3D Object Manipulation: Mouse vs. Hand Gesture

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PREFACE

This thesis document is part of my graduation project for a MSc. title in Game and Media Technology. It consists of a preface, a technical paper and an appendix. The paper presents a research in which task performance and usability on a 3D object manipulation task is investigated while users interact through a computer mouse or with hand gestures. Advanced and accurate hand gesture recognition hard- and software has just recently become available. Therefore, this research reopens the path to further investigate the added value of using hand gestures as an interaction method and compare it to traditional methods as the computer mouse. Compared to prior research, this research conducts additional analyses of speed and accuracy trade-offs, usability factors and the correlation between actual and perceived speed and accuracy. It takes into account personal differences and is more elaborate in terms of amount of participants and manipulation actions. It combines different areas of expertise such as computer vision, human computer interaction and virtual motion and object manipulation. These areas can be linked to various courses in the Game and Media Technology master curriculum, namely the Computer Vision course, Multimodal Interaction course and Motion and Manipulation course respectively. Due to the innovative nature of hand gesture recognition and its market potential, I found it important to research and broaden my view on this new kind of interaction and find its pros and cons.

One particular task that would benefit from hand gesture input is 3D object manipulations. Contemporary computer aided design application use widgets to manipulate objects. However, it takes practice to master these widgets due to their complex mapping from real world action onto virtual world action. With the introduction of hand gesture input, the mapping from real world to virtual world can be done more intuitively. This might improve 1) performance in terms of speed and accuracy as well as 2) usability. Another advantage is that the user does not have to physically interact with a device and using hand gestures is thus more sterile. This is a huge advantage in, for example, a medical environment.

The research I have performed in the last ten months focused on designing, implementing and conducting an experiment to investigate the difference in performance and usability between hand gestures and the mouse on a virtual 3D object manipulation task. In the experiment, 39 participants were required to translate, rotate and scale objects with both the mouse and hand gestures. By measuring speed and accuracy as well as assessing usability through a questionnaire I compared the advantages of both classes of input. I found that hand gestures enabled users to perform faster object manipulations, but with similar accuracy, when comparing it to the mouse. Moreover, hand gestures scored higher in the usability assessment and were preferred by most participants.

3D Object Manipulation: Mouse vs. hand gesture, their objective and subjective performance

G. J. (John) Schaap, Egon L. van den Broek, Frank Meijer, and Boudewijn P. F. Lelieveldt

Abstract—Traditional computer mouse-based interaction is compared with the Natural User Interfaces hand gesture-based interaction for 3D object manipulation. So far, no direct comparison between both interaction paradigms has been made in a structured manner, including both objective and subjective aspects. With both computer mouse and hand gestures, 39 participants conducted translations, rotations, scaling, and their compound with the same 7 objects for each manipulation. Speed and accuracy were measured as well as experienced speed, accuracy, learnability, usability, use in daily life, and fatigue and strain. The Speed Accuracy Tradeoff of hand gesture showed superior to mouse-based control, which was also confirmed by the participants' experience. Also learnability, usability, and use in daily life of hand gestures were judged favorably, despite the reported accompanying fatigue and strain. So, hand gestures are strongly advised as the preferred Natural User Interfaces for 3D object manipulation applications.

Index Terms—3D, object manipulation, interaction, mouse, hand tracking, speed, accuracy, usability

1 Introduction

Ever since computers became accessible for consumers, engineers faced the challenge how these consumers should interact with computers in an intuitive manner [1]. Starting 50 years ago, the computer mouse has fulfilled a major role in this challenge, enabling smooth Human Machine Interaction (HMI) [2]. However, in recent years HMI increasingly moves away from the traditional desktop environment [3]. Consequently, the computer mouse's usefulness as an interaction method in the new digital era is questioned. Furthermore, the digital world increasingly overlaps with the real world. This coalescence of the real and the digital yields the need for Natural User Interfaces (NUI) [4], [5], as digital interactions are expected to represent those of the real world more and more. Nevertheless, nowadays interaction practice shows that the computer mouse and its traditional alternatives (e.g., keypad, pen, and joystick) are here to stay and, consequently, 50 years after its invention, the computer mouse is still *the* interaction device to be challenged. This article takes up this challenge, taking the computer mouse as benchmark device and comparing it with one of the most promising new interaction means: hand tracking. More specifically, we present a rigorous comparison between both interaction means for 3D object manipulation.

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In virtual and augmented realities, being able to manipulate virtual 3D objects (e.g., translating, rotating, and scaling) is crucial. Such 3D manipulation of virtual objects is performed in various domains including aerospace, architecture, defense, design, education, (serious) gaming, and in medical imaging [6]. To obtain a good mental representation of a 3D object, not only visual cues are required, also manual interaction is needed [7], [8], [9], [10]. Moreover, when interacting with 3D objects, not only performance measures such as speed and accuracy are important, also the user's experienced speed and accuracy as well as technology acceptance aspects (e.g., usability) are essential [11], [12], [13], [14].

In the past decades, a substantial amount of research has been conducted on virtual 3D object manipulation [4], [15], [16]. One of the pregnant challenges is done in 3D manipulation space, with each object having nine degrees of freedom (DOF): x-, y-, z-position for position (translation), rotation, and scaling. To manipulate the object in nine DOF with the computer mouse, additional interaction means are required (e.g., buttons, modifier keys, and widgets) [17]. Users experience these additional controls as nonintuitive and, consequently, its use requires a lot of mental effort and training. As such, mouse-based 3D object manipulation violates the principle of NUI. Nevertheless, the computer mouse is the most common interaction device for this applications.

Being a NUI, with a rapidly increasing performance (e.g., [18]) and steep decline in price (e.g., [19]), gesture-based interaction is an attractive alternative for 3D object manipulation with the computer mouse. In virtual 3D object manipulation, hand gestures can be used to translate and rotate an object as if the hand represents the virtual object. On the one hand, the mapping is intuitive, possibly making it faster and easier to learn than using the mouse [17], [20], [21]. On the other hand, it is hard to hold the hand in a still pose, which can decline accuracy and can cause fatigue or even strain in the arm, hand, and fingers [20], [22]. Moreover, scaling in general is an nonintuitive mapping because it has no real world equivalent.

Many studies have been conducted on how to use either the mouse or hand gestures for manipulating virtual objects; for recent overviews, we refer to [17], [21], [22], [23], [24], [25], [26], [27]. However, most of them only considered one input method instead of comparing multiple methods. Moreover, due to differences in interaction devices, experiment design (e.g., tasks and objects), and number and type of participants, generic conclusions are impossible to draw regarding hand gesture-based 3D object manipulation compared to traditional computer mouse-based manipulation (cf. [21], [23]). To the authors' knowledge, there is no study that studied the difference between using the mouse and hand gestures for 3D object manipulation directly in a controlled and structured manner. Moreover, an integral approach is often missing. Either recorded speed and accuracy are analyzed or technology acceptance (e.g., usability) issues are investigated [7], [21], [28], [29]; these traditionally distinct approaches are hardly ever combined for 3D object manipulation. This article presents a rigorous study that compares mouse-based and gesture-based 3D object manipulation directly. It is applied in a controlled and structured manner, including speed, accuracy, and technology acceptance. Consequently, it fills a gap in our knowledge base on 3D object manipulation.

This article's main research question can be brought down to: *Is the computer mouse here to stay?* In other words, the computer mouse as interaction paradigm of the past and the present versus its emerging promise: computer vision-based gesture/hand tracking.

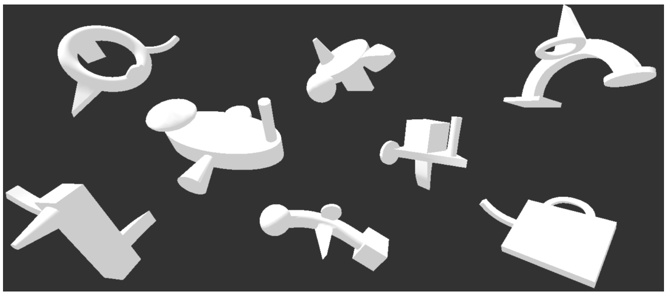

Fig. 1. The objects used in the experiment.

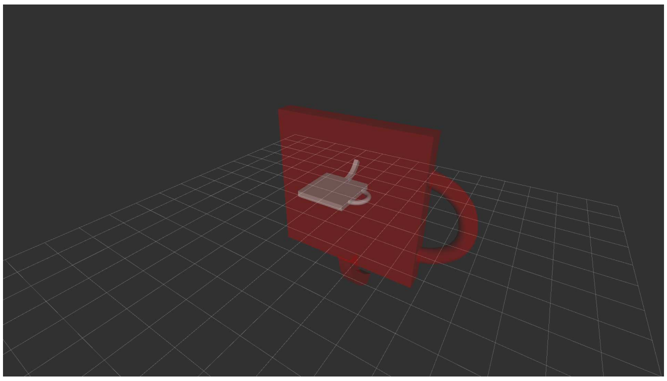

Fig. 2. The virtual world the participants conducted the 3D object manipulation in, showing a gray manipulation object and a red transparent target object.

In this comparison, we decompose our research question and make it executable using the following performance measures:

- Objective: speed, accuracy, and the Speed Accuracy Trade-off (SAT) [30] and
- Subjectively experienced: speed, accuracy, SAT, and technology acceptance aspects.

Together, these performance measures can provide a complete image of the utility of both mouse and gesture/hand tracking for 3D object manipulation. Moreover, objectively recorded and subjectively experienced measures will be compared to unveil their relation. Pros and cons of both interaction paradigms for 3D object manipulation will be unveiled. And a cautious forecast for the future of HMI will be made.

In the next section, we will discuss the research methods we applied. Section 3 presents the result on speed, accuracy, and technology assessment, and, subsequently, discusses their relation. We end this article in Section 4 with a discussion.

2 Method

2.1 Participants

Thirty-nine participants, age of $17-33$ years ($\mu = 22, \sigma = 3.29$), participated in this study. The participants were naïve concerning the purposes of the experiment. All the participants had (corrected to) normal visual and physical abilities.

The participants were placed in a lab environment at an office desk in an office chair. The computer screen 70 cm away from them, at the height of their eyes. The computer mouse and keyboard were positioned such that the participant could rest their wrists on the desk.

2.2 Material and Apparatus

A notebook computer (Dell: Latitude E5540; Dell Inc.) with a 15.6” display (resolution: 1920x1080), running at 60Hz with Windows 8.1 (Microsoft Corporation) as operating system, was used in the experiment. Attached to the notebook was a wireless Logitech M310 mouse (Logitech Inc.) and a Leap Motion (Leap Motion Inc.). The Leap Motion was used with its default settings [19]. A Dell Performance USB Keyboard SK-8125, A00 (Dell Inc.) was used to switch between manipulation operation modes (i.e. translation, rotation and scaling) and to end a task. The experiment was created within Unity3D (v4.6.0) (Unity Technologies), using a plugin for the Leap Motion (v2.2.1).

Seven asymmetric virtual 3D objects were taken from Meijer and van den Broek [8]. These objects were constructed from a set of seven geon-like components [31], each consisting of four geons attached to one bigger geon (see Fig. 1). The objects were shown in gray scale and were equal in their illumination and luminance. An additional asymmetric virtual 3D object was created for use in the introduction.

The virtual environment had a dark-gray background and contained a white transparent wire frame ground plane (see Fig. 2). A perspective camera and directional light were placed such that it provided an optimal (i.e., canonical [32]) view. With each task, two objects with the same shape were shown: a gray transparent object that the participant could manipulate and a red transparent target object (see Fig. 2).

The controls for activating manipulation operation modes was the same for both the mouse input and hand gesture input. The participant had to press [1] to activate/deactivate the translation mode, [2] to activate/deactivate rotation mode, and [3] to activate/deactivate scaling mode. Object manipulation with the mouse was done with 3D widgets (see Fig. 3). When dragging a widget in a certain direction, it would turn yellow to indicate that the participant was dragging that particular widget. Object manipulation with hand gestures was done with the position and orientation of the hand and fingers. Translation was achieved by moving the hand. Rotation was realized by changing the orientation of the hand. Scaling was done by changing the distance between the index finger and the thumb.

2.3 Design and procedure

The complete study took about 45 minutes. At the start of the experiment, the participants were tested on their Visuo-Spatial Ability (VSA) using the Mental Rotation Test (MRT-A) [33], [34]. MRT-A’s results indicate participant’s ability to form a mental representation of objects [35].

The main study consisted of five phases: the introduction, translation, rotation, scaling, and compound phase, completed

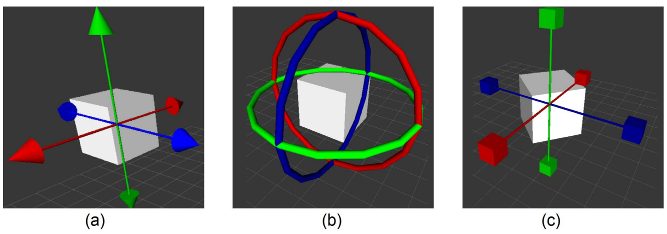

Fig. 3. The (a) translation, (b) rotation, and (c) scaling widget.

with the mouse and hand gestures. The order of the translation, rotation, and scaling phase was counterbalanced. For all participants, the transformations were identical. The participants were told that speed and accuracy were equally important, to prevent bias towards one of both, which is an often occurring problem with similar studies [].

In first phase the study was explained, including the controls to use and the tasks to be completed. Seven tasks were defined for each of the remaining four phases. For each of the tasks, the participants had to translate, rotate, and/or scale the gray manipulation object, such that it matched the red target object (see Fig. 2). The seven objects were presented in random order.

The difference between the manipulation and the target objects, were defined as follows: For the translation phase, the Manhattan distance between the two was equal to six. For the rotation phase, the target object was randomly rotated with steps of 60° in each direction (i.e., in line with the VSA test [33]). For the scaling phase, the target object's scale was randomly multiplied within the range of 1.25 and 5.00. For the compound phase, the seven objects were manipulated randomly on all three aspects, using the recipes just defined.

Three types of questionnaires were used in this study: At the start, general information was gathered, including: name, age, email, profession, gender, handedness, education, visual/physical handicap and experience and frequency with computers, gaming, 3D gaming, and 3D object manipulation. At the end of the study, questions were asked related to the input method, such as preference, possible improvements, and the study in general. Additionally, after each phase, the participants were asked to rate six technology assessment statements on a Likert-scale ranging from 1 to 5 that assessed the experienced speed, accuracy, difficulty of the task, difficulty of learning the controls, strain, and real life usage.

3 Results

The goal of this study was to compare speed, accuracy, and technology acceptance for direct 3D object manipulation between mouse and hand gesture input. Both objective measurements and the participants' experiences will be reported. The accuracy was calculated using the Manhattan distance between manipulation and target object for position (translation) and angle (rotation) and the Euclidean distance for size (scaling).

For the analysis of speed and accuracy measurements, a parametric test will be adopted, as group sizes are equal, data in each group is normally distributed, and the data samples are of a sufficient size (i.e., > 15) [36]. For the analysis of the technology assessment via questionnaires, a non-parametric test will be adopted, as this data is ordinal and a normal distribution cannot be assumed [36]. Initial analyses showed that the following factors did not have a significant influence on participants' performance: age, profession, gender, handedness, education, experience with computers, gaming experience, VSA, and experience in object manipulation. Therefore, these factors were excluded from further analysis.

For all the analyses, a significance threshold of $p = .05$ was used. μ indicates the mean and σ the standard deviation,. With the parametric tests, as measure of effect size, partial eta squared (η^2) is reported, which indicates the proportion of variance accounted for (i.e., a generalization of r/r^2 and R/R^2 in correlation/regression analysis) [37].

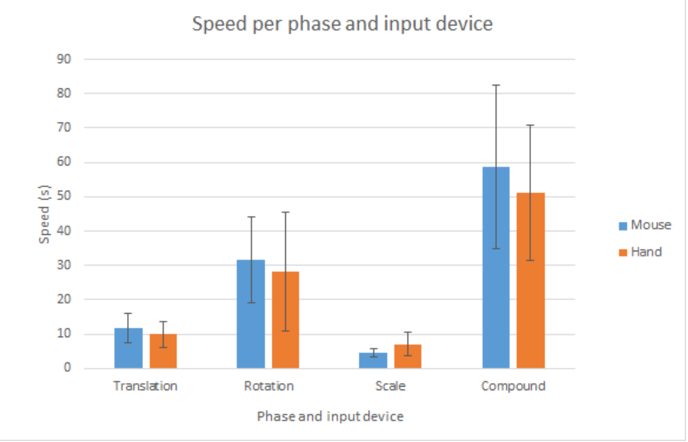

Fig. 4. Average speed per phase per input device.

3.1 Speed

A 2 (input devices) $\times$ 4 (phases) $\times$7 (tasks) doubly multivariate Repeated-Measures ANalysis Of VAriance (ANOVA), evaluated with Pillai's trace test, was performed to examine the effects on speed. Please note that the study's raw data (i.e., not normalized and including outliers) was used as input for this analysis. The average speed per phase is shown in Fig. 4.

Hand gesture input ($\mu = 26.33; \sigma = 1.56$) is faster than the mouse input ($\mu = 26.60; \sigma = 1.57$), $F(1,38) = 5.276, p = .029, \eta^2 = .15$. The rotation phase ($\mu = 32.71; \sigma = 1.85$) and the compound phase ($\mu = 59.464; \sigma = 3.53$) took more time to complete than the translation phase ($\mu = 11.54; \sigma = .68$) and the scaling phase ($\mu = 6.15; \sigma = .41$), $F(3,38) = 84.45, p < .001, \eta^2 = .900$. The results indicate that the speed decreases monotonically for every task that is completed. The participants were faster in the first round ($\mu = 20.57; \sigma = 1.45$) than the last round ($\mu = 33.02; \sigma = 2.01$), $F(6,38) = 15.930, p < .001, \eta^2 = .793$.

There was an interaction between input and phases, $F(3,38) = 18.780, p < .001, \eta^2 = .670$. Although the hand gestures are faster in most cases, the opposite is true for scaling (mouse: $\mu = 4.82$; $\sigma = .25$ and hand: $\mu = 7.48$; $\sigma = .62$).

There was a statistically significant interaction between input and rounds, $F(6,38) = 11.88, p < .001, \eta^2 = .740$. The speed of object manipulation with the mouse declined monotonic over the execution of the study, starting with $\mu = 18.48$ ($\sigma = 1.77$) and ending with $\mu = 38.00$ ($\sigma = 2.62$). For gesture-based object manipulation, also a monotonic decline in speed was present, although not as strong, starting with $\mu = 22.66$ ($\sigma = 1.54$) and ending with $\mu = 28.03$ ($\sigma = 1.74$).

3.2 Accuracy

In contrast with speed, a comparison in accuracy over the 4 phases did require a normalization of the data, as accuracy was measured in distinct units (also, see Section 2): rotation is measured in degrees (range: $0° - 360°$), position in distance (range: $0 - \infty$), and scale in size (range: $0 - \infty$). For each of the 39 participant, the 2 input devices, the 4 phases, and 7 blocks, a separate unity-based normalization was applied (cf. [38]), as follows:

$$A' = \alpha A + \beta, \tag{1}$$

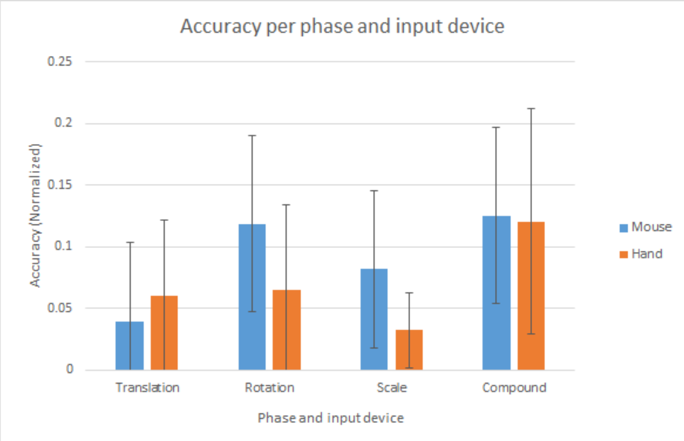

Fig. 5. Average normalized accuracy per phase per input device.

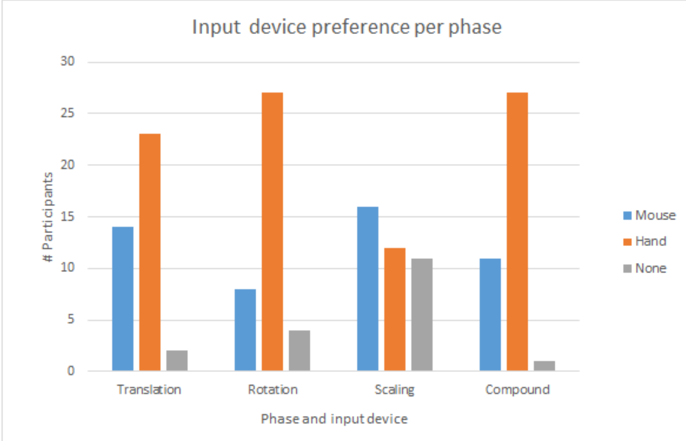

Fig. 6. The preferred input device for every phase.

where A' is the normalized accuracy, A is the measured accuracy of the participant,

$$\alpha = \frac{max - min}{max_p - min_p}, \qquad \text{and} \qquad \beta = max - \alpha\, max_p, \qquad (2)$$

with *max* and *min* being respectively the maximum and minimum error over all participants, within the block on which the normalization was applied, and max_p and min_p being the maximum and minimum error of the individual participant within this block.

A 2 (input devices) × 4 (phases) × 7 (tasks) doubly multivariate Repeated-Measures ANOVA, evaluated with Pillai's trace test, was performed to examine the effects on accuracy. The average speed per phase is shown in Fig. 5. Please note that the study's raw data (i.e., not normalized and including outliers) was used as input for this analysis, except for the comparison between phases, where the normalized data (see Eq. 1; but, still including outliers) was used as input.

There is no significant difference in accuracy for the mouse input ($\mu = 4.46; \sigma = .42$) and the hand gesture input ($\mu = 5.19; \sigma = .81$). However, there was a main effect of phases ($F(3,38) = 36.180, p < .001, \eta^2 = .800$) and rounds ($F(6,38) = 3.785, p = .008, \eta^2 = .476$). Accuracy decreased monotonic for every task executed with both mouse-based and hand gesture-based 3D object manipulation. The mouse started with less accuracy $\mu = 1.87 (\sigma = 0.66)$ than the hand $\mu = 4.27 (\sigma = 1.21)$. With both input devices the accuracy decreased throughout time, resulting in accuracies of $\mu = 5.72 (\sigma = 0.94)$ and $\mu = 6.48 (\sigma = 1.95)$ for the mouse and hand, respectively.

3.3 Technology assessment

To analyze the difference in usability between the input devices, a Wilcoxon signed rank non-parametric test was conducted for every phase. Given the distribution of the data, this test will have better properties than classical parametric tests (e.g., ANOVA) in terms of power, efficiency, or Type I error biases [36]. Fig. 6 shows the preferred input device for each phase.

For translation, participants experienced hand gestures ($\mu = 4.15, \sigma = 0.71$) as faster than mouse controlled object manipulation ($\mu = 3.69, \sigma = 0.89$), $Z = -2.627, p = .009$. Also, participants experienced hand gestures ($\mu = 4.15, \sigma = 0.74$) as more accurate than mouse controlled object translation ($\mu = 3.67; \sigma = 1.01$), $Z = -2.425, p = .015$. However, they also reported that hand gestures ($\mu = 4.46, \sigma = 0.72$) are harder to learn than mouse controlled object translation ($\mu = 4.72, \sigma = 0.65$), $Z = -1.968, p = .049$. Participants reported no significant difference between both input methods regarding their ease to use for translation, $Z = -1.833, p = .067$. Moreover, the participants indicated no preference on how to perform translation operations in real life.Participants reported more fatigue and strain when using gestures ($\mu = 3.46, \sigma = 1.17$) than when using the mouse ($\mu = 4.51, \sigma = 0.88$) for translation, $Z = -4.364, p < .001$.

For rotation, participants experienced hand gestures ($\mu = 3.13, \sigma = 1.24$) as faster than mouse controlled object manipulation ($\mu = 2.26, \sigma = 0.88$), $Z = -3.492, p < .001$. Also, participants experienced hand gestures ($\mu = 3.31, \sigma = 1.20$) as more accurate than mouse controlled object rotation ($\mu = 2.41, \sigma = 0.94$), $Z = -3.388, p = .001$. On the one hand, participants reported hand gestures ($\mu = 3.31, \sigma = 1.28$) as harder to learn than mouse operations ($\mu = 3.97; \sigma = 0.96$) for rotation, $Z = -2.686, p = .007$. On the other hand, hand gestures were experienced as easier to use ($\mu = 3.10, \sigma = 1.33$) than mouse controlled rotation ($\mu = 2.15, \sigma = 0.87$), $Z = -3.712, p < .001$. Additionally, participants indicated that they would prefer hand gestures ($\mu = 3.46, \sigma = 1.45$) over the mouse ($\mu = 2.36, \sigma = 1.06$) when performing rotation operations in real life, $Z = -2.976, p = .003$. Also, gesture-based rotation caused more strain ($\mu = 2.95, \sigma = 1.07$) than mouse-based rotation ($\mu = 4.18, \sigma = 1.10$), $Z = -4.182, p < .001$.

For scaling, participants experienced no difference between gestures and mouse-based scaling for either speed or accuracy. Moreover, participants report no difference between gestures and mouse-based scaling on their ease of learning, ease of use, and preference for scaling operations in real life. However, participants did report more fatigue and strain with hand gestures ($\mu = 3.77, \sigma = 0.93$) than with mouse-based object manipulation ($\mu = 4.62, \sigma = 0.81$), $Z = -3.905, p < .001$.

For the compound task, participants experienced hand gestures ($\mu = 2.77, \sigma = 0.93$) as faster than mouse controlled object manipulation ($\mu = 1.62, \sigma = 0.78$), $Z = -4.807, p < .001$. Participants also experienced hand gestures ($\mu = 2.87, \sigma = 1.00$) as more accurate than mouse controlled object manipulation ($\mu = 1.90, \sigma = 0.97$), $Z = -4.082, p < .001$. Moreover, participants reported no difference in ease of learning between gestures and mouse-based manipulation. Participants did experience hand gestures as easier to use ($\mu = 2.87, \sigma = 1.13$) than mouse controlled manipulation ($\mu = 1.77, \sigma = 0.78$), $Z = -4.204, p < .001$. Moreover, participants indicated that they would prefer hand gestures ($\mu = 3.41, \sigma = 1.23$) over the mouse ($\mu = 2.33, \sigma = 1.11$) when performing rotation operations in real life, $Z = -3.029, p = .002$. However, participants participants also reported that gesture-based manipulation caused more strain ($\mu = 2.69, \sigma = 1.13$) than mouse-based manipulation ($\mu = 4.13, \sigma = 1.13$), $Z = -4.510, p < .001$.

3.4 Speed and accuracy: Objective versus subjective

One of the aspects this article deviates from related articles is that it includes both objective measurements and a subjective assessment of the technology. In this section, we take this endeavor one step further by exploring the relation between these two distinct performance indicators. This exploration was operationalized via a search for linear, quadratic, and/or cubic regression models that describe the relation between both performance indicators. ANOVAs have been conducted to determine the goodness of fit of the model. Next, we report those models that reported a significant relation. For reasons of brevity, we only provide the summaries of the strongest models. Moreover, we omit the models' parameter estimates (i.e., the intercept or constant, the (standardized) βs, and standard error) as well as the (adjusted) R^2s.

3.4.1 Speed

For mouse-based translation and the scaling phases, no relation was found between the recorded and the experienced speed. For mouse-based rotation ($F(2,270) = 8.366, p < .001$) and compound ($F(2,270) = 7.831, p < .001$) phases a strong quadratic relation was found between the recorded and the experienced speed. Additionally, cubic relations were found for these phases and a linear relation for the compound phase.

For all phases of hand gesture based 3D object manipulation, a cubic relation was found: translation ($F(3,269) = 7.471, p = .001$), rotation ($F(3,269) = 13.794, p < .001$), ($F(3,269) = 7.781, p < .001$), and ($F(3,269) = 2.766, p = .042$). Additionally, strong linear and quadratic relations were found for all phases, except the compound phase.

3.4.2 Accuracy

Only for mouse-based scaling, a linear ($F(1,271) = 11.098, p = .001$) as well as quadratic and cubic relations were found between the recorded and the experienced accuracy. For the other three phases, no relation was unveiled between recorded and experienced accuracy.

For both the hand gesture-based translation ($F(1,271) = 3.880, p = .050$) and rotation ($F(1,271) = 19.920, p < .001$) phases a linear relation was found between the recorded and the experienced accuracy. Additionally, for rotation, also a quadratic and cubic relation was found. For hand gesture-based scaling and compound phases, no relation was found between the recorded and the experienced speed.

4 Discussion

In the current study, mouse-based and gesture-based 3D object manipulation (i.e., translating, rotating, scaling, and their compound) was compared via both objective measurements (i.e., speed and accuracy) and technology acceptance aspects (e.g., experienced speed and accuracy and usability). Here, we summarize and interpret the results. We end with a final conclusion.

In general, hand gesture-based interaction was significantly faster than mouse interaction, which can be attributed to its intuitive interaction [17], [20], [21], [39] (see Fig. 4). Only on scaling tasks, the mouse showed to be faster. Scaling was done uniformly, which explains this result; that is, participants only had to control one variable instead of three as with translating and rotating. So, the advantage of the higher DOF of hand gestures was lost with scaling as only one DOF was necessary (see also Section 1). Although expected otherwise, manipulations with the mouse and hand gestures appeared to be equally accurate. Possibly this is explained by the participants' focus on accuracy. This relates to the SAT [30], which would imply that the participants choose to use the speed advantage of the hand gestures to increase its accuracy. With equal manipulation time allowed for mouse and hand gesture, the latter would most likely outperform the former. So, with respect to the SAT, hand gestures outperform mouse-based 3D object manipulation.

HMI is not only determined by the objective performance, see Section 1. Subjective aspects have to be taken into account as well to assess its technology acceptance [11], [12], [13], [14]. As anticipated, hand gestures cause considerably more effort for every phase. Participants had to hold their hand in the air most of the time, which caused fatigue and, even worse, strain [20], [22].

We expected that mouse would have an important advantage over hand gesture based interaction as participants were already familiar with mouse-based interaction. Moreover, differences between participants were expected, based on substantial differences in experience. However, no difference in learnability was found between the two interaction methods. This could be explained by the simple nature of the scaling phase and the compound phase always being last.

It should be noted that participants experienced rotation and compound tasks much harder than translation and scaling tasks, which resulted in considerably more time spend on the former two tasks than the latter two tasks. For rotating, this can be explained by the required creation of a mental representation of the object, which is an mentally intensive process. Consequently, fatigue made the performance decrease gradually the more tasks the user performed. Noteworthy is that the performance dropped more rapidly with mouse-based than with hand gesture interaction. On the one hand, this could be explained by the steep learning curve of hand gestures, which partly canceled out the effects of fatigue. On the other hand, this can be attributed by hand gestures being a NUI, where mouse-based manipulation is not. Most likely, this has helped in creating the mental representation of the object [7], [8], [9], [10].

This study compared computer mouse-based with hand gesture-based interaction. It would be to compare the winning interaction technology with other emerging interaction technologies such as sensor-based interaction (e.g., mid-air pointers and data gloves), other apparatus for direct manipulation, and other computer vision-based devices. Another issue are the controls used, which were optimized for both performance and usability. Nevertheless, it would be interesting to study other controls such as a virtual track ball to rotate the object with the mouse, using the distance between the palms of both hands to scale the object with hand gesture, and do the object manipulation in local space instead of global (or both).

During the study, some of the participants noted that they missed the ability to control the camera, as they experienced trouble in seeing depth. Alternatively, depth perception could be enhanced using a stereoscopic display [40]. It would be interesting to see how such features would affect the results. So, the research field of NUI is still an open one, with many degrees of freedom that need to be studied. Consequently, robust, concrete, generally accepted guidelines are largely absent. This study is meant to be a modest contribution to the development of such guidelines.

Taken together, hand gesture-based 3D object manipulation is faster than mouse-based 3D object manipulation. Considering the equal level of accuracy obtained with both interaction methods, learnability, usability, and use in real life, hand gestures were favorably. This despite the reported fatigue and strain caused by hand gestures. This all can be explained by hand gesture-based interaction being a NUI, where mouse-based interaction is not. This study confirms this long claimed statement convincingly. Participants' preference for the use of hand gestures over mouse-based interaction suggests that hand gesture input is the better choice for 3D object manipulation applications. More in general, gesture-based interaction and, more in general, NUI will become the interaction paradigm of the near future.

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Annotated Appendix

1 Introduction

In this annotated appendix, relevant information regarding the research will be explained in more detail. This Section starts with a description of the workload as well as give an overview of the deliverables. Section 2 explains technical details as well as describe visuals of the application. I learned a lot during the research, especially statistics. Therefore, Section 3 is dedicated to that particular aspect. The acquired data is described in Section 4. An overview of the results of all participants measured by the application (speed and accuracy) is shown in Section 5 and an overview of the results of all participants collected through the questionnaire (usability) is displayed in Section 6.

1.1 Workload

The workload of this research can be split into seven areas. The amount of hours spend on each of those areas can be found in table 1. E.L. van den Broek, F. Meijer and B.P.F. Lelieveldt were supervising the research and their spent time is not included in the table. The hours spent on meetings is displayed in *Discussion*. *Research* shows the time spent on preliminary research as well as on literature study. The *Application* describes the amount of time it took to develop the application used in the experiment. *Experiment* refers to the hours spent on finding participants and performing the experiment. The time it took to write the paper is displayed by *Document*. The spent time to research statistical aspects and performing them is contained in *Statistics*. *Presentation* describes the hours spent on preparing the master thesis defense.

About 60 percent of the time was spent at the *Leids University Medical Center* and 40 percent at the *Utrecht University*.

Part of research	*Time in hours*
Discussion	46
Research	288
Application	461
Experiment	207
Document	319
Statistics	108
Presentation	31
Total	1460

TABLE 1
The work in hours on this research divided into seven areas.

1.2 Deliverables

A lot of software, documents, and results have been produced during the experiment. All these files are included in the deliverables. The root folder has the following structure:

- **Application** The Unity3D project. A standard Unity3D directory including all the source code, assets and libraries.
- **Build** An executable of the application used to perform the experiment.
- **Documents**
  - **Log** Detailed information on what was worked on per date.
  - **Paper** The latex files of the paper and a PDF version of the paper.
  - **Presentation** The latex files of the presentation and a PDF version of the presentation for the master thesis defense.
- **Help Programs** A number of programs used to fix errors in the data files, reformat the data, or to modify the data for statistical analyses reasons.
- **Media**
  - **Images**Images related to the research.
  - **Videos** A demo video of the application.
- **Results**
  - **Overview** An excel sheet with all the results presented in a readable manner.
  - **Raw** The collected data for every participant.
  - **SPSS** The SPSS files, including the data, scripts and output.
- **Visuospatial Ability**
  - **Objects** The geon based objects.
  - **Test** The test used to measure the visuospatial ability of the participants.

2 Application

The paper explains the major part of the application. However, it does not cover all the technical details. In this Section, technical aspects of the project are explained. Screenshots of the application are shown and will display the explanation and the questionnaires presented to the participant during the experiment.

2.1 Technical aspects

2.1.1 The project

The application was created in *Unity3D* (v4.6.0). Therefore, the project directory looks like a typical Unity3D directory. To open the project you can either load it from within Unity3D or open one of the *.unity* files in the *Assets/Scenes* directory. The *PlainLeapScene*, *Explanation*, *GeneralQuestionsBefore*, *IntroPhase*, *TaskPhase*, *TaskQuestions*, *GeneralQuestionsAfter* and the *ThankYou* scenes are used in the application. The scenes in the *HelpScenes* directory are used for screenshots and exploring the capabilities of the Leap Motion.

As with any Unity3D project, the relevant parameters for every scene can be found in the scripts attached to the objects present in the scene. Through the inspector these parameters can be changed.

The written code can be found in the *scripts* directory. The name of the files as well as the comments in the code are explanatory enough to understand the code.

2.1.2 The application

A build of the application can be found in the *Build* folder. The purpose of the first scene was to test if the Leap Motion was connected correctly. If this was the case, the researcher pressed *[A]* on the keyboard to continue. The rest of the application was explained to the participant through text. Therefore, the researcher was only needed to explain the VSA test and the controls for the mouse and hand gestures.

If you wish to compile your own application, you need to manually copy *LeapCSharp.dll*, *LeapCSharp.NET3.5.dll*, *libLeap.dylib*, *libLeapCSharp.dylib*, *SystemWipeRecognizerDll.dll*, *SystemWipeRecognizerDll.exp*, *SystemWipeRecognizerDll.lib* and *Leap.dll* into the build directory for the Leap Motion to work.

2.2 Screenshots

Prior to the experiment, the participant was thanked for participating and was explained some rules that applied during the experiment. This is shown in Figure 1.

After the first screen, the participant performed the VSA test. Subsequently, he was told was expected of him during the experiment (see Figure 2)

The participant filled in a questionnaire regarding some personal information such as age and gender. This is displayed in Figure 3, 4, 5, and 6.

After each phase, the participant had to rate six usability statements as shown in Figure 7.

When the participant was done with every phase for both input methods, another questionnaire regarding preference and possible improvements was shown (see Figure 8 and 9).

An overview of the experiment flow is shown in Figure 11.

3 Statistics

During this research I have learned and applied a lot of statistical methods. I was quite new to statistics; I was only familiar with simple t-tests. Therefore, a considerable amount of time has been spent on understanding and performing the statistical analyses. For that reason, I would like to highlight what I learned in terms of statistics as it was a major part of the research.

During the research I learned how to perform (Multivariate Linear) Regression Analysis, One-Way ANOVAs, Repeated-Measure ANOVAs, and MANOVAs with SPSS. I had to research what the methods do, what they analyze and what their output mean. Because we wanted to remove outliers and due to the limitations of some of the analyses, I had to research how to handle missing values. I learned about single imputation, multiple imputation, and generalized linear models. Besides these complex analyses I also learned how to work with SPSS to perform these complex (and some simpler) analyses.

I consider the statistics (and the experiment design) as the most important thing I have learned during the research.

4 Data

During the experiment, a lot of data was measured by the application. When a participant finished the experiment, this data was written to a file (*[ID].txt*) in the *Data* directory. This file is easy to read. The data was also written to a file (*[ID]_alt.txt*). This file was created to make it easier to process the data. The files contain the following information.

- ID, date, time and duration
- Personal information such as gender (see subsection 6)
- Answers to the general questions (see subsection 6)
- The order of the phases
- For every phase:
  - The preferred input
  - For the mouse and hand gestures:
    - For each of the seven tasks:
      - The speed since the start of the task
      - The speed since the first manipulation
      - The translation, rotation and/or scaling error
    - The sum and averages over the seven tasks of the above

5 Quantitative Data Analysis

The speed and accuracy data was measured by the application and is shown in the figures 12 to 23. The application measures the speed and accuracy per task and calculates the sum and averages of these values. The speed per input device, per phase and per group is displayed in Figure 17. The same is displayed for accuracy in Figure 23.

The speed was measured from the start of the task as well as from the first time a manipulation was done. The time since the first manipulations are not shown in the figures because they are similar to the speed since the start of the task.

The accuracy was measured at the end of the task. The translation, rotation and/or scaling error was saved to indicate accuracy (depended on the phase).

6 Qualitative Data Analysis

A questionnaire was implemented within Unity3D. It was used to gather personal and subjective data. To which object manipulation experience group and VSA group each participant belongs to is shown in Figure 10. The subjective data is shown in figures 24 to 53.

The personal data consisted of the following information:

- Name
- Age
- Gender
- Email
- Profession
- Education
- Kind of education
- Handedness
- Eye handicap
- Physical handicap
- Experience with:
  - Computers
  - 3D object manipulation
  - Gaming
  - 3D gaming
- Frequency of:
  - Using computers
  - Doing 3D object manipulation
  - Gaming
  - 3D gaming

The subjective data consisted of the following:

- Per phase:
  - Input preference
  - Per input:
    * How fast it felt
    * How accurate it felt
    * How easy it was to use
    * How easy it was to learn
    * How much strain it caused
    * How likely it would be to use the input method in a real life situation

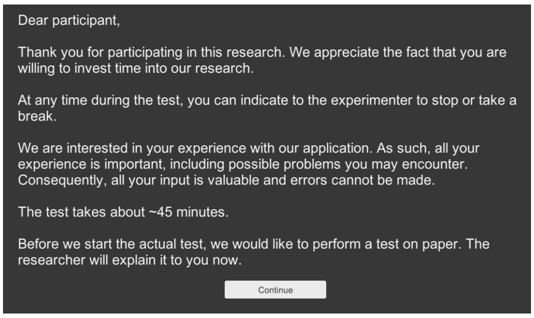

Fig. 1. General info given to the participant at the start of the experiment.

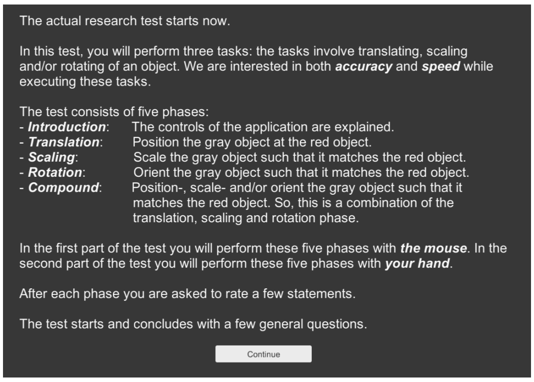

Fig. 2. The explanation of the experiment given after the VSA test.

Fig. 3. General questions asked before the start of the application (page 1).

Fig. 4. General questions asked before the start of the application (page 2).

Fig. 5. General questions asked before the start of the application (page 3).

Fig. 6. General questions asked before the start of the application (page 4).

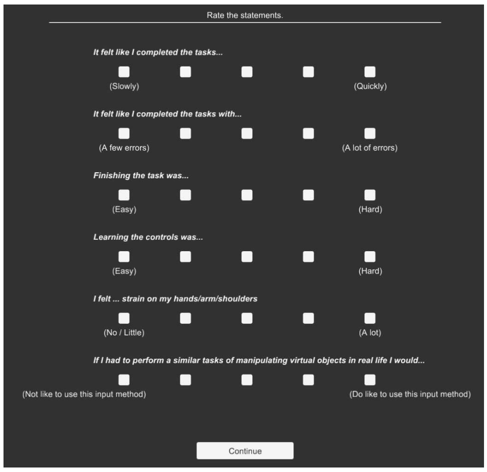

Fig. 7. The statements shown after each phase.

Fig. 8. The questions shown after the experiment (page 1).

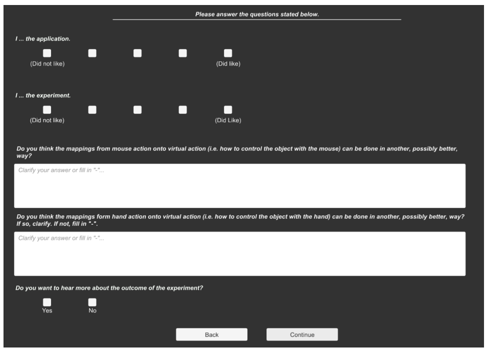

Fig. 9. The questions shown after the experiment (page 2).

ID	Object Manipulation Experience Group	Visuo-Spatial Ability Group
0	0	2
1	0	2
2	0	1
3	0	1
4	0	1
5	0	0
6	0	0
7	0	1
8	0	1
9	0	2
10	0	1
11	0	2
12	0	1
17	0	1
60	1	1
61	1	0
62	1	2
63	1	1
64	1	1
65	1	2
66	1	1
67	1	2
68	1	1
69	1	2
70	1	1
71	1	1
120	2	2
121	2	1
122	2	1
123	2	0
124	2	2
125	2	1
126	2	1
127	2	1
128	2	2
129	2	1
131	2	1
137	2	0
148	2	2
# Group 1	14	5
# Group 2	12	22
# Group 2	13	12

Fig. 10. The groups to which each participant belonged to.

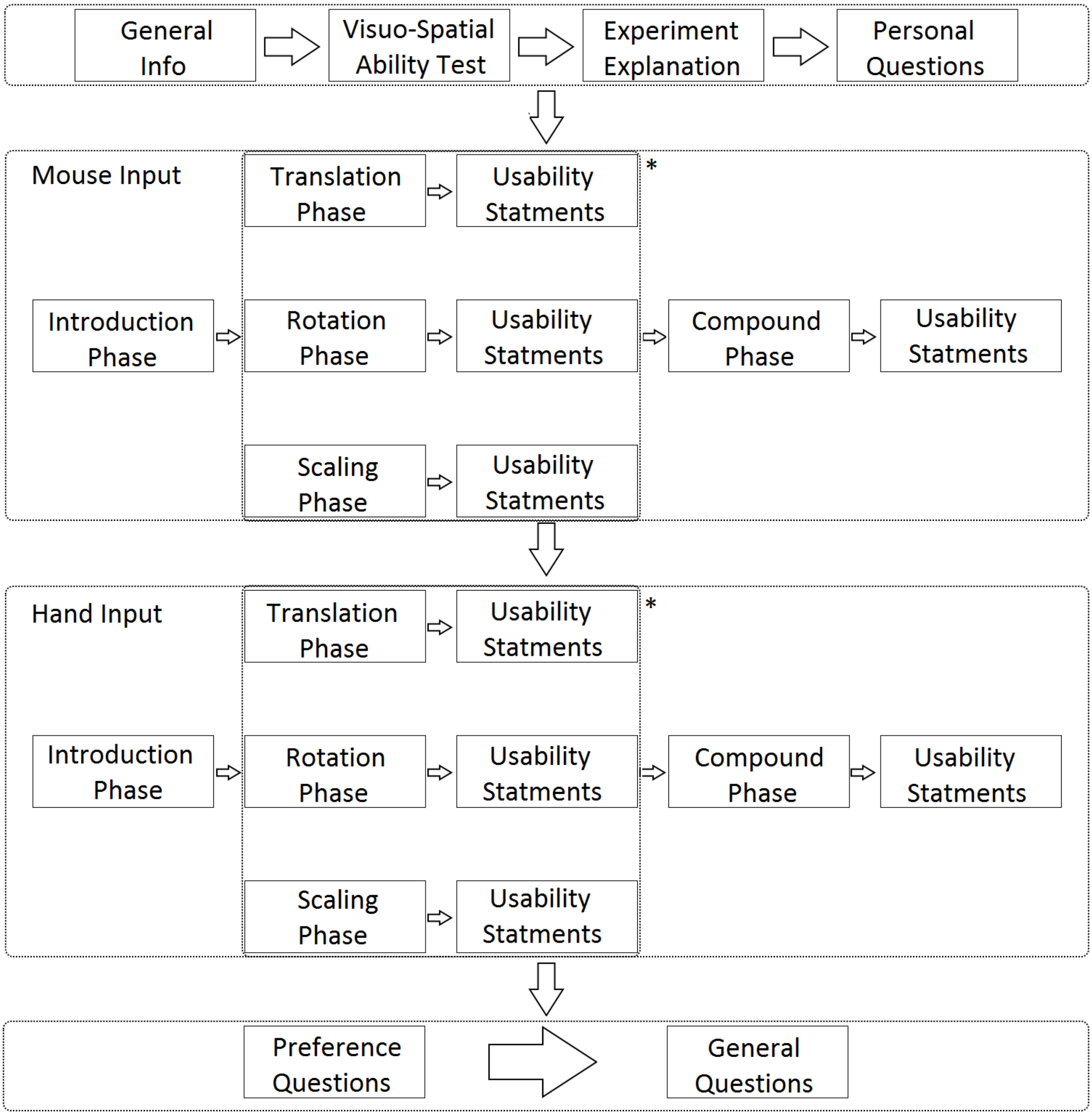

Fig. 11. An overview of the phases and the flow of the experiment.
*: The order is based on the participant ID.

	Translation		Rotation		Scaling		Compound	
ID	Mouse	Hand	Mouse	Hand	Mouse	Hand	Mouse	Hand
0	14.638	9.919	26.979	25.359	3.185	4.459	63.094	54.984
1	11.073	9.049	37.878	21.939	5.316	5.463	61.182	63.862
2	8.326	5.913	21.566	12.155	3.382	3.049	42.111	33.533
3	15.432	8.027	29.747	30.444	4.766	8.138	55.569	34.774
4	14.698	13.189	35.604	48.033	5.594	12.856	106.596	77.415
5	14.415	19.518	60.119	111.146	4.043	10.771	148.807	111.846
6	13.627	15.033	52.468	58.29	6.904	19.896	68.088	87.052
7	6.557	11.815	32.009	33.913	3.523	4.63	44.318	39.269
8	10.036	10.024	36.382	25.953	4.4	7.37	77.599	55.244
9	16.051	17.211	29.918	38.218	5.154	9.183	62.816	48.368
10	13.093	7.185	34.496	18.753	6.976	6.932	70.959	27.932
11	8.345	7.656	35.371	20.049	4.322	6.407	45.215	51.933
12	9.349	7.863	28.519	17.416	4.112	5.717	41.555	34.068
13	14.315	14.529	32.484	50.682	7.874	12.041	55.6	77.466
14	10.35	6.474	23.197	28.622	3.862	6.771	45.918	56.868
15	18.051	10.038	26.02	27.918	5.986	7.644	74.859	49.557
16	5.377	6.809	13.218	9.434	3.513	4.895	27.566	21.625
17	5.166	4.046	13.549	13.049	2.293	2.868	24.394	19.53
18	9.13	5.646	31.007	28.489	3.185	5.441	41.914	40.594
19	8.885	9.301	22.077	23.673	3.848	4.002	35.785	35.188
20	21.652	15.473	27.029	33.668	5.777	14.676	58.806	63.008
21	9.37	10.69	22.384	27.818	4.008	8.447	59.639	55.029
22	11.792	5.489	20.079	23.424	3.758	5.591	44.601	47.721
23	7.496	7.215	43.93	23.806	4.288	4.971	65.07	52.52
24	11.71	9.285	29.133	21.183	5.665	6.331	76.324	56.935
25	9.399	9.401	25.754	18.935	4.966	7.135	42.014	36.662
26	10.861	9.059	26.163	29.205	4.043	5.503	56.007	55.736
27	20.346	16.127	46.13	40.449	5.776	11.577	80.945	73.984
28	9.77	10.31	38.732	30.565	5.006	6.959	83.411	51.657
29	14.084	9.815	22.529	22.864	4.369	3.798	60.185	51.572
30	7.953	7.931	20.11	27.578	4.464	5.467	37.507	43.098
31	16.434	18.15	50.328	33.861	6.279	8.631	100.95	72.312
32	8.595	6.897	17.252	11.549	3.439	4.174	32.187	20.498
33	7.365	8.678	26.253	19.213	4.49	4.086	43.559	30.096
34	5.558	4.488	30.417	14.84	2.376	1.691	45.41	39.35
35	14.227	11.099	48.395	14.5	6.214	9.615	58.873	57.375
36	9.668	7.67	18.465	21.409	4.552	7.002	40.584	45.362
37	21.611	11.649	70.155	30.681	6.107	8.283	68.628	86.267
38	10.35	7.066	24.484	12.569	4.552	4.626	39.172	34.762
Average	11.67064103	9.890692308	31.54692308	28.24748718	4.676076923	7.105025641	58.66197436	51.15517949

Fig. 12. The average speed per phase and per input device for each participant.

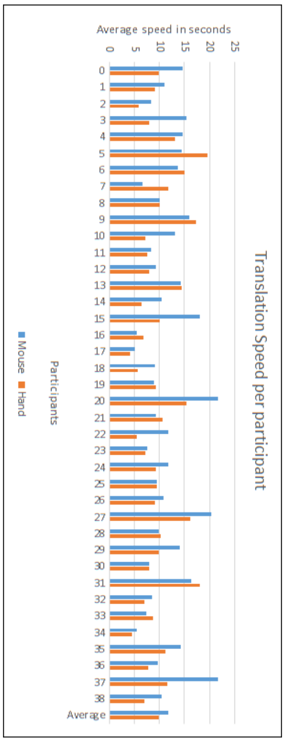

Fig. 13. The average speed per input device for each participant for the translation phase.

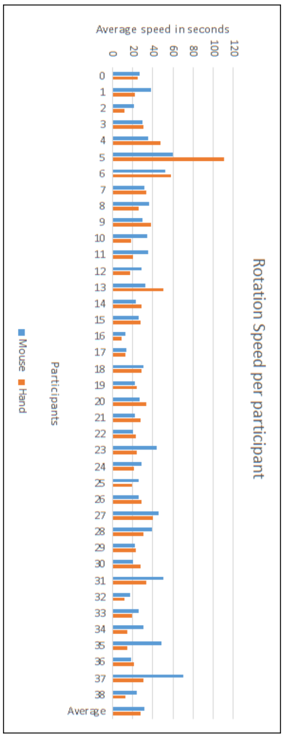

Fig. 14. The average speed per input device for each participant for the rotation phase.

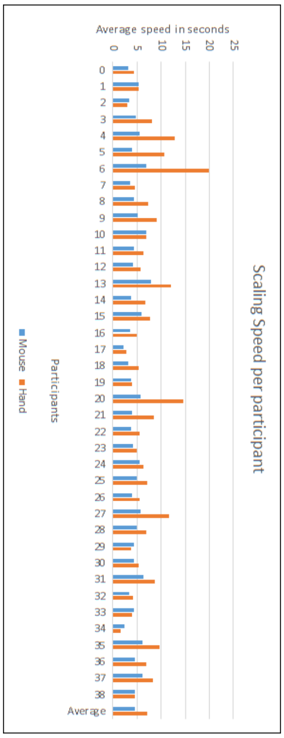

Fig. 15. The average speed per input device for each participant for the scaling phase.

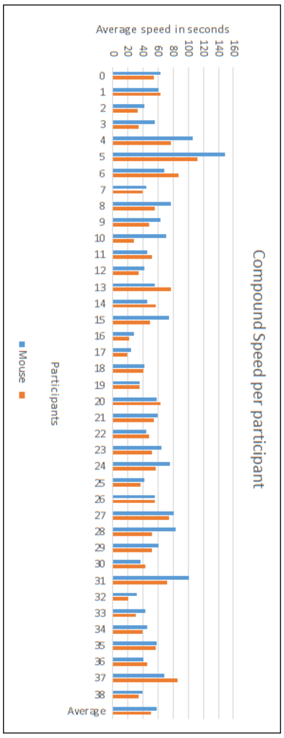

Fig. 16. The average speed per input device for each participant for the compound phase.

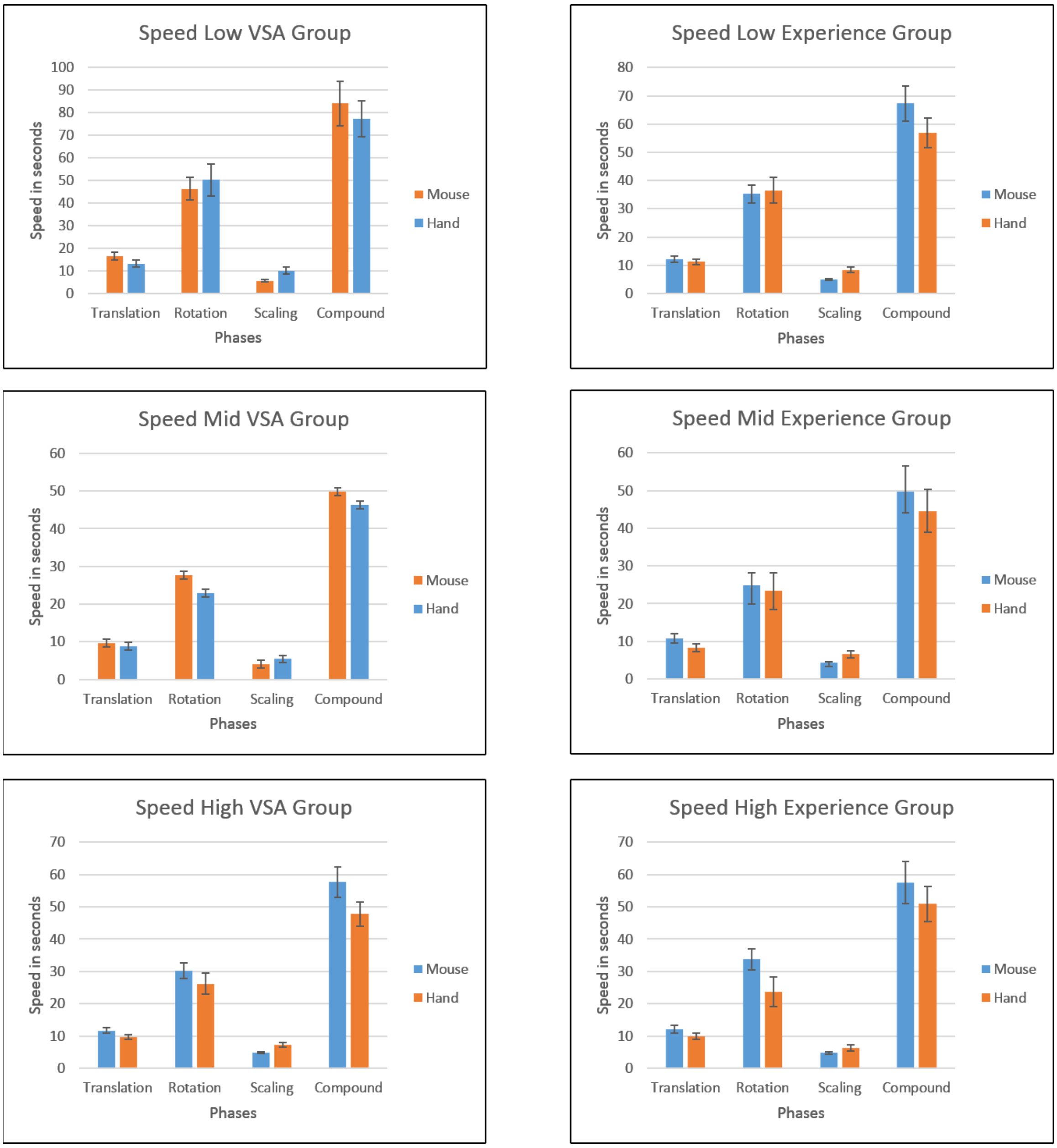

Fig. 17. The speed per input device, phase and group.

	Translation		Rotation		Scaling		Compound	
ID	Mouse	Hand	Mouse	Hand	Mouse	Hand	Mouse	Hand
0	0.202	0.465	5.315	13.771	0.011	0.021	0.151	0.052
1	0.201	0.414	18.267	8.118	0.016	0.019	0.116	0.087
2	0.252	0.817	17.297	9.035	0.016	0.026	0.201	0.094
3	2.814	3.193	9.399	8.383	0.009	0.006	0.225	0.276
4	0.094	0.199	2.774	43.999	0.007	0.044	0.121	0.235
5	0.213	1.038	16.007	8.085	0.028	0.027	0.157	0.668
6	0.211	0.506	41.317	51.091	0.016	0.022	0.166	0.159
7	0.438	1.723	22.68	81.103	0.043	0.073	0.313	0.381
8	0.117	0.66	11.177	6.736	0.012	0.027	0.189	0.220
9	0.19	0.468	9.735	4.716	0.019	0.01	0.355	0.317
10	0.203	0.759	18.189	28.114	0.022	0.062	0.487	0.441
11	4.3	3.713	20.071	10.203	0.022	0.026	0.501	0.914
12	0.237	0.305	5.727	3.662	0.01	0.011	0.128	0.098
13	1.044	0.479	25.136	9.36	0.019	0.014	0.582	0.467
14	0.813	0.369	12.663	32.838	0.01	0.06	0.208	0.265
15	0.111	0.259	13.433	7.814	0.008	0.018	0.372	0.329
16	0.248	0.412	9.08	8.549	0.032	0.023	0.292	0.316
17	0.395	1.298	18.755	33.378	0.097	0.15	0.288	0.295
18	0.14	0.486	44.949	6.578	0.018	0.03	0.137	0.108
19	0.346	1.11	22.652	20.383	0.023	0.045	0.386	0.432
20	1.756	1.917	17.42	2.991	0.014	0.02	0.244	0.233
21	0.151	0.508	6.195	9.836	0.017	0.026	0.065	0.141
22	0.51	0.485	27.883	9.069	0.016	0.027	0.173	0.201
23	0.269	0.312	21.86	10.938	0.015	0.027	0.100	0.145
24	0.13	0.3	16.023	7.67	0.011	0.019	0.101	0.088
25	0.085	0.246	9.318	10.313	0.021	0.021	0.143	0.162
26	0.065	0.49	5.282	6.299	0.015	0.035	0.134	0.204
27	0.154	0.489	10.249	5.025	0.011	0.032	0.145	0.170
28	0.113	0.381	10.96	34.957	0.009	0.032	0.284	0.820
29	0.335	0.325	24.798	13.966	0.021	0.2	0.332	0.272
30	0.382	1.178	26.22	11.43	0.023	0.045	0.135	0.200
31	0.139	0.17	16.701	5.792	0.012	0.01	0.113	0.099
32	0.631	0.997	40.095	52.067	0.049	0.045	0.217	0.273
33	0.341	1.154	12.237	12.936	0.026	0.03	0.309	0.363
34	0.883	0.798	34.789	16.357	0.045	0.073	0.280	0.133
35	0.163	0.125	7.907	75.208	0.015	0.019	0.240	0.088
36	0.142	0.365	12.577	17.044	0.016	0.048	0.183	0.557
37	0.363	0.627	15.185	63.801	0.01	0.059	0.540	0.261
38	0.095	0.615	5.827	5.505	0.015	0.06	0.075	0.093
Average	0.49425641	0.773205128	17.08074359	19.66974359	0.020487179	0.039538462	0.236	0.273

Fig. 18. The average accuracy per phase and per input device for each participant.

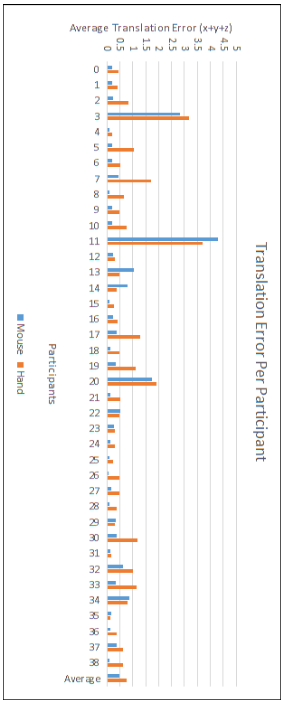

Fig. 19. The average accuracy per input device for each participant for the translation phase.

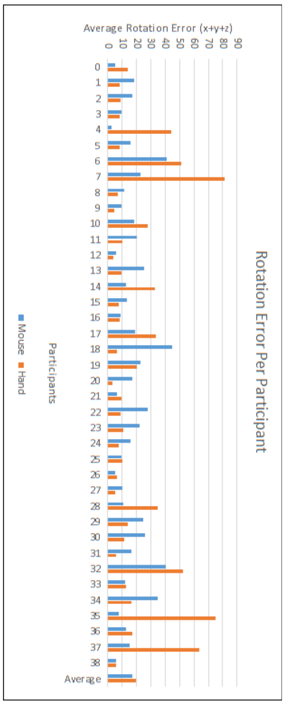

Fig. 20. The average accuracy per input device for each participant for the rotation phase.

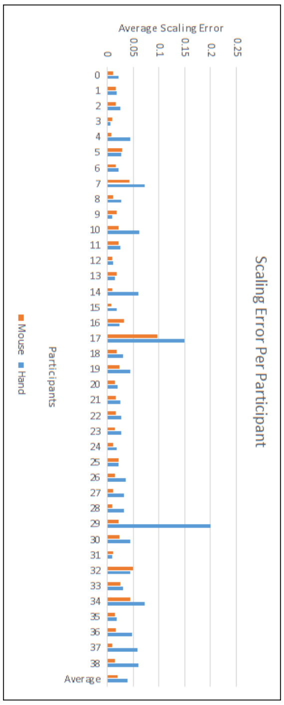

Fig. 21. The average accuracy per input device for each participant for the scaling phase.

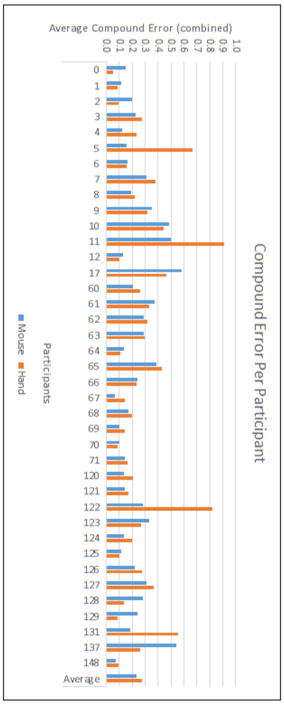

Fig. 22. The average accuracy per input device for each participant for the compound phase.

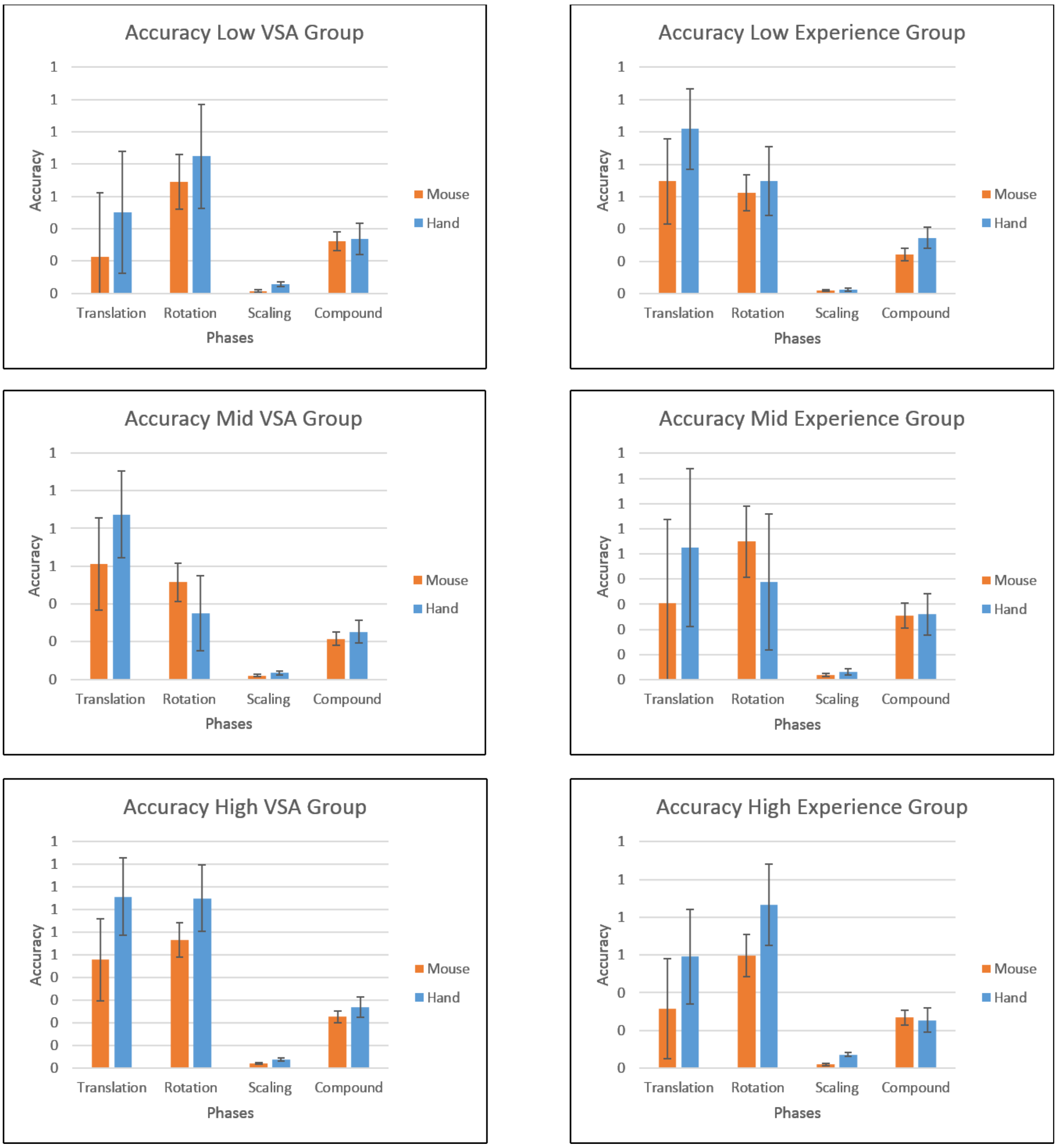

Fig. 23. The accuracy per input device, phase and group. The accuracy and standard deviation of the rotation phases is divided by 30 for readability purposes.

	Translation		Rotation		Scaling		Compound	
ID	Mouse	Hand	Mouse	Hand	Mouse	Hand	Mouse	Hand
0	2	4	1	4	3	5	1	4
1	3	4	1	3	4	5	1	3
2	4	4	4	4	4	5	3	4
3	4	5	3	2	5	5	1	2
4	2	3	1	1	2	2	1	1
5	4	3	2	1	4	2	1	3
6	4	5	2	2	5	5	3	3
7	4	3	2	1	5	4	1	1
8	5	4	3	3	5	5	2	2
9	3	4	2	2	5	5	1	3
10	3	5	2	5	4	5	1	2
11	3	4	2	4	4	4	1	3
12	3	4	1	5	4	5	1	2
13	4	5	3	4	5	5	4	4
14	2	4	1	2	5	4	1	1
15	4	4	3	4	4	4	2	3
16	5	5	4	5	5	5	3	4
17	4	4	4	3	5	5	2	3
18	2	4	2	4	4	4	2	3
19	3	3	1	1	4	4	2	2
20	4	4	2	3	5	5	1	3
21	4	5	3	4	4	4	2	4
22	4	4	2	3	4	4	2	3
23	4	5	3	4	5	4	3	4
24	2	4	2	3	4	4	1	3
25	4	4	2	2	5	4	2	3
26	4	3	3	1	5	5	1	1
27	3	3	2	4	5	5	1	4
28	5	4	3	3	5	4	1	2
29	4	4	2	3	5	5	1	2
30	5	3	3	2	5	4	2	1
31	5	5	2	5	5	5	1	3
32	3	5	1	3	5	5	1	3
33	4	5	2	4	5	5	2	3
34	5	5	1	3	5	5	2	3
35	4	4	3	4	5	4	1	4
36	4	5	3	4	4	4	1	3
37	4	4	2	2	4	4	2	3
38	4	5	3	5	5	5	2	3
Average	3.692307692	4.153846	2.256410256	3.128205	4.512820513	4.435897	1.615384615	2.769231

Fig. 24. The felt fast statement per phase and per input device for each participant.

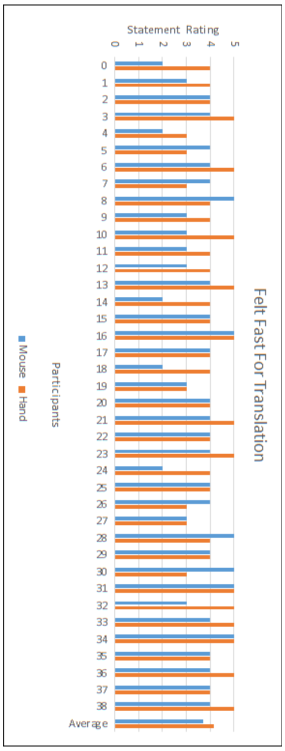

Fig. 25. The felt fast statement per input device for each participant for the translation phase.

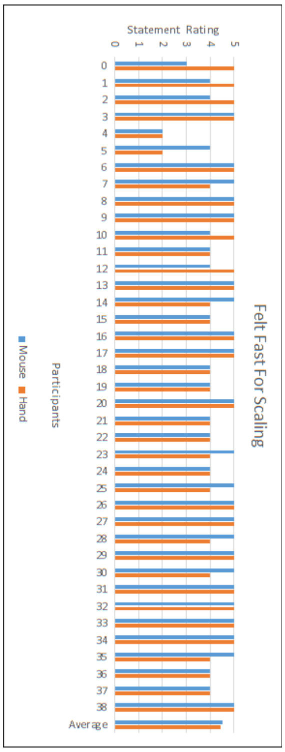

Fig. 27. The felt fast statement per input device for each participant for the scaling phase.

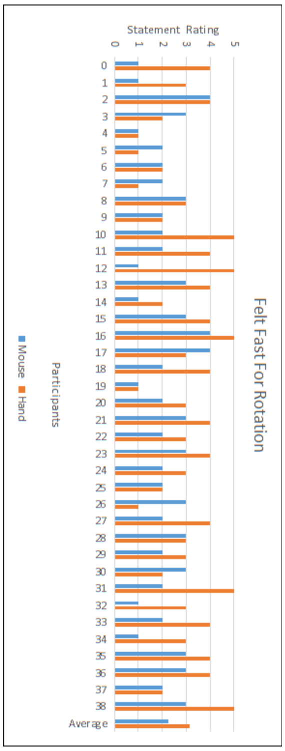

Fig. 26. The felt fast statement per input device for each participant for the rotation phase.

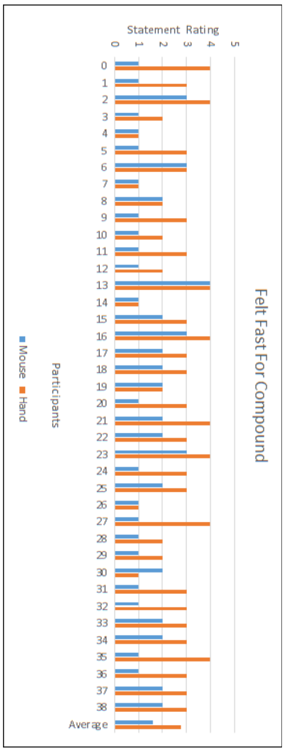

Fig. 28. The felt fast statement per input device for each participant for the compound phase.

	Translation		Rotation		Scaling		Compound	
ID	Mouse	Hand	Mouse	Hand	Mouse	Hand	Mouse	Hand
0	2	5	4	4	4	5	2	4
1	2	4	1	3	4	5	1	3
2	5	5	4	5	5	5	4	5
3	3	4	2	3	5	5	2	2
4	4	5	2	1	5	3	1	1
5	4	4	2	2	3	3	3	3
6	4	5	3	2	5	5	3	3
7	4	2	2	1	5	4	2	1
8	4	4	2	4	4	5	1	2
9	3	3	4	2	5	5	1	3
10	5	5	2	4	4	5	1	5
11	4	4	2	5	5	5	2	4
12	2	3	1	5	5	4	1	3
13	4	4	1	4	4	5	1	3
14	3	5	2	2	5	4	2	1
15	3	4	2	3	3	4	1	3
16	5	5	4	5	5	5	3	4
17	4	4	3	2	4	5	3	3
18	2	4	1	4	3	4	3	3
19	3	3	2	2	4	4	3	2
20	5	5	2	5	5	5	1	2
21	4	4	4	4	5	4	2	3
22	2	5	3	4	3	5	1	3
23	5	5	3	3	5	3	4	4
24	2	4	1	3	4	4	2	3
25	5	5	3	3	5	5	2	2
26	4	4	2	1	5	5	1	2
27	2	4	2	4	5	3	1	4
28	5	3	3	3	5	4	2	2
29	4	5	3	5	5	4	1	3
30	4	4	1	4	5	5	3	2
31	5	5	2	4	5	5	1	3
32	3	4	4	4	2	5	2	4
33	4	3	2	4	5	5	2	2
34	4	4	3	4	2	5	2	4
35	4	4	2	2	5	4	1	3
36	4	4	3	3	4	4	1	2
37	3	4	3	2	5	4	4	4
38	4	4	2	4	5	4	1	2
Average	3.666667	4.153846	2.410256	3.307692	4.410256	4.435897	1.897436	2.871795

Fig. 29. The felt accurate statement per phase and per input device for each participant.

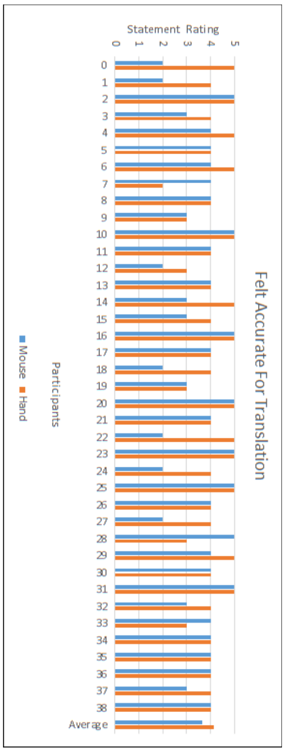

Fig. 30. The felt accurate statement per input device for each participant for the translation phase.

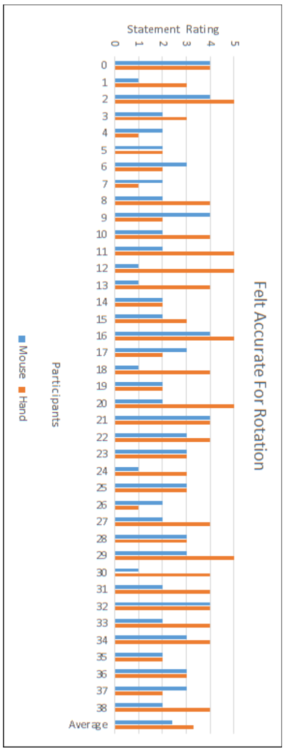

Fig. 31. The felt accurate statement per input device for each participant for the rotation phase.

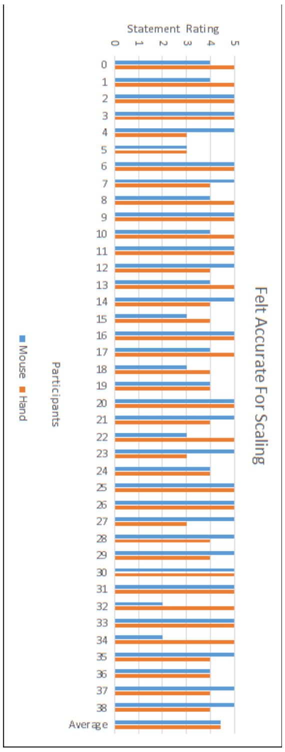

Fig. 32. The felt accurate statement per input device for each participant for the scaling phase.

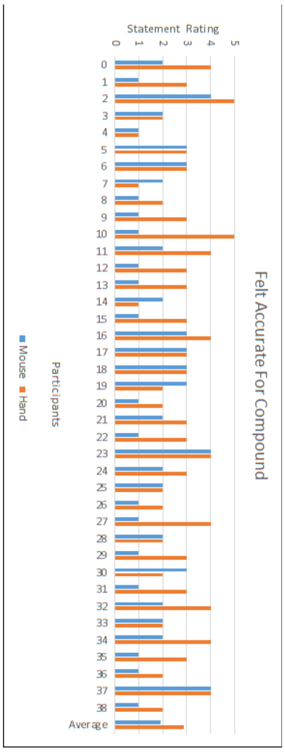

Fig. 33. The felt accurate statement per input device for each participant for the compound phase.

	Translation		Rotation		Scaling		Compound	
ID	Mouse	Hand	Mouse	Hand	Mouse	Hand	Mouse	Hand
0	3	5	2	5	4	5	1	4
1	2	4	1	3	4	5	1	2
2	4	5	4	5	5	5	3	5
3	3	5	3	2	5	5	1	2
4	4	5	3	2	5	4	2	2
5	4	4	2	1	5	2	2	2
6	5	4	2	2	5	4	3	2
7	5	2	2	1	5	5	3	2
8	4	4	3	3	4	5	2	2
9	3	3	2	2	5	5	2	3
10	5	5	3	5	4	5	2	5
11	4	5	2	5	4	5	3	4
12	3	3	2	4	5	5	1	4
13	3	5	2	2	5	5	1	4
14	5	4	2	2	5	5	1	2
15	2	4	2	3	4	4	1	2
16	5	5	4	5	5	5	2	4
17	4	5	2	2	5	5	2	3
18	3	5	1	4	5	5	3	4
19	4	3	1	1	5	5	2	1
20	4	3	2	3	5	3	1	1
21	5	4	4	4	5	5	3	3
22	4	5	1	3	5	5	2	2
23	5	5	2	4	5	5	3	3
24	3	5	2	3	4	4	1	4
25	4	4	2	3	5	4	1	2
26	2	3	1	1	5	5	1	1
27	3	5	1	5	5	5	1	4
28	5	4	2	4	5	4	1	2
29	4	4	4	4	5	5	1	3
30	5	5	1	1	5	5	3	4
31	5	5	1	4	5	5	1	3
32	4	4	3	3	2	5	2	4
33	5	4	2	3	5	5	1	3
34	5	4	2	3	5	5	2	4
35	4	4	2	4	5	4	2	4
36	4	4	3	4	5	4	1	3
37	4	4	2	1	5	4	2	1
38	4	5	2	5	5	5	2	2
Average	3.948718	4.25641	2.153846	3.102564	4.74359	4.641026	1.769231	2.871795

Fig. 34. The easy to use statement per phase and per input device for each participant.

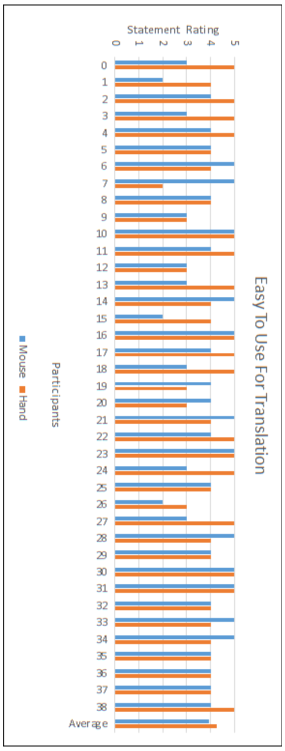

Fig. 35. The easy to use statement per input device for each participant for the translation phase.

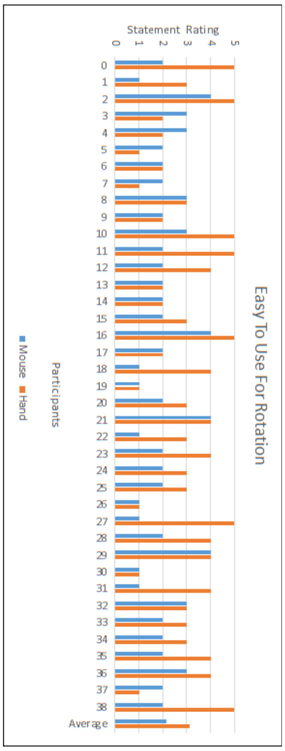

Fig. 36. The easy to use statement per input device for each participant for the rotation phase.

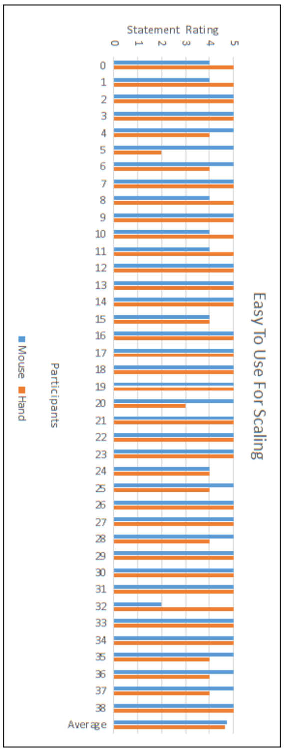

Fig. 37. The easy to use statement per input device for each participant for the scaling phase.

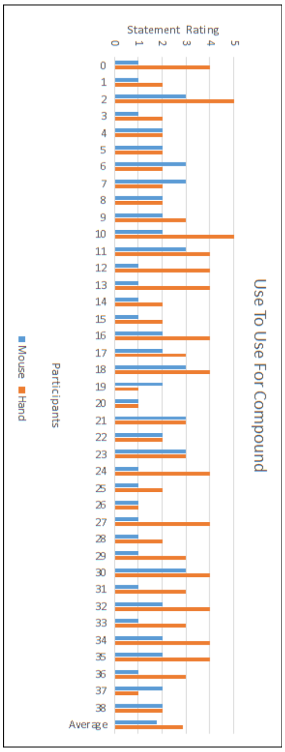

Fig. 38. The easy to use statement per input device for each participant for the compound phase.

	Translation		Rotation		Scaling		Compound	
ID	Mouse	Hand	Mouse	Hand	Mouse	Hand	Mouse	Hand
0	5	5	2	5	4	5	4	5
1	5	5	3	5	5	5	1	5
2	5	5	4	5	5	5	4	5
3	5	5	5	2	5	5	4	5
4	5	5	5	4	5	5	4	3
5	5	4	4	2	5	3	4	2
6	4	4	3	1	5	3	3	4
7	5	2	3	1	5	4	5	3
8	5	4	4	3	5	5	4	3
9	5	4	4	2	5	5	3	4
10	5	5	5	5	5	5	5	5
11	5	5	4	5	5	5	5	5
12	5	5	2	5	5	5	1	5
13	5	5	5	4	5	5	5	4
14	5	4	2	2	5	3	2	2
15	2	3	4	3	4	4	4	3
16	5	5	5	5	5	4	4	4
17	5	4	4	2	5	5	3	3
18	4	5	4	4	5	5	4	5
19	5	3	4	1	5	5	4	1
20	5	5	4	3	5	5	4	5
21	5	4	5	3	5	4	3	4
22	5	5	4	3	5	3	4	4
23	5	5	5	4	5	5	4	4
24	4	4	3	2	4	5	2	3
25	5	4	3	2	5	3	5	3
26	4	4	4	2	5	5	3	2
27	5	5	4	4	5	5	2	5
28	5	4	4	4	5	4	4	4
29	5	5	3	3	5	5	4	4
30	5	5	5	3	5	5	5	5
31	5	5	5	4	5	5	5	4
32	4	4	4	4	3	5	4	5
33	5	5	5	5	5	5	5	5
34	5	4	5	3	5	5	4	3
35	5	5	5	5	5	5	5	5
36	4	5	2	2	4	4	2	3
37	3	4	4	3	4	4	4	4
38	5	5	5	4	5	5	5	4
Average	4.717949	4.461538	3.974359	3.307692	4.820513	4.564103	3.769231	3.897436

Fig. 39. The easy to learn statement per phase and per input device for each participant.

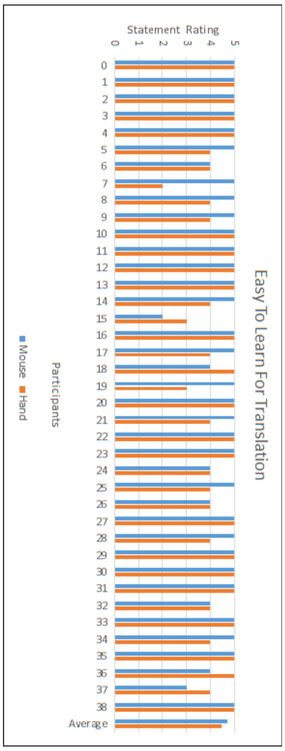

Fig. 40. The easy to learn statement per input device for each participant for the translation phase.

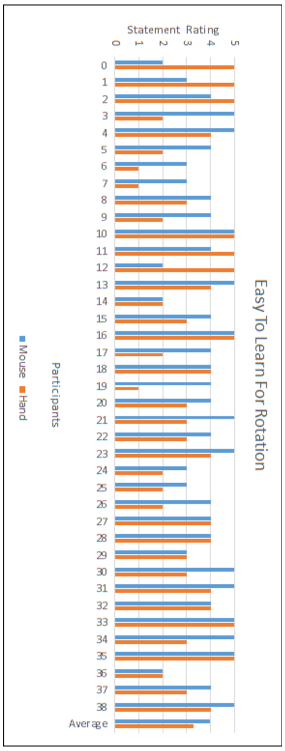

Fig. 41. The easy to learn statement per input device for each participant for the rotation phase.

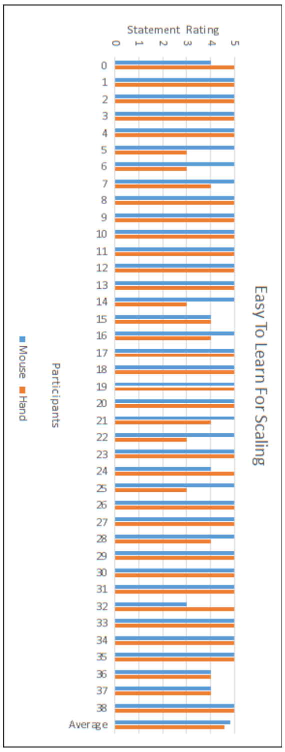

Fig. 42. The easy to learn statement per input device for each participant for the scaling phase.

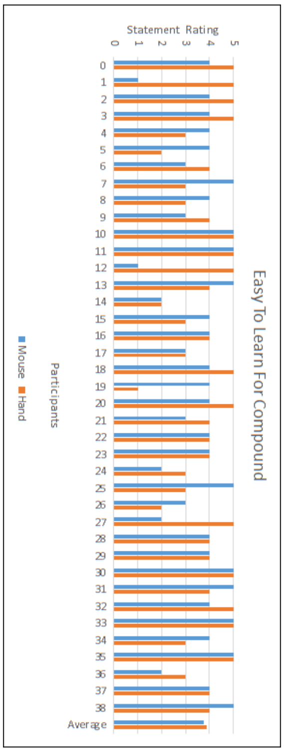

Fig. 43. The easy to learn statement per input device for each participant for the compound phase.

	Translation		Rotation		Scaling		Compound	
ID	Mouse	Hand	Mouse	Hand	Mouse	Hand	Mouse	Hand
0	5	4	5	3	5	4	4	3
1	5	3	5	4	5	4	5	3
2	2	3	3	4	2	4	3	4
3	4	1	5	2	5	2	3	1
4	5	3	4	1	5	3	5	1
5	5	4	5	3	5	4	5	3
6	4	4	2	4	3	4	2	4
7	4	2	3	1	4	2	3	1
8	5	3	5	3	5	3	4	2
9	5	1	5	2	5	4	2	3
10	5	4	5	3	5	5	5	2
11	5	5	5	5	5	5	5	4
12	5	5	5	4	5	5	5	4
13	2	2	2	2	2	2	1	2
14	5	5	5	2	5	5	5	1
15	4	3	3	2	4	3	3	2
16	5	4	5	4	5	4	5	4
17	5	4	5	3	5	4	5	3
18	5	2	5	1	5	2	5	2
19	5	4	5	2	5	4	5	2
20	2	2	2	2	4	2	2	1
21	4	3	3	4	4	4	3	4
22	5	5	5	3	5	5	5	4
23	4	3	4	3	5	4	4	2
24	4	3	4	3	4	3	3	3
25	5	4	4	3	5	4	4	2
26	5	3	5	2	5	4	5	3
27	5	4	4	2	5	4	5	2
28	5	5	5	4	5	5	5	4
29	5	5	4	5	5	5	5	4
30	5	5	5	4	5	3	5	4
31	5	1	2	2	5	3	3	1
32	5	3	5	4	5	4	5	4
33	5	5	5	4	5	5	5	4
34	5	3	5	2	5	4	5	1
35	5	4	4	4	5	4	4	4
36	4	4	3	3	5	3	4	2
37	3	3	2	2	3	4	4	2
38	5	4	5	4	5	4	5	3
Average	4.512821	3.461538	4.179487	2.948718	4.615385	3.769231	4.128205	2.692308

Fig. 44. The strain statement per phase and per input device for each participant.

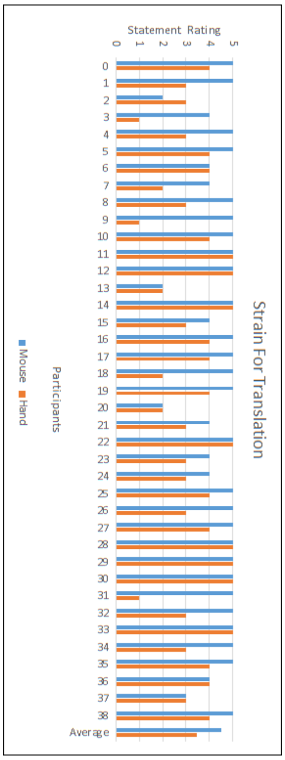

Fig. 45. The strain statement per input device for each participant for the translation phase.

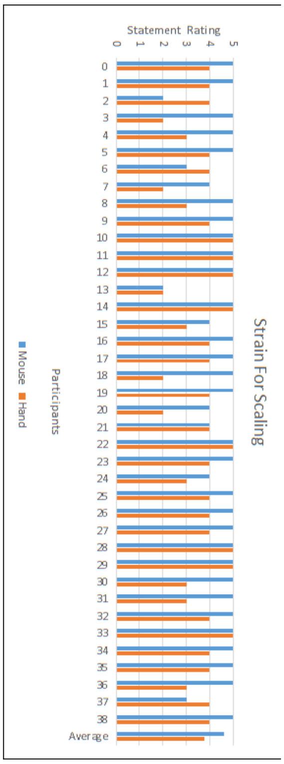

Fig. 47. The strain statement per input device for each participant for the scaling phase.

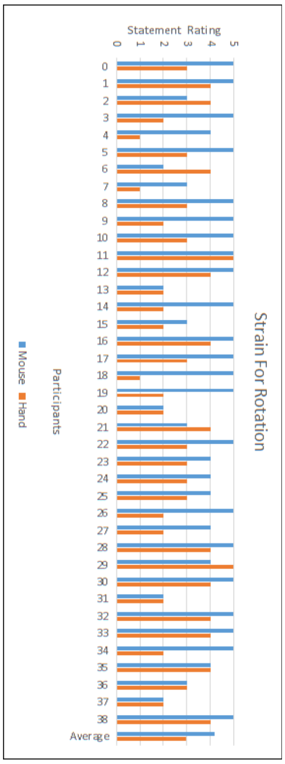

Fig. 46. The strain statement per input device for each participant for the rotation phase.

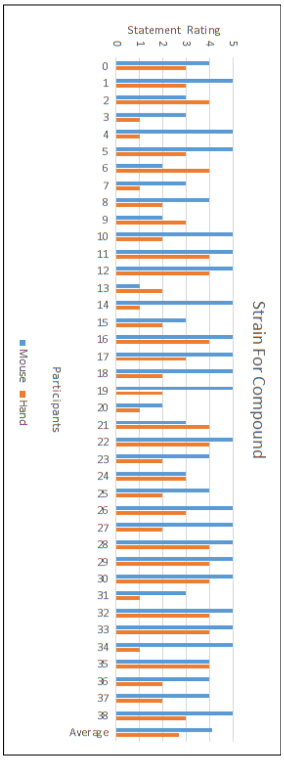

Fig. 48. The strain statement per input device for each participant for the compound phase.

	Translation		Rotation		Scaling		Compound	
ID	Mouse	Hand	Mouse	Hand	Mouse	Hand	Mouse	Hand
0	4	5	3	5	4	4	2	4
1	4	5	2	5	5	5	2	5
2	2	5	2	5	2	5	2	5
3	4	5	3	3	5	5	2	3
4	4	2	2	2	5	1	3	1
5	4	4	3	1	4	3	3	4
6	4	4	2	1	4	4	2	3
7	4	2	2	1	5	3	2	1
8	5	3	4	5	5	5	4	4
9	3	1	1	3	5	4	1	4
10	5	4	3	4	4	4	3	3
11	2	5	1	5	2	5	3	5
12	1	4	1	5	4	5	1	5
13	1	4	1	4	1	4	1	4
14	4	4	2	2	5	3	3	1
15	4	3	3	3	4	3	3	3
16	5	4	3	5	5	4	4	4
17	3	3	3	1	5	4	1	4
18	2	5	1	5	2	4	2	5
19	3	3	3	1	4	3	3	2
20	2	5	1	4	4	4	1	5
21	4	4	2	4	3	3	2	4
22	4	5	3	4	5	3	2	4
23	4	4	4	3	5	4	4	3
24	1	4	1	4	3	3	1	4
25	5	3	3	4	4	3	2	4
26	3	1	2	3	5	5	2	3
27	3	4	1	3	4	4	1	3
28	4	5	4	5	4	5	1	4
29	3	4	2	5	4	5	4	3
30	5	3	5	1	5	3	5	1
31	5	5	1	5	5	3	1	3
32	4	4	3	3	4	5	2	4
33	4	5	2	4	5	5	3	4
34	5	3	1	3	5	4	2	2
35	4	5	2	5	4	3	2	5
36	4	5	3	4	4	3	2	3
37	5	4	4	1	4	1	5	1
38	4	4	3	4	5	5	2	3
Average	3.615385	3.897436	2.358974	3.461538	4.153846	3.820513	2.333333	3.410256

Fig. 49. The real life use statement per phase and per input device for each participant.

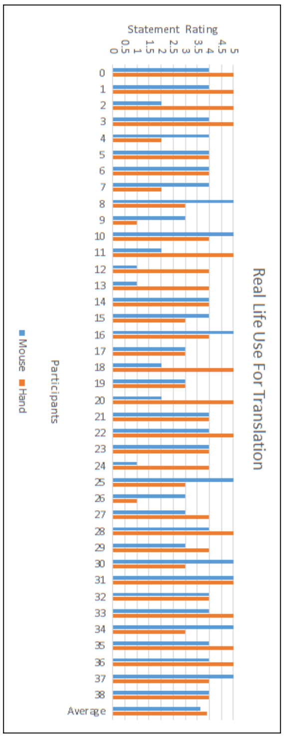

Fig. 50. The real life use statement per input device for each participant for the translation phase.

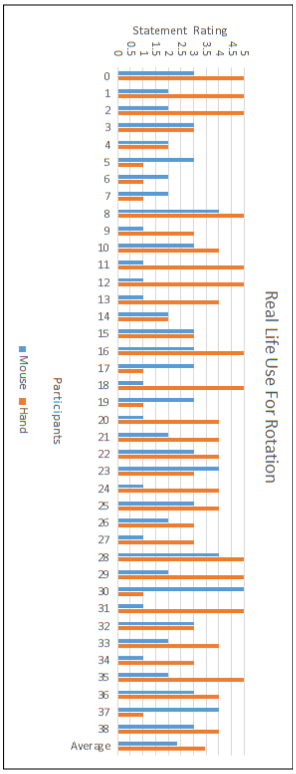

Fig. 51. The real life use statement per input device for each participant for the rotation phase.

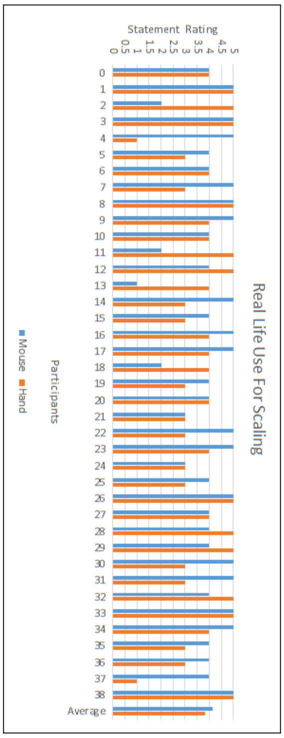

Fig. 52. The real life use statement per input device for each participant for the scaling phase.

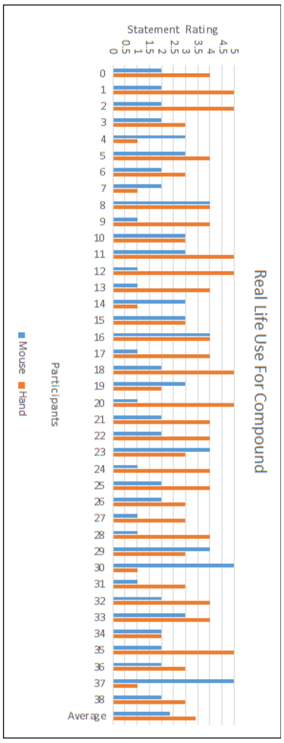

Fig. 53. The real life use statement per input device for each participant for the compound phase.