How Fitts' Fits in 3D: A Tangible Twist on Spatial Tasks

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Abstract

This study expands Fitts' Law into a 3D context by analyzing PointARs: a mixed reality system that teaches pointers through an object manipulation task. We explored nine distinct configurations, varying in sizes of objects and their distances from each other, to gauge task complexity through metrics such as completion time, error rate, and throughput. Our results align with Fitts' Law in that increased distances amplify task difficulty. However, contrary to the law's predictions, we found that tasks with larger objects also increased in complexity, possibly due to the system's limitations in tracking larger objects. Based on our findings, we recommend to use tangible cubes that are at least 1.5" and at most 2" in size, and maintain a maximum distance of 2" for optimal interaction within the system's 3D space. Future research should investigate additional configurations and shapes to further validate Fitts' Law within the realm of 3D object manipulations such as that in PointARs' context.

Keywords

Fitts Law, tangibles, direct manipulation, spatial interaction

1. Introduction and Background

Learning pointers can be difficult, especially for novice programmers. However, it is noteworthy that pointers are essential concepts in computer science, therefore mastering them is crucial for beginner programmers. We present the PointARs prototype (see Figure 1), a Mixed Reality Training System (MRTS) that combines Mixed Reality (MR) and tangible user interfaces (TUI) to help novices understand pointers. In this study, we built upon PointARs' existing design as a foundation for iterative improvements and empirical evaluations. We focused on redesigning PointARs' current tangible cubes, particularly focusing on their present dimensions (2x2x2 inch cubes, as seen in Figure 2) by performing a series of target acquisition tests. All of which are aimed at improving future comparative studies assessing the effectiveness of PointARs in complementing traditional learning methods (e.g., coding demonstrations and video presentations).

Tangible interactions have been a subject of exploration in the realm of education, offering various advantages. They have the potential to elevate engagement and stimulate reflection by combining physical actions with digital augmentations [1]. Furthermore, these systems support embodied cognition and nurture 3-dimensional (3D) mental visualizations [2]. Adopting tangible

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Figure 1: Current actual space setup of the PointARs prototype

interactions is presumed to be inherently natural, effectively lowering barriers to participation, especially for novices [1]. The difficulties novice programmers face in understanding how pointers work can be addressed using MR TUIs to enhance learning experiences by providing an interactive environment that allows learners to physically manipulate objects to create a more tangible and intuitive experience [3]. Moreover, MR TUIs can help simplify the concept of pointers, making them easier to understand [4].

Through this study we aim to enhance 3D object manipulation using Fitts' Law by examining how the size and arrangement of the tangible cubes affect interaction metrics like completion time, error rate, and throughput (TP) within PointAR's tangible space. Figure 3 shows an overview of our evaluation pipeline, which will be explained further in the following sections and followed by a discussion on our findings and conclusions.

2. Proposed Improvements and Rationale

In this study we aim to expand the application of Fitts' Law in 3D object manipulation, drawing inspiration from the methodologies used by Ha and Woo (2010), which investigated various virtual hand techniques in a Tangible Augmented Reality (TAR) environment. Our study will focus on how the size and spatial arrangement of tangible cubes influence key interaction metrics such as completion time, error rate, and throughput within PointARs' tangible space.

The primary task for participants is to bump a tangible cube to the other stationary tangible cube located at varying distances from the center of the projection space. This task mirrors the object manipulation task of 3D cubes in our main reference study [5] but is adapted in the

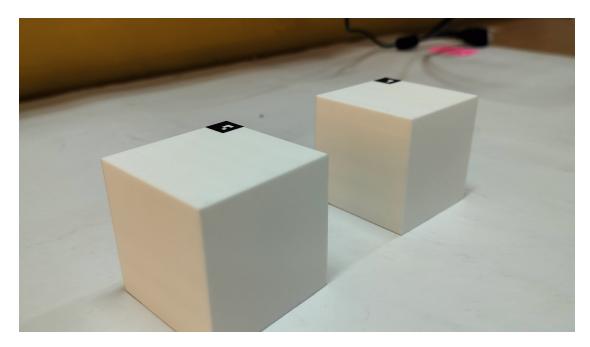


Figure 2: The shape of the tangibles in the current PointARs system

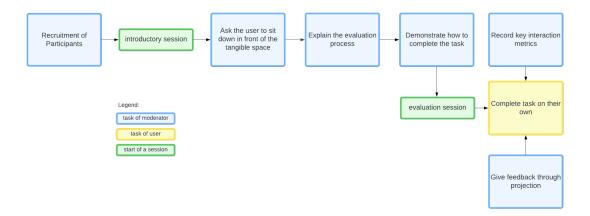


Figure 3: This study's evaluation protocol

context of PointARs' tangible space. By varying the size of the tangible cubes and the distance between them, we aim to analyze the effect of these cubes on the aforementioned interaction metrics. We measured the completion time in milliseconds (ms) from the moment that a user grabbed a tangible cube until they successfully completed the task. We also measured the error rate in millimeters (mm) using the Euclidean distance from the central position of the stationary target tangible cube and the movable tangible cube.

Our objectives are to (a) assess how the size of the tangible cubes affects the identified key interaction metrics, (b) evaluate the effects of different distances between tangible cubes on the

key interaction metrics, (c) evaluate the effects of varying pairings of the tangible cubes based on size on the key interaction metrics, and (d) apply these insights to refine the dimensions of the tangible cube for enhanced user interaction. In line with these objectives, we speculate the ff.: (a) As the size of the tangible cube increases, completion time and error rate will increase, and TP will decrease.; (b) Greater distances between the tangible cubes will increase completion time and error rate and decrease TP, as users will need more time to move the tangible cube over a longer distance.; (c) Pairs of tangible cubes with varying sizes will increase completion time and error rate and decrease TP.; and (d) Optimizing the size and spacing of tangible cubes based on the collected data will result in reduced user reaction times, indicating more efficient interaction. Lastly, potential confounding variables of this study include the familiarity of users with handling cube-shaped tangibles and the size of their hands.

3. Methodology

3.1. Description of the Tangible Fitt's Law Test Program

3.1.1. Object Grabbing Detection

To measure the completion time we integrated an object grabbing detection application into PointARs' current Unity-based system. This helped us detect when a participant grabbed a tangible cube so we can measure the completion time. The application integrates MediaPipe Hands for hand detection and tracking, Ultralytics' YOLO, specifically the yolov5s model, for real-time object detection, and OpenCV for real-time video processing. It detects interactions between hands and the tangible cubes by assessing if fingertips are near a tangible cube's center. If a grabbing action is detected, the application visualizes this action by displaying text "Grab Detected!" on the frame and sends a "grabbed" message to a predefined server address and port using UDP sockets.

3.1.2. Unity Program

We implemented a DataReceiver script in PointARs' system alongside the object grabbing detection program described earlier. This script employs UDP networking as well to receive messages from the grabbing detection program, facilitating real-time adjustments to PointARs' tangible space based on user interactions. The script manages a sequence of 5 trials per test where participants first adjust the tangible cubes to match target positions, with progress tracked through user input and proximity between objects. Real-time feedback on task duration is displayed on the projection space, and task completion triggers the whole projection space to have a green-colored background. The script also records interaction metrics like completion times and error rate, storing these in a CSV file, for later analysis.

3.2. Data Collection

Using a purposive convenience sampling method, we involved 3 undergraduate computer science students from De La Salle University Manila as participants. They were tasked to interact with the tangible cubes of different sizes (1.5x1.5x1.5, 2x2x2, 2.5x2.5x2.5 inches) placed

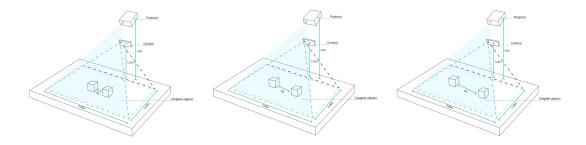


Figure 4: Tangible space schematics of the experiment setup during data collection

at varying distances (2, 3, and 4 inches apart) from each other, as illustrated in Figure 4 and paired based on sizes (2" & 2", 1.5" & 2", 2" & 1.5", 2.5" & 2", 2" & 2.5", 1.5" & 2.5", 2.5" & 1.5", 2.5" & 2.5", and 1.5" & 1.5", where the former sizes are the sizes of the stationary tangible cubes and the latter are the sizes of the movable tangible cubes).

We collected data using PointARs' actual setup and recorded the completion time and error rate of each participant in completing the designated task. We conducted a total of 9 tests per participant consisting of 5 trials for all 3 tasks, one test per varying pairing based on dimension consisting of tasks per varying distance. A task is completed once the movable tangible cube is bumped to a stationary tangible cube and a projected feedback is observed. Lastly, before the evaluation, we ensured that participants were given an explanation and demonstration of the task.

4. Results and Analysis

4.1. Fitts' Law

The formulation of Fitts' Law is a foundational work in understanding users' capacity in sensoryperceptual and perceptual-motor functions. This law states that the time required to move towards a target (Movement Time, MT) is a function of the target's width (W) and distance (D) [6]. It delves into the relationship between the Index of Difficulty (ID) and MT. The Index of Difficulty (ID), as shown in Equation 1, is the measure of the complexity of a movement task, calculated based on the ratio of the movement distance (Amplitude, A) to the target. MT, as shown in Equation 2, is a function of a task's ID and is directly proportional to it. We measured the average completion time of each task and used the results as the MT. Since the original experiments conducted by Fitts (1954) focused on pointing tasks in a 1-dimensional (1D) context, we took inspiration from the ID equation by Ha and Woo (2010) to extend Fitts' Law in 3D object manipulation within PointARs' tangible space context. For our ID formula we used Equation 3 where O_1 is the width of the stationary tangible cube and O_2 is the width of the movable tangible cube. Aside from the ID and MT, we also considered the Throughput (TP) to evaluate the performance of PointARs within the scope of our primary task. TP, as shown in Equation 4, is an efficiency measure (measured in bits per second/bps) for human-computer interaction tasks, combining both speed and accuracy to assess the overall performance of an input device

Comparison of object widths and distances based on their completion time

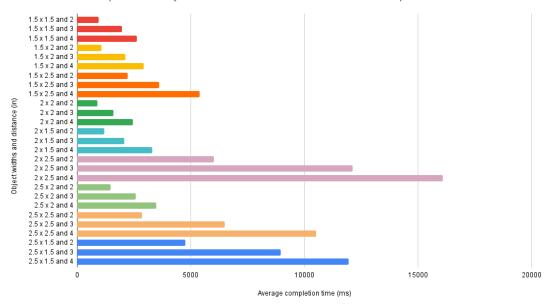


Figure 5: Average completion times per object size and distance

or system [7].

$$ID = \log_2(\frac{A}{W} + 1) \tag{1}$$

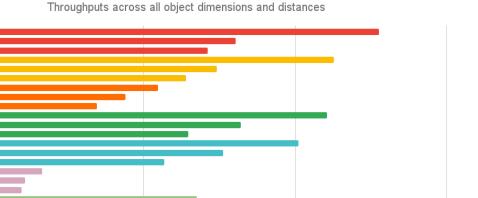
$$MT = a + b \times ID \tag{2}$$

$$ID = \log_2(\frac{A}{\min(O_1, O_2)} + 1)$$
 (3)

$$TP = \frac{ID}{MT} \tag{4}$$

4.2. Results

Figure 5 illustrates a summary of the average completion time of the primary task across varying combinations of tangible widths (in inches) and distances (in inches) from each other. These results are consistent with the premise of Fitts' Law which suggests that tasks with larger distances between targets took more time to complete. Contrary to expectations from Fitts' Law, which also posits that smaller targets increase task complexity, our findings suggest an inverse relationship with tangible cube size; larger stationary tangible cubes correlate with increased completion times. This could be due to the PointAR system's challenges in accurately tracking larger tangibles. The impact of the size of the movable tangible cube is also evident; for a stationary tangible of 1.5 inches, completion times rise with the movable tangible's size.



Throughput

0.0010

0.0015

Figure 6: Throughputs per object size and distance

1.5 x 1.5 and 2 1.5 x 1.5 and 3 1.5 x 1.5 and 4 1.5 x 2 and 2 1.5 x 2 and 3 1.5 x 2 and 4 1.5 x 2.5 and 4 1.5 x 2.5 and 3 1.5 x 2.5 and 3 1.5 x 2.5 and 3

2 x 2 and 3 2 x 2 and 4 2 x 1.5 and 2 2 x 1.5 and 3 2 x 1 5 and 4 2 x 2.5 and 2 2 x 2.5 and 3 2 x 2.5 and 4 2.5 x 2 and 2 2.5 x 2 and 3 2.5 x 2 and 4 .5 x 2.5 and 2 2.5 x 2.5 and 3 2.5 x 2.5 and 4 2.5 x 1.5 and 2 2.5 x 1.5 and 4

0.0000

Object widths and distance (in)

When the stationary tangible cube is 2 inches, the quickest average completion time is observed with a movable tangible cube of the same size, but it drops when the movable tangible cube increases to 2.5 inches. Interestingly, a 2-inches movable tangible cube also ensures the lowest average completion time when the stationary tangible cube is 2.5 inches, whereas using a smaller 1.5-inches movable tangible cube results in the highest average completion times.

0.0005

Figure 6 shows the Throughputs of PointARs considering our study's primary task using varying the tangible cube widths and distances. These results are also consistent with the formula for TP where MT is inversely proportional to TP. For instance, when the tangible cubes are both 1.5 inches and are 2 inches apart, the average completion time is low, while the corresponding TP is high.

Moreover, our data reveals a trend consistent with Fitts' Law, indicating that higher ID values correlate with increased MT, in line with the law's prediction that more complex tasks require more time to complete. This trend was substantiated by a correlation coefficient (\mathbb{R}^2) of 0.047, confirming a positive linear relationship between our ID and MT despite some overlapping data points in Figure 8. This overlap in data points suggests that our chosen ID equation might need refinement to better differentiate between our different configurations.

Lastly, for the average error of the different configurations, we observed that as the difference in sizes of the stationary tangible cube and the movable tangible cube becomes larger, the greater the average error becomes, as illustrated in Figure 7. This could also partly be attributed to the increased complexity of the task when dealing with larger movable tangible cubes.



Figure 7: Error Rate per object size and distance

4.3. Analysis

Out of all our configurations, the one where both the stationary and movable tangible cubes are 2 inches in size and are 2 inches apart yielded the lowest MT. In contrast, the configuration where the movable tangible cube is 2.5 inches in size and the stationary tangible cube is 2 inches in size and are 4 inches apart yielded the highest MT.

Results also showed that the PointARs configuration which yielded the highest TP is when both the stationary and movable tangible cubes are 1.5 inches in size and are 2 inches apart. This means that it is the configuration which led to the highest efficiency, which suggests that the participants can quickly and accurately finish the task using it. Conversely, the configuration with the lowest TP was when the movable tangible cube was 2.5 inches in size, the stationary tangible cube was 2 inches in size, and the tangibles are 4 inches apart. This suggests that completing the primary task using this configuration was less efficient for the users.

All in all, these results could be attributed to the movable tangible's size being larger than the stationary tangible, making the completion of the primary task more difficult and the likelihood of error higher.

5. Conclusion and Recommendations

In this study, we extended Fitts' Law to a 3D space by evaluating the current PointARs system using a primary task involving 3D object manipulation within the current PointARs tangible

Movement Time VS Index of Difficulty



Figure 8: Correlation of movement time with the index of difficulty

space. For our experimental setup, we came up with 9 configurations of different pairings of varying tangible cube dimensions and distances from each other and evaluated them by measuring interaction metrics such as average completion time (MT), average error, and throughput (TP). Our findings suggest that our results were consistent with one of Fitts' Law's premise which posits that the larger distances between targets increase task complexity. However, we observed that as the size of the tangible cubes increases, the more complex our chosen primary task became, which contradicts another premise of Fitts' Law that smaller targets increase task complexity. This might be due to the difficulty of the current PointARs system in handling tangible cubes with large sizes. Consequently, we recommend the redesign of the current PointARs tangible cubes from 2-inches sized cubes to at least 1.5-inches sized to at most 2-inches-sized ones and we suggest having at most 2 inches of space between tangible cubes when dealing with multiple 3D objects within PointARs' projection space. Lastly, for future studies, we recommend using other configurations and tangible shapes to extend Fitts' Law to other 3D object manipulation tasks to evaluate the current PointARs system.

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