Adapting Fitts' Law and N-Back to Assess Hand Proprioception

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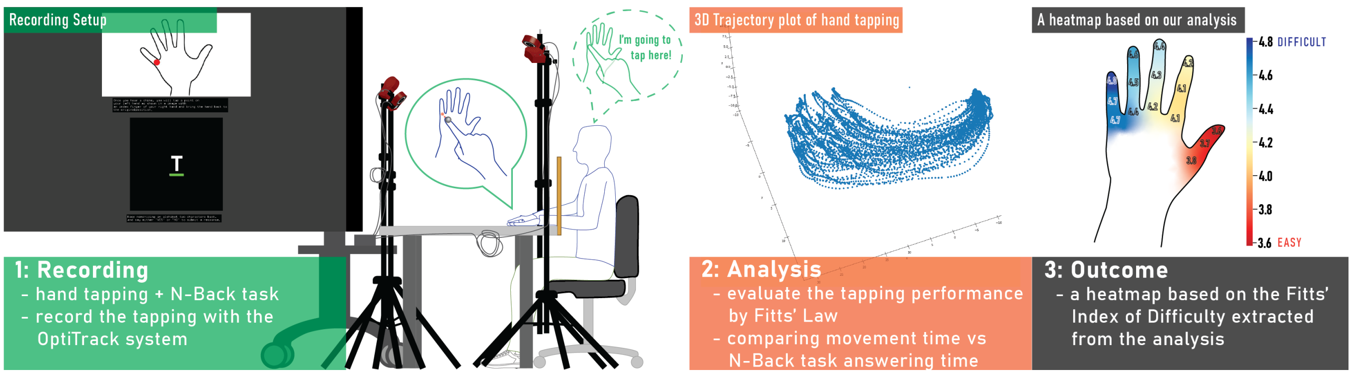

Figure 1: An overview of the study: we conducted a hand tapping motion recording, evaluation of the tapping performance by Fitts' Law, and investigation of hand proprioception.

ABSTRACT

Proprioception is the body's ability to sense the position and movement of each limb, as well as the amount of effort exerted onto or by them. Methods to assess proprioception have been introduced before, yet there is little to no study on assessing the degree of proprioception on body parts for use cases like gesture recognition wearable computing. We propose the use of Fitts' law coupled with the N-Back task to evaluate proprioception of the hand. We evaluate 15 distinct points at the back of the hand and assess the musing extended 3D Fitts' law. Our results show that the index of difficulty of tapping point from thumb to pinky increases gradually with a linear regression factor of 0.1144. Additionally, participants perform the tap before performing the N-Back task. From these results, we discuss the fundamental limitations and suggest how Fitts' law can be further extended to assess proprioception

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CCS CONCEPTS

• **Human-centered computing** → *HCI design and evaluation methods*; **User studies**.

KEYWORDS

proprioception, kinaesthesia, Fitts' Law, N-Back

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1 INTRODUCTION

Humans typically need five senses (sight, sound, touch, taste, and smell) to perceive and navigate their immediate environment. However, our mechanosensory neurons allow us to still operate even without the presence of visual stimuli, the most dominant form of sensory feedback [6]. This "sixth sense" is referred to as proprioception [34]. Sometimes called kinaesthesia [4], these neurons exist within the muscles, tendons, and joints [13]. Proprioceptive nerves are a related but separate nerve system to the touch sensation nerve network. In the arm, cutaneous mechanoreceptor nerves for touch sensation are found in the skin. The density of these mechanoreceptors gradually increases down the arm, with the highest density in the fingertips [14, 23, 31, 38].

Past research has looked into evaluating proprioception. For example, the proprioceptometer was widely used to measure proprioception [35, 41]. It essentially blocks the vision of the participant while asking them to move a specific joint according to only their positional sense. They then measured the difference between the angle of the joint with the perceived angle of movement from the participant. This study focused on the joints as a target while we investigate distinct landmarks on the body (such as bone position or surfaces with different textures) that may be easily identifiable with the only touch due to different topological factors. In a two-handed task, the proprioceptive nerve networks of both hands influence performance, which is understood as a motor control strategy to allow the use of the two hands as a single instrument in skilled tasks [22]. Evaluations of accuracy gains due to proprioception are important for research that aims to uncover whether gestures using specific body locations on the body are more easily carried out, with implications for hands-free interaction and placement of wearable devices.

In this work, we propose adapting the Fitts' law to assess hand proprioception. Fitts' law is a performance modeling method used in ergonomics, and HCI research [27, 28]. It is often used to evaluate the performance of pointing devices in graphical user interfaces or interfaces that rely on novel input mechanics [33]. Furthermore, Fitts' law is also often used for body part movement, such as pointing with the finger to evaluate their movement time [21]. Due to these reasons, we believe that Fitts' law can also be utilized to evaluate the degree of proprioception of different body parts and landmarks. Additionally, real-world usage constitutes the operation of devices and gestures under varying mental loads. To that end, we combine the pointing task from Fitts' law with an additional N-Back task as a form of cognitive load induction to measure proprioception. Our contributions are the following:

(1) We propose adapting Fitts' Law to evaluate hand landmark proprioception
(2) We introduce a cognitive load task based on N-Back to assess proprioception during high cognitive load
(3) We discuss potential limitations and future applications where this method of assessment can be used for HCI related research

2 RELATED WORKS

In this section, we look into past researches that explored proprioception as well as the use of both Fitts' Law and N-Back for user evaluation.

2.1 Uses of Fitts' Law and N-Back

According to Fitts' law [12], the movement time (MT) to select a specific target is a function of the target width (W) and the distance from the start point to the target (A), thus $MT = a + b\log_2(2A/W)$. In this equation, a and b are constants determined from linear regression, and they depend on the specific pointing product, the environment in which the product is used, the sensory-motor channel being used, and the person who is using this product. The log term refers to the index of difficulty (ID), which reflects how difficult the combination of W and A is to a user. Fitts' law was generally applied to evaluate cursor performance in graphical user interfaces and 2D tasks[7, 27, 29]. However, recent works have shown that Fitts' law can be further extended to 3D tasks such as 3D virtual environment and virtual reality [3, 8, 9, 32].

Murata and Iwase [32] looked at the extension of Fitts' law to a 3D pointing task. Users interacted on a vertical plane (all of the targets were 2D and were on this same plane), and response movements required less accurate proximal muscles. A receiver was attached to the right index fingernail of a subject who used this as a "mouse." The task was to point with this receiver to the target. The results showed that the conventional Fitts' model did not fit very well with the observation unless an additional factor was added. The modified ID formula was $ID = log2((A/W)+1)+csin\theta$,where the optimal value of c was found to be 0.5. This extended Fitts' model had to contain the inclinations angle to the target to "provide a better fit," both in terms of R^2 and the standard error of the residual between the measured movement time and the value predicted by the model. Cha and Myung [8] extended this to accommodate 3D target arrangement to implement 3D movement directions in a spherical coordinate system accurately. To explain the 3D target arrangement for the 3D pointing tasks, both azimuth angle (θ_2) and inclination angle (θ_1) were used in the formula. F was the index finger track pad's size. According to empirical data, the model's fitting effect on 3D touch was better than that of the previous model. The modified Fitts' formula was $MT = a + b\theta_1 + csin\theta_2 + dlog2(2A/(W + F))$ and the modified ID formula was $ID = log2(2A/(W + F))$. Our study assumes that our target is two-dimensional because the left hand is placed flat over the table. Additionally, the right hand has the freedom to roam in 3d space as our task is a combination of 2D target and 3D movement. Hence we use Murata, and Iwase [32], as well as Cha and Myung's [8] methods to evaluate the different landmarks proprioception scores on the hand.

The N-Back task is a continuous performance task commonly used as an assessment in psychology and cognitive neuroscience to measure a part of working memory, and working memory capacity [25]. We used the 2-Back task where a participant is required to memorize the order of letters that appears on the screen, at least two letters prior to what they are currently seeing. When we prompt them, they will then need to answer if the current letter being displayed is the same as the two letters before or not. We selected $N = 2$ because recent works have shown that it can induce sufficient cognitive load without the task being too difficult or distracting from the main task [10, 16]. To our knowledge, we have not seen any research that explores and assesses proprioception using Fitts' law and N-Back task.

2.2 Measuring Proprioception

Past works have established the benefit of properly measuring and quantifying the degree of proprioception, though it was often closely related to sensory acuity. A study by Fechner focused on the psychophysics of active movement, which is the correlation between a physical stimulus and subjective perception [11]. This study was later built upon by Cattell et al. Adams, who removed visual cues while measuring body movements, was forcing the participants to rely on proprioception [1]. Fast forward to today, Wycherley et al. [41] developed a portable device that required the participant to match a finger hidden from view to a surface-mounted silhouette, allowing for easy measurement of proprioception in hand, which can then facilitates studies of rheumatological disorders in the hand and joint mobility.

There have been several related works on methodologies to evaluate proprioception for the human body, which started as early as 1860 [11]. This study assessed the amount of force required by the limbs to overcome gravity while lifting weights. Looking at more modern works, Wycherley et al. [41] developed a portable device used to measure joint position sense, specifically the metacarpophalangeal joint of both the index fingers. Such a measurement device, called a proprioceptometer, was also used by Smitt et al. [35] to measure proprioception for musicians and dancers, particularly string players. However, it relies on custom hardware and only measures the index fingers for both hands. Besides the hand, there has also been research that targets the proprioception of the ankle because it is critical for maintaining balance [24]. Dubbed the ankle reproduction test, the participants are required to, without looking, adjust the angle of their ankle based on a given value which will then be measured in terms of its accuracy. Han et al. [19], and Hillier et al. [20] provided an in-depth review on the various methods to assess proprioception currently being explored. However, there is no single measure of proprioception as it highly depends on the proposed task.

2.3 Proprioceptive Interactions

Proprioception has been a key factor when designing interactions in the HCI community. For example, there are several body landmarks on the hand that are both tactually and visually distinct when compared to their neighboring surfaces [39]. These distinctions allow for several intuitive interaction possibilities, such as placing epidermal electronics, electronic tattoos, or on-skin displays [36]. It was even found that people tend to group important items around areas of the skin that are more distinct [5]. This includes anatomical landmarks with higher proprioception like the fingertips or personal landmarks like the location of tattoos and scars. Personal landmarks can possibly be a solution to increase the distinction on the areas of the skin that would otherwise be flat and more uniform. For example, there have also been works that try to increase the distinction on the skin by increasing its tactility via thin fabrics. Fabriclick [15] looked at integrating pushbuttons into the worn fabric, though it impedes the tactual sensation of the skin surface itself to a certain degree.

It was found that 1) observation of the hand while performing an action, 2) tactile cues sensed by the palm, and 3) tactile cues sensed by the pointing finger contribute to hand and palm-based interfaces [18]. This means that the tactile sensation on the palm and pointing finger could possibly allow for high proprioceptive interactions when visual cues are lacking. Gustafson et al. [17] then leveraged this finding to develop an imaginary phone interface where the right index finger acts as the pointer and the left palm acts as a smartphone display in a grid-style layout. Compared to the palm, the back of the hand contains a more distinct skeletal landmark like the knuckle-bone, as well as different textures like the smoother nail surface. Depending on the state of the hand, the deformation of the skin and skeletal components are so distinct that they have proven to be useful for sensors to detect [37, 40].

From these works, we can see that 1) proprioceptive interfaces and interactions are commonly leveraged, yet 2) there exists a gap in methods to objectively evaluate proprioception in HCI. Additionally, 3) measures of proprioception were rarely under different cognitive load levels, which is highly likely in the everyday scenario and will influence proprioception. These problem statements led us to propose the use of Fitts' Law with N-back task to assess proprioception.

3 PROPOSED METHODOLOGY

The goal of the study is to determine the level of proprioception for topographic regions of the back of the hand under high cognitive load by adapting Fitts' law. We achieve this by having the participants perform tap gestures with their right index finger onto different landmark points at the back of the left hand with their vision obscured. Furthermore, they need to perform the N-Back task simultaneously. We then evaluate the tapping accuracy based on the Fitts' law scoring method.

3.1 Participants

We recruited a total of sixteen participants between the range of 18 to 35 years old (eight females, mean = 25, SD = 3.65) for this study. All of the participants are right-hand dominant and do not have any physical injuries or deformities on the hand. They also do not suffer from any neurological, musculoskeletal, or psychological disorders that are associated with the hand or general proprioception. Each participant receives a $10 shopping voucher as compensation at the end of the study.

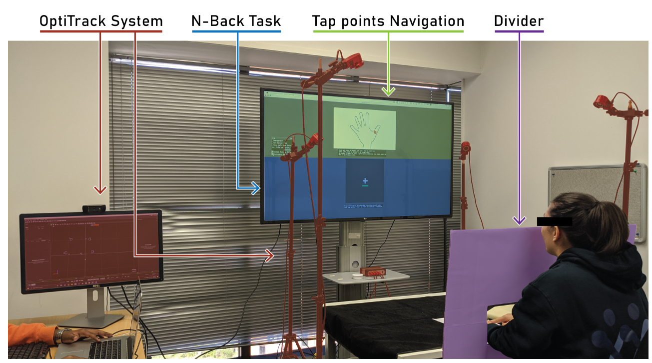

Figure 2: System design

3.2 Apparatus

A notebook computer (15-inch Apple MacBook Pro) is connected to a 65-inch monitor that is used to display both the N-Back task as well as an illustration of the left hand-annotated with a red dot. The red dot on the hand illustration is to notify the participant of the exact position to tap. For precise hand tracking, we use four OptiTrack Flex 13 cameras[1] which capture the position of the retro-reflective markers attached to the participants' hands. The cameras are placed around the table and connected to a separate desktop

[1] https://optitrack.com/cameras/flex-13/

computer (Core i7-8700 with Nvidia Geforce RTX2070 and 32GB memory). The real-time data from OptiTrack cameras is recorded by the Motive 2.2.0 software[2] and streamed to the notebook computer via a local wireless network. The notebook computer runs software built with C++ and openFrameworks[3] which functions both to receive the hand movement data from the desktop, as well as to log the input from the participants for the N-Back task. To remove any chance of visual aid, we use a large piece of cardboard attached to the edge of the table as a divider to obstruct the participants' vision of their own hands. One of the challenges we faced was to devise a method for participants to consistently return their right hand to the point of origin without looking. Furthermore, the left hand must remain as static as possible throughout the experiment. This is following the design of the actual Fitts' task, which requires a static target point (left hand) and a cursor (right hand) that needs to return to the point of origin every time to calculate the travel time uniformly [12]. After some pilot testing, we resulted in using 3D printed hand stoppers for the left hand. The stoppers are attached to a piece of paper that outlines the hand, which in turn is attached to the table. For the right hand, we sculpted a foam block that is attached to the table so that the participant can place their hand in it with the index finger pointed outward. These solutions are to ensure that the hands are returned to the original position after each task without the need for looking.

3.3 Procedure

Prior to the experiment, the OptiTrack system is first calibrated to ensure accurate positioning throughout the study. The participants then sign a consent form stating that they are willingly participating in the experiment and that at any time, they are free to withdraw if they wish to do so. Next, the width of the right index finger and each finger of the participants' left hand is measured using a vernier caliper and saved to a comma-separated value (CSV) file. We then attach a total of sixteen retro-reflective markers; fifteen of them are attached to the left hand (knuckle, middle joint, and the nail of each finger) and the last marker onto the nail of the right index finger. The participant is instructed to place both hands to the designated areas on the table (the left hand onto the hand outline on paper and the right hand into the sculpted foam), which we then record in order to collect the resting position coordinates and save this information to a CSV file. The markers on the left hand are then removed (the right index marker stays on) so that the pointing task will not be obstructed.

After the experimental briefing, the participant first begins with a short three-minute practice round to familiarize themselves with the procedure. When the actual study begins, the monitor displays both the location of the hand at the top of the screen as well as the N-Back task at the bottom. The task will display an alphabetical character for 500 milliseconds, followed by a time window of four seconds where the participant needs to answer true or false. We use N = 2, which has been proven to induce a sufficiently high cognitive load. This means the answer is true if the character shown is the same as what was shown two characters ago. Otherwise, the answer is false. The participant simply says their choice out loud into a microphone placed in front of them, of which we run a simple text-to-speech engine to log the answer.

On the top half of the screen where the left-hand outline is displayed, a red dot would randomly appear on any of the knuckles(MCP), middle joints(PIP), or nails (DP) of the left hand. The participant has to tap that point with their right index finger and return to the original position before the next point appears. An audio cue from the laptop notifies the participants when the target point changes in the screen. A total of 15 points x 3 repeats = 45 taps were required from each participant, which only takes about five minutes in total. Both the N-Back and pointing tasks are performed simultaneously. The overall study takes around 10 minutes for the participant to complete.

3.4 Computing the Fitts' formula

The movement data consists of the position coordinate, timestamp, velocity, and the marker's angular velocity. The N-Back response data consists of the participant's answer and the timestamp. We use the Fitts' law extension by Murata, and Iwase [32], and Cha and Myung [8] to compute the Fitts' Index of Difficulty (ID). To achieve this, we made a Python script to calculate the distance parameter (A), width parameter (W), and movement time (MT). Based on the measured finger width (W), we created a bounding box around the target point, shown in Figure 3 on the right. At every frame, we measure the traversal distance between the right index and the middle point of the bounding box. From there, we can find the minimum distance (A) for when the right index enters the bounding box before returning to the origin. MT is the time taken during the right-index trajectory movement towards the target.

According to the revised Fitts' law by Murata and Iwase [32], the inclination angle (θ_1) is formulated using trigonometric calculations of the minimum distance point (t), origin point (o), and ground plane (n) as these points form a triangle, as shown in Figure 3. Using these three points, we calculate the inclination angle using the formula below:

$$\theta_1 = \arcsin \frac{\|o - n\|}{\|o - t\|}$$

For the revised Fitts' Law by Cha and Myung, [8], to compute the azimuth angle (θ_2) value, we use trigonometric evaluation of three points: the origin point (o), the ground plane (n), and the displacement of the minimum distance point of the origin plane (t'). These points form a triangle, shown in Figure 3 with which we calculate the azimuth angle using the formula below:

$$\theta_2 = \arcsin \frac{\|n - t'\|}{\|o - t'\|}$$

4 RESULTS

In this section, we look into the obtained results from both the Fitts' ID analysis as well as the movement time against N-back answering time.

4.1 Analysis of Fitts' ID vs MT

Figure 4(left and middle) shows the comparison between the two Fitts' ID's by Murata and Iwase [32] and Cha and Myung. [8]. It can be seen that Murata and Iwase's ID linear regression value is closer

[2] https://optitrack.com/software/motive/
[3] https://openframeworks.cc/

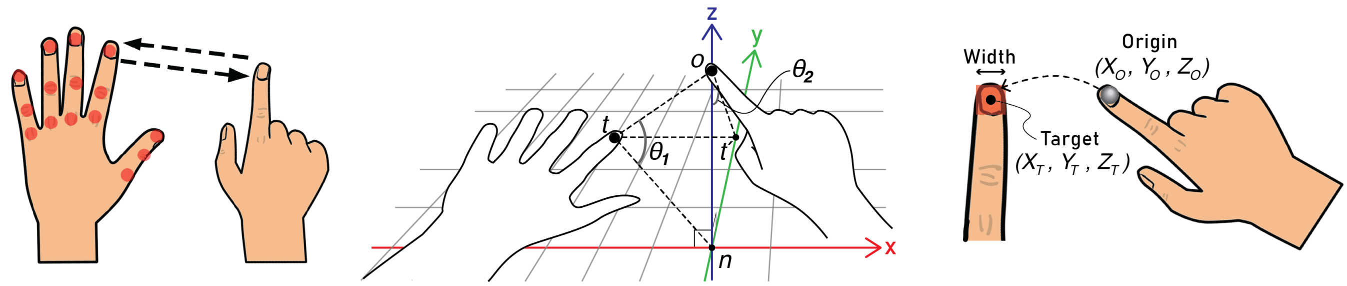

Figure 3: Hand Tapping Target points (Left), Azimuth Angle and Inclination Angle Computation (Middle), Target Size and Minimum Distance Point (Right)

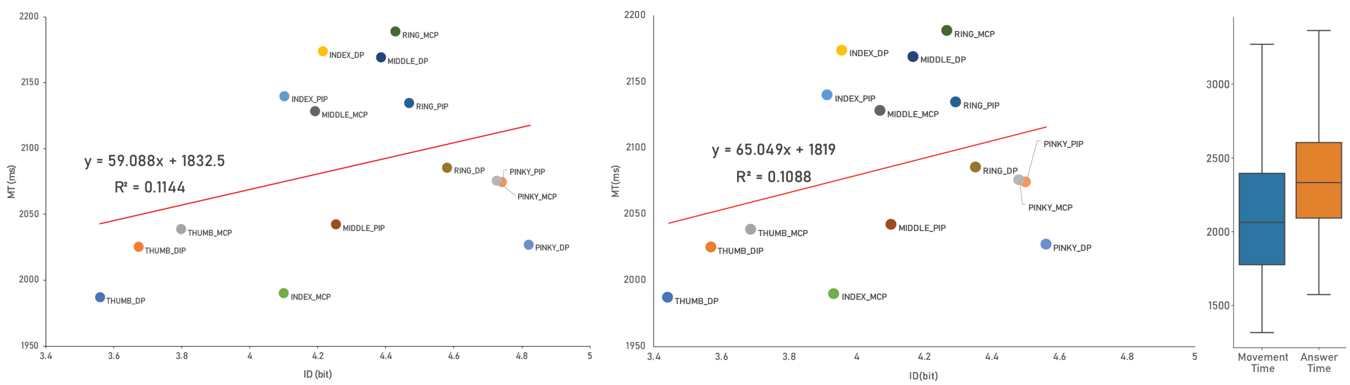

Figure 4: Relationship between MT and ID using the method proposed by Murata and Iwase (left), as well as by Cha and Myung (middle) respectively. We also compare the Movement Time and the N-Back Answer Time(Right)

to 1, meaning it has a stronger linear relationship compared to Cha and Myung's Fitts' ID, although both did not perform very well with our data. The Fitts' IDs are mainly affected by the conditions of distance and target size. The effect of distance shows MT gradually increases as the target fingers move from the thumb to the pinky. The variance in target size due to the different finger widths of the participants is also a reason for the non-linearity in the in Figure 4 between MT vs. ID. The data were modeled using the revised Fitts' ID formula for 3D tasks [32]. Based on the equation for 15 different conditions, there were 15 ID levels. The model regression coefficients are $R^2 = 0.1144$ and $R^2 = 0.1088$ for Murata and Iwase, and Cha and Myung, respectively (computed based on the aforementioned Fitts' formula detailed in Section 2.1). From the ID calculated using Murata and Iwase extended Fitts' law, we created a heatmap that depicts the distribution of Fitts' ID from thumb to pinky, as shown in Figure 1(right).

4.2 Analysis of Movement Time vs. Answer Time

Since the participants are required to simultaneously perform the tapping task and N-Back task, there will arguably be a delay in one of them. This will allow us to understand user behavior as well as performance accuracy while performing a proprioceptive task under high cognitive load. Movement time (MT) is the time taken by participants to move from the origin to the target. Answer Time (AT) is the time taken by the participant to give an answer for the N-Back test. The rightmost plot in Figure 4 depicts the box plot comparing MT and AT. the y-axis is represented in milliseconds. There is a general trend among all the participants that they try to first touch the target and then give an answer to the N-Back test. Running a paired t-Test gives $t(6.07) = 478, p < 0.001$, which shows there is significance between MT (M = 2128.4, SD = 452.4) and AT (M = 2360.5, SD = 380.8).

5 DISCUSSION

Our results showed that both the Fitts' models are non-linear. If the ID is high, the tap point is more difficult to reach and has less gesture accuracy. The ID gradually increases from the thumb to pinky, which correlates with the sensory somatotopic mapping of the human hand and may potentially explain the variance in the Fitts' ID between fingers. The index and thumb fingers have proven to show a larger activation volume in the somatosensory cortex during an fMRI study [30], with the index finger showing the largest activation cluster.

For the fingers excluding the thumb, the ID is the lowest for the knuckle, followed by the middle joint, and finally the fingertip. Even though the tip has the highest number of neuron endings, it has a higher ID than the rest, which can be explained by two factors.

Firstly, according to Long et al. [26], humans perceive their body, especially the fingers, to be smaller when there are no visual cues. Secondly, there is more concentrated muscle mass in the palms compared to the fingers, which equals more mechanoreceptors. Our study is based on participants trying to perform two tasks simultaneously; to touch the target point and to answer the N-back test. We have also identified a trend from the analysis of the AT of the N-Back test and MT, which is that participants will try to first touch the target, followed by answering the N-back test. This is possibly due to a proprioceptive-based task generally requiring much less mental load compared to the N-back task[2]. In a real-life scenario where such a tapping task may be integrated into wearable devices for input and interaction, this potentially indicates that users may still be able to perform them accurately without a visual aid, such as while driving, though further studies are required to validate this. This can be done by first comparing the results with and without the use of N-back, followed by different levels of N for different induced cognitive load level. By modeling the correlation between cognitive load and proprioception, we can potentially change the interactive zones and gestures depending on user context for our future works.

6 LIMITATIONS AND FUTURE WORKS

In our study, we only tested a specific body part as well as a specific orientation. These two factors can greatly affect the Fitts' ID since there will be a drastic change in the user's motion and proprioceptive sense as well. In the future, we will explore other parts of the body and different orientations to understand this. Furthermore, conventional Fitts' law researches require line of sight of the task to perform, whereas ours do not. There are also different types of actual target sizes for Fitts' law, and distances remain the same throughout the study. However, the target's distance was the same in our study, but the target size was not the same due to the participants' finger-width being different sizes. That is why there are discrepancies in the linearity of the model. These considerations lead us to believe that there is room in our future works to propose an extended Fitts' law specifically for assessing hand proprioception, as opposed to adapting currently known models. For example, we consider including an additional parameter in the ID formula that manages variability in the target size. Another limitation is that different people have different tolerance towards the cognitive load. We can build on this by investigating different N-Back levels to induce different cognitive load levels and have that integrated into the Fitts' ID. We can then link this to the design of the custom Fitts' law model for us to directly measure the correlation between cognitive load level and Fitts' score.

7 CONCLUSION

In this work, we propose the use of an extended 3D Fitts' law and N-Back to evaluate the proprioception of the human hand. Specifically, we evaluate 15 points of the hand that are topographically distinct using a tapping task. It was found that the ID overall increases from thumb to pinky and that participants choose to perform the tapping task before completing N-Back. These results align with past findings regarding how the human hand is perceived as well as the mechanoreceptor density on the hand. From these results, we discuss key limitations and how our method can be further improved in future works.

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