# Usability and performance of Leap Motion and Oculus Rift for upper arm virtual reality stroke rehabilitation

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## ABSTRACT

Intensified rehabilitation is important for stroke survivors but difficult to achieve due to limited access to physiotherapy. We present a virtual reality rehabilitation system, Target Acquiring Exercise (TAGER), designed to supplement center-based physiotherapy by providing engaging and personalized exercises. TAGER uses natural user interface devices, the Microsoft Kinect, Leap Motion and Myo armband, to track upper arm and body motion. Linear regression was applied to 3D user motion data using four popular forms of Fitts's law and each approach evaluated. While all four forms of Fitt's Law produced similar results and could model users effectively, it may be argued that a 3D tailored form provided the best fit. However, we propose that Fitts's Law may be more suitable as the basis of a more complex model to profile user performance. Evaluated by healthy users TAGER proved effective, with important lessons learned which will inform future design.

## 1. INTRODUCTION

Upper limb rehabilitation following a brain injury, stroke, or other condition affecting upper limb movement, is carried out by occupational therapists and physiotherapists to recover and adapt the patient's movement and improve Activities of Daily Living (ADL). Research confirms that rehabilitation is capable of improving arm function during both the early and late phases of stroke. However, effective therapy must be intense and requires the repetitive practice of task related movements and actions (Kwakkel et al. 1999). Repetitive task training involves intensive repeated practice of relevant functional tasks and is thought to reduce muscle weakness and form a physiological basis of motor learning (Bütefisch et al. 1995).

Virtual reality (VR) has significant potential to support self-management of such rehabilitation, in that it allows individuals to interact and train within interesting, realistic virtual environments. It provides users with the opportunity to practice intensive repetition of meaningful task-related activities necessary for effective rehabilitation (Crosbie et al. 2007). A recent Cochrane review of 12 trials involving 397 participants for the upper limb, stated that the use of VR and interactive video gaming may be beneficial in improving upper limb function and ADLs; when used as an adjunct to usual care or when compared with the same dose of conventional therapy (Laver et al. 2015). This Cochrane review concluded that it is unclear at present which characteristics of VR are most important. However, they emphasized the need for pilot studies assessing usability and validity as part of the development process if designing new VR programs for rehabilitation purposes; these studies may also afford insight on the key VR characteristics for retraining of movement e.g. in reach and pointing tasks.

In this paper we present a multi-sensory VR system, Target Acquiring Exercise (TAGER), and evaluate its usability and performance for upper limb rehabilitation. We evaluate Fitts's law as the basis of an adaptive system to model movement performance for reach and touch tasks in a 3D virtual space. TAGER evolved from previous VR and augmented reality (AR) testbeds developed by our research group (Burke et al. 2009) and particularly from initial research undertaken with the Leap Motion controller (Charles et al. 2014). TAGER utilizes several natural user interface (NUI) devices to track the user, namely the Leap Motion, Microsoft Kinect V2, and the Myo armband, and affords the option of wearing of a VR headset (in this experiment the Oculus Rift DK1). In the experiment outlined in this paper, the tasks comprise basic 3D reaching and pointing exercises so we can effectively evaluate the system and user model. The experiment reported here focused on testing with healthy users to help us evaluate the user interface ahead of planned experiments with impaired users, and has


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helped us refine the user profiling system. We took a participatory approach to system and experimental design, engaging with physiotherapists and occupational therapists in local health trusts, namely the Regional Acquired Brain Injury Unit (Musgrave Hospital, Belfast), Stroke Unit at the Royal Victoria Hospital (Belfast), and Brain Injury Matters (Belfast).

## 2. RELATED WORK

A core interest in VR as a rehabilitation tool is due to its potential to provide an enjoyable experience. However, VR systems are flexible technologies supporting feedback, capability adaption, high intensity, repetitive, functional exercises to encourage motor control and motor learning. There are an increasing number of studies that are particularly focused on using commercially available hardware devices to support upper limb rehabilitation (Laver et al. 2015). However, new cheaper, high quality commercial hardware, such as Leap Motion and the Myo, offer new opportunities for effective center and home based self-managed rehabilitation. When combined with other existing technology, they have the potential to improve accuracy and reliability of performance monitoring, although research is limited on these technologies. Feedback is particularly important to patients and VR systems have the potential to excel in providing rich, informative, personalized, just-in-time responsive feedback. Feedback cues in VR environment, when appropriately designed, can help users improve interaction performance. Rehabilitation systems have implemented multi–modal cues such as visual, tactile and auditory cues. The organization of movement is related to the quality of the viewing environment, particularly visual cues between the user's arm and the objects to improve spatial awareness (Levin et al. 2015). Tactile cues have also been reported to improve motor performance (Cameiroa et al. 2008), they are mainly used to help users identify success of interaction. Positive auditory cues provide user motivation to perform intensified repetitive tasks, represent temporal and spatial information very well and improving motor learning (Avanzini et al. 2009).

Adaptation is an important usability factor within a VR rehabilitation user interface design, to enable a system to adapt to a diversity of motor control capabilities and as rehabilitation progresses (Burke et al. 2009). This is important as a user may become frustrated if the tasks are too difficult or bored if tasks are too easy; thus maintaining engagement which is vital in rehabilitation. Techniques proposed in the literature for adaptive VR rehabilitation systems include fuzzy logic and Fitts's Law (Karime et al. 2014). Fitts's Law is well known in the user interface community and has also been applied with the stroke rehabilitation (Zimmerli et al. 2012) context. Fitts's Law models a user's motor skills by predicting the time to reach and touch a target based on a target's size ($W$) and the distance ($D$) from an origin (Equation 1). The logarithmic element of the equation, known as the "Index of Difficulty" ($ID$), is used to quantify the difficulty for reaching a particular target. Thus, the movement time ($MT$) required to acquire a target is linearly dependent on $ID$, where smaller and further away objects are more difficult to attain.

$$MT = a + blog_2\left(2\frac{D}{W}\right) \tag{1}$$

Equation 1 shows Fitts's original equation but other researchers have devised variations of the equation to provide an improved model in different situations. Two popular adaptations of Fitts's Law are Shannon/McKenzie (equation 2) and Welford (equation 3), which were originally tailored to quantifying human movement behavior for 1D and 2D tasks. They have also been applied to 3D environments, but recently new forms of the equation have been devised to more accurately represent 3D interactive movements. Equation 4 (Murata & Iwase 2001) adapts Shannon/McKenzie (2) to include the addition of a movement direction parameter, to account for the consideration that MT is also dependent on the user's angle of motion ($\theta$) from an origin to a target.

$$MT = a + blog_2\left(\frac{D}{W} + 1\right) \tag{2}$$

$$MT = a + blog_2\left(\frac{D}{W} + 0.5\right) \tag{3}$$

$$MT = a + blog_2\left(\frac{D}{W} + 1\right) + \sin\theta \tag{4}$$

## 3. EXPERIMENTAL DESIGN

The research described within this paper has an exploratory emphasis and focuses on investigating VR NUI design – particularly the reliability of tracking systems and the modelling of user motion via Fitts's Law and its variants, the aesthetic design of multi-modal cues, and the usability and acceptability of the VR headset. The purpose in conducting this research – and the subsequent follow up with impaired users – is to ensure that the underlying interactive interface and adaptive motion tracking system is as robust as possible before adding further user interface elements, game components, and connected health systems. Ultimately our intention is that the system will be robust enough for unsupervised usage by stroke patients.

### *3.1 Participant Recruitment*

Healthy participants were enrolled in the experiment from students and staff at Ulster University. Inclusion criteria included that participants should be 18 years old and over, have no vision issues (e.g. blurred vision, color distortion, light sensitivity, depth perception), nor any disability that affected the upper extremity. Participants completed a questionnaire to gather information regarding IT and gaming literacy and to determine inclusion in the experiment.

### *3.2 Target Acquiring Exercise (TAGER)*

TAGER is a custom designed 3D pointing exercise for upper limb rehabilitation, designed based on requirements from research (Hochstenbach-Waelen & Seelen 2012) and clinician involvement. TAGER utilizes a number of technologies that work together to monitor and provide feedback to users while completing upper arm rehabilitation tasks. The Leap Motion controller is a small desktop NUI which contains an infrared camera specifically design to track fingers, hands and arms. It tracks up to 20 bones per hand, at up to 200 frames per second with 150° field of view and approximately eight cubic feet of 3D interactive space. TAGER uses the Leap Motion as the main interactive device within the virtual world for tracking motion and facilitating target acquisition. Microsoft's Kinect V2 is similar to the Leap Motion, though instead of sensing hands it senses motion of the human skeleton. We collect data of all joints in the upper body in motion with the goal in a future version providing guidance on suitable functional task movements and other factors. It is natural for a person with an affected limb to move their whole body forward rather than extending their arm, especially if tired. As this would hinder improvement through the rehabilitation process, system feedback and guidance can be crucial. The Oculus Rift DK1 (VR Headset) contains a 7″ screen with resolution of 1280×800 (16:10 aspect ratio) and a 90° field of view, and enables head positional and rotational tracking allowing the user to control the view point within the virtual worlds. The Oculus is investigated in this experiment to determine if it is acceptable for use and could potentially be used to increase spatial awareness. The Myo armband slides on to the forearm, and uses electromyography (EMG) technology with eight medical grade EMG nodes attached, that read electrical signals from the muscles. The Myo armband also includes an accelerometer and gyroscope to track movement and orientation on the forearm. The use of the Myo armband here is to collect data to be stored for future studies helping identify changes in muscles, which could highlight factors such as fatigue and correctness of exercise. The Myo armband also includes tactile mechanisms for example, vibrations on the skin, which are used to introduce tactile cues into the system.

### *3.3 Experimental Setup*

The experimental process comprised three stages: (1) a training stage which gives the participant ten minutes to familiarize themselves with the technology and practice interaction. The training tasks are very similar to the real trials. Through system testing and observing with users before the actual experiment it was decided that ten minutes training would be sufficient enough for the participant to familiarize themselves but not cause fatigue. After training, the patients are given a short two minutes' rest period before the next stage (2), which is the complete TAGER trial. In stage 3, after each user completes the trial, a short discussion takes place gathering any comments the participant might have and for the investigator to ask questions related to the user's experience of the system. Throughout the experiment the participant is closely monitored by the investigator and provides assistance if any problems arise. The experiment is strictly controlled; the location of each trial was always the same as well as the equipment used. The equipment is arranged exactly the same for each patient ensuring no other possible variables could affect the collected results. The experiment was conducted on a commercial 64 bit Windows 8.1 laptop with Intel Core i5 @ 2.5 GHz, 8GB RAM, and 500GB hard drive attached to a 22″ monitor at (1920x1080) resolution. Figure 3 illustrates the layout of the environment.

TAGER's 3D virtual environment is the inside of a basic walled room (no wall at the front) with a large start button on the floor of the room, the user is prompted to push the button with their virtual hand to begin. The icosahedron shape is purposely chosen as the target object for its geometric properties, particularly as visual cues are required to enhance spatial awareness. With changes in viewing angles, objects with a greater number of faces and edges such as icosahedrons, give greater clarity of visual cues (Powell & Powell 2014). Each repetition (4 per level) contains 27 icosahedrons to target, all at different locations, a total of 108 per level (4*27). When the start button is pushed a single icosahedron appears randomly at any of the 27 locations. The user moves their virtual hand around the 3D environment touching each icosahedron that appears. When touched the icosahedron disappears and another icosahedron appears on the floor of the room at the location of the start button. We call this object the origin; this approach is used to provide consistent movement trajectories. All objects are intentionally placed at fixed locations and at fixed distances from the user's view to simplify analysis.

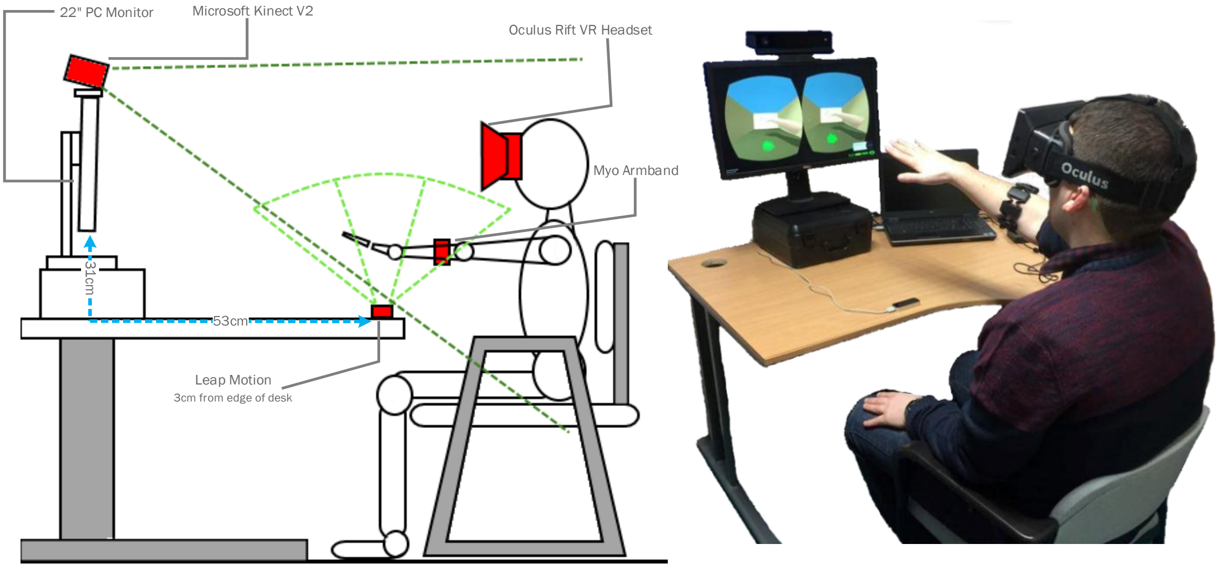


**Figure 1.** *Experimental setup.*

The TAGER VR software for this research was constructed with ten levels; the first and last levels are identical enabling us to compare performance over the period of the session – considering learning and/or fatigue effects. All other levels are unique in terms of scene attributes such as target object scale, multi-modal cues and VR headset use; to investigate the impact they have on movement behavior (Figure 2). Levels 2-9 are randomized per user to eliminate potential bias in the ordering, a rest period is given between each level and repetition. The unique levels comprise different combinations of scene attributes such as shadowing and proximity color change for visual cueing. Tactile cues are included using the Myo Armband where a vibration is sent to the user's arm upon successful target acquisition. We also change the scale of the objects; objects are sized accordingly as 2, 3.5 and 5cm. Objects are scaled to discover the impact it has on cues. For example, larger objects are expected to give greater clarity to visual cues and thus quicker arm kinematics. These scene attributes help build knowledge on the impact they have on arm kinematics, spatial awareness, movement speed and accuracy.

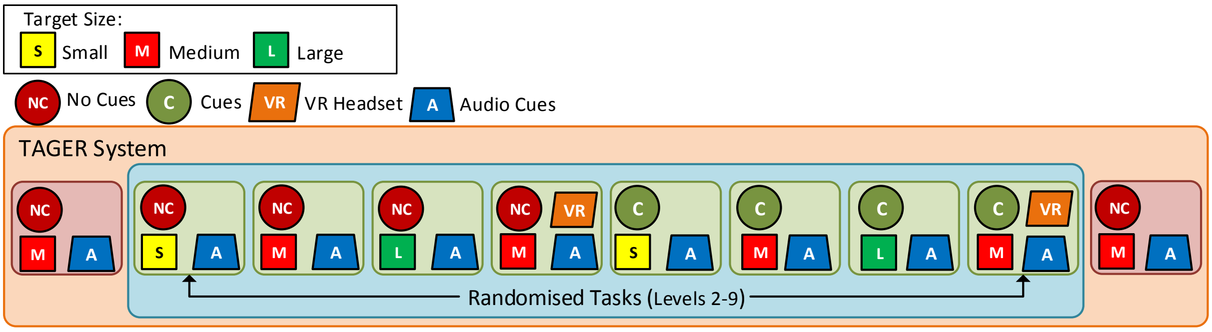


**Figure 2.** *TAGER's level layout and scene attributes.*

## 4. RESULTS

The above experiment was undertaken to investigate core aspects of TAGER. After the experiment, participants were invited to comment on usability and perceived effect on performance of the use of the VR headset, the Leap Motion, and user interface. Data was recorded every tenth of a second from all input devices and *MT* calculated and recorded to file automatically from tasks for analysis of the movement models. Of the 26 participants, three were excluded from data analysis due to missing data or system issues (loss of tracking).

### *4.1 Usability*

Of all 26 participants, 77% reported that their experience using the VR headset was enjoyable, no motion sickness or other health related effects were reported. 43% of people commented that they perceived their performance to have improved while wearing the headset, while 50% said that they needed time to adjust when first wearing the headset. We compare user performance between the VR headset and monitor use, with and without cues. We used a paired t-test to determine significant differences between users average *MT*, we found no significant difference in: Cues ($T$=1.681; $DOF$=21; $p$=0.053) or No Cues ($T$=1.591; $DOF$=21; $p$=0.063), though there was a consistently slower user response when using the headset (Table 2). In other words, the participant's subjective experience was at odds with the objective measurement. Though this is not a significant issue so long as the effect is consistent among users, and it is a consideration for future interaction design. Discussion with health professionals reinforced the importance of aesthetic cues in rehabilitation VR system design. We provide feedback on target proximity and acquisition through lighting and shading, as well as vibration from the Myo armband. Figure 3 shows variation of interaction difficulty with cues (C) and without cues (NC) for different sized objects (large – LRG, medium – MED and small – SML). While results are generally as expected – i.e. cues support improved efficiency in target acquisition. It is not clear that cues improve performance for MED cue acquisition and more investigation is required. More detail will be covered on the effect of cues in the next sub-section.

**Table 2.** *Mean movement time comparing VR headset and PC monitor: cues(C), No cues (NC).*

| **Exercise** | **VR (NC)** | **Monitor (NC)** | **VR (C)** | **Monitor (C)** |
|---|---|---|---|---|
| Mean MT (ms) | 1174.2 | 1107.4 | 1165.0 | 1115.4 |
| T-test P=(0.05) | 0.063 | | 0.053 | |

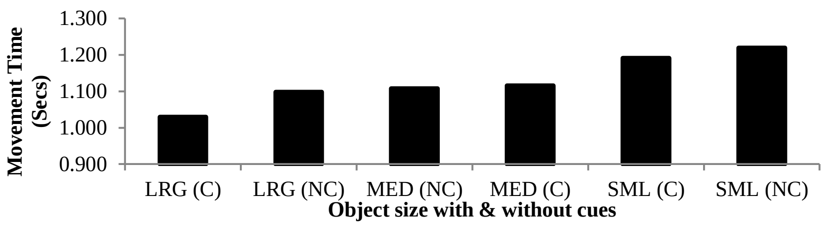


**Figure 3.** *Variation of Interaction Difficulty arranged by magnitude.*

An objective way to evaluate system feature effectiveness in TAGER is to record target acquisitions (hits) against movement times. A target has been successfully acquired when the user's hand collides with the surface of the target object without leaving the Leap Motion's detection area. Hits are classified as unsuccessful when the user's hand leaves the boundaries of the Leap Motion's detection area before hitting the target, users are required to return to within the boundaries to hit the target. Users cannot progress until they acquire the current target, even after registering an unsuccessful hit. It was found that targets positioned at the center depth (relative to the user) were more successfully acquired – a mean of 29 per task over all participants (Front = 22, Back = 26). Closer objects appear to have been harder to attain, suggesting we may need to consider moving the minimum distance further away (along the z-axis) or move objects closer to the z-axis along the x and y axes. The later suggests a cone area (Cha & Myung 2013) for object placement – with the cone pointing towards the user – rather than a cuboid (which maps well to the Leap Motions detection area). This might account better for arm kinematic differences in attaining targets in close and far locations. Users attained targets in all areas with reasonable success, though on average there were 31(28%) unsuccessful acquisitions per level from a total of 108 targets. This may be considered to be quite high, if the Leap Motion is mounted on the VR headset, pointing forward (users facing direction) it could possibly provide a more natural interactive space, and reduce unsuccessful acquisitions. TAGER's experimental design implements two identical levels one at the beginning and end of the experiment, enabling investigation of the potential learning effects indicated by improved performance or user fatigue resulting in performance decline. The mean completion times for all users for the start task was 1257.8 ms while for end task completion times it was 1081.4 ms suggesting that, despite having 10 minutes training time at the start, user performance significantly ($T$=4.60, $DOF$=21, $p$=7.7E-05) improved over the experiment. There are also some indications of fatigue (or loss of concentration) among several users. Analysis of experimental data in the next section enables us to investigate the intricacy of user profiles.

### *4.2 Model Effectiveness*

As outlined earlier we recorded user motion data in reaching from an origin to touch an object target at various distances. Figure 4 shows the lines fitted to the data through regression for four well known forms of Fitts's Law.

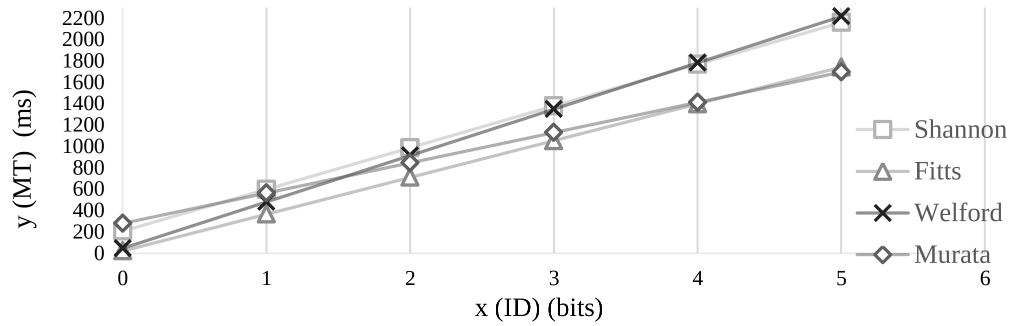


**Figure 4.** *Regression Line from our Data for Four Popular Variants of Fitts's Law.*

**Table 5.** *Average y-intercept across each level for all equations.*

| EQ | SML (NC) (ms) | SML (C) | MED (NC) | MED (C) | LRG (NC) | LRG (C) | VR (NC) | VR (C) | Start | End | Overall Mean |
|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | 189.3 | 77.4 | 270.7 | 161.6 | 392.7 | 343.4 | 70.6 | -41.6 | 254.1 | 356.7 | 207.5 ± 89.3 |
| (2) | -25.3 | -152.2 | 95.9 | -30.8 | 254.4 | 209.2 | -107.9 | -293.5 | 49.6 | 213.2 | 21.3 ± 110.9 |
| (3) | 86.4 | -37.9 | 121.5 | -7.5 | 210.2 | 166.6 | -122.8 | -250.8 | 74.7 | 224.4 | 46.5 ± 107.0 |
| (4) | 319.3 | 203.3 | 279.9 | 243.4 | 357.7 | 346.6 | 203.8 | 185.0 | 288.3 | 374.2 | 280.2 ± 83.6 |

**Table 6.** *Average slope across each level for all equations.*

| EQ | SML (NC) (ms) | SML (C) | MED (NC) | MED (C) | LRG (NC) | LRG (C) | VR (NC) | VR (C) | Start | End | Overall Mean | Bits Per Sec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | 339.3 | 370.1 | 355.8 | 406.2 | 366.9 | 356.2 | 463.7 | 510.8 | 427.3 | 308.4 | 390.5 ± 46.0 | 2.5 |
| (2) | 315.7 | 343.2 | 316.6 | 358.4 | 311.0 | 301.9 | 392.7 | 454.3 | 378.1 | 271.6 | 344.4 ± 41.1 | 2.9 |
| (3) | 362.8 | 396.7 | 396.6 | 451.2 | 421.8 | 409.4 | 515.8 | 566.6 | 475.7 | 344.6 | 434.1 ± 51.2 | 2.3 |
| (4) | 247.7 | 273.1 | 275.1 | 290.5 | 282.1 | 261.7 | 318.5 | 324.1 | 322.9 | 236.2 | 283.2 ± 32.7 | 3.5 |

Tables 5 and 6 show the average regression values of the y-intercept and slope values for the all participants. Murata's 3D equation (4) provides y-intercept values ranging from 196 to 363, which are more representative of human movement response (typically 200 to 300 ms), it also provides a more gradual gradient giving a more appropriate model of *MT* against *ID* (Heiko 2013). Thus, while all four equations provide similar results, we focus on Murata for further analysis. Figure 5 shows typical results with and without cues for large sized targets and Murata's 3D form of Fitts's law. This experiment is fundamentally exploratory in nature. We use Fitts's law and linear regression to develop a user model, which will help us understand how best to create an adaptive system that can personalize interactive tasks. Table 7 provides user profiles from a proposed model comprising parameters such as regression line data, statistics on the residuals of the line fit, task performance and user information. Considering the explicit performance metrics (hits, movement times), target hits provides an informative statistic and capable users are readily distinguishable from less able. Only one person had a score of less than 500 /1080 with the lowest score 472. The highest score was 900 and the average score was 754.74. Mean hits per person rose from 73.91 at the start to 77.22 at the end from a total of 108. The mean percentage improvement in hits over the experiment was 6.92% illustrating diversity of learning and fatigue effects among participants. The mean percentage reduction in *MT* was 13.79%. Average change in line fit according to $R^2$ and associated values are not significant (due to the spread of data values there are a number of valid lines). Change in hits between the start and end tasks in the experiment are potentially revealing of a possible learning effect (improvement) or mental/physical fatigue. A learning effect provides a challenge to adapting task difficulty per user – it is preferable to adapt difficulty based on Fitts's law only after the learning effect stabilizes. Nonetheless, it is helpful to identify that a user remains in a learning phase, so that additional support can be provided. However, *MT* and hits should not be considered independently, as some users may slow down deliberately in order to improve hit performance. The mean slope gradient decreased by 26.85% and the mean intercept by 29.82%. Shallower slopes indicate a more skilled response as there is less difference between acquiring close and far objects, while a rise in the intercept value moves the intercept closer to physiological reflex norms (generally between 200 and 300 ms). Additional user profile information can be gained from the residual statistics of regression lines and the changes between start and end tasks. Mean standard deviation dropped by 19.28% and mean variance also fell by 32.49%, suggesting that on average users were becoming more accurate. Range dropped by 10%, supporting this proposal. Kurtosis of residuals increased by over six times the magnitude (positive values) suggesting an increased number of data points with a small deviation from the regression line. On the other hand, skew also increased 44.4% (also positive), which after examining the regression graphs of users we believe is due to users overshooting the target position and having to change direction. From our results we did not identify a strong relationship between performance and user age or gender. Figure 5 shows Murata 3D linear regression model of user 1009's movements per location for acquiring large targets with and without cues.

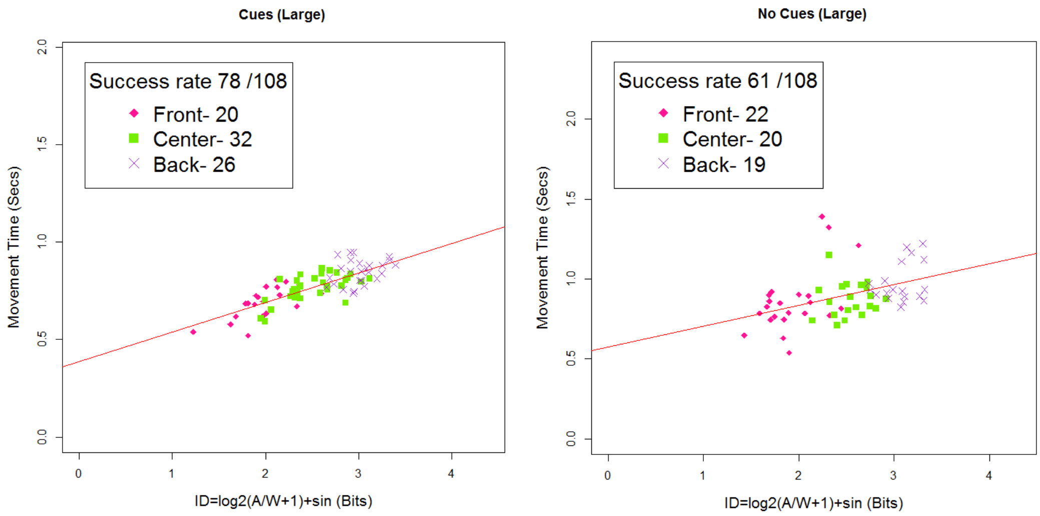


**Figure 5.** *Murata's 3D model of movement without the VR headset. Successful targeting of objects is distinguished by 3 locations in the virtual scene relative to the user: front (red diamonds), center (green squares), and back (purple crosses).*

Data from seven of the twenty-three participants provided a poor fit to the model based on start task motion data. Data after the end session from five participants had a poor regression fit, though two of these participants were different from the seven identified from the start data. These two people may have been overly tired or bored, rather than being incapable, highlighting the need for intricacy and careful analysis of the profiles. To consider this further it is necessary to examine a few representative individual user profiles (Table I). User 1026 is an informative example, who started well with a successful profile but whose hits and mean MT declined significantly during the end task. Despite having residual statistics during the end task that show less variability (indicating more effective target acquisition for a significant number of targets), hit score actually decreased, while skew and kurtosis both increased (suggesting more overshooting of the target), and $R^2$ and the associated P-value suggested an unreliable regression fit (possibly due to an increase in outliers). 1026's mean MT dropped by a 23.96%, which suggests, with respect to the profile context, that during the end task this user may have adopted a high-risk strategy. This is in contrast to 1019, who appears to have become more conservative, and by moving slower (13.64% increase in mean MT) improved their hit score by 12.82%. This considered approach by user 1019 and other participants seems to improve the likelihood that the user motion data corresponds to Fitts's law (and variants). User 1002 had the weakest start having the lowest number of hits in the initial task but improved hit performance by 50% and mean MT by 31.59%. However, even by the end task this user's motion could not be applied to Fitts's law reliably and they had less than a 50% hit success rate in the final task. User 1023 exhibited arguably the most sustained success, having the highest overall hit success and start and end scores of 90 and 91 respectively and overall an improved profile (based on regression values). As with user 1019, 1023 is not particularly fast but improved speed over the experiment. Three participants got slower over the experiment and all of these achieved higher scores in doing so. Five participants got lower hit scores and all of these but one had much less adequate regression fit and three of these exhibited faster mean MTs. Further investigation is required to understand whether users with these profiles exhibit a decline of interest – the tasks were repetitive and several of these participants were quite skilled at the tasks – or due to mental/physical fatigue.

## 5. CONCLUSIONS

In this paper we presented an initial version of TAGER VR upper arm stroke rehabilitation system, which utilizes several low cost, commercially available input devices and a VR headset. We reported on an experiment that focused on usability of the system and on the use of various forms of Fitts's law to linearly model user motion - movement time against an index of difficulty – for reach and touch tasks in a 3D environment using a Leap Motion controller as an input device. Most users enjoyed using the Leap Motion device and perceived tasks to be easier with the VR headset on. No motion sickness or other negative health related effects were reported. The importance of cues has been reported widely in the literature and while our results show a general improvement in object acquisition with visual cues, we found the impact on targeting medium sized objects to be unclear. We outlined results from fitting user motion data to four forms of Fitts's law with each of the equations exhibiting similar success. Examining the statistics of the regression process based around Fitts's law we found that these equations could be used to linearly model user motion with the Leap Motion controller in a range of setups including the use of a VR headset. However, the data point variance across the regressed line is quite high and Fitts's law should not be applied as a simple linear model of user motion equally to all users. We recommend that a form of Fitts's law, for example Murata's 3D version, could be used as part of an intelligent system to profile users. Although the motion of most users could be modelled effectively using Fitts's law, we found a few users who found the NUI so difficult that they could not be modelled linearly. Most of these users required more training than we expected but in some cases users appeared to become tired or bored. A more complex profiling system helps to identify training requirements and distinguish between loss of interest and mental or physical fatigue. We intend to develop the profiling system with further experiments and subsequently investigate the system with impaired users.

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**Table 7.** *User statistics over time including residuals, regression and performance data to define a user performance profile.*

| User | 1001 | 1002 | 1004 | 1005 | 1006 | 1007 | 1008 | 1009 | 1010 | 1011 | 1012 | 1013 | 1014 | 1015 | 1016 | 1017 | 1019 | 1020 | 1021 | 1022 | 1023 | 1025 | 1026 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Start (Residual)** | | | | | | | | | | | | | | | | | | | | | | | |
| Standard Deviation | 0.354 | 0.461 | 0.270 | 0.352 | 0.344 | 0.343 | 0.300 | 0.257 | 0.270 | 0.321 | 0.361 | 0.368 | 0.448 | 0.163 | 0.528 | 0.293 | 0.313 | 0.293 | 0.203 | 0.490 | 0.408 | 0.343 | 0.378 |
| Sample Variance | 0.125 | 0.213 | 0.073 | 0.124 | 0.118 | 0.117 | 0.090 | 0.066 | 0.073 | 0.103 | 0.130 | 0.136 | 0.201 | 0.026 | 0.279 | 0.086 | 0.098 | 0.086 | 0.041 | 0.241 | 0.167 | 0.117 | 0.143 |
| Kurtosis | 0.085 | -1.141 | 0.082 | -0.964 | -0.609 | -0.019 | -0.209 | 0.031 | -0.468 | -0.61 | -1.051 | -0.238 | -0.773 | 2.559 | -0.382 | -0.824 | -0.331 | 0.170 | 0.536 | -0.787 | -0.262 | 0.290 | 0.376 |
| Skewness | 0.986 | 0.394 | 0.535 | 0.561 | 0.486 | 0.963 | 0.700 | 0.996 | 0.783 | 0.522 | 0.740 | 0.286 | 0.241 | 1.703 | 0.505 | 0.603 | 0.394 | 0.934 | 1.080 | 0.359 | 0.785 | 0.526 | 0.980 |
| Range | 1.519 | 1.522 | 1.431 | 1.261 | 1.226 | 1.367 | 1.212 | 1.036 | 1.024 | 1.242 | 1.081 | 1.558 | 1.752 | 0.724 | 2.464 | 1.075 | 1.431 | 1.272 | 0.893 | 1.819 | 1.594 | 1.596 | 1.528 |
| **End (Residual)** | | | | | | | | | | | | | | | | | | | | | | | |
| Standard Deviation | 0.111 | 0.275 | 0.263 | 0.249 | 0.338 | 0.294 | 0.363 | 0.194 | 0.156 | 0.293 | 0.400 | 0.242 | 0.280 | 0.117 | 0.330 | 0.326 | 0.420 | 0.281 | 0.129 | 0.391 | 0.285 | 0.374 | 0.235 |
| Sample Variance | 0.012 | 0.076 | 0.069 | 0.062 | 0.114 | 0.086 | 0.132 | 0.038 | 0.024 | 0.086 | 0.160 | 0.058 | 0.078 | 0.014 | 0.109 | 0.106 | 0.177 | 0.079 | 0.017 | 0.153 | 0.081 | 0.140 | 0.055 |
| Kurtosis | 5.852 | 0.985 | -0.834 | -0.417 | -0.470 | 0.509 | -0.860 | 2.540 | 2.127 | -0.797 | 0.889 | -0.627 | -0.160 | 8.916 | 1.000 | -0.488 | 1.927 | 0.943 | 4.376 | -0.802 | 1.197 | -0.594 | 0.498 |
| Skewness | 1.834 | 1.227 | 0.721 | 0.751 | 0.824 | 0.943 | 0.282 | 1.515 | 1.573 | 0.428 | 0.925 | 0.187 | 0.315 | 2.597 | 1.067 | 0.751 | 0.952 | 1.111 | 1.897 | 0.342 | 1.143 | 0.520 | 1.289 |
| Range | 0.657 | 1.259 | 0.948 | 1.027 | 1.330 | 1.329 | 1.419 | 1.016 | 0.689 | 1.108 | 1.934 | 0.983 | 1.321 | 0.704 | 1.657 | 1.382 | 2.227 | 1.313 | 0.737 | 1.442 | 1.340 | 1.688 | 0.920 |
| **Start Regression** | | | | | | | | | | | | | | | | | | | | | | | |
| $R^2$ | 0.115 | 0.076 | 0.448 | 0.062 | 0.036 | 0.167 | 0.073 | 0.228 | 0.244 | 0.298 | 0.023 | 0.453 | 0.056 | 0.124 | 0.056 | 0.287 | 0.343 | 0.197 | 0.379 | 0.040 | 0.112 | 0.385 | 0.189 |
| P-Value | 4.05E-03 | 9.28E-02 | 4.11E-13 | 3.52E-02 | 1.89E-01 | 1.14E-04 | 6.28E-02 | 8.60E-07 | 1.03E-06 | 3.12E-06 | 2.83E-01 | 1.78E-08 | 6.18E-02 | 5.29E-04 | 3.20E-02 | 1.04E-07 | 1.79E-08 | 8.55E-06 | 1.72E-10 | 1.45E-01 | 1.17E-03 | 8.35E-10 | 3.92E-05 |
| Slope | 0.268 | 0.312 | 0.527 | 0.203 | 0.126 | 0.310 | 0.189 | 0.273 | 0.309 | 0.416 | 0.136 | 0.602 | 0.235 | 0.143 | 0.280 | 0.406 | 0.517 | 0.313 | 0.339 | 0.199 | 0.348 | 0.587 | 0.388 |
| Intercept | 0.352 | 0.360 | -0.336 | 0.463 | 0.813 | 0.549 | 0.733 | 0.268 | 0.113 | -0.100 | 0.686 | -0.289 | 0.863 | 0.375 | 0.761 | -0.042 | -0.212 | 0.430 | -0.084 | 0.879 | 0.475 | -0.306 | -0.121 |
| **End Regression** | | | | | | | | | | | | | | | | | | | | | | | |
| $R^2$ | 0.266 | 0.024 | 0.186 | 0.021 | 0.002 | 0.116 | 0.239 | 0.348 | 0.111 | 0.065 | 0.133 | 0.446 | 0.140 | 0.126 | 0.290 | 0.123 | 0.224 | 0.328 | 0.164 | 0.165 | 0.392 | 0.314 | 0.004 |
| P-Value | 3.80E-05 | 2.54E-01 | 3.07E-05 | 2.08E-01 | 7.45E-01 | 1.07E-03 | 4.11E-05 | 2.83E-09 | 2.90E-03 | 5.25E-02 | 1.53E-03 | 7.42E-09 | 2.30E-03 | 5.48E-04 | 1.04E-07 | 5.72E-04 | 3.18E-06 | 1.09E-09 | 6.95E-05 | 1.18E-03 | 2.44E-11 | 1.68E-08 | 5.77E-01 |
| Slope | 0.133 | -0.109 | 0.287 | 0.085 | 0.034 | 0.215 | 0.387 | 0.293 | 0.122 | 0.169 | 0.369 | 0.445 | -0.256 | 0.104 | 0.405 | 0.271 | 0.481 | 0.422 | 0.123 | 0.399 | 0.509 | 0.509 | 0.033 |
| Intercept | 0.359 | 1.220 | 0.110 | 0.640 | 0.933 | 0.606 | 0.130 | 0.092 | 0.458 | 0.555 | 0.023 | -0.070 | 1.747 | 0.441 | 0.029 | 0.333 | 0.116 | -0.058 | 0.403 | 0.067 | -0.216 | -0.010 | 0.703 |
| **Performance** | | | | | | | | | | | | | | | | | | | | | | | |
| Targets Hit(1080) | 794 | 554 | 828 | 690 | 633 | 821 | 472 | 848 | 818 | 680 | 667 | 638 | 586 | 862 | 856 | 874 | 828 | 879 | 876 | 594 | 900 | 873 | 788 |
| Start Hits | 70 | 38 | 91 | 72 | 49 | 84 | 48 | 96 | 88 | 64 | 53 | 55 | 63 | 93 | 82 | 86 | 78 | 93 | 88 | 55 | 91 | 80 | 83 |
| End Hits | 73 | 57 | 87 | 78 | 53 | 89 | 64 | 85 | 78 | 58 | 73 | 59 | 64 | 91 | 85 | 93 | 88 | 96 | 91 | 61 | 92 | 87 | 74 |
| % Change Hits | 4.29 | 50.00 | -4.40 | 8.33 | 8.16 | 5.95 | 33.33 | -11.46 | -11.36 | -9.38 | 37.74 | 7.27 | 1.59 | -2.15 | 3.66 | 8.14 | 12.82 | 3.23 | 3.41 | 10.91 | 1.10 | 8.75 | -10.84 |
| Start Mean Time | 1.167 | 1.292 | 1.212 | 1.082 | 1.203 | 1.475 | 1.339 | 1.063 | 1.035 | 1.191 | 1.111 | 1.522 | 1.548 | 0.797 | 1.612 | 1.195 | 1.391 | 1.346 | 0.920 | 1.483 | 1.497 | 1.395 | 1.055 |
| End Mean Time | 0.768 | 0.884 | 0.975 | 0.901 | 1.039 | 1.233 | 1.307 | 0.952 | 0.823 | 1.093 | 1.178 | 1.270 | 0.954 | 0.755 | 1.254 | 1.143 | 1.580 | 1.166 | 0.776 | 1.293 | 1.262 | 1.466 | 0.802 |
| % Change Mean Time | -34.19 | -31.59 | -19.49 | -16.74 | -13.63 | -16.37 | -2.42 | -10.42 | -20.50 | -8.23 | 6.04 | -16.54 | -38.37 | -5.33 | -22.24 | -4.39 | 13.64 | -13.38 | -15.66 | -12.82 | -15.66 | 5.03 | -23.96 |
| **User** | | | | | | | | | | | | | | | | | | | | | | | |
| Age | 20 | 20 | 19 | 24 | 22 | 30 | 26 | 42 | 22 | 37 | 44 | 24 | 30 | 26 | 31 | 50 | 66 | 56 | 44 | 46 | 54 | 67 | 24 |
| Gender | F | F | F | M | F | F | F | M | F | F | F | M | M | M | M | M | F | M | M | F | F | M | F |