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Emerging Challenges in Technology-based Support for Surgical Training

Minsik Hong, and Jerzy W. Rozenblit

Abstract—**This paper stipulates several technological research and development thrusts that can assist in modern day approaches to simulated training of minimally invasive laparoscopic and robot surgery. Basic tenets of such training are explained, and specific areas of research are enumerated. Specifically, augmented and mixed reality are proposed as a means of improving perceptual and clinical decision-making skills, haptics are proposed as mechanism not only to provide force feedback and guidance, but also as a means of reflecting a tactile feel of surgery in simulated training scenarios. Learning optimization is discussed to fine tune the difficulty levels of various exercises. All the above elements can serve as the foundation for building computer-based virtual coaching environments that can reduce the training costs and provide a broader access to learning highly complex, technology driven surgical techniques.**

Keywords—**Surgical training, minimally invasive surgery, virtual coaching, force guidance, haptics, mixed reality, learning optimization**

I. Introduction

MINIMALLY invasive surgery (MIS) was introduced in the late 1980s and has been widely performed for various surgical procedures such as kidney removal, cholecystectomy, otolaryngology, and splenectomy in the last three decades [1]. Such procedures significantly reduce recovery time and postoperative pain with lower perioperative complications and less blood loss. However, the MIS technique is more challenging than conventional open surgery and has a steeper learning curve. This effect is due to limitations such as restricted vision with 2D images through an endoscopy and special tools that offer a limited range of motion with the fulcrum effect [2]. Furthermore, trainees are inundated with recognition of intraoperative anatomy, avoidance of potential complications, and listening to staff instruction, which can result in sensory overload during the learning process.

A significant advancement in the evolution of MIS was the development of a clinical, FDA-approved robotic platform in the late 1990s using a master-slave type of robotic system [3]. Subsequent new generations of surgical robots overcome several limitations of conventional MIS. For example, 3D vision is facilitated through stereo endoscopy to minimize the limitation of depth perception issues caused by 2D visualization in conventional MIS. Also, the articulated movements of robotic arms with 7 degrees of freedom have expanded the reconstructive ability to match that of the human hand. Furthermore, the robotic systems eliminate hand tremors, thereby facilitating fine-grained, precise instrument movements [4].

M. Hong is with the Department of Electrical and Computer Engineering, University of Arizona, Tucson, AZ 85721 USA (e-mail: mshong@email.arizona.edu).
J. W. Rozenblit is with the Department of Electrical and Computer Engineering, University of Arizona, Tucson, AZ 85721 USA (e-mail: jerzyr@arizona.edu).

Although robotic surgery platforms resolve and mitigate the limitations of conventional MIS, the predominant robotic systems (e.g., da Vinci, Intuitive Surgical, Inc.) do not provide any haptic and tactile feedback. Therefore, surgeons are purely dependent on visual cues while performing an operation. In the current system, they must rely on visual cues of tissue deformation to assess the force on the tissues.

There are various surgical training simulators for conventional MIS, where physical reality and virtual reality setups have been widely utilized to develop such systems. The most common physical reality simulator (PRS) is a box trainer designed to practice the fundamentals of laparoscopic surgery (FLS) [5]. Such a trainer consists of two surgical instruments with a camera, a trainer box, and consumables such as a peg board, suture blocks, and gauze pads for FLS tasks. It is a cost-effective solution but there are no guidance features. To provide a certain level of guidance (e.g., objective performance evaluation), computer-enhanced PRSs (e.g., CELTS [6], LTS3E [7]) have been proposed with assessment metrics [8] such as completion time and path length. Virtual reality simulators (VRSs) [9], [10] generally utilize computer graphics to provide simulated training environments with a specialized instrument interface. Unlike PRSs, VRSs can allow trainees to practice simulated surgical procedures such as cholecystectomy with objective assessments so that they can learn such procedures. However, VRSs do not provide natural haptic feedback (e.g., tactile feedback by tool-tissue interactions) while PRSs deliver such feedback. To overcome this issue, several VRSs have been utilized haptic rendering techniques for artificial haptic feedback so that trainees feel a certain degree of feedback [11], [12].

As opposed to conventional MIS training, mature and well-developed robotic surgery training procedures are still under development (e.g., the Fundamentals Robotic Surgery (FRS) program proposed in [13]). These robotic surgery training procedures are designed for preclinical training which is generally recommended before surgical trainees enter the operating room. For this training, various dry or wet lab tasks, and virtual reality-based training tasks were proposed [14]. Also, several virtual reality simulators (e.g., dV-Trainer and dVSS [15]) with assessment schemes [16] have been developed and are commonly used for such training.

The remainder of this article is organized as follows: our research objective is presented in Section 2. Then, we describe our proposed virtual coaching framework and illustrate ongoing research activities in Section 3 and Section 4, respectively. In Section 5, discussion and conclusion are presented.

II. Objectives

In general, MIS procedures have a steep learning curve. Therefore, the historical pathway of “see one, do one, teach one” is not cost-effective, nor optimal from a quality and safety standpoint in MIS training. To enhance skills acquisition procedures, we propose a design framework to utilize intelligent virtual coaching techniques for both conventional and robotic MIS training. The coaching framework is motivated by several factors such as the need to train surgeons on low resource settings in remote rural areas and the lack of extensive access to expert surgeons who could devote sufficient time to didactic activities.

III. Methods

In real life, when someone learns new motor skills (e.g., playing tennis) with human instructors, an instructor generally provides: 1) a demonstration before practicing an exercise task, 2) instant feedback (e.g., verbal instruction) while performing a particular task, and 3) post-procedure feedback based on the instructor’s assessment. This is a mentor-apprenticeship process. In MIS training, training procedures [16] are as follows: trainees are firstly asked to take e-learning or video training courses to acquire theoretical knowledge. Then, they generally use preclinical simulators (e.g., various PRSs or VRSs) to learn fundamental motor skills such as instrument manipulations, object transferring, suturing, and cutting. After completing such preclinical training, they could participate in performing surgery under expert surgeons’ supervision in the operating room. During both preclinical and clinical training sessions, trainees could also get feedback (e.g., debriefing) from experts.

Existing training systems with simulated tasks are primarily designed for preclinical training and motor skills (e.g., instrument manipulation) acquisition. However, motor skills alone may not be sufficient to develop surgical expertise. Also, expert surgeons’ supervision is generally required for trainees to acquire such hands-on skills. Therefore, we propose a virtual coaching scheme to provide the better training experience so that trainees enhance their skills effectively without experts (i.e., robotic systems become an instructor). In [17], the authors suggested several recommendations to develop the next-generation simulators by utilizing force guidance with haptics and proficiency-based learning. In this section, we propose how to design such novel simulators by introducing various technologies.

A. *Perceptual-cognitive skills acquisition based on mixed reality*

In the operating room (OR), surgeons may frequently face various unexpected, non-routine situations while performing surgery. Thus, they must possess sophisticated perceptual-cognitive skills to resolve a surgical issue by making quick decisions and use their motor skills to execute the best course of action to rectify problems. While a few studies have been published regarding cognitive aspects of surgical expertise [18], [19], to our knowledge, there are no reported simulators for trainees to acquire perceptual-cognitive skills simultaneously with motor skills in minimally invasive surgery.

We propose here mixed reality (MR) [20] environments for the perceptual-cognitive training by emulating some aspects of the inherent sensory load in the OR environment, where the OR is a dynamic setting with team communication, visual and audio signals, and other sensory inputs. By utilizing MR rendering with audio cue augmenting, we can create simulated critical situations and facilitate the practice of perceptual-cognitive skills. Through such simulated training setups with the corresponding evaluation metrics, we can also assess decision-making skills as well as the resulting motor execution of the training scenarios.

To generate critical situations (e.g., simulated bleeding) effectively given an MR rendering interface, algorithms for real-time interactions between real and virtual objects [20] are needed. For instance, a depth map generation algorithm is utilized to handle occlusion interactions [21]. Object recognition and tracking schemes [22] are also required for the MR rendering. The following scenario illustrates how the MR rendering works for perceptual-cognitive skills training: while a trainee performs an instrument navigation task (e.g., move an instrument to a goal position without hitting obstacles), a bleeding effect can be activated and rendered when a trainee makes collisions frequently. To enhance the degree of realism, we should keep tracking the interactions among instruments and a training environment (e.g., a 3D printed kidney model).

To support more complex tasks such as suturing with critical situations, more advanced techniques (e.g., deep learning for moving object detection [23]) with a variety set of data (e.g., videos and instrument movements) are required. The deep learning (DL) technique [24] can be used to construct a depth map given a physical reality setup for high fidelity MR rendering. Such depth map generation schemes can also be applied for both standard and robotic surgery training systems.

Audio augmenting is realized using recorded or synthesized audio cues. The corresponding audio file plays for realistic effects like a trainee is in the OR environment. Also, the audio augmentation can be used for generating noise distraction so that a virtual coaching system evaluates trainees’ perceptual-cognitive skills under a stressful environment.

B. *Adaptive force guidance based on reinforcement learning*

Several force-based guidance systems have been proposed in standard (e.g., VRS [25] and dual-user interface [26] for training) and robotic (e.g., [27], [28] for tele-operation) MIS setups. In [29], an adaptive force guidance scheme was proposed for laparoscopic surgery skills training given a physical reality setup with augmented reality based visual guidance. Such guidance was applied for the Computer Assisted Surgical Trainer (CAST) for trainees to practice instrument navigation effectively. As a hands-on interface, CAST and a human trainee share surgical instruments. CAST can teach surgical movements in a manner that mimics a human instructor who would teach trainees by holding their hand, where the force guidance was realized using virtual fixtures with the corresponding motor control algorithms. However, such force-based training systems [25], [26], [29] are mainly designed for relatively simple tasks such as instrument navigation and object transferring.

To teach a trainee given an advanced task (e.g., suturing) and to provide personalized active guidance, more advanced motion planning and control schemes are required. Virtual fixtures have been widely used to assist human for teleoperation, handwriting, and other human-machine collaboration tasks [30]. Depending on the purpose, such fixtures can regulate or promote a specific motion. In surgical training, a guidance virtual fixture (GVF) can be utilized to assist a trainee to navigate a task-specific pathway. To construct a GVF with defining the pathway, we can utilize existing motion planning algorithms [31] or demonstration-based path generation [32]. In general, surgical tasks do not always have fixed goals and trajectories. Therefore, we propose utilizing a demonstration-based scheme to construct GVF for suturing and other complicated tasks. For instance, surgical motions from expert surgeons are collected given a particular task and then their motions are characterized to develop a probabilistic model. The generated model can be utilized to find a common representation [33] and to define the corresponding GVF geometry (e.g., a virtual tube to represent surgical movements).

To develop an advanced control scheme given a GVF, we can consider the utilization of the reinforcement learning (RL) [34]. RL allows us to teach a controller through high volume of “trial and error” interactions. For this learning procedure, a simulated setup is generally required instead of using an actual system. To construct such simulated setups, we can introduce digital twin technology [35]. As a human-in-the-loop control problem, we should consider interactions among the RL agent, the environment, and the user for RL-implementations. Also, a different control policy may be needed as the user behaves differently. By utilizing this RL-base control scheme, we expect that the robotic guidance system teaches novice trainees in laparoscopic surgery skills training by providing personalized instant force guidance.

C. Feel of surgery based on haptics

Tactile feedback in surgery is critical and one of the biggest hurdles in VRSs and MR simulators for both standard MIS training and robotic surgery. Specifically, current robotic surgery platforms do not provide any tactile feedback. A recent systematic review identified if tactile feedback improved surgical performance [36]. Most studies reported that such feedback improved performance (e.g., reducing task completion time). However, one study reported a negative result, where participants felt that feedback force was too high and therefore not realistic.

To deliver more realistic and satisfactory tactile feedback for training simulators, novel haptic rendering [37] schemes are required, where the haptic rendering generates reaction force based on collision detection and collision response. Several VRSs could provide some level of haptic feedback by using commercial haptic devices (e.g., Touch, 3D systems inc., USA) [38]–[40] or their custom devices [41]–[43]. As a simple approach, we can utilize linear haptic feedback. However, such linear feedback causes vibration and resonance when encountering a structure but cannot replicate the force of the structure. Therefore, the realistic feeling of transitions between soft tissue and bone as well as tissue deformation cannot be achieved [44].

We propose here a tissue-specific feedback scheme to deliver more realistic tactile interactions for simulators. Also, a multimodal sensing approach is suggested for robotic surgery platforms. For the tissue-specific tactile feedback, we can use computed tomography (CT) scanning images to segment structures of the human body part with tissue stiffness. The segmented results can also be used for VR or MR rendering with the corresponding deformation models [45]. Based on the segmentation outcomes, we then assign a non-linear stiffness coefficient for each segment (e.g., bone and soft tissue) so that the haptic rendering algorithm generates reactive force for tissue-specific tactile feedback. To model such coefficient, we can consider using animal cadavers for data collection and mechanical characterization [46].

Several tactile feedback mechanisms have been proposed for robotic surgery systems in academic research settings, however currently no clinical robotic platform has been able to achieve such feedback. For the tactile sensing, three approaches have been reported - sensors on the grasper [47], [48], sensor-less force estimation [49]–[51], and sensors near the tool mounting point [52], [53]. These approaches are mainly for force-based tactile feedback. If we integrate more sensing modalities with force sensing, it will enhance surgical outcomes as well as training learning curve by providing extra tactile sensory information such as softness and temperature. For instance, we expect that addition of thermal conductivity will increase navigation of the surgical tool especially when vision is obstructed as it allows the operator to “feel” the difference between tissue types through their distinct thermal conductivity signature [54]. To support such multimodal approaches, the sensors should be small and sterilizable enough to install on the gripper.

Finally, the most important consideration of the haptic feedback mechanism is to guarantee system stability and transparency. For instance, haptic rendering generally requires an update rate of around 1 kHz for stable and realistic force interactions [37]. Especially in robotic surgery platforms, haptic displays should not impact controls of the robot (i.e., transparency). Therefore, a wearable haptic display may be suitable solution for robotic surgery.

D. Proficiency-based learning based on learning optimization

During a mentor-apprenticeship learning process, instructors can adjust the difficulty of the training task based on the progress of trainees to maximize the learning rate. Several proficiency-based learning approaches were presented for minimally invasive surgery skills training [55], [56]. For instance, a training curriculum was proposed to consider proficiency using FLS tasks [57]. Allowable errors and recommended completion time were suggested based on expert performance to design this curriculum.

We propose the integration of a learning optimization [58] technique into surgical training simulators so that trainees enhance training experiences in MIS. Such a learning optimization can be applied for both motor and perceptual-cognitive skills. We firstly suggest defining proper proficiency for both skills. For instance, motor skills' proficiency can be characterized objectively using completion time, idle time, path length, and average time [8]. To assess perceptual-cognitive skills, we can consider situational awareness and decision-making aspects given a specific task with key situations. For such an assessment, eye movements may be one of objective metrics that reflect the perception of the operating field.

While facing critical situations with mental stress, a trainee may 1) need more reaction time, 2) focus solely on the local area (e.g., capture a trainee's view by using eye-tracking), 3) make a wrong decision, and 4) finally execute improper actions (e.g., errors such as collision and dropping). To design objective and subjective evaluation metrics for perceptual-cognitive skills, the NASA task load index (NASK-TLX) [59] can be utilized.

Based on the defined proficiency with evaluation metrics, we then design a learning optimizer so that the coaching system can adaptively adjust task difficulty by generating specific critical situations and providing comprehensive tasks. As an intelligent tutoring system (ITS) [60], the proposed coaching system aims to mimic the behavior of a human tutor by monitoring trainees' surgical actions, identifying when feedback is required, and providing appropriate individualized force feedback in real time. Therefore, the coaching systems adjust the difficulty of training tasks (e.g., adaptive training – a novice trainee is asked to practice a partial task at first instead of completing the entire task) to maximize the learning rate.

Once trainees have mastered the motor skills needed to accurately control the device, the coaching system adds complexity and stress to the training tasks to better emulate the situations doctors encounter in the OR as well as the decisions they make. Both complexity and stress are increased gradually in a manner that is matched to the trainee's level of expertise. Such additions will be adjusted from trial to trial according to match the trainee's skill level. For instance, when a trainee makes a correct response, the next trial will tend to be harder (higher complexity and/or stress). Conversely, when a trainee makes a mistake, the next trial will tend to be easier (lower stress and/or lower complexity).

IV. Results

To realize the intelligent virtual coaching system, we may need to include all the technical realizations – mixed-reality rendering based critical events generations, adaptive force based personalized guidance, haptics for feel of surgery, and learning optimization with objective assessment methods. In this section, we briefly introduce our ongoing technical realization approaches to develop specific modules for a mixed reality simulator (MRS) in laparoscopic surgery skills training or a robotic surgery platform as preliminary research.

A. Mixed reality interface to generate critical events

In [24], a deep learning (DL) model was proposed to construct a depth map given synthetic data with a single camera setup. For the real-time implementation of the real and virtual objects interactions in the MRS, we are developing a light-weight deep learning scheme to estimate a depth map given a physical reality environment. Our target computation time is under 30ms to support 30 FPS real-time MR rendering. For such a goal, we are investigating various DL models inspired by [24] with the Unity game engine and its high definition rendering interface (HDRP) which allows us to configure a virtual world and then to collect training data sets. Such a data collection procedure can also allow us to overcome challenges in real world MIS environments (e.g., collecting ground-truth depth data from an endoscope). Fig. 1 illustrates an example of Unity HDRP virtual world and its sample data.

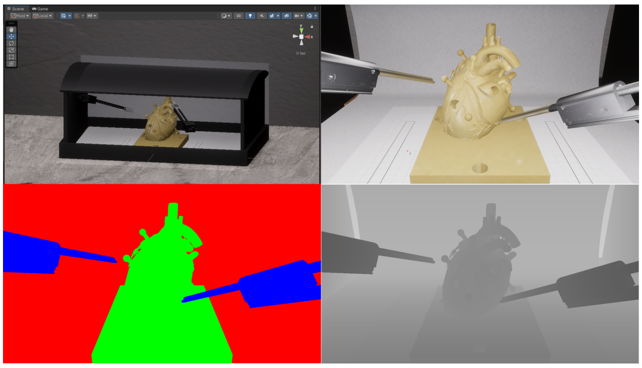

Fig. 1. From top-left to bottom-right: (a) an Unity HDRP virtual world, (b) a color image, (c) a segmentation image where red, blue, green represent a background, instruments, and objects, respectively, and (d) a depth map, where (c)-(d) are ground truth images for DL models.

We are also pursuing a DL model to track moving objects to support advanced suturing tasks given a robotic surgery platform. A da Vinci S robotic surgery system is used to such development, where the system is decommissioned from human use. Given stereo images captured from the da Vinci system, an encoder-decoder based DL network [61] was initially utilized to track surgical instruments as shown in Fig. 2. We are pursuing various techniques [23] to track instruments as well as tiny surgical objects such as needles to achieve a computationally effective solution.

B. Haptics to deliver tactile feedback

To simulate functional endoscopic sinus surgery (FESS), we are developing a VR-based FESS simulator. For such a system, we have established a communication interface between

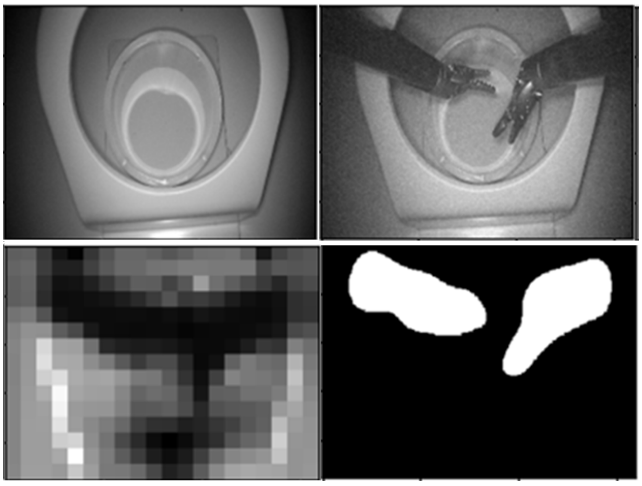

Fig. 2. From top-left to bottom-right: (a) a background image without moving objects, (b) a test image, (c) an attention map while prediction, and (d) estimated moving objects (e.g., instruments).

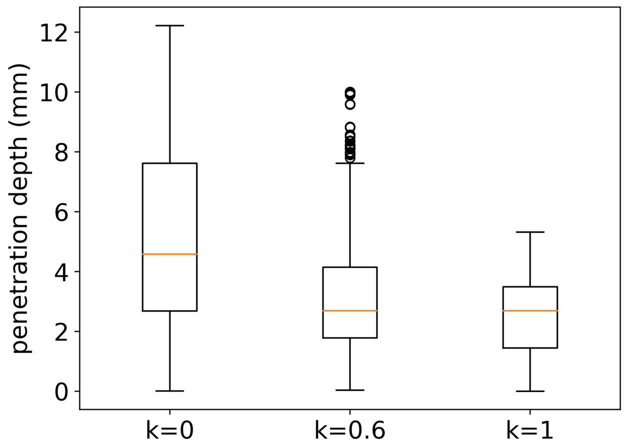

Fig. 3. Effectiveness of tactile feedback regarding penetration depths, where k=0 represents no feedback, and k=0.6, k=1 simulate medium and hard materials, respectively.

a computer-enhanced PRS which has a custom instrument interface and a VR headset. Using the Unity game engine, a simple virtual scene which consists of two surgical instruments and a virtual block was constructed to evaluate a linear model of haptic tactile feedback. As a user manipulates two surgical instruments, the PRS sends instrument movements information to Unity every sampling period (e.g., 50ms). Whenever the game engine receives the information, the virtual scene is updated, and then the collision information (i.e., surface contact point and surface normal vector) sends back to the PRS. Using the collision information, control outputs (e.g., $u = k\Delta d$ where k is a stiffness coefficient, Δd is the depth of penetration) for three motors (i.e., each motor responsible for yaw, insertion, and pitch, respectively) are generated for tactile feedback. While the user manipulates the instruments, the tactile feedback is delivered only to the right-hand instrument.

Fig. 3 shows the significant difference between with and without tactile feedback in terms of the depth of penetration. There are three simulated scenarios - no feedback at all (k=0), medium stiffness (k=0.6), and hard stiffness (k=1) where k represents softness of the virtual block. A user was asked to intentionally keep hitting the virtual block using the instrument and stop the movement when the user visually inspects the collision or fells strong resistance force. The user could penetrate without any restrictions when k=0. Therefore, the user could recognize the collision depending only on the visual feedback. In case of medium and hard stiffness scenarios, the user could feel reaction force after collision. However, the median values of the penetration depths (2.68mm for k=0.6 and 2.69mm for k=1.0; red lines in the box plots) indicate that there is no significant difference between k=0.6 and k=1.0 even though the maximum values (i.e., outliers) in the box plots show the difference. However, the tactile feedback prevents huge penetration in general, and the user could have some degree of tactile sensation.

Throughout this preliminary development, we showed the feasibility of tactile feedback and potential benefits in training. However, we have faced technical limitations under the current system configuration. As mentioned in Section 3, haptic rendering to generate reaction force requires an update rate of around 1 kHz for stable and realistic force interactions. Under the low frequency operation in the PRS, a user may consider that a hard virtual object feels softer, and the end-user device is vibrating in the worst case. Based on this observation, we are improving the PRS hardware and software modules to support the high frequency operation. A novel non-linear feedback algorithm is also being investigated to deliver realistic tactile sensation.

We have conducted a feasibility study to develop a novel multimodal sensing framework for robotic surgery platforms. We first prepared a simulated test bed which consists of a robotic arm to emulate the slave robot, force-sensitive resistors (FSRs) on the robot gripper, a game joystick to mimic the surgeon console, and a wearable vibrator to deliver haptic feedback. To control the wearable haptic displace, we have implemented a fuzzy reasoning [62] based control algorithm. We utilized FRS values, robot gripper states, the robot end effector positions, and joystick commands to design the reasoning algorithm. The control system generates a proper comment to actuate vibrators, where six unique vibrating patterns were mainly designed to represent (1) first touch by a gripper, (2-4) holding and object with light, moderate, or strong pressure, (5) pressing an object, and (6) hitting the ground by the end effector. Using this test bed, we are investigating the best haptic tactile feedback method for robot surgery training by designing miniaturized sensors as well as a novel wearable haptic display.

C. Computational models for a learning optimizer

The learning optimizer for motor skills will use a computational model of human motor performance and human motor learning to make online adjustments to the training task to maximize the rate of learning. The motor performance can be characterized as a feedback control system, and we are building such a model. A representative task (e.g., instrument navigation tasks) has been designed to collect data for the modeling, and we are conducting a human subject study followed in compliance with IRB guidelines. Also, we are preparing the following use case: a novice trainee uses the computer-enhanced MRS with the learning optimizer for standard MIS motor skills training. First, the learning optimizer will provide fundamental tasks for the trainee to learn a basic skill (e.g., overcoming depth perception issues). A typical task here is instrument navigation in a 3D space with obstacles. Based on the trainee's progress, the learning optimizer will adjust the difficulty of the task by changing the desired trajectory to maximize the rate of learning. As skill develops, the coaching system will dynamically adjust active guidance features such as visual/force feedback. The model of perceptual-cognitive skills will be designed with the corresponding evaluation metrics when we have the MR-based critical event generator.

V. Discussions and Conclusions

In our view, this paper lays a foundation for developing the theory-based concepts and attendant technologies to support computer-assisted surgical training in non-patient (i.e., simulated) environments. The benefits of such training are clear in that skills acquisition can be done in a repeatable, safe, and objective manner. It can be tailored to the users and deployed in low-resource (for example, rural and less economically developed) settings. We believe that the research thrusts proposed here, as well as the preliminary results that we have obtained lend themselves well to more technologically sophisticated systems than those presently available on the market.

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