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Novel Virtual Reality based Training System for Fine Motor Skills: Towards Developing a Robotic Surgery Training System

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Background: Training surgeons to use surgical robots is becoming part of surgical training curricula. We propose a novel method of training fine-motor skills such as Microscopic Selection Task (MST) for robot-assisted surgery using Virtual Reality with objective quantification of performance. We also introduce Vibrotactile Feedback (VTFB) to study its impact on training performance.
Methods: We use a VR-based environment to perform MST with varying degrees of difficulties. Using a well-known Human-Computer Interaction paradigm and incorporating VTFB, we quantify the performance: speed, precision, and accuracy.
Results: MST with VTFB showed statistically significant improvement in performance metrics leading to faster completion of MST with higher precision and accuracy compared to that without VTFB.
Discussion: The addition of VTFB to VR-based training for robot-assisted surgeries may improve performance outcomes in real robotic surgery. VTFB, along with proposed performance metrics, can be used in training curricula for robot-assisted surgeries.

KEYWORDS
Surgical robot, True Positive rate, Human-Computer Interaction, vibrotactile feedback, psychomotor.

Abbreviations: VTFB, Vibrotactile Feedback; MST, Microscopic Selection Tasks; VR, Virtual Reality; MT, Movement Time; PPV, Positive Predicted Value; HCI, Human-Computer Interaction.

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1 | INTRODUCTION

Surgical robots are increasingly being used in almost every multi-specialty hospital. Currently, they have multiple applications in pelvic, abdominal, select-chest, and neurosurgical procedures [1, 2, 3, 4, 5, 6]. The technology of surgical robots today has advanced sufficiently to provide a high degree of freedom in the robots' arm movements, control, and stereoscopic vision. The improved user-interface of these technologies has led to better on-the-job performance and faster learning curves in the use of surgical robots such as da Vinci® [7], ROSA® [8, 9] and Senhance™ [10].

Psychomotor skills play a vital role in surgical task performance with increased speed, Accuracy, Sensitivity, and precision. Surgical robotic systems typically seek to help surgeons perform surgeries with higher accuracy, faster responses to intraoperative complications, and increased dexterity. Quantification of psychomotor skills became essential with robotic surgical training systems that emphasize rare complex surgical scenarios, challenges, and evaluations of these skills. Training and evaluation of these skills are crucial for effective analysis of the surgeons in the tasks as mentioned earlier. The evaluation of the performance is currently through cognitive, technical, and non-technical skills. Technical skills (TS) include psychomotor skills, user perception, visuospatial orientation, and adaptation [11]. The reason technical skills are essential from a surgeon's perspective is that they reduce operating time, reduce patient exposure to operative risks, improve the handling of intraoperative complications, and reduce post-operative morbidities [12]. Using a training system permits a quantifiable evaluation of the technical skills of the surgeon before performing actual surgeries.

Robotic surgical training systems are available in two variants:

1. **Classical training paradigms** which include methods such as On-the-job and Off-the-job training systems (e.g., Directly on the robots or cadavers, etc.)
2. **Emerging training paradigms** include Virtual Reality simulations for Robotic surgical training as the skills learning method [11, 13, 14, 15, 16] can be performed without the use of expensive robots, while at the same time being self-driven, mentor free, and it can use modifiable levels of difficulties and challenges.

One of the unique requirements for robot-specific surgical training is the incorporation of variation in the levels of difficulty, which are defined by various parameters. One of them is the Movement Scale, which refers to the ratio of the movement of the input device (surgeon's console) to the movement of the robotic arm. Other parameters include distance to target and size of the target. These parameters are used to enhance the capability of the user to control and manipulate small objects. When the objects are small, the task becomes more challenging. Such Selection Tasks are termed Microscopic Selection Tasks (MST). Training for MST is essential, because Movement Scales and visual magnifications [17] are incorporated into current surgical robots [18]. We thus provide challenging scenarios to the user in performing and training for MST.

In the current literature, two major issues are missing: 1) Although the literature has few VR based training systems for robotic surgery [19, 20], there is limited study on training fine-motor skills that is critical for robotic surgical training. 2) The improvement in the performance of fine motor skills training through haptics which is the science of the sense of touch. Haptic feedback is critical when the surgeon is feeling the tissue characteristics through a robot.

Incorporation of haptics in robotic surgery is an important advancement as it allows the surgeons to feel tissues being handled by the robot. Psychomotor skills training with haptic feedback has shown improvements in the learning curve for surgical simulations in virtual reality [21, 22, 23]. One of the unique challenges in robotic surgery is the lack of haptic feedback, which includes tactile and proprioceptive sensations [24]. Tactile sensation involves a sense of pressure and vibration, whereas the proprioceptive sensation involves the sense of position, movement, and forces. Most surgical robots today cannot sense and transmit such information to the surgeon. In a surgical robot console, a surgeon relies entirely on visual cues from 3D cameras. This lack of haptic feedback makes the surgical task difficult [25], especially for novice surgeons. Therefore, tactile feedback could assist surgeons using robotic consoles [25, 26, 27]. Moreover, to deal with intraoperative complications, handling of tissue, and suturing, haptic feedback plays a vital role. Intraoperative bleeding during surgeries is a critical complication that is dealt with by accurately and precisely identifying the source of the bleed and gently stopping the bleed [28]. Studies by Ebrahimi [29] and Kontarinis [30] reported that Vibro-Tactile Feedback (VTFB) enhances the performance of manipulation tasks in virtual environments by reducing reaction times. Koehn and Kuchenbecker [31] reported that both surgeons and non-surgeons prefer the VTFB in simulated robotic surgery. However, these studies did not quantify the psychomotor skills required for robotic surgery. More recent studies have shown that VTFB is a vital sensory adjunct to surgeons operating a surgical robot [32, 33, 34, 35, 36]. Thus, the addition of VTFB during training can improve the learning curve, especially for psychomotor skills.

1.1 | Proposed Solution

Our paper aims at creating a VR based training system that allows for the objective evaluation and learning of psychomotor skills for robotic surgery, specifically fine motor skills. We include vibrotactile feedback (VTFB) in our training system to improve the performance of fine motor skills and augment the experience of human-computer interaction. This study proposes a performance index and compares the performance with and without VTFB. Our main goals are: (1) To objectively quantify the psychomotor performance of fine motor skills such as **Microscopic Selection Task** (MST) in a fully-immersive 3D virtual environment (2) To verify if the performance of the MST improves with the use of VTFB.

To summarize our contributions in this work:

1. We introduce a VR based training of tasks involving fine motor skills such as MST essential for robotic surgery.
2. We introduce a method for quantifying psychomotor skills in MST by adapting existing HCI laws. Our work can be used as a tool to quantify and improve psychomotor performance during the training of surgeons in a robotic surgical curriculum [11].
3. We introduce VTFB as a tool for improvement of performance in MST and show that VTFB significantly improves the performance of fine motor skills.

2 | HUMAN-COMPUTER INTERACTION (HCI) LAW FOR MST

A surgical robot's console is a Human-Machine-Interface (HMI). Interaction with such interfaces is referred to as Human-Computer-Interaction (HCI). With the advent of HMI and HCI tools [37, 38], there are many ways to objectively quantify psychomotor performance using any input device such as the aforementioned surgical robot's console. One such method is Fitts's law, which is a widely accepted powerful tool for modeling human movement. Although Fitts's law was introduced in 1954 originally [39], the first application of it to HCI was by Card et al. [40] in 1978 for comparison of different input devices. Fitts's law is a linear relation between task completion time and difficulty of the task. The difficulty of the task is described by two parameters, as shown in Figure 1. The first parameter D is the distance the cursor (which is driven by the user's hand) has to travel to the target (red ball). The second parameter is W, which is the width of each ball. The different values of D and W define each level of difficulty that the user encounters. Mathematically, the performance of an individual for a given task is described by a linear equation shown in Equation 1

$$t = a + b\,\mathrm{ID} \tag{1}$$

where 't' is the Movement Time (MT) to reach the target in seconds, 'ID' (Index of Difficulty) is a measure of the difficulty of a given task, 'a' refers to a minimum time required to complete the easiest task (ID = 0), and

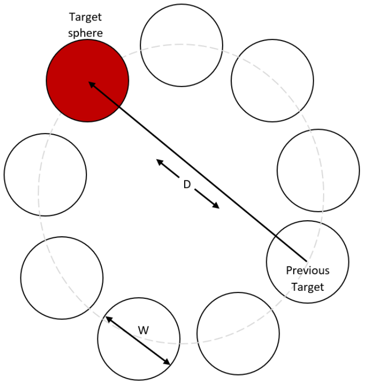


FIGURE 1 A typical Fitts's multi-tapping task [41] which depicts nine spheres, each with diameter W, arranged in a circle of diameter D. D and W are varied to change the difficulty level of the task.

'b' describes how MT changes as ID changes. Both a and b depend on the choice of the input device, which in our study is the surgical robotic console. The measure of the index of difficulty is computed by the ratio D/W. Thus, as the distance D decreases or the width W increases, the task becomes progressively easier as the surgeon's hand has to traverse shorter distances to reach a larger target. Similarly, as D increases or W decreases, the task becomes progressively harder. Mathematically, the values of D/W can, therefore, range from 0 to infinity. In order to scale this down, the next step in constructing the measure of the Index of Difficulty is to use the logarithm of D/W. Although this makes the scale more manageable, we still have to deal with the possibility of log(0). Hence we measure the Index of Difficulty by calculating the log of (D/W + 1). For this purpose, we use a logarithmic scale so that when D = W, the Index of Difficulty becomes 1. Hence, we define the index of difficulty according to equation (2) below given by Soukoreff and MacKenzie [42].

$$\mathrm{ID} = log_2\left(\frac{D}{W}+1\right) \tag{2}$$

A measure of performance of a user in carrying out the selection of targets is termed as Throughput [41]. It refers to the number of targets selected per unit time. In the context of robotic surgery, Throughput indicates how quickly the surgeon selects the target during robotic surgery training.

High Throughput is demanded in robot-assisted surgeries, especially Urological and Neurological surgeries, which involve a precise selection of microscopic tissues quickly. The Movement Scale settings are already existing in the da Vinci® surgical robot and are given as Normal (1:1/2), Fine (1:1/3), and Ultra-fine (1:1/5) scales. However, quantification of performance in these scales has not been reported yet.

2.1 | 3D Fitts's Law and MST

The concept of scaling in visual and motor domains are widely studied [43, 44, 45]. In our earlier work [46], we studied various Movement Scales for 2D tapping tasks using Fitts's law. The results have shown that the performance was an inverted U-shaped function of the Movement Scale. The same tapping tasks can be extended to 3D Virtual Reality (VR), where the user perceives depth information. Current literature has extended Fitts's law application from 2D to 3D virtual environments where depth influences performance [47, 48, 49]. Each of these papers mention methods by which Fitts's law in the 2D virtual world can now be applied to a 3D virtual environment. However, Balakrishnan [47] suggests that Fitts's law may not always hold in all VR conditions. Other studies suggest that Fitts's law fails in selection tasks where the target size is of few pixels [45, 17]. The problems in the acquisition of small targets are well established in the HCI research literature [17]. Teather and Stuerzlinger [48] have shown that Fitts's law holds when the 3D pointing task is performed with the stereoscopic monitor. They also observed that depth perception influences the performance of the participants. This result was confirmed later by Chun et al. [50] and Pfeiffer [49].

Fitts's law holds well in 3D coordinated hand movements [51, 52] in which hand tracking is done by IR tracking devices such as Kinect™ and Leap Motion™. The law is also used for the gaze-based tasks [53, 54], which have shown that the Throughput is lesser compared to that of using a mouse or hand-held controllers.

Our previous work [46] found an optimum Movement Scale in a 2D environment by considering four different Movement Scales in the macro range (1:2, 1:2 4, 1:3.3, 1:4.9). The following are the differences in the present work compared to our previous work: First, the environment used in the present study is 3D, which involves depth effect, and it is an entirely immersive VR space, whereas the previous study is a desktop screen which is not fully-immersive. Second, the Movement Scales considered in the present work are less than one (micro-scale), whereas the previous work involved macro scales. When the Movement Scale is less than 1, there is a diminution of output movement for any specific input movement. Third, the present study's comparison of Throughput with and without tactile feedback was not part of the earlier study. Fourth, unlike the earlier work, which used conventional Fitts's law, the current work uses modified Fitts's law, which is defined in the next section. Finally, the previous work uses Throughput as the only performance measure of the task, whereas the current work emphasizes quantification of performance in an MST through speed, dexterity, and precision along with Throughput.

3 | MATERIALS AND METHODS

Our objective is to propose a training system and demonstrate its effectiveness in improving the performance of virtual psychomotor tasks. In this section, we show the construction and working of the training system. We also explain the parameters used to objectively quantify and analyze the performance of the user. The experiment is performed in a 3D virtual environment designed in such a way that the subject can perform MST similar to operating a generic surgical robot console. The study is approved by the Institute Ethics Committee (Reference number IHEC/2020-02/MM/02/03).

3.1 | Apparatus Setup and Specifications

The experiment was conducted in a room with the temperature set at 24°C (this is considered a comfortable temperature given the geographical and cultural context of the venue where the experiment was conducted), where the subject is made to sit in a chair comfortably and their arms resting on the table in front, as shown in Figure 2a.

The experiment was conducted using the HTC Vive™ which consists of a head-mounted display (HMD) with two base stations for tracking, positioned at opposite ends of the room. The Organic Light Emitting Diode (OLED) display embedded in the HMD provides a refresh rate of 90 Hz and an FoV of 110 degrees, making sure that the user is completely immersed in the VR environment. The user holds a Vive controller, as shown in Figure 2a, for interacting with the virtual environment. They are used to track the position of the user's hands in real-time with sub-millimeter level accuracy and map them into the virtual environment space. The Vive™ controller also provides vibrotactile feedback (VTFB) by means of an embedded linear resonant actuator (LRA). It is an electromagnetic device that can produce vibrations at 235 Hz. The latency between the movement of the Vive™ controller and the movement of the cursor in the VR environment was measured and is in the range of 10-20 ms. The effect of latency on the subject can be neglected since the latency of the system is well below the allowable limits as per Ravali et al. [55] for visual-haptic feedback. The virtual environment shown in Figure 2b is created using the Unity 3D game engine [56] along with the SteamVR SDK [57].

3.2 | Subject Selection Criteria

All participants signed informed consent and no compensation given to any participant to attend the experiment. We conducted the experiment with fifteen subjects with a mean age of 25.3 years ± 4.7 years.

Inclusion criteria: Healthy subjects in the age range from 21 - 30 years. None of the subjects should have any prior knowledge of our hypothesis, experimental environment, or experience in VR.

Exclusion criteria: Subjects with any neurological motor or sensory disorders. Presence of any visual deficits despite corrected vision.

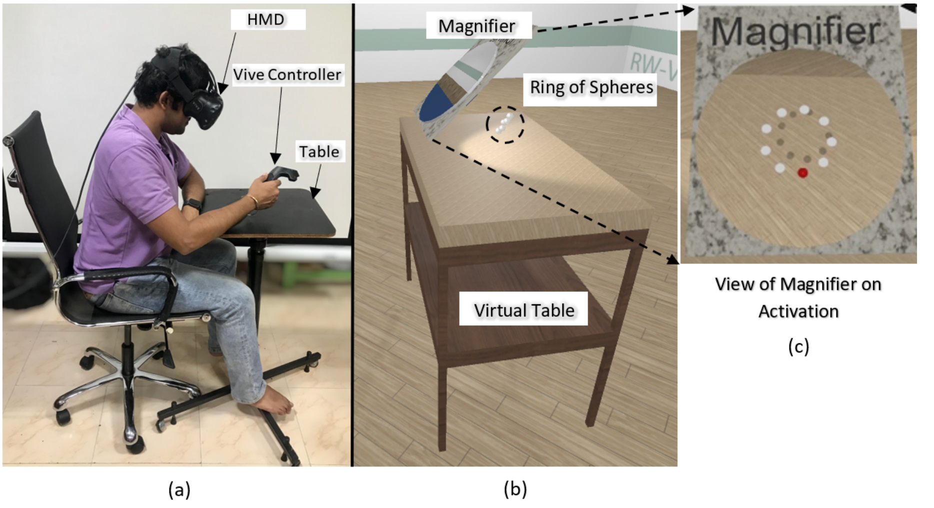


FIGURE 2 The setup used to perform the experiment. The subject is made to sit in a chair comfortably, and their arms are resting on the table in front, as shown in Figure 2a. Figure 2b is the view of the experiment in the virtual environment, while Figure 1b shows the real-world perspective of the experiment. The subject is made to sit comfortably on a chair with their arms resting on the table to prevent fatigue during the experiment. The virtual dummy is shown to represent the position of the subject during the experiment and not present during the actual experiment. A magnifier is shown on the left and is positioned in front of the subject that offers an FoV of 50°. The ring of circles is illuminated by a small light that causes a shadow that is used for depth cues.

The experimental protocol stated in Section 3.3.4 below, was explained to all the subjects clearly. Any questions they had were answered to their satisfaction, and they were given a trial to familiarize themselves with the equipment before the start of the actual experiment. Subjects received no remuneration, and there were no fees to participate in this study.

3.3 | Experimental Procedure

The experimental task performed by the subjects is a modified version of the ISO 9241-9 standard (2002) multi-tapping experiment [58].

3.3.1 | Virtual Environment Setup

The VR environment consists of a virtual room in which the subject is made to sit in front of a table, as shown in Figure 2a. Every subject carries out the entire study with a fixed level of zoom in order to be able to see microscopic objects. In a totally immersed 3D VR environment, any zooming-in to see small objects can create a vertiginous effect on the user. In the real world, such an effect can be nullified by the user by taking his view off the field and looking at a standard 1:1 magnified world. However, in our experimental protocol, since the subject is using an HMD, the only way to look away from the zoomed VR world is by dismounting the HMD. This creates a noticeable and laborious interruption to the experiment. We, therefore, devised a visual magnifier in the VR environment that allows the subject to zoom in to the target. During any vertiginous episode, the subject can look away from the magnifier even in the virtual environment to get back to a 1:1 VR world without zoom. This avoids the necessity for the HMD to be dismounted. The experiment can then continue smoothly when the subject returns to look through the magnifier. Thus, we have placed in the VR environment a virtual visual magnifier. This offers a 50° field of view.

Through the virtual visual magnifier, the subject can

TABLE 1 Set of (D,W) pairs used for the experiment. These pairs are selected such that they cover a good range of ID values for the experiment. The table is sorted by descending order of ID.

Set	D (mm)	W (mm)	ID (bits)
Pair 1	5	8	0.70
Pair 2	8	6	1.22
Pair 3	10	4	1.81
Pair 4	15	6	1.81
Pair 5	20	4	2.58
Pair 6	15	2	3.08
Pair 7	10	1	3.46
Pair 8	20	1	4.39

see nine virtual spheres of diameter W arranged in a large ring of diameter D on a plane inclined 50° to the table, as shown in Figure 2b. The spheres are all colored white, and one of the spheres is highlighted in red, which is the target sphere. The subject holds the Vive™ controller using their dominant hand to control a virtual cursor, which mimics a typical surgical tool. The ring of spheres is illuminated by the magnifier such that a shadow is formed behind it. The shadow serves as a depth cue for the subject during the task. Another depth cue is provided by the stereoscopic rendering of the magnifier (the view is rendered for each eye separately, thereby mimicking a real magnifier). The origin of the nine spheres is the lowermost sphere in the ring. This origin is chosen such that the subject can rest their hands on the table during the experiment and avoid fatigue during the task.

3.3.2 | The task to Perform - Microscopic Selection Task

The task of the subject is to move the cursor to the target sphere and select it as fast as possible by clicking the Vive controller. The subject is encouraged to click as close to the center of the target sphere as possible. Once the target sphere is selected by the cursor, another sphere diagonally opposite to the current sphere becomes the target, and the process repeats. This repetition occurs once for each sphere (totaling nine repetitions), and then the D and W change to a new set. The set of D and W values is predefined initially, as shown in Table 1. Each pair of (D, W) is given to each subject exactly once from Table 1 in random order until all the pairs are exhausted. This reduces the learning bias that may occur during the experiment.

There are two different variations of our experiment; one is with VTFB every-time when the cursor collides the target to be selected, another is without VTFB in which the subject purely relies on the visual cues only. The subjects perform the experiment in both variations.

3.3.3 | Movement Scale

The Movement Scale in this paper refers to the ratio between the distance traveled by the subject's Vive controller (x) to the distance traveled by the virtual cursor (x/r), as shown in Figure 3. When the Vive controller moves a distance x in the real world, the cursor moves by a distance $\frac{x}{r}$. When $r = x$, the movement of the cursor is the same as the movement of the Vive controller. When $r < x$, the movement of the cursor is lesser than the movement of the Vive controller. The experiment involves five different scales (1:1, 1:$\frac{1}{2}$, 1:$\frac{1}{3}$, 1:$\frac{1}{4}$, 1:$\frac{1}{5}$).

3.3.4 | Protocol of the experiment

The 15 subjects were divided into two groups, as follows: Group A with seven subjects and Group B with eight subjects.

Step 1: Instruct the subject to read the informed consent and fill out an initial questionnaire before and a feedback questionnaire after the experiment.

Step 2: Request the subject to sit comfortably on a chair and to hold the Vive controller while resting their arms on the desk. After sitting, help them wear the HMD.

Step 3: Explain to the subject that their task is to look through the virtual magnifier, to select the target

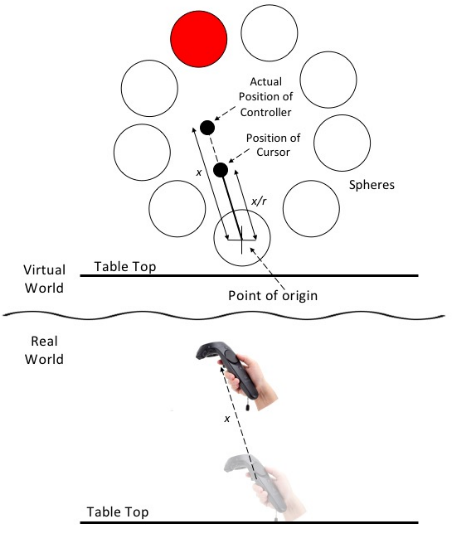


FIGURE 3 Illustration explaining the concept of scale. When the Vive controller moves a distance x in the real world, the cursor moves by a distance $\frac{x}{r}$. The value of r ranges from 1 to 5 as in scale 1:$\frac{1}{r}$

sphere in the virtual space as close to the center of the sphere as possible by clicking on the Vive controller and then to traverse as fast as possible to the next red target sphere.

Step 4: Inform the subject to look away from the magnifier within the VR environment in the event of any vertiginous episode resulting from the zooming effect of the magnifier.

Step 5: Provide a preliminary trial task to the subject to get acquainted with the VR environment and the experiment.

Step 6: Begin the actual experiment. At the end of each set, provide a break of 2 minutes.

Step 7: Provide the tasks with VTFB first and then without VTFB for group A, whereas for group B, provide the tasks in the reverse order.

Step 8: Instruct the subject clearly that they can stop the experiment at any point in time if they feel any discomfort in performing the tasks.

If the experiment is stopped for any reason during a particular (D, W) pair trial, then that trial is repeated, and data from the previous incomplete (D, W) pair trial is discarded.

3.4 | Quantification of the Microscopic Selection Task

3.4.1 | Task Parameters

Several parameters are collected from the experiment performed on all the subjects. These parameters are then used to find the performance of the subject using Fitts's Law.

| Movement Time (MT)

Movement Time is defined as the average time taken for the subject to select the nine spheres for a particular (D, W) pair. For each (D, W) pair, the timer gets initiated from the instant the subject selects the first target sphere until the next target sphere. Consequently, eight values get recorded for each trial. The average of these values indicates Movement Time (MT) in seconds for that particular (D, W) pair.

| Effective Index of Difficulty (ID_e)

In certain surgical tasks, surgeons must select small tissues more accurately, sometimes at the cost of speed during events such as debridement, cauterization, resection, and suturing. Clicking at the center of the target sphere emphasizes the need to select target tissues accurately in a VR environment. Based on these requirements, the D and W given in Equation 2 are modified into effective diameter (D_e) and effective width (W_e) [59, 46]. W_e represents the average distance between the point where the cursor is clicked and the center of the sphere, D_e represents the average distance from one sphere to another traversed by the subject with the cursor. Hence Equation 2 is modified to give the effective index of difficulty ID_e as in Equation 3

	Object present in specific location	Object not present in specific location
User clicks the select button	True Positive (TP)	False Positive (FP)
User does not click the select button	False Negative (FN)	True Negative (TN)

FIGURE 4 2 x 2 Confusion Matrix for MST

$$\mathrm{ID}_e = log_2\left(\frac{D_e}{W_e} + 1\right) \tag{3}$$

ID_e is unique for each subject and depends on their performance during the experiment. Performing tasks with low W_e and high D_e results in a better Throughput. Hence the subject is encouraged to click as close to the center of the target as possible to reduce (W_e) and in the shortest time possible.

| Throughput

Each subject performs a trial with eight different ID values, as shown in Table 1. After completion of all the trials for a given subject, these ID values translate into eight different ID_e values with their respective MTs. These are then used to plot the relation between ID_e and MT by linear regression of data obtained for MT vs. ID_e. The effective Throughput (I_p) is calculated as the inverse of the slope of the linear relation between ID_e and MT. This parameter is the main factor to quantify the performance of the subject in the experiment.

| Sensitivity and Positive Predictive Value

We define True Positive Rate (TPR) as Sensitivity, which is defined below, and we define Precision as Positive Predictive Value (PPV), which is also defined below. Since our objective is to compare the performance with VTFB and without VTFB, we calculate the relative change in TPR and Precision [60, 61, 62, 63]. In order to calculate the Sensitivity and PPV, the number of True Positives (TP), the number of False Positives (FP), and the number of False Negatives (FN) are recorded, as shown in Figure 4. A TP is when the subject correctly clicks inside the target sphere during a trial. An FP is when the subject clicks outside the target sphere. An FN is when the subject enters the target but fails to click.

From these values, the Sensitivity and PPV are calculated for each Movement Scale as given in equations 4 and 5.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{4}$$

$$\text{PPV} = \frac{TP}{TP + FP} \tag{5}$$

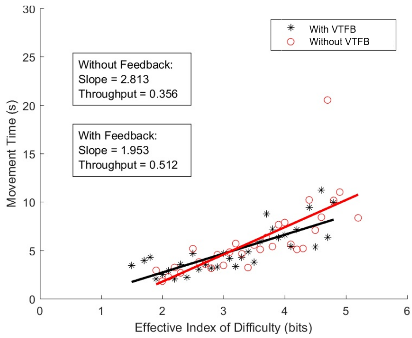
Using the Sensitivity of the tasks with VTFB and the tasks without VTFB, the relative change in Sensitivity and PPV are calculated as follows

$$\text{Relative change in Sensitivity} = \frac{\text{Sensitivity}_{\text{with VTFB}} - \text{Sensitivity}_{\text{without VTFB}}}{\text{Sensitivity}_{\text{without VTFB}}} \tag{6}$$

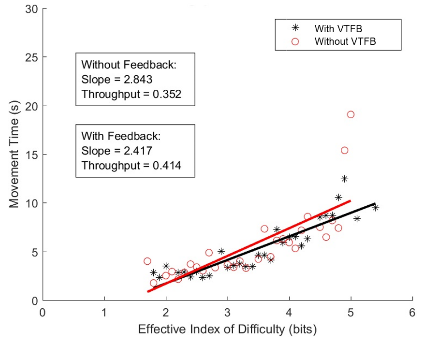
$$\text{Relative change in PPV} = \frac{\text{PPV}_{\text{with VTFB}} - \text{PPV}_{\text{without VTFB}}}{\text{PPV}_{\text{without VTFB}}} \tag{7}$$

3.4.2 | Data Analysis

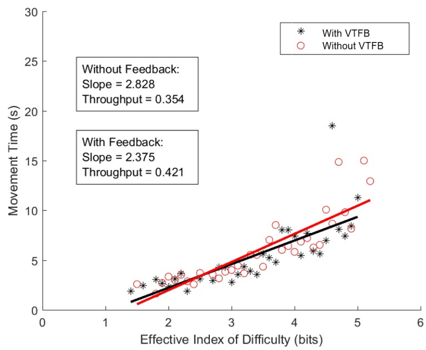
According to Jude et al. [59], using a means-per-user and mean-of-means method instead of Soukereff and MacKenzie's method [42] improves the goodness-of-fit (R^2) and Pearson's r coefficient. This is since the variance of the MT increases when the difficulty of the task increases, hence fitting a line to these points could have errors. Therefore, in our paper, we implement the mean-of-users and then the mean-of-means approach, which reduces these errors.



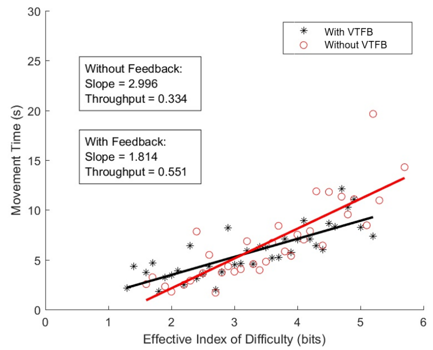
(a) Movement Time vs ID$_e$ at Movement Scale 1:1



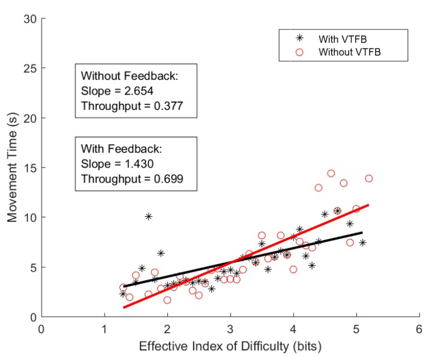
(b) Movement Time vs ID$_e$ at Movement Scale 1:1/2



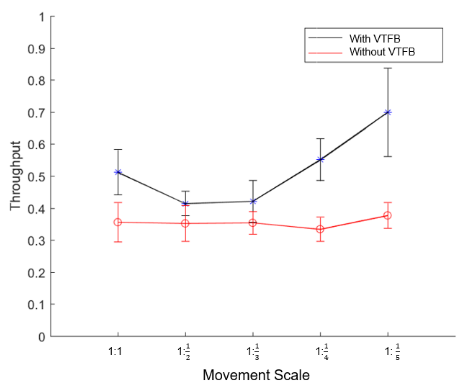
(c) Movement Time vs ID$_e$ at Movement Scale 1:1/3



(d) Movement Time vs ID$_e$ at Movement Scale 1:1/4



(e) Movement Time vs ID$_e$ at Movement Scale 1:1/5



(f) Throughput vs Movement Scale with and without VTFB

FIGURE 5 Consolidated Results showing MT versus ID obtained from the experiment which shows one plot for each scale setting (1:1, 1:$\frac{1}{2}$, 1:$\frac{1}{3}$, 1:$\frac{1}{4}$, 1:$\frac{1}{5}$) used in the experiment. In each plot, the black asterisks correspond to the experiment conducted with tactile feedback, and the red circles correspond to the experiment conducted without tactile feedback. Similarly, the black line and the red line correspond to the linear fit using the black points and the red points, respectively. The inverse of the slope of these fits is the Throughput (subplot f) of the participants in the specified scale setting. We can observe that the slope is positive in all the cases (MT increases with ID), leading to the validity of the Fitts's law. The corresponding error-bars represent the standard deviation of each scale.

4 | RESULTS AND DISCUSSION

Our main objective is to quantify the psychomotor performance of a surgeon, training to carry out microscopic selection tasks (MST). This is conducted in a fully-immersive 3D virtual environment where the trainee undergoes tasks with varying levels of difficulties. We have designed our experiments to find a user-specific optimum Movement Scale by measuring Throughput in MST for each scale (1:1, 1:$\frac{1}{2}$, 1:$\frac{1}{3}$, 1:$\frac{1}{4}$, 1:$\frac{1}{5}$). Moreover, the Throughput, Sensitivity, and PPV improvements for the tasks with and without VTFB are also studied.

4.1 | Fitts's Task

The Movement Time (MT) data collected from our experiments (with and without VTFB) are consolidated and shown in Figure 5, where each plot corresponds to a scale (1:1, 1:$\frac{1}{2}$, 1:$\frac{1}{3}$, 1:$\frac{1}{4}$, 1:$\frac{1}{5}$), which shows that the MT increases as ID_e increases. In each scale setting, 15 subjects experimented twice (with and without VTFB). This results in two sets of points (ID_e , MT) one with VTFB and another one without VTFB. In order to calculate the Throughput, a linear regression model is used. The ID_e is rounded to one decimal point, resulting in multiple MTs for each ID_e. The mean of these MTs is calculated per unique ID_e and plotted in Figure 5. Any point with an MT higher than the 20s (chosen as it is 2-sigma away from the mean MT) was considered as an outlier and was removed from the plot. The remaining points were then used for the linear fit. The linear fit is evident in Figure 5 for both the tasks with and without VTFB. For both linear fits, Pearson's r coefficient is above 0.8, and the goodness-of-fit is above 0.6.

The ID_e, in our experiment, ranges from 1 bit to 5.5 bits, where the latter can be considered as a most difficult task. In all the cases, we have a visual magnifier with fixed magnification through which the entire ring of spheres can be visualized.

TABLE 2 Pairwise Z-score test for Throughput with VTFB. $\alpha = 0.05$ and $Z_\alpha = 1.645$.

Scale	1:1/1	1:1/2	1:1/3	1:1/4	1:1/5
1:1/1		*6.776*	*5.324*	*-2.342*	*-6.983*
1:1/2	*-6.776*		-0.536	*-10.607*	*-11.582*
1:1/3	*-5.324*	0.536		*-8.232*	*-10.594*
1:1/4	*2.342*	*10.607*	*8.232*		*-5.697*
1:1/5	*6.983*	*11.582*	*10.594*	*5.697*	

TABLE 3 Pairwise Z-score test for Throughput without VTFB. $\alpha = 0.05$ and $Z_\alpha = 1.645$.

Scale	1:1/1	1:1/2	1:1/3	1:1/4	1:1/5
1:1/1		0.25	0.15	*1.683*	*-1.643*
1:1/2	-0.25		-0.157	1.472	*-2.048*
1:1/3	-0.15	0.157		*2.203*	*-2.558*
1:1/4	*-1.683*	-1.472	*-2.203*		*-4.613*
1:1/5	*1.643*	*2.048*	*2.558*	*4.613*	

4.2 | Significance Tests

Group A with seven subjects performed tasks without VTFB first and then with VTFB, and group B with eight subjects performed the same tasks in the reverse order. The Movement Time (MT) data from these two groups were analyzed to check whether there is a component of learning that can bias the Throughput results when VTFB is introduced after the user has already performed the MST without VTFB. The Paired t-test analysis has shown that the comparison of Throughput between these two groups is not significant ($t(4) = -2.193, p = 0.151$, for $\alpha = 0.05$) which leads to the inference that the order of introducing VTFB does not influence the performance. Therefore, all the data are combined for the quantification of psychomotor performance.

Pairwise Z-score tests were performed between the Throughput of Movement Scales combining both groups (A and B) with and without VTFB. The results of the tests are shown in Table 2 and Table 3. In what follows, we refer to a cell in the table by its corresponding row and column. The green cell indicates that the Throughput of the Movement Scale in that cell's row is significantly ($p < 0.05$) greater than the corresponding

Throughput of the Movement Scale in its column. Conversely, the blue cell indicates that the Throughput of the Movement Scale in the cell's row is significantly ($p < 0.05$) lesser than the Throughput of the Movement Scale in its corresponding column.

According to Table 2, at our significance level (α=0.05), there is an increase in Throughput when the scale is set to 1:$\frac{1}{4}$ and 1:$\frac{1}{5}$ with VTFB. This shows that finer movements in the virtual world increase the overall Throughput of the subject when performing the MST. However, there is also a performance drop at scales 1:$\frac{1}{2}$ and 1:$\frac{1}{3}$. This could be due to the trade-off between ID_e and MT. When performing tasks at a smaller scale, Movement Time increases, which reduces the Throughput. When reducing the scale even further, the subject clicks the target more towards the center, which increases ID_e. This increase is more than the increase in MT, which results in a lower slope, improving the Throughput. Hence the scales 1:$\frac{1}{4}$ and 1:$\frac{1}{5}$ yield higher Throughput in terms of precise movements. Natural 1:1 movements have higher Throughput in terms of short MTs.

The interpretation of each cell in Table 3 is similar to that of Table 2. In Table 3, the Throughput is high when the scale is 1:$\frac{1}{5}$ without VTFB compared to other Movement Scales. However, the overall magnitude of the Throughput across all scales is significantly lower than that with VTFB. This is also seen in an ANOVA test, where there is a significant difference in Throughput with VTFB (μ = 0.52, σ = 0.12) and without VTFB (μ = 0.35, σ = 0.01); $t(8)$ = 3.14, p = 0.013. The result is the same as a paired t-test since the test was performed on two groups. This proves that using VTFB is preferable when performing MST. On the whole, the results suggest that the Throughput is higher for the tasks with VTFB leading to the need for VTFB in surgical robots and training simulations for robotic surgery.

4.3 | Optimum Movement Scale

It is evident from Figure 5f that Throughput is improving as the Movement Scale decreases for tasks with VTFB. In our study, with the range of five Movement Scales used, it can be seen that Movement Scales less than $\frac{1}{3}$ results in significant ($p < 0.05$) improvement in Throughput. However, for the tasks without VTFB, there is no improvement in Throughput as the Movement Scale decreases. In the current literature, the relation between the Throughput and the Movement Scale is an inverted U shaped curve for macro scales. However, our results do not exhibit this relationship with or without VTFB. The reason could be that the experiment involves micro scales.

It is also evident from Figure 5f that Throughput is monotonically increasing after Movement Scale $\frac{1}{3}$ until $\frac{1}{5}$. As the Movement Scale settings available in the current surgical robots do not exceed 1:$\frac{1}{5}$, experiments beyond this scale is not considered in this study.

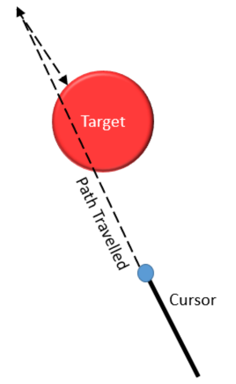
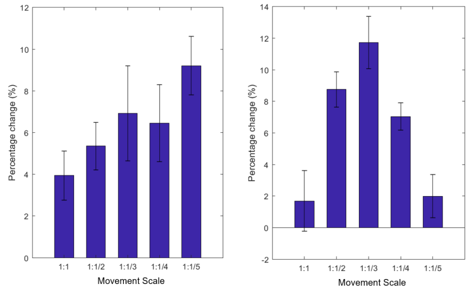


FIGURE 6 Illustration for the overshooting phenomenon where the cursor passes through the target and then travels back to the target.

4.4 | Role of Tactile Feedback

The Sensitivity and PPV are calculated from the TP, FP, and FN data collected during the experiment. Relative change (percentage) of the Sensitivity and PPV with VTFB with respect to that of without VTFB are calculated and shown in Figure 7a and Figure 7b, respectively. When we consider Figure 6a, there is a significant ($p < 0.05$) improvement in the relative Sensitivity for the cases with and without VTFB. It is observed that the Sensitivity is improving for the case with VTFB, espe-



(a) Relative change in Sensitivity

(b) Relative change in PPV

FIGURE 7 The percentage change of Sensitivity and PPV for each scale. Each bar in the plots is the relative change of the Sensitivity and PPV of the tasks with and without VTFB. The corresponding error-bars represent standard deviation of each scale.

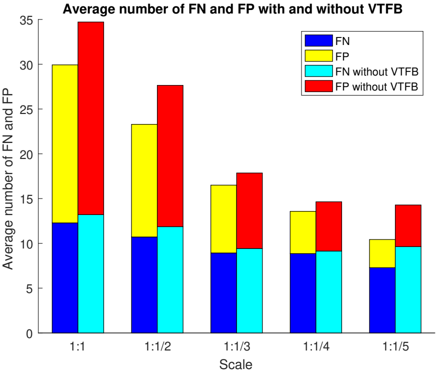


FIGURE 8 The average number of FN (False Negatives, the subject does not click when the cursor is inside the target) and FP (False Positives, the subject clicks outside the target) for each scale with and without VTFB.

cially in scales 1:1/3 and 1:1/5. Moreover, the relative PPV in Figure 6b shows a significant ($p < 0.05$) improvement for cases with and without VTFB, especially for scale 1:1/3.

The overall effect is that the use of VTFB improves the performance of the task as the Movement Scale decreases. This could be due to the fact that the sense of touch is faster than the other senses of the human body. According to [64], the average response time for tactile stimuli is 0.385 ms, with a standard deviation of 0.071 ms. This is faster than the average response time for visual stimuli, which is 0.517 ms, with a standard deviation of 0.181 ms. The average response time for auditory stimuli is also slower, which is reported to be 0.493 ms with a standard deviation of 0.178 ms.

Also, the reaction time greatly affects the performance of an individual when overshooting and undershooting during selection tasks. Overshooting is a phenomenon (shown in Fig. 6) during the selection task where the user moves the cursor through the target without selecting the target and then moves back to the target after a small distance. This event creates a false negative. Undershooting is a similar phenomenon where the user moves the cursor less than the required distance to the target and then moves again to reach the target. Undershooting can be neglected in our scenario since the distances between the targets are minimal, and overshooting is greatly predominant. During the overshoot, when the cursor passes the target, the user can either visually notice the error and perform the corrective movement or feel the tactile feedback and perform the correction. As stated earlier, the tactile feedback is faster than the visual feedback, which then results in the quicker movement back to the cursor and reducing or even avoiding the overshoot. This difference is seen in Fig. 8 where the number of FN (False Negatives, the subject does not click when the cursor is inside the target) reduces when incorporating VTFB. The FN also reduces as the scale decreases less than one. A similar trend is seen in the number of FP (False Positives, the subject clicks outside the target). When compared to that without VTFB, the number of FN and FP also shows a consistent decrease with decreasing scale.

Another reason why VTFB is preferred over any visual feedback is that the visual system is already overloaded during surgery; therefore, tactile feedback is better [65, 66]. Massimino [67] concluded that redundant Visual Feedback (VF) slowed task performances, perhaps an example of "sensory overload." None of these experiments focused on the magnitude of force generated by the user but on performance in terms of time to completion. Debus and colleagues [68] conducted studies showing that vibrotactile feedback significantly lowered the mean applied force error by using a teleoperator system composed of 2 PHANTOM haptic devices (SensAble Technologies, Woburn, Mass). In these studies, VF was not as effective as VTFB.

4.5 | MST in Surgical Skill Training Curricula

Our study focuses on developing a performance measurement that is objectively quantifiable for MST. This measurement can be easily translated for performance in other tasks involving fine motor abilities in surgeries using robots. We believe that the progress in the robotic surgery skills training may be monitored better with the performance evaluation in our study. Furthermore, we recommend the inclusion of the training method and performance evaluation reported in our study into the Robotic Surgery Training curricula.

The Robotic Surgery Training curricula are well addressed and reviewed in the literature [69, 70], however, with few limitations. Roger Smith et al. [69] clearly explained the process of developing the educational content of a robotic curriculum, especially technical skills. They have defined the seven principles that should be applied in selecting or designing a psychomotor skills training device for robotic surgery. Chen et al. [70] reported a comprehensive review of the robotic surgery curriculum and training. They have discussed various robotic surgery training methods such as web-based training curricula, on-site robotic-assisted surgery training programs, and surgical robotic training simulators. In their review, they have mentioned that the psychomotor skills are considered as one of the four separate modules of the Fundamentals of Robotic Surgery (FRS) curriculum. The purpose of FRS training modules is to develop the proficiency of the surgeon's skills during robotic surgery. Psychomotor skills are considered important even in the on-site robotic-assisted surgery training programs, and surgical robotic training simulators, as reported in Chen et al. No literature has addressed the MST based skills that are critical for robotic surgery.

Modern curricula for the robot specific surgical training through simulation are being developed and improved to revolutionize robotic surgeries [71]. These simulations are aimed at developing self-driven and mentor-free skills using fully-immersive 3D virtual environments, which is often referred to as Virtual Reality (VR) [72]. However, neither quantifiable psychomotor skills nor haptic feedback is present in these training simulations. The results from our study implies that incorporating both of these features may improve the performance of MST in the actual robotic surgery.

5 | CONCLUSIONS AND FUTURE WORKS

The objective of this study is to quantify the psychomotor performance of microscopic selection task (MST) in a fully immersive 3D virtual environment that can be used in training with surgical robots. We have adapted Fitts's law, which has been used extensively in the literature on HCI to quantify psychomotor performance. We conclude from our Throughput curve that there is no optimum Movement Scale less than 1:1, and there is a significant improvement in the Throughput of MST with vibrotactile feedback (VTFB). From our experiment, we infer that the implementation of VTFB in real and training scenarios for surgical robots has a significant impact on performance, as mentioned in our results. Furthermore, the quantification method described here can be implemented in psychomotor skills assessment for robotic surgery, and training curricula. The experiment can be tested in surgical robots such as da Vinci® , ZEUS® , and ROSA® in the future to quantify psychomotor skills along with the incorporation of VTFB in those robots. The goal to improve both the Sensitivity and PPV along with speed for target manipulation that forms an essential part of an adequate training module in robotic surgery training curricula.

The current study can be extended in many ways: 1) The haptic feedback considered here is a high-frequency vibration. Also, we can incorporate proprioceptive feedback into the simulation. 2) It involves only one-handed tasks; it can be extended to two-handed Fitts's tasks mimicking the surgical robotic console. 3) It considers a fixed magnification for a virtual visual magnifier, and this can be extended to variable magnification levels for studying the performance of MST under different magnification levels. 4) One of the inclusion criteria for subjects in this study is that they are naive to the performance of MST. Future work can involve surgical trainees and experienced surgeons. 5) The surgical setup is designed such that it mimics a generic tool for performing surgical training. Specific design options such as eye holders for surgeons can be incorporated in a future work. 6) Finally, the communication delay between the real and virtual environments is not considered in the current study. Communication delay is usually present when real surgical robots use haptics. In our future work, we can simulate the delay due to the tactile or proprioceptive feedback and study the resulting psychomotor performance.

The microscopic selection task described here, along with the quantification by Fitts's law, can be a psychomotor performance assessment tool. By using the task and analysis described here, mentor-free skills learning in robotic surgery through a quantifiable VR simulation can be achieved.

Our study did not involve expert surgeons since this study is a necessary first step in the process of developing and validating a training module for the performance of fine motor skills such as MST. MST is a minimum set of skills essential in the performance of surgeries using robots. Therefore, the next step would be to extend the techniques developed in this paper to train surgeons using robots in the performance of fine motor skills required in robotic surgeries.

This paper is the first part of a two-part study for training robotic surgeons. The first part is the study in which the use of VTFB is proven to improve the performance of a novice trainee when they perform MSTs. The second part is the implementation of this system to mimic any surgical device, which is in the market, and then test the system with surgeons for validation. Hence our work can be considered as two stages: 1) introducing the quantifiable performance metrics for the MST robotic surgery training curricula and validating the performance metrics with novice subjects, 2) extending the study with surgeons, and evaluating their learning curves in the future study.

Conflict of Interest

The authors report no conflict of interest.

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