Effects of Image Size and Structural Complexity on Time and Precision of Hand Movements in Head Mounted Virtual Reality

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Abstract

The effective design of virtual reality (VR) simulators requires a deeper understanding of VR mediated human actions such as hand movements, with specifically tailored experiments testing how different design parameters affect performance. The present experiment investigates the time and precision of hand (index finger) movements under varying conditions of structural complexity and image size in VR without tactile feed-back from object to hand/finger. 18 right-handed subjects followed a complex and a simple physiological structure of small, medium and large size in VR, with the index finger of one of their two hands, from right to left, and from left to right. The results show that subjects performed best with small-size-simple structures and large-size-complex structures in VR. Movement execution was generally faster and more precise on simple structures. Performance was less precise when the dominant hand was used to follow the complex structures and small object size in VR. It is concluded that both size and structural complexity critically influence task execution in VR when no tactile feed-back from object to finger is generated. Individual learning curves should be monitored from the beginning of the training as suggested by the individual speed-precision analyses.

Index Terms: Computing methodologies—Computer Graphics—Graphic systems and interfaces—Virtual reality; Human-centered computing—Human computer interaction (HCI)—Interaction paradigms—Virtual reality; Human-centered computing—Human computer interaction (HCI)—Interaction devices; Human-centered computing—Interaction design; Software and its engineering—Software organization and properties—Virtual worlds software—Virtual worlds training simulations

1 Introduction

Virtual reality (VR) is frequently used in training applications or simulators to save on the time and cost of learning. VR systems have become even more popular with the recent increase in market, availability, and accessibility of immersive VR headsets [34]. This opportunity also prompted VR designers to create powerful applications in different environments and fields of application, and one of these is the biomedical field. Different types of VR training applications or simulators are in use for different purposes with a variety of methods [6, 34, 38]. Even though these systems are widespread, too little is still known to fully understand the cognitive feedback effects of immersive VR and its influence on human perception and action.

Spatial performance analysis for 3D immersive VR head mounted displays usually exploits the task execution times to assess a subject's motor performance. Analysis based on a single dependent variable is, however, not enough to evaluate the full scope of motor performances of subjects, and to assess their progress on simulators and applications [9–12]. Especially for beginners, action-specific hand movements could be affected by several factors, such as the head position, the overall environmental complexity, the color context, and so on [5, 26]. To fully understand human motor behavior in VR applications, several complementary behavioral indicators should be taken into consideration, operationalized experimentally in terms of different related dependent variables.

Also, among the independently variable factors which should be taken into account in the case of surgical simulators or VR applications as pre-clinical test environments, for example, is structural complexity of the virtual image or object. Several studies have previously been conducted on virtual object size [18, 24]. It was noticed that subjects were performing better with bigger objects compared to smaller objects [4]. On the other hand, structural complexity of the objects should also be considered, as it may affect human skills and motor performance depending on the context [16]. Although previous authors have addressed the problem of structural complexity and its possible effects on reaching for objects in VR environments (eg. [26, 39]), there still is a need for deeper research into the effects of structural complexity on the time and the precision of hand movements towards or along the borders of virtual objects and other motor skill indicators.

In research on surgical simulators, it was found that active learning (when a subject interacts with the object) leads to better motor performance in VR than passive learning (when a subject just observes the virtual scene) [20]. Moreover, the motor skills of subjects increase when they are provided with tactile [21] or auditory feedback [41]. For example, Swapp and his colleagues [37] showed that tactile feedback improved the speed of subjects in a 3D VR stereo environment. Furthermore, handedness which is affiliated with touch information among other primary somatosensory cortex functions also affects the motor performance of subjects [13]. For instance Batmaz and his colleagues [12] showed that while an inexperienced subject performed the task slower with his dominant hand to pay attention to complete the task, an experienced subject performed the experiment faster with his dominant hand because of individual motor learning. Consequently, the effects of handedness with beginners in virtual environments need further investigation.

To that effect, time and precision of finger movements along the axis of alignment of virtual objects as a function of their size, structural complexity, hand movement direction, and handedness are studied in this paper, in an interactive VR application using Leap Motion and Oculus DK2.

2 Methods

2.1 Participants

Eighteen right handed subjects ranging in age between 20 and 33 (average = 26.33) who had no experience with either VR or surgery, participated in the experiments. Handedness was confirmed using the Edinburgh inventory for handedness designed by Oldfield [29]. Subjects were screened for spatial ability on the basis of the PTSOT (Perspective Taking Spatial Orientation Test) developed by Hegarty & Waller [17] and all participants scored 10 or more out of the 12 items of the test, which corresponds to performances well above average.

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2.2 Research Ethics

The study was conducted in conformity with the Helsinki Declaration relative to scientific experiments on human individuals with the full approval of the ethics board of the corresponding authors host institution (CNRS). All participants were volunteers and provided written informed consent. Their identity was not revealed.

2.3 Apparatus

A DELL computer, equipped with an Intel Xeon CPU E5-1620 with 16 GB memory (RAM) and a NVidia GForce GTX980 graphics card, was used for the experiments. Graphic card was connected to Oculus Rift DK2 3D VR Head mounted display for the experimental setup and to a FULL HD EIZO LCD Color Edge CG275W screen (596,74 mm 335,66 mm) with in-built color and luminance calibration (colorimeter) for the experimenter. A Leap Motion was placed in front of the Oculus Rift hardware as the motion sensor to get the real-world hand gesture data. This hardware and motion sensor setup have been used in the previous medical studies [15, 33, 34, 40] as well as in other studies [19, 30, 35]. To perform the experiments, Unity 3D 5.3.4 64-bit game engine was used with the Leap Motion Orion Software Development Kit (SDK) and Oculus 0.8 SDK. Motion sensor was directly connected to the computer to increase the bandwidth of the data acquisition.

2.4 Objects on the VR Scene

During the experiments, subjects saw two different objects in the VR scene; their virtual skeleton hand and medical images to follow. The skeleton hand was selected particularly for the experimental procedure; joints of the subjects were highlighted by spheres (Fig. 1). The whole hand was shown to subjects to help them to understand the direction and rotation of their hand and to get the full spatial coordination reference in 3D virtual space.

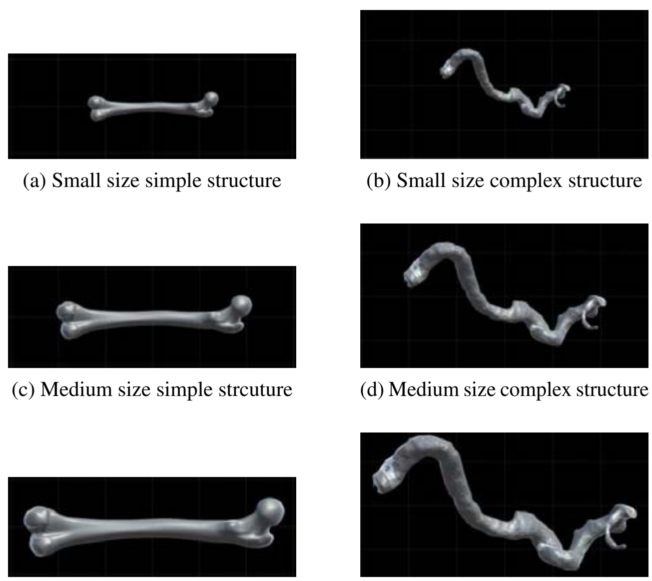
Figure 1: Experimental setup with Oculus DK2 and motion sensor. The image on the 2D screen experimentally reflected the subject's left eye vision.

The motion sensor's static and dynamic hand movement stability measurements were performed by several current studies [3, 23, 36] and these studies showed that Leap Motion is stable enough to use in VR applications. Thus, only the hand position data received from the Orion SDK was used during the data acquisition. No additional algorithm was written to process hand data. Head position tracking camera turned off to during the experiments. Subjects were instructed to show their full hand to the motion sensor (as seen in Fig. 1) to get the best performance from the data acquisition. This method reduced the lack of hand visualization problem. Detailed instructions to collect more stable data is given in the experimental procedure section. Recalibration of motion sensor was done according to the instructions given in the motion sensor's website [28].

During the experiments, two different rendered representations of human body parts were used. The first one was a femur bone, which was made by computer graphic artists for medical usage. The femur bone was called simple structure for this experiment, because while the subject followed the object with the fingertip, one way movement in horizontal plane was enough to finish the experiment. The second one was a part of a Willis circle, which was generated by computer software via MRI data. The Willis circle was called complex structure, because subjects had to move their index finger tip in the three-dimensional space; not just on one plane but on all three dimensions. They also had to be careful at the curves, curls and other natural forms on the object to complete the experiment.

According to study of Dankedar and colleagues [14], average human index finger tip width varies between 1.6 cm and 2 cm. For this reason, narrowest cross sectional area of the simple structure was scaled to the maximum average human index finger tip width, to 2 cm. This size was called as small (Fig. 2(a)). For the medium (Fig. 2(c)) and the large (Fig. 2(e)), the narrowest cross-sectional areas were 3 cm and 4 cm respectively. The simple structure was uniformly scaled in order not to distort the shape of the femur bone.

Small (Fig. 2(b)), medium (Fig. 2(d)) and large (Fig. 2(f)) complex structures were the same length as the small, medium and large sized simple structures. All complex structure sizes were also uniformly scaled in order not to distort the shape of the Willis circle. Lengths of simple and complex structures were: for small 28 cm, medium 42 cm and for large 55 cm. This design aimed to observe the effects of complex structure on the motor behavior; subjects had to follow the same distance as they did for the simple structure but they had to move their hands in VR without tactile feedback.



(a) Small size simple structure
(b) Small size complex structure
(c) Medium size simple strcuture
(d) Medium size complex structure
(e) Large size simple structure
(f) Large size complex structure

Figure 2: Simple structure (a) small, (c) medium and (e) large, and complex structure (b) small, (d) medium and (f) large in VR.

Two cubes were also placed on each side of the simple object. These cubes were called the 'starting point' and the 'finishing point', according to the direction of the hand movement (these cubes are red in Fig. 1).

To get the index fingertip movement data, collision detection algorithm of the game engine was used. Six transparent cylindrical collision detection objects were placed inside the simple structure. For the complex structure, the object geometry was divided into 52 sub-parts, each sub-part containing less than 255 vertices which was the maximum number of vertices supported by the game engine for the collision detection. Each sub-part was shaped as roughly the same size cylindrical objects. The two endpoints of these sub-parts in the complex structure were also called as the 'starting point' and the 'finishing point' to record the fingertip movements.

The center of the complex and simple objects was placed 30 cm in front of the eye level of the subjects. Both structures were placed parallel to screen and subject. Because head tracking was turned off, head position of subjects was fixed and they were not allowed to navigate in the VR. Subjects were only able to rotate their head.

Before starting experiments, index fingertip width of the each subject was measured and the average was found as 1.7 cm with the minimum 1.6 cm and maximum 1.9 cm. Furthermore, the minimum comfortable distance required the reach the most extreme points of large size complex and simple objects was measured as 42 cm. Before starting experiments, the distance between the shoulder and index fingertip of each individual was measured and the minimum was found as 62 cm. It is assured that each subject could reach the most extreme points of all the virtual objects comfortably. Individuals who were not comfortably able to reach to these most extreme points were not allowed to perform the experiment.

2.5 Experimental Procedure

To that effect, time and precision of finger movements along the axis of alignment of virtual objects as a function of their size, structural complexity, hand movement direction, and handedness in an interactive VR application using Leap Motion and Oculus DK2 is studied.

Participants were comfortably seated at an adjustable chair. Before starting the experiments, they were instructed by the experimenter and shown how to perform the experiment correctly. The subjects were asked to strictly comply with the following rules:

- The outer side of the active hand had to always face the subject
- Subjects had to open their active hand and spread their fingers in order to show the outer side of all fingers to the motion sensor. The whole active hand had to be visible to the motion sensor.

During the experiments, the subjects were constantly reminded of these rules which were necessary to collect stable index finger tip data from the motion sensor.

For the simple structure, subjects had to start from the 'starting point' and follow the structure with their index fingertip until the 'finishing point'. The 'starting point' turned green when subject's index fingertip was placed at the 'starting point'. At the same time the simple structure turned gray. Data collection started when the tip of the subject's index finger left the 'starting point' which then turned back to red.

For trials on the simple structure, the whole of the virtual object turned red whenever the subject's fingertip left the structures inner surface at any moment during the experiment. Once the fingertip was back inside the object, the color of the object changed back to green (In Fig. 1, the simple structure is green as the subject's fingertip was inside the structure). With the color change, visual feedback about errors was provided to the subject [27].

When the index fingertip of the subject reached to the 'finishing point', the given structure turned red and the 'finishing point' turned green to indicate the end of the trial set.

For trials on the complex structure, a similar approach was used. At the beginning of the experiment, all 52-sub parts of the complex structure were gray. 'Starting' and 'finishing' points of the complex structure turned green when the subject's index fingertip was inside, and turned red when it was outside. During the experiment, if the tip of the subject's index finger left the objects surface, that individual sub-part, not the whole object, turned red. Likewise, when the tip of the subject's index finger remained inside the sub-part, only that sub-part of the object remained green.

Every individual experiment always started with a "warm-up" run for each of the different conditions. Participants were instructed to "retrace the central axis of alignment of the simple and complex structures as precisely and swiftly as possible".

2.6 Experimental Design

Each experiment consisted of 10 successive trial sets per experimental condition for 18 subjects and there were 24 experimental conditions: each subject followed two different structures (Structural Complexity condition - SC_2), with their dominant-hand and their non-dominant hand (Hand condition - H_2), in left to right and right to left directions (Direction condition - D_2) for small, medium and large sizes (Size condition - S_3). The order of size conditions was counterbalanced between subjects and structures to avoid specific habituation effects. For the same reason, the order of the handedness and direction of finger movement conditions were also counterbalanced between subjects. Factorial design was properly counterbalanced excluding any systematic effect of order. Each subject performed 240 trials. In total 4320 trials were performed. The full factorial plan of the experiment can be presented as SC_2 x H_2 x D_2 x S_3 x 10 trial sets x 18 subject.

2.7 Data Generation

Subjects had to perform the experiment starting at the 'starting point' and ending at the 'finishing point'. Data relative to time and precision of finger movements were recorded in real time between these two points. There was no trial abortion or repetition in case of any errors. Subjects had to fully complete ten trial sets to validate the sets for each condition.

The frame rate for the experiment was about 80 FPS. The data relative to fingertip position (precision) and time of movement were recorded for each frame. No negative performance effects (reduced FPS or jumpiness, discontinuities, etc. in data acquisition) related to the motion sensor was observed during the experiments.

3 Results

Two different dependent variables were exploited for analyzing a subject's motor performance. The first dependent variable here is called 'execution time'. Timing by the computer started when the index fingertip of the subject left the 'starting point' and it stopped when the index finger tip reached the finishing point. All the raw 10 repetitive trial set execution times were used for data analysis.

The second dependent variable was called 'task error'. Whenever a subject's fingertip went out of a virtual objects inner surface, an error was recorded. For each trial, the total number of finger-outs was counted. The all raw 10 repetitive trial data was used for data analysis.

A four-way ANOVA was run in MATLAB (7.14) on the raw data for 'execution time' and 'task error'. In the four-way analysis design there was two levels of the structural complexity factor (SC_2), three levels of the size factor (S_3), two levels of the handedness factor (H_2), and two levels of the direction of finger movement factor (D_2). The full factorial design plan for four-way ANOVA SC_2 x S_3 x H_2 x D_2 with 18 subjects and 10 repetitive trials produced a total of 2 x 4320 data for the dependent variables 'execution time' and 'task error'. Only significant results were investigated here. *Post-hoc* comparisons were performed using the Holm-Sidak procedure (* is $p<0.05$,** is $p<0.01$ and *** is $p<0.001$).

In the Pearson's correlation analysis between 'execution time' and 'task error', there was a positive correlation between the two dependent variables $r=0.448$, $p<0.001$ (N=4320).

3.1 Medians and Extremes

Medians and extremes of the individual data relative 'execution time' and 'task error' for the different experimental conditions were analyzed first. The results of this analysis are represented graphically as box-and-whiskers plots here in (Fig. 3) for (a) simple structure and (b) complex object ‘execution time’, and (c) simple object and (d) complex object ‘task error’.

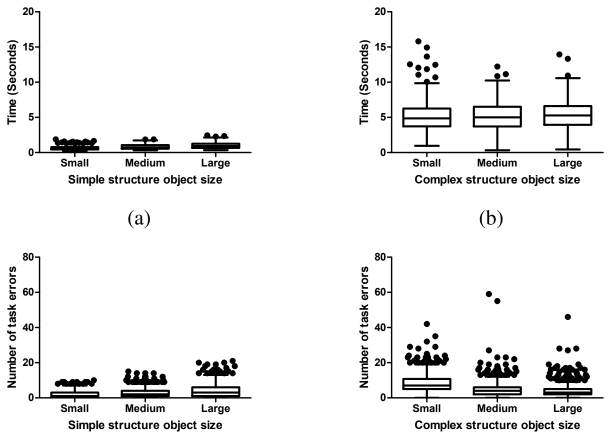


Figure 3: Tukey’s Box and-whiskers plots with medians and extremes of the individual distributions for (a) simple and (b) complex structure on ‘execution time’, and (c) simple and (d) complex structure on ‘task error’.

3.2 One-Way Effects

Outliers in the Fig. 3 data were indeed rare and given the large amount of data collected for each condition, correcting these few by replacing them by averages would not have changed the statistical analyses. Two outliers at the upper extremes of the distributions around the medians relative to ‘task error’ of complex structure medium object size dominant hand right to left movement direction, and one outlier at the upper extremes of the distributions around the medians relative to ‘task error’ of complex structure medium object size non-dominant hand left to right movement direction were corrected by replacing them by the mean of the distribution.

ANOVA revealed a significant difference between simple and complex structures for ‘execution time’ $F(1,4319)= 9886.38$; $p<0.001$ (Fig. 4(a)) and ‘task error’ $F(1,4319)= 557.49$; $p<0.001$ (Fig. 4(b)). Significant differences in two levels of the handedness was observed for ‘execution time’ $F(1,4319)= 5.81$; $p<0.001$ (Fig. 4(c)) and in ‘task error’ $F(1,4319)= 21.64$; $p<0.001$ (Fig. 4(d)). Three levels of the size condition was significantly different for ‘execution time’ $F(2,4319)= 13.04$; $p<0.001$ (Fig. 4(e)) and in ‘task error’ $F(1,4319)= 63.83$; $p<0.001$ (Fig. 4(f)). The data are shown in Table 1. According to the results, subjects were faster and more precise with the simple structure compared to complex structure, were slower and less precise with their dominant hand, and produced more errors and faster movements on the small objects compared with the medium and large objects. Neither the ‘execution time’ nor the ‘task error’ was significant for the direction of the fingertip movements.

3.3 Two Way Interactions

Significant interactions were found between the factors structural complexity and handedness on ‘execution time’ $F(1,4319)=10.729$; $p<0.001$ (Fig. 5(a)) and ‘task error’ $F(1,4319)=20.3104$; $p<0.001$ (Fig. 5(b)), between the factors object size and handedness on ’execution time’ $F(2,4319)=4.40$; $p<0.05$ (Fig. 5(c)) and ‘task error’ $F(2,4319)=7.33$; $p<0.001$ (Fig. 5(d)) and factors size and structural complexity on ‘task error’ $F(2,4319)=295$; $p<0.001$ (Fig. 5(e)). Means and SEMs of these results are given in Table 2.

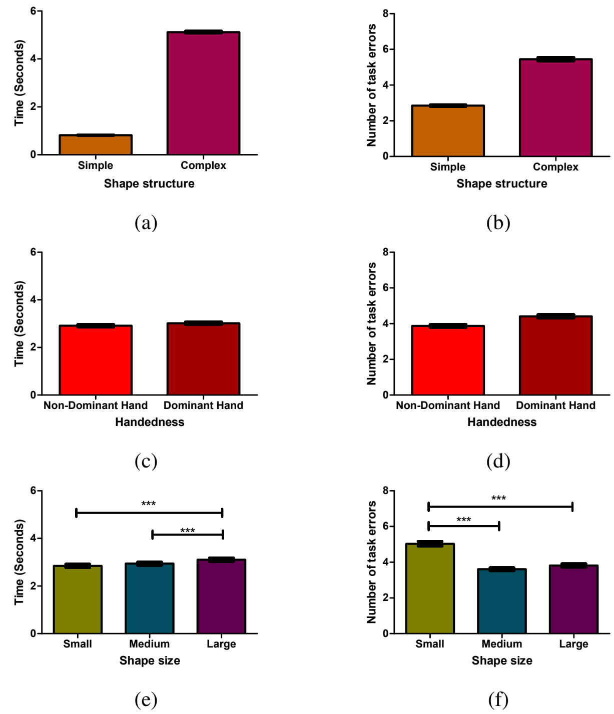


Figure 4: Significant effects of object complexity on (a) ‘execution time’ and (b)‘task error’, of handedness on (c)‘execution time’ and (d)‘task error’, of object size on (e) ‘execution time’ and (f)‘task error’.

Table 1: Results (Means and SEMs) from the one-way analysis for ‘execution time’ and ‘task error’

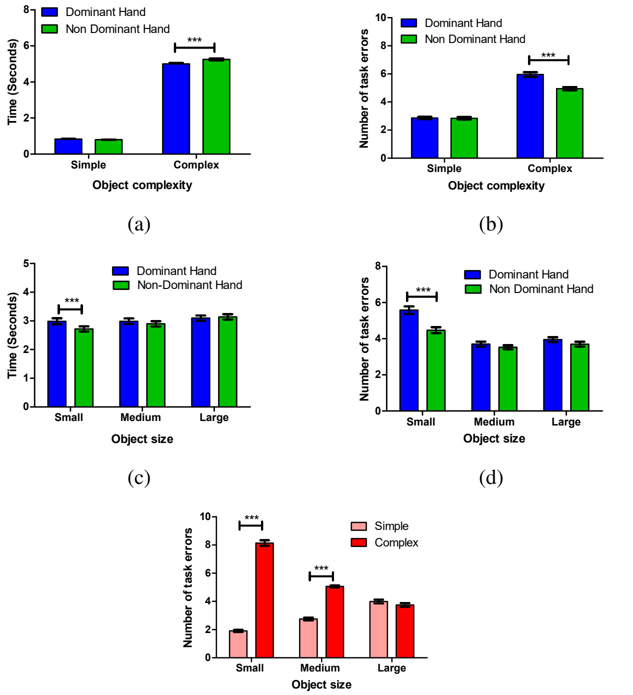
Factor	Level	Time		Task error	
		Mean	SEM	Mean	SEM
Object Complexity	Simple	0.820	0.008	2.851	0.064
	Complex	5.123	0.042	5.456	0.101
Handedness	Non Dominand	2.919	0.054	3.897	0.080
	Dominand	3.023	0.058	4.410	0.097
Object Size	Small	2.853	0.069	5.026	0.134
	Medium	2.942	0.067	3.613	0.089
	Large	3.119	0.067	3.822	0.095

Fig. 5(a) and Fig. 5(b) results on complex structure showed a speed and precision trade-off: subjects were faster but less precise with their dominant hand on the complex structure. Besides, participants were slower (Fig. 5(c)) and less precise (Fig. 5(d)) with their dominant hand on small object size. Subjects were also getting more precise when the complex structure was getting larger and they were less precise when the simple structure size was getting smaller (Fig. 5(e)).

3.4 Detailed Handedness Results Exploration

Subject were both faster and less precise in complex objects, and slower and less precise in small object size with their dominant hand. Structural complexity, handedness and object size three-way ANOVA interaction was not significant for ‘execution time’ $F(2,4319)= 2.63$; NS and ‘task error’ $F(2,4319)= 2.74$; NS.

In the detailed analysis of complex structure and handedness ((Fig. 5(a)) and (Fig. 5(b)), a two-way ANOVA was per-



(a) (b)

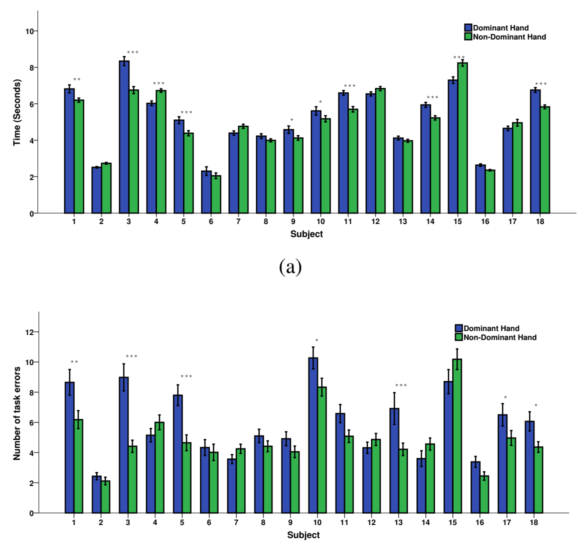
(c) (d)

(e)

Figure 5: Significant two-way interactions between object complexity and handedness on (a) 'execution time' and (b) 'task error', and between object size and handedness on (c) 'execution time' and (d) 'task error', and between structural complexity and size on (e) 'task error'.

Table 2: Results (means and standard errors) for 'execution time' and 'task error' on two-way interactions

		Time		Task error	
		Mean	**SEM**	**Mean**	**SEM**
Structural Complexity	**Handedness**				
Simple Structure	Non Dominant	0.801	0.010	2.840	0.097
	Dominant	0.838	0.011	2.681	0.083
Complex Structure	Non Dominant	5.25	0.056	4.952	0.119
	Dominant	5.00	0.057	5.959	0.161
Object size	**Handedness**				
Small	Non Dominant	2.719	0.090	4.472	0162
	Dominant	2.987	0.105	5.581	0.212
Medium	Non Dominant	2.897	0.092	3.524	0.113
	Dominant	2.987	0.099	3.701	0.137
Large	Non Dominant	3.141	0.095	3.696	0.135
	Dominant	3.096	0.095	3.949	0.135
Object size	**Structural Complexity**				
Small	Simple	F(1,4319)= 1.948; NS		1.91	0.079
	Complex			8.143	0.197
Medium	Simple			2.749	0.101
	Complex			5.065	0.075
Large	Simple			3.987	0.134
	Complex			3.747	0.136



(a)

(b)

Figure 6: 18 Subjects' (a) 'execution time' and (b) 'task error' data on complex structure, dominant and non-dominant hand.

formed over 18 subjects' complex structure, dominant and non-dominant hand data with a Cartesian plan of $P_{18}xH_2$, 18 participants (P_{18}) and two levels of handedness factor (H_2) over 60 trials (including object size S_3 x index fingertip movement direction D_2 x 10 repetitive trials), yielding a total of 2x2160 data for 'execution time' and 'task error'. In two-way interactions, twelve subjects (Subject 1,3,5,6,8,9,10,11,13,14,16,18) were slower with their dominant hand and eight of these results (Subject 1,3,5,9,10,11,14,18) were significantly different $F(17,2159)=9.38$; $p<0.001$ (Fig. 6(a)). Thirteen subjects (Subject 1,2,3,5,6,8,9,10,11,13,16,17,18) were less precise with their dominant hand and seven of these results (Subject 1,3,5,10,13,17,18) were significantly different $F(17,2159)=4.92$; $p<0.001$ (Fig. 6(b)). Eleven subjects (Subject 1,3,5,6,8,9,10,11,13,16,18) were both slower and less precise with their dominant hand and in total, five of these results (Subject 1,3,5,10,18) were significantly different for both dependent variables.

In the detailed analysis of small object size and handedness ((Fig. 5(c)) and (Fig. 5(d)), a two-way ANOVA was performed over 18 subjects' small object size, dominant and non-dominant hand data with a Cartesian plan of $P_{18}xH_2$, 18 participants (P_{18}) and two levels of handedness factor (H_2) over 40 trials (including structural complexity SC_2 x index fingertip movement direction D_2 x 10 repetitive trials), yielding a total of 2x1440 data for 'execution time' and 'task error'. In two-way interactions, thirteen subjects (Subject 1,3,5,6,8,9,11,12,13,14,16,17,18) were slower with their dominant hand and only one of these results (Subject 3) was significantly different $F(17,1440)=0.7$; NS (Fig. 7(a)). Besides, thirteen subjects (Subject 1,2,3,4,5,6,8,9,10,13,16,17,18) were less precise with their dominant hand and five of these results (Subject 3,5,13,17,18) were significant $F(17,1440)=2.08$; $p<0.01$ (Fig. 7(b)). Ten subjects (Subject 1,3,5,6,8,9,13,16,17,18) were both slower and less precise with their dominant hand and only one of these results (Subject 3) was significantly different for both dependent variables.

In both Fig. 6 and Fig. 7, Subject 3 (female, 25 years old, index fingertip width 1.7 cm, distance between shoulder to index finger tip 66 cm) was slower and less precise with her dominant hand compared to non dominant hand in small object size and complex object structure. Individual execution time-precision curves of the subject 3 is given in Fig. 8. On the contrary, Subject 15 (female, 26 years old, index fingertip width 1.8 cm, distance between shoulder to index finger tip 73 cm) was faster and more precise with her dominant hand compared to non dominant hand in small object size and complex object structure. Subject 15 is selected for comparison with Subject 3 because both subjects were female, had similar ages, fin-

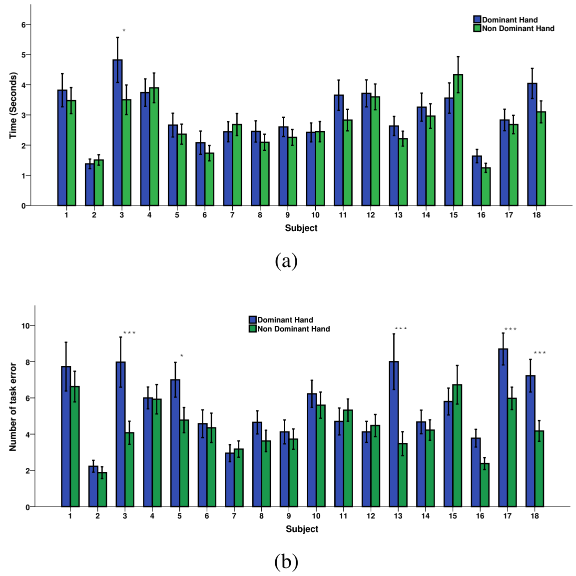


Figure 7: 18 Subjects' (a)'execution time' and (b) 'task error' data on small object size for dominant and non-dominant hand.

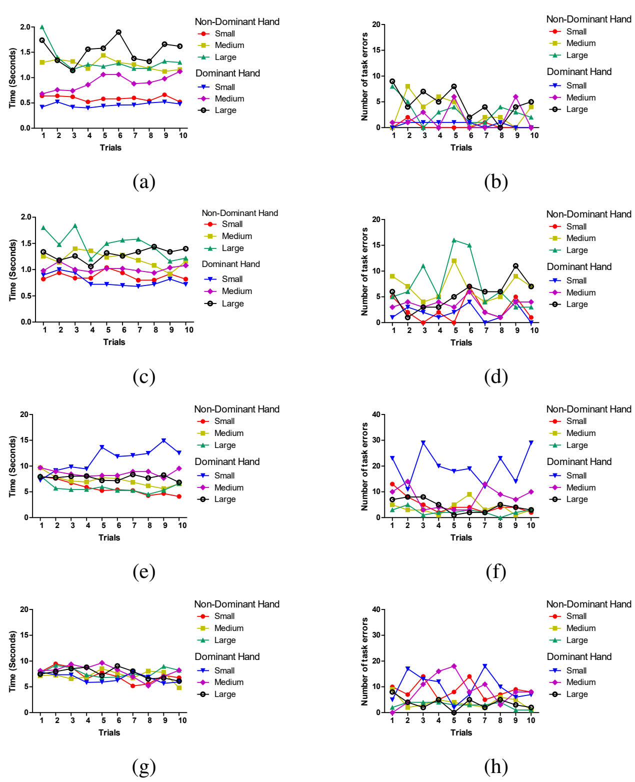


Figure 8: Subject 3 individual speed-precision curves. Simple structure left to right moving direction on (a) 'execution time', (b) 'task error' and right to left moving direction on (c) 'execution time', (d) 'task error'. Complex structure for left to right moving direction on (e) 'execution time', (f) 'task error' and right to left moving direction on (g) 'execution time', (h) 'task error'.

gertip widths, shoulder to index finger tip distance and contradicting handedness results on Fig. 6 and Fig. 7. Individual time-precision curves of the Subject 15 is given in Fig. 9.

Subject 3 was getting faster in right to left movements in both simple (Fig. 8(c)) and complex (Fig. 8(g)) structures, yet she was not getting any precise in 'task error'(Fig. 8(d) and Fig. 8(h), respectively). She was getting more precise in left to right movements in simple structure (Fig. 8(b)), however she was not getting any faster (Fig. 8(a)). She was getting faster (Fig. 8(e)) and more precise (Fig. 8(f)) in right to left movement in complex structure except for dominant hand small object size: she was getting slower and her precision results were oscillating. Subject 15 was getting faster only in left to right movements in complex object (Fig. 9(e)). Her time results were stable for simple (Fig. 9(c)) and complex (Fig. 9(g)) structure left to right movements except for simple structure small size dominant hand results (blue line in Fig. 9(c)). She was getting slightly slower (Fig. 9(a)), but more precise (Fig. 9(b)) in left to right movement direction in simple structure. Her precision results were oscillating for left to right hand movements on simple structure (Fig. 9(d)) and right to left hand movements on complex structure (Fig. 9(f)). Her precision was also oscillating in right to left movement direction for complex structure (Fig. 9(h)) except for large objects. In both subject results, simple structure showed far less change than the complex structure for 'execution time' and 'task error'.

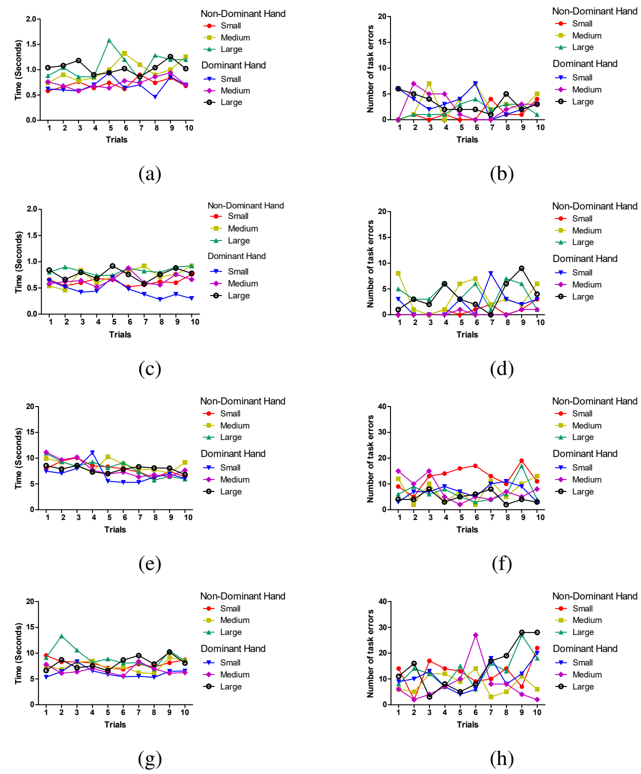


Figure 9: Subject 15 individual speed-precision curves. Simple structure for left to right moving direction on (a) 'execution time', (b) 'task error' and right to left moving direction on (c) 'execution time, (d) 'task error'. Complex structure for left to right moving direction on (e) 'execution time', (f) 'task error' and right to left moving direction on (g) 'execution time', (h) 'task error'.

Subject 3 was getting slower (Fig. 8(e)) and less precise (Fig. 8(f)) in complex structure small size dominant hand right to left movement. Likewise, Subject 15 was getting less precise in complex structure large object size dominant and non dominant hand results on right to left movement direction (Fig. 9(h)). These rare task results were not the first or the last trials of subjects. Furthermore, in the figures of 18 subjects' individual 'execution time' and 'task error' data (not shown here due to the space limitations), there was no sudden or obvious increase in the 'execution time' or decrease in the 'task error' that might represent task fatigue or rushing.

Pearson's correlation analysis in these rare result conditions between 18 subjects' 'execution time', 'task error', index fingertip width and shoulder to index fingertip length data showed only correlations between 'execution time' and 'task error'. In complex structure small size dominant hand right to left movement, there was a positive correlation between 'execution time' and 'task error' with r=0.690, p<0.01 (N=18). Similarly, complex structure small size dominant hand right to left movement, there was a positive correlation between 'execution time' and 'task error' with r=0.686, p<0.01 (N=18).

4 Discussion

Human motor skills were investigated here in terms of the time and precision of directed fingertip movements in VR with virtual objects of varying complexity and size.

Positioning an object in a VR scene without controlling for size and complexity may cause a conflict between design and task demands, and mislead conclusions about individual progress or performance evolution during training. When subjects were retracing a simple structure in VR with the tip of their index finger, they were more precise with small size objects. When the image size was increased, motor performance of the subjects decreased. On the other hand, when subjects were retracing a complex structure, they were more precise with large size objects. When the object size increased, motor performance of the subjects also increased. These seemingly contradictory results show that virtual object size and complexity are interdependent, and need to be controlled when assessing motor performances with VR training applications or simulators. Besides, when the task environment is simple, the size of the display should be kept small. However, if the virtual object space is complex, then the display size should be large enough to minimize errors. In practical use, beginners should start training on larger representations of complex objects in VR. For skill assessment in VR, object size may need to be individually calibrated for complex actions [8–10] such as knot tying in laparoscopic surgery, for example. More generally, in the absence of prior data or knowledge, virtual objects should be displayed at a medium size for optimal motor performance as a thumb rule.The results here highlight the importance of the object complexity in VR and lead to conclude that, whenever possible, a simple structure should be preferred over a complex structure.

It was known already that handedness can affect performance in VR displays [32] especially for beginners. Significant differences between dominant and non-dominant hand were observed for the complex structure and small object size with a better precision score for the non-dominant hand. This may seem surprising in the light of previous studies (e.g. [13]). In the detailed analyses here with dominant hand and non dominant hand, possible reasons can cause this difference were inspected. In individual 'execution time' and 'task error' results over 10 repeated trials of 18 subjects, no task fatigue or rushing was observed that could affect the results. Furthermore, the distance from shoulder to index fingertip and index fingertip width showed no correlation with 'execution time' and 'task error'. Several explanations may account for the handedness results here.

Majority of the subjects (11 out of 18) were both slower and less precise with their dominant hand in complex structures. Besides, majority of the subjects (10 out of 18) were both slower and less precise with their dominant hand in small object size. These non-dominant hand speed and precision results could be explained by the fact that subjects were more attentive to task constrains when forced to use the hand they do not use preferentially. This is related to the feeling of agency during motor control [7, 9, 31]. When subjects use the hand they prefer using, they feel more in control and may become less attentive to contains.

Besides, subjects were asked to retrace the objects in VR while their fingers were wide open and the outer side of the active hand was facing the motion sensor. This method was particularly selected to acquire stable data from the motion sensor and to overcome the lack of hand visualization. Complex structure was not a symmetrical object. Retracing different curvature segments of the complex object from different angles with dominant and non dominant hand with the limited hand gesture could explain these results. Although subjects did not indicate any fatigue or ergonomic comments, motor performance of participants could be affected by the hand movement restrictions.

An another explanation of the handedness results can be the fact that the finger movements of the subjects were controlled through visual feedback only, not tactile or auditory feedback. Color change alone might not be enough to provide 'task error' feedback in specific object designs to guide the subject to correct his/her errors. From previous studies [22, 37, 41], it is known that additional feedback can provide useful information during task execution and lead to improve the motor performance of the subjects. Moreover, previous studies on handedness also shows the unexpected results can acquire due to the inexperience of the subjects on the task [12]. The results here point towards potentially intricate links between handedness effects and feedback conditions in VR environments, and deserve to be studied further.

The other important result here is the significant difference between subjects' task dependent individual performance strategies. This strategy difference occurs spontaneously and in the absence of performance feedback [1, 2, 16, 25]. In this case, it is important to monitor subjects' speed-precision curves, which reveals their choice between speed and precision strategy goals. For instance, Subject 15 was getting slower (Fig. 8(a)), but more precise (Fig. 8(b)) in simple structure. On the other hand, in the same conditions, Subject 3 had the similar time results after 10 trials (Fig. 8(b)), but she was getting more precise (Fig. 8(b)). Instead of using unsupervised learning, instructing subjects to prioritize precision at the begging of their training [9] would help them optimize their motor performance learning in VR and eliminate unexpected results.

5 Conclusion & Future Research

Virtual object complexity and size critically and interdependently determine the time and the precision of human hand and finger movements along axes of alignment of object borders. Virtual objects need to be calibrated for optimal tracking of individual performance evaluation in VR environments and simulators. Individual speed precision curves should be monitored from the outset to optimize motor performance during learning. Handedness in no touch systems is a discriminative performance factor. The effects of handedness found here should be explored further in experiments with different speed-accuracy instructions, different motion sensors allowing flexible hand movements, and additional sensory feedback.

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