartesian motion data of the user (i.e., x, y, and z). Moreover, despite prior research that used the entire data of the whole experiment, SkillNet needs 20 seconds intervals of the operational data. This feature enables SkillNet to be deployed in real-time applications in future work.
- The generalizability of SkillNet in capturing spatio-temporal features contributing to the skill levels of a user makes it insensitive with the type of input motion trajectory (i.e., there is no requirement for the motion trajectory being periodic or coming from a particular task or robot).
- The developed skill transfer algorithm can help to transfer the skills of an expert surgeon to the trajectories of a trainee. To the best of our knowledge, there is no work in transferring the skills from a mentor to another trainee that deploys this method with this level of generality in the application.

The structure of this paper is organized as follows: Section II provides the procedure of skill extraction, skill transfer, and skill execution from a mentor to another novice trainee. In Section III, qualitative and quantitative methods to evaluate the quality and performance of the outcome of the proposed algorithm will be elaborated. In Section IV, experimental results with Phantom Premium Haptic Device and discussion about the results will be provided. Conclusions and future work of this research are mentioned in Section V.

II. Methodology

In this section, we will explain how skill-related features are extracted by a deep convolutional neural network and then transferred to a trainee through an optimization algorithm. The main focus of this section is to introduce a novel algorithm that improves the trajectory of the trainee in such a way that it is more representative of skillful behavior. The enhanced trajectory can be used as the reference for the robotic surgery platform to generate the virtual fixture and guide the user's hand toward a more skillful behavior.

A. Skill extraction

The first and the most fundamental step of this work is to extract skill-related features from the Cartesian space motion of a user. Previous works have shown that deep learning can be used to extract the numerical representation of temporal patterns in motions of a user and assess his/her level of expertise in accomplishing a task [14]–[16]. These models were trained and evaluated based on given annotated dataset, JIGSAW containing kinematics data of several robotic surgery tasks with the corresponding labels indicating the level of expertise of each user [13].

Inspired by prior research that a casual observer can discover the skillful behavior of a surgeon by looking at his/her hand motion patterns [17], we trained our network, SkillNet just by using Cartesian motion data (i.e., x, y, and z) of the hand of the surgeon. This feature makes the SkillNet a lighter model, with more compatibility with other robotics platforms, and an ideal choice for real-time skill processing tasks. As we will see in Section III, SkillNet captures the smoothness of the input trajectory as an important skill-related feature from Cartesian motion data. Since smoothness is a feature that is attributed to the velocity or acceleration of the trajectory, it suggests that the SkillNet develops its convolutional filters during the training process to capture velocity/acceleration-related features in deeper layers of the network based on x, y, and z motion inputs. Different from prior works in skill assessment that need extensive data of the entire experiment, SkillNet can extract skill-related features based on data coming from shorter intervals of task performance because the skill level of a task can be determined by observing a short snapshot of the operational data [18]. This feature makes our network different from (and at some level, better than) other work in this area. A brief description of designing and evaluation of the SkillNet is provided in the following sections.

1) Model architecture: The input of the model is a T-second interval of the task performance that has N data points for each of x, y, and z axes. In Fig. 1, we take T=20

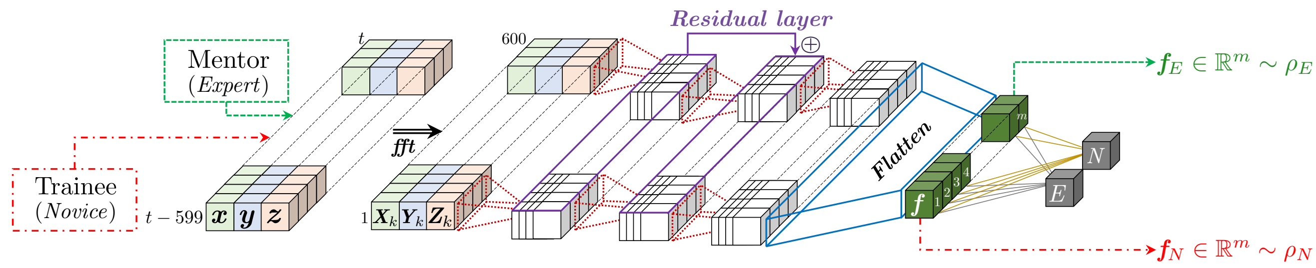

Fig. 1. SkillNet architecture with 1D convolutional layers and residual topology. SkillNet classifies expert (E) and novice (N) users based on 600 sampled points of their Cartesian motion data. Latent features $\boldsymbol{f}\in\mathbb{R}^m$ and their probability distribution ρ can be extracted by passing 3×600 *fft* coefficients of x, y, and z axes trajectories through convolutional layers. These features can be used as the skill representation of the input data in the skill assessment and skill transfer algorithms.

seconds and $N{=}600$ as an example for illustration purpose. Recent studies show that frequency features are good representative of spatio-temporal features of user activity such as smoothness and fluidity [19]. Cartesian space time-series will be fed into the *fft* block and the resultant coefficients will be used as input for the 1-D convolutional neural network. Each convolutional block of Fig. 1 consists of a stack of Batch Normalization and Conv1D with rectified linear unit (ReLu) activation followed by dense layer. The first and the second layers of the 1-D convolutional network have 4 filters, with a kernel size of 3 and the 'same' padding. The third convolutional layer has 8 filters, with the kernel size of 3 and a stride of 2 for dimensionality reduction.

The output of the first convolutional layer is added to the output of the second convolutional layer (see Fig. 1). Using such feedforward path (i.e., residual topology [20]) allows low-level information of the input trajectory to be preserved in the depth of the network and be used in the latent feature layer $\boldsymbol{f}$ (see Fig. 1). Extracted features from the input trajectory will be mapped to the latent feature layer $\boldsymbol{f}$ and then by a fully connected layer will determine the level of expertise of the input trajectory. As illustrated in Fig. 1, SkillNet maps the expert and novice input trajectories to vectors $\boldsymbol{f_E}\in\mathbb{R}^m$ and $\boldsymbol{f_N}\in\mathbb{R}^m$ in the latent feature space, respectively, where m is the number of neurons in the latent feature layer.

2) Dataset: For training the SkillNet to capture the skill-related features of the user motion, we use JIGSAWS dataset [13]. This dataset consists of annotated surgical activity data collected from eight right-handed surgeons with three different levels of expertise (i.e., expert, intermediate, and novice based on their experience of working with the *da Vinci* Surgical System) performing three primary surgical tasks: needle-passing, knot-tying, and suturing. The sampling frequency for recording the trajectory of the user's hand was set to 30 Hz. JIGSAWS contains 76 dimensional kinematics data, coming from four robots of the *da Vinci* surgical system, two surgeon-side and two patient-side manipulator robots.

Considering 20 seconds intervals of motional data are long enough to let the network capture the temporal features related to the level of expertise of subjects and at the same time, is short enough to be used in a real-time processing system for future work. To make the SkillNet a suitable feature extractor for the skill transfer algorithm, we do not consider intermediate participants because we want to train a network that purely classifies skillful and novice behaviors from each other. Inspired by the same reason, non-dominant (left) hand displacement data is prone to act as outlier data in determining the true skill level of each surgeon and has been neglected in the training stage of the SkillNet. Accordingly, the first three kinematics data (i.e., the Cartesian displacement of the right hand) were used to classify expert and novice surgeons.

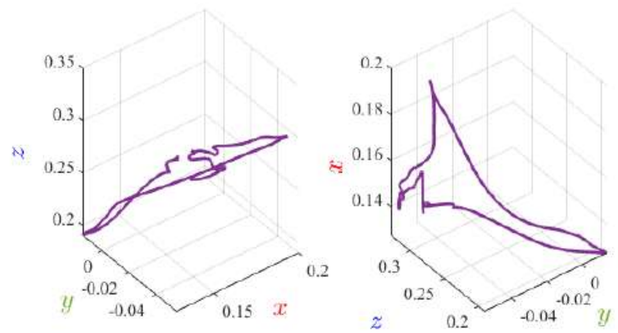

Fig. 2. Different representation of the same trajectory in two different coordinate systems. The left coordinate system maps the right one first by $+90$ deg rotation about the z axis, followed by a -90 deg rotation about the moved x axis, and a final -90 deg rotation about the moved z axis.

To achieve a better generalization for the SkillNet, we can expand the size of the training set by sliding over the time-series of one surgical operation and create multiple samples from one experiment. Moreover, if we arbitrarily rotate the Cartesian motion trajectory of a subject, the level of expertise of that trajectory does not change. A trivial example of this idea is that if we input the $[y\ z\ x]^\top$ vector instead of $[x\ y\ z]^\top$ to the skill classifier network, the output of the network should remain the same (see Fig. 2). All of $3!{=}6$ combinations of x, y, and z axes can be used to expand the dataset volume 6 times larger than its original size.

B. Skill transfer

Inspired by the concept of image style transfer in the field of computer vision [21], the goal of the skill transfer algorithm is to synthesize enhanced combined trajectory $\vec{C}$

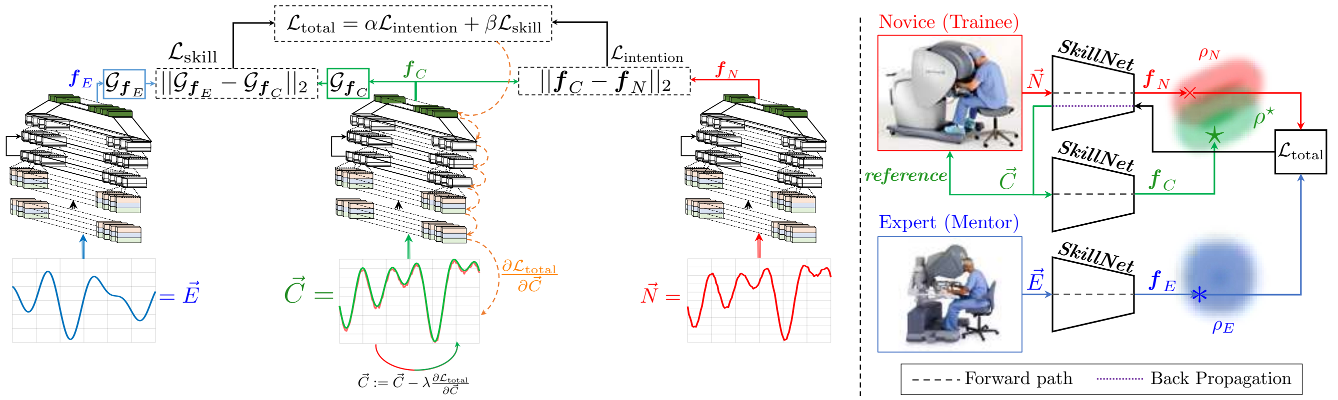

Fig. 3. Skill transfer algorithm. As shown on the left side, mentor's and trainee's trajectories are passed through the same SkillNet to extract and store intention and skill representations $\boldsymbol{f_N}$ and $\boldsymbol{f_E}$ in the right and the left side of the figure, respectively. Then the algorithm tries to optimize the enhanced combined trajectory $\vec{C}$ from the base novice trajectory $\vec{N}$ at the middle of the figure. The algorithm based on the latent feature vector $\boldsymbol{f_C}$, iteratively updates $\vec{C}$ to simultaneously minimize the skill loss and intention loss of the combined trajectory $\vec{C}$ concerning the mentor's trajectory $\vec{E}$ and the base trainee's trajectory $\vec{N}$. The visualization of this method is shown on the right side of the figure. Enhanced trajectory $\vec{C}$ can be continuously used as the reference trajectory for the trainee's robot to provide minor correction forces to improve the performance of the task.

initialized by the novice user's trajectory $\vec{N}$ in such a way that $\vec{C}$ is more representative of skillful behavior with the minimum deviation relative to its initial value $\vec{N}$. This can be achieved by minimizing two losses: the *skill loss* (i.e., the difference between the probability distributions of the expert and novice latent feature variables $\boldsymbol{f_E}$ and $\boldsymbol{f_N}$, respectively) and the *intention loss* (i.e., the Euclidean distance between the latent feature variables of base trajectory $\boldsymbol{f_N}$ and that of the enhanced combined trajectory $\boldsymbol{f_C}$).

To transfer the skills of the mentor, we generate a new trajectory based on the trainee's input trajectory that matches the user intention and skillful representation by jointly minimizing intention and skill losses

$$\mathcal{L}_{\text{total}}=\alpha\mathcal{L}_{\text{intention}}(\vec{C},\vec{N})+\beta\mathcal{L}_{\text{skill}}(\vec{E},\vec{C}) \tag{1}$$

where α and β are positive weighting factors indicating how much we care about the intention of the trainee and the skill level of the outcome trajectory. For $\frac{\alpha}{\beta}\gg 1$ the algorithm preserves the trajectory content more than improving the skill (useful for very delicate tasks or when the trainee has some level of expertise and is not completely novice). If $0<\frac{\alpha}{\beta}<1$, the algorithm strongly improves the skill level of the trajectory with a sharp learning curve (useful for novice surgical training purposes that there is no patient in the loop). $\vec{C}$ is initialized by $\vec{N}$ and will be updated through the gradient descent method with the learning rate of λ

$$\vec{C}:=\vec{C}-\lambda\frac{\partial\mathcal{L}_{\text{total}}}{\partial\vec{C}}. \tag{2}$$

Note that if we define both $\mathcal{L}_{\text{intention}}$ and $\mathcal{L}_{\text{skill}}$ as differentiable functions, the gradient of the total loss with respect to $\vec{C}$ exists. The algorithm and graphical representation of skill transfer is demonstrated in Algorithm 1 and in the middle part of Fig. 3, respectively.

1) Skill loss: Vector $\boldsymbol{f}$ contains features of multiple layers and obtains both multi-scale and stationary representation, contributing to the skill level, not the global arrangement of the input trajectory. $\boldsymbol{f_E}$ and $\boldsymbol{f_N}$ are two samples from mentor and trainee latent feature space, respectively. Squared Maximum-Mean Discrepancy (MMD^2) of $\boldsymbol{f_N}$ and $\boldsymbol{f_E}$ is a statistic measure to calculate the difference between the distributions of these two samples. Trainee's input trajectory can approach to the skillful behavior by minimizing $\mathrm{MMD}^2[\boldsymbol{f_E},\boldsymbol{f_N}]$. Minimizing the MMD^2 measure by appropriate kernel function leads to matching means, variances, and higher-order moments of two samples from two different distributions [22]. Our method transfers the skill-related features of a mentor to a trainee's trajectory by minimizing MMD^2 loss.

It has been theoretically proven that matching Gram matrices of two samples from two distributions is equivalent to minimizing the MMD^2 of those samples [23], where the Gram matrix is the inner product between the vectorized feature maps of $\boldsymbol{f_E}$ and $\boldsymbol{f_N}$. If we start from the base trainee's trajectory $\vec{N}$ and make an improvement to create the enhanced combined trajectory $\vec{C}$, the skill loss can be defined by the Euclidean distance between the Gram-based representations of $\boldsymbol{f_C}$ and $\boldsymbol{f_E}$

$$\mathcal{L}_{\text{skill}}(\vec{E},\vec{C})=\|\mathcal{G}_{\boldsymbol{f_E}}-\mathcal{G}_{\boldsymbol{f_C}}\|_2. \tag{3}$$

The schematic representation and formulation of this concept is shown on the left side of Fig. 3.

2) Intention loss: In the field of human-robot interaction, especially for the minimally invasive surgery robots, increasing the level of robot autonomy leads to regulatory, ethical, and legal challenges [24]. The intention of the surgeon presents itself in the trajectory and by minimally manipulating the trajectory the surgeon is minimally deviating from the goal. In this work, the network improves the user's input trajectory with the minimum deviation from his/her intention by minimizing the intention loss (or trajectory content loss)

$$\mathcal{L}_{\text{intention}}(\vec{C},\vec{N})=\|\vec{C}-\vec{N}\|_2. \tag{4}$$

Minimizing this loss is equivalent to minimizing the Euclidean distance between latent feature vector of the base

Algorithm 1: Skill Transfer.

Input: Expert trajectory $\vec{E}$, Novice trajectory $\vec{N}$, *iteration*, α, and β
Result: Enhanced trajectory $\vec{C}$
$\boldsymbol{f_E}$ = ***SkillNet***$(\vec{E})$
$\boldsymbol{f_N}$ = ***SkillNet***$(\vec{N})$
$\vec{C} = \vec{N}$
$\boldsymbol{f_C} = \boldsymbol{f_N}$
while *iteration* > 0 **do**
  $\mathcal{L}_{\text{skill}} = ||\mathcal{G}_{\boldsymbol{f_E}} - \mathcal{G}_{\boldsymbol{f_C}}||_2$
  $\mathcal{L}_{\text{intention}} = ||\boldsymbol{f_C} - \boldsymbol{f_N}||_2$
  $\mathcal{L}_{\text{total}} = \alpha\mathcal{L}_{\text{intention}} + \beta\mathcal{L}_{\text{skill}}$
  $\vec{C} \leftarrow \vec{C} - \lambda\frac{\partial\mathcal{L}_{\text{total}}}{\partial\vec{C}}$
  $\boldsymbol{f_C} \leftarrow$ ***SkillNet***$(\vec{C})$
  iteration $\leftarrow$ *iteration*-1
end
return $\vec{C}$

novice trajectory $\boldsymbol{f_N}$ and that of the enhanced combined trajectory $\boldsymbol{f_C}$ in the feedforward path of the SkillNet (see Fig. 3). The intention loss can be expressed as

$$\mathcal{L}_{\text{intention}}(\vec{C},\vec{N}) = ||\boldsymbol{f_C} - \boldsymbol{f_N}||_2. \quad (5)$$

Equation (4) is the reconstruction loss of the user's trajectory and extremely constrains the exact sample values of the enhanced trajectory. On the other hand, Equation (5) preserves higher-level features from higher layers in the network and preserves the high-level content of the input trajectory during the skill transfer algorithm. Both defined intention losses can be useful based on the type of the operation, required level of autonomy, and safety. In this work, both losses had almost the same performance in enhancing the skill level of the user. For novel situations or surgical tasks, Equation (4) seems more secure option. The schematic representation and formulation of this concept is shown on the right side of Fig. 3.

Empirically, it is preferred to improve the skill level of the trainee up to about 20% to have a good balance between intention and skill loss and get a reasonable result. Note that, this behavior happens in real-world conventional training, because a trainee cannot make huge improvement after one session of practicing and only experiences small gradual changes in his/her learning curve.

C. Skill execution

In real-time, SkillNet continuously injects the extracted skill-related features into the trainee's trajectory and returns the enhanced combined trajectory, $\vec{C}$ along with the confidence of the skill classification network, ε about the trainee's trajectory $\vec{N}$ (see Fig. 4). For simplicity, we use the last two points of the enhanced trajectory, $\boldsymbol{C}[t]$ and $\boldsymbol{C}[t-1]$ to estimate the next point $\hat{\boldsymbol{C}}[t+1]$:

$$\hat{\boldsymbol{C}}[t+1] \approx \boldsymbol{C}[t] + \frac{\Delta T(\boldsymbol{C}[t] - \boldsymbol{C}[t-1])}{\Delta T} = 2\boldsymbol{C}[t] - \boldsymbol{C}[t-1] \quad (6)$$

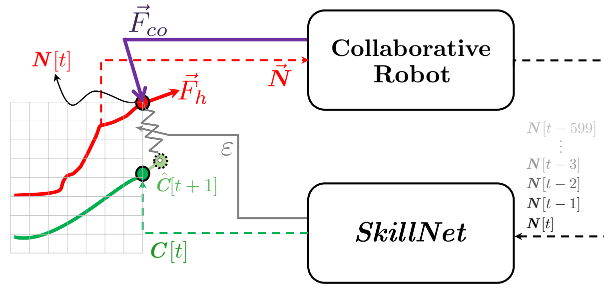

Fig. 4. Skill transfer architecture, resulting from the cooperation of SkillNet, collaborative robot, and novice trainee. Intuitively, SkillNet manipulates one end of a virtual spring toward enhanced trajectory (green solid line) while the spring's other end is virtually connected to the user's hand. In this approach, novice trajectory (red solid line) will be absorbed toward more skillful behavior by offering mild and compliant guidance forces from the skill execution platform.

where ΔT is the sampling time of the system. This rough estimation is based on the assumption that in surgery tasks, there is no sudden motion in the surgeon's activity and velocity is almost the same between two sampling intervals with the adequate sampling frequency. For more delicate tasks that a smoother and more accurate estimation of the next point $\hat{\boldsymbol{C}}[t+1]$ is needed, a median filter over the last k trajectory sample points can be incorporated as a better choice. As illustrated in Fig. 4, the collaborative robot provides the user with a mild correction force $\vec{F}_{co}$ to guide him/her toward the estimated enhanced reference point $\hat{\boldsymbol{C}}[t+1]$ using a variable impedance controlling paradigm

$$\vec{F}_{co} = \varepsilon\boldsymbol{K}(\hat{\boldsymbol{C}}[t+1] - \boldsymbol{N}[t]) \quad (7)$$

where $\boldsymbol{K} = \text{diag}(k_x, k_y, k_z)$ is the matrix of virtual compliance coefficients in three directions of the Cartesian coordinate system. The correction force increases when the distance between the current point of the trainee's trajectory $\boldsymbol{N}[t]$ and the estimated enhanced reference point $\hat{\boldsymbol{C}}[t+1]$ increases or the network detects increased novice behavior in the past 600 samples of trainee's motion. The effect of the increased novice behavior is applied to the controller by multiplying gain ε to the whole correction force. Parameter ε is the adaptive term for the variation of compliance coefficient $\boldsymbol{K}$ in the presented variable impedance paradigm.

III. Evaluation Methods

After training the SkillNet based on the JIGSAWS dataset, the model reached the accuracy of about 98% over the test dataset which makes it a reliable candidate to extract latent patterns from kinematic data in the motions of the user. Due to this result, SkillNet is used in the skill transfer algorithm to improve the skill level of the trainee's trajectory. In this section, qualitative and quantitative methods to evaluate the performance of SkillNet and the skill transfer algorithm will be presented.

A. Qualitative Evaluation

The left column of Fig. 5 is showing two different mentor's trajectories performed by two different expert surgeons with

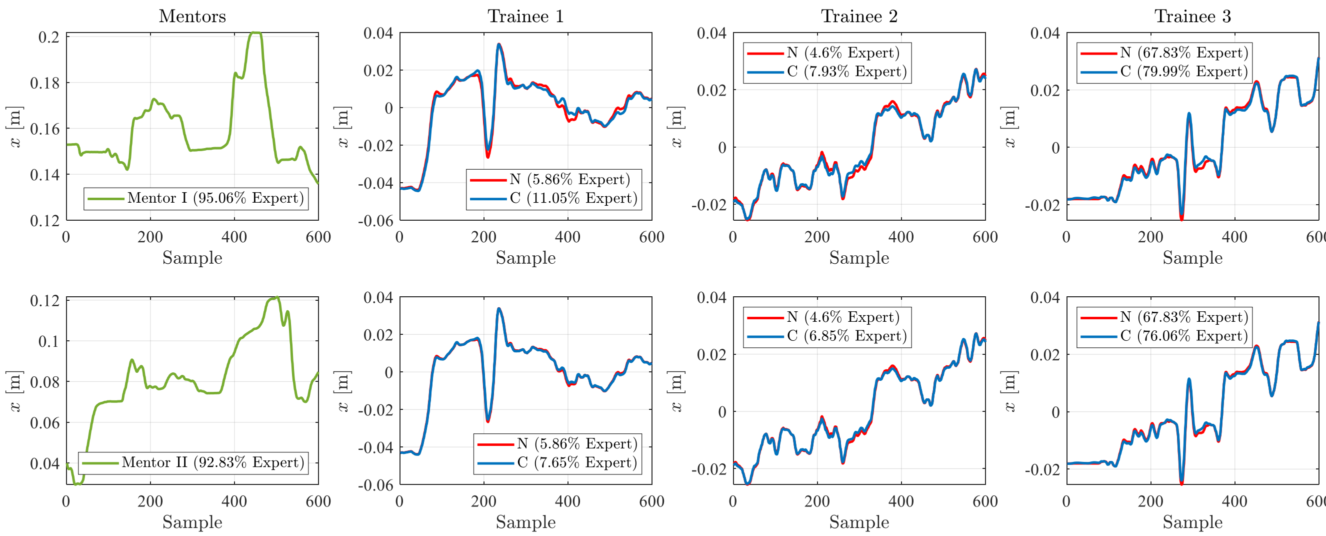

Fig. 5. Base trajectories (red lines) and their enhanced combined trajectories (blue lines) for three different trainees with different levels of expertise. Trainees' trajectories in the first row have been enhanced based on the skill features of Mentor I and those in the second row have been enhanced over the skill features of Mentor II (different person with the different level of expertise).

different levels of expertise based on the confidence of the classification network. SkillNet uses mentor's trajectory as $\vec{E}$ and injects extracted skillful behaviors of them into trainees' trajectory shown in the right three columns of Fig. 5 in one iteration by choosing α=β=10^{-3} and λ=0.1. Note that decreasing the value of $\frac{\alpha}{\beta}$ in Equation (1) results in higher skill enhancement during the skill transfer algorithm.

The network gives better enhancement for the trainee's trajectory when it injects the extracted skill behaviors from a mentor with a higher level of expertise. In other word, trainees will be trained better under the supervision of a more experienced mentor. In Fig. 5, Mentor I has a higher level of expertise and the enhanced trajectories of all three trainees have better improvement when they are guided by Mentor I rather than Mentor II. This achievement is because of the fact that a more experienced mentor has a stronger effect on the trajectory of a trainee while minimizing the total loss in Equation 1.

Additionally, the suggested enhanced trajectory for each trainee has the same correction pattern when that trajectory is improved based on different mentors. Both enhanced trajectories of three trainees in Fig. 5 have the same correction patterns when they are guiding by different mentors. This behavior of the network is aligned with our expectation. A trainee should be trained in the same manner while being supervised by different mentors. Using the deep neural skill transfer approach instead of conventional training methods can reduce the influence of mentor on training outcomes. Another advantage of this behavior based on our observation is that if we increase α or the iteration number for a less experienced mentor, we get the same enhanced trajectory $\vec{C}$ resulting from the supervision of a highly experienced mentor.

Another tangible attribute of skill transfer occurs when the input of the algorithm is the trajectory from a more expert trainee, i.e., a trainee that the classifier has higher confidence about his/her level of expertise. The right column of Fig. 5 shows the trajectory of Trainee 3 with higher skill level (67.83% expert) relative to Trainee 1 and 2. Trainee 3 achieved higher skill enhancement (about 10%) without significant deviation from the base trajectory $\vec{N}$ in comparison with the other two trainees. It can be concluded that the more skillful trainee will get higher skill enhancement with lower intention loss, $\mathcal{L}_{\text{intention}}$. In general, a more skillful trainee has fewer fundamental mistakes in the way of becoming classified as an expert and minor correction clues from the mentor will impose significant improvement to the quality of the outcome.

All of the above sensible qualitative findings are indicating that the representation of skill is not case-dependent for a specific trajectory and SkillNet is extracting fundamental features related to the skill of the user. These results can be attributed to the generalizability and accuracy of the network in detecting skill-related features of the input trajectories. Besides these qualitative evaluations, we incorporate other quantitative measures to prove the performance of our approach in transferring skills from a mentor to another trainee. These quantitative assessments can be classified into two main groups: theoretical and practical evaluation methods.

B. Evaluation Metrics

In this section, we will introduce quantitative measures for algorithm evaluation. Expert robotic surgeons tend to perform more predictable and smoother motions relative to novice surgeons. Predictability and smoothness of user's motion were incorporated in skill evaluation of surgical tasks and yielded promising results [25]. Here, we demonstrate that the enhanced trajectory generated from our proposed method has increased predictability and smoothness compared to its base trainee's trajectory.

Approximate Entropy (ApEn) is a measure of complexity and regularity of a system and has been widely used in action quality assessment in a variety of tasks [25]. ApEn assigns lower values for predictable and ordered time-series data and higher values for unpredictable data with randomness in their nature.

To investigate the smoothness improvement, we can calculate the Euclidean norm of higher frequency coefficients of the Fourier transform of the trajectory before and after the enhancement procedure. The frequency range between 8 and 12 Hz is attributed to the hand tremor of the user [26] and 13 Hz to higher frequencies are mainly related to noise (i.e., measurement noises). We separately investigate the effect of the skill transfer in hand tremor reduction and noise cancellation.

By applying the skill transfer method under the supervision of mentor 1 in Fig. 5 over 30 different novice and less expert trajectories in the JIGSAWS dataset, not only we had improvement in the confidence of the classification network about the level of expertise of the enhanced trajectory with a negligible deviation of the user's intended trajectory (at most 1 mm), but also we had improvement in the predictability of motion, tremor reduction, and noise cancellation. The percentage of skill enhancement, ApEn and hand tremor reduction, and noise cancellations for the enhanced trajectory with relative to the trainee's original data are shown in Fig. 6 (b). Mean values (red lines) and distribution of data points (blue data points) in each diagram of Fig. 6 (b) indicates a considerable improvement in skill enhancement and the other three quantitative criteria.

Close observation over more dexterous trainees, mainly those with the level of expertise higher than 50% such as Trainee 3 in the right side of Fig. 5 reveals that despite the observation that these trainees gain a large amount of improvement in their skill level during the skill transfer procedure, their enhancement in ApEn and hand tremor reduction is significantly lower compared to other more novice users (noise cancellation is almost the same).

IV. Experimental Results and Discussion

To evaluate SkillNet's performance in practice, we used completely different input trajectories to check the network's generalization when it is facing new data coming from new subjects and a completely different robotic platform. Since the input of the network is the Cartesian motion patterns of the user and is completely indifferent to the structure of the collaborative robot, we have a convenient procedure of transfer learning from one robotic platform to another one. As shown in Fig. 7, we used motion data resulting from the collaboration of the user and Phantom Premium 1.5A Haptic Device, Geomagic Inc. The experiments were approved by the University of Alberta Research Ethics and Management Online under study ID Pro00055825. To circle around the need for expert and novice users, we considered dominant hand motion trajectories of the user as expert data and trajectories coming from the other hand as novice data in the task of tracking a squiggly line. Our dominant hand during our lifetime had a lot of chance to be trained to perform very delicate tasks such as writing and drawing and has become more skillful in doing elaborate motions with higher precision, lower hand tremor, and more predictable behavior compared to non-dominant hand.

Five right-handed users performed the task of tracking squiggly line in 6 trials. Each of them had the chance to perform the task before the actual experiment with their dominant hand (i.e., right hand) to increase their dexterity over this specific task. The confidence of the network about the dexterity level of the right hand in 29 out of 30 inputs was higher than that of the left hand (see Fig. 6 (a) for the confidence difference of right and left hands). This result indicates that SkillNet has high accuracy and generalization in capturing skill related features when facing completely new data.

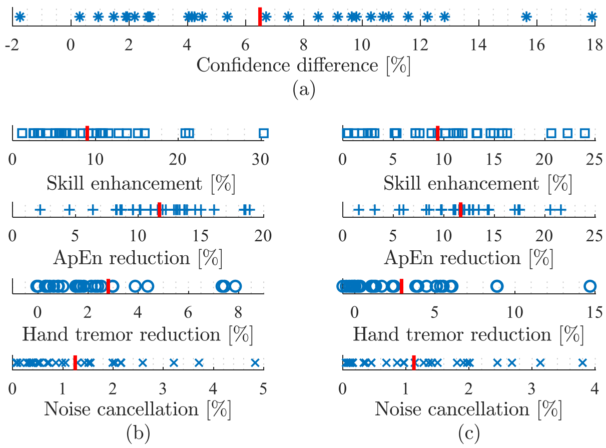

Fig. 6. The percentage of confidence difference of network about dominant hand skill level with respect to that of non-dominant hand (a), skill enhancement, ApEn and hand tremor reduction, and noise cancellations for the enhanced signal for the novice input data from 30 experiments from (b) JIGSAWS dataset and (c) with Phantom Premium Haptic Device. Scattered points represent experiments' data and the red line in each diagram indicates the mean value of 30 points.

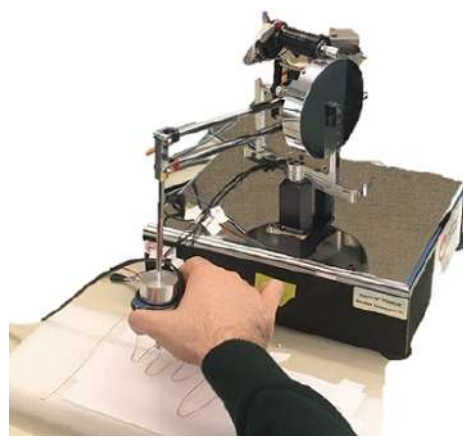

Fig. 7. Using Phantom Premium 1.5A Haptic Device in the squiggly line tracking task to test the generality of SkillNet and performance of the skill transfer algorithm in practice with different user data and another robotic platform.

The skill transfer algorithm under the supervision of Mentor I from the JIGSAWS dataset was applied over our experimental data to generate more skillful trajectories. The percentage of skill enhancement, ApEn and hand tremor reduction, and noise cancellations for the enhanced trajectory relative to the base trajectory (i.e., raw data coming from the left hand) are shown in Fig. 6 (c). Mean values (red lines) and data distribution of points (blue data points) in each diagram of Fig. 6 (c) indicates a considerable improvement in the skill enhancement and the other three quantitative criteria.

Due to the generality of SkillNet and based on the experimental results, the skill transfer algorithm can be adopted as a reference trajectory generator for robotic surgery training programs to guide the trainee's hand toward a better motion with more skillful behavior while minimizing the deviation from the intention of the user. The skill transfer algorithm is similar to a high-performance filter that removes noises, reduces hand tremors, improves the predictability and regularity of the motion, and in general helps the user to perform the surgical task in a more skillful manner.

V. Conclusions and Future Work

In this work, we present a deep convolutional neural network, SkillNet, for extracting the skill-related features of a user working with *da Vinci* surgical system and in general, teleoperated and collaborative robots. Extracted features were used in skill transfer algorithm to generate a new reference trajectory with minimum deviation from the base trajectory and more skillful features. The enhanced trajectory can be applied as a virtual fixture in the robotic platform to guide the trainee's hand toward more skillful behavior. The SkillNet demonstrated a very good generalization in capturing skill-related features of user's motion over JIGSAWS dataset and our own experimental data. The skill transfer algorithm made considerable enhancement over the trainee's trajectory in terms of predictability of motion, hand tremor reduction, and noise cancellation.

For future work, due to the generalization and light architecture of SkillNet, the skill transfer approach will be used to continuously generate enhanced trajectories for training purpose in a real-time platform. The proposed framework can investigate how an inexperienced trainee will improve with successive interactions with the framework (i.e., learning curve studies). SkillNet can be improved to incorporate objective metrics such as economy of motion or task execution time to have a more comprehensive representation of the skill level of the input trajectory. This approach can be utilized in other applications such as driver training and physical rehabilitation tasks by minor changes in the definition of mentor and trainee (e.g., in physical rehabilitation, the mentor is an intact human and the trainee is a person with disability using an exoskeleton).

References

[1] Mahya Shahbazi, et al. Robotics-assisted mirror rehabilitation therapy: a therapist-in-the-loop assist-as-needed architecture. *IEEE/ASME Transactions on Mechatronics*, 21(4):1954–1965, 2016.

[2] Mojtaba Sharifi, et al. Stable nonlinear trilateral impedance control for dual-user haptic teleoperation systems with communication delays. *Journal of Dynamic Systems, Measurement, and Control*, 139(12), 2017.

[3] Ran Tao, et al. Modeling and emulating a physiotherapist's role in robot-assisted rehabilitation. *Advanced Intelligent Systems*, 2(7):1900181, 2020.

[4] Kamran Shamaei, et al. Design and evaluation of a trilateral shared-control architecture for teleoperated training robots. In *2015 37th annual international conference of the IEEE engineering in medicine and biology society (EMBC)*, pages 4887–4893. IEEE, 2015.

[5] Roland Sigrist, et al. Augmented visual, auditory, haptic, and multimodal feedback in motor learning: a review. *Psychonomic bulletin & review*, 20(1):21–53, 2013.

[6] Marzieh Ershad, et al. Adaptive surgical robotic training using real-time stylistic behavior feedback through haptic cues.

[7] Xiaoyu Tan, et al. Robot-assisted training in laparoscopy using deep reinforcement learning. *IEEE Robotics and Automation Letters*, 4(2):485–492, 2019.

[8] Ehsan Zahedi, et al. Towards skill transfer via learning-based guidance in human-robot interaction: An application to orthopaedic surgical drilling skill. *Journal of Intelligent & Robotic Systems*, pages 1–12, 2019.

[9] Fekri, et al., Pedram. Deep Learning-Based Haptic Guidance for Surgical Skills Transfer. *Frontiers in Robotics and AI*, 7, 2020.

[10] Sylvain Calinon, et al. Human–robot skills transfer interfaces for a flexible surgical robot. *Computer methods and programs in biomedicine*, 116(2):81–96, 2014.

[11] Naveen Madapana, et al. Desk: A robotic activity dataset for dexterous surgical skills transfer to medical robots.

[12] Md Masudur Rahman, et al. Transferring dexterous surgical skill knowledge between robots for semi-autonomous teleoperation. In *2019 28th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*, pages 1–6. IEEE, 2019.

[13] Yixin Gao, et al. Jhu-isi gesture and skill assessment working set (jigsaws): A surgical activity dataset for human motion modeling. In *Miccai workshop: M2cai*, volume 3, page 3, 2014.

[14] Zhiteng Jian, et al. Multitask learning for video-based surgical skill assessment.

[15] Ziheng Wang and Ann Majewicz Fey. Deep learning with convolutional neural network for objective skill evaluation in robot-assisted surgery. *International journal of computer assisted radiology and surgery*, 13(12):1959–1970, 2018.

[16] Xuan Nguyen, et al. Surgical skill levels: Classification and analysis using deep neural network model and motion signals. *Computer methods and programs in biomedicine*, 177:1–8, 2019.

[17] Carolyn Chen, et al. Crowd-sourced assessment of technical skills: a novel method to evaluate surgical performance. *Journal of surgical research*, 187(1):65–71, 2014.

[18] Ershad , et al., Marzieh. Meaningful assessment of surgical expertise: Semantic labeling with data and crowds. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 508–515. Springer, 2016.

[19] Aneeq Zia, et al. Automated assessment of surgical skills using frequency analysis. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 430–438. Springer, 2015.

[20] Kaiming He, et al. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

[21] Gatys , et al., Leon A. Image style transfer using convolutional neural networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2414–2423, 2016.

[22] Yujia Li, et al. Generative moment matching networks. In *International Conference on Machine Learning*, pages 1718–1727. PMLR, 2015.

[23] Yanghao Li, et al. Demystifying neural style transfer.

[24] Guang-Zhong Yang, et al. Medical robotics—regulatory, ethical, and legal considerations for increasing levels of autonomy. *Science Robotics*, 2(4):8638, 2017.

[25] Aneeq Zia and Irfan Essa. Automated surgical skill assessment in rmis training. *International journal of computer assisted radiology and surgery*, 13(5):731–739, 2018.

[26] Ahmad Anouti and William C Koller. Tremor disorders. diagnosis and management. *Western journal of medicine*, 162(6):510, 1995.