DEVELOPMENT OF AN ADAPTIVE SERIOUS GAME FOR ASSESSING COGNITIVE ENGAGEMENT

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ABSTRACT OF THE THESIS

Development of an Adaptive Serious Game for Assessing Cognitive Engagement

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Cognitive Engagement is defined as The act of beginning and carrying on of activity with a sense of emotional involvement or commitment and the deliberate application of effort. Therefore, the concept of cognitive engagement in rehabilitation is operationally defined here as a deliberate effort and commitment to working toward the goals of rehabilitation interventions, typically demonstrated through active, effort-full participation in therapy and cooperation with treatment providers Lequerica and Kortte [1]. Neurorehabilitation robots have been used with tremendous success to restore and improve motor recovery. However, cognitive engagement, which is an essential aspect of the therapy has been partially incorporated into the current therapeutic strategies. The most common methods of assessing cognitive engagement such as self-reports or physiological signals are either subjective or compromised by the disease itself. Hence, these measurements have limited usability in the therapy. There is thus an unmet need to objectively quantify cognitive engagement and integrate it into adaptive rehabilitation strategies.

In this work, we developed a serious game based on the Go No-Go paradigm with built-in adaptability. The serious game is designed on the concept of Multiple Object Tracking (MOT), where the participant has to focus on multiple dots on the screen

and distinguish between tracking and distractor dots by a Go or No-Go stimulus. The game is adaptive, and adapts the games speed and the number of dots, by accuracy and reaction time respectively. We aim to test robust adaptive strategies and test their outcome on therapy sessions. We observe parameters such as speed, accuracy, reaction time, count and distance moved to try and gauge how adaptability affects the game. We aim to draw reliable inferences and better understand the factors that affect adaptability. We know that serious games play a vital role in rehabilitation, as they help add liveliness and entertainment in repetitive exercises in therapy sessions and help the patient achieve their goals. Cognitive Engagement plays a crucial role in serious games, as they are the factor that helps keep patients engrossed in the game and adaptation allows us to make sure that the levels of Cognitive Engagement stay up.

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Chapter 1

Introduction

Advancements in neuroscience and rehabilitation have led not only to a recovery in patients suffering brain lesions, but also speeding up that recovery. However, certain processes during recovery still require a lot of hard work, both for patients as well as therapists. One of the significant challenges that therapists face is providing targeted treatment while ensuring the patient focuses on the task.

This has led researchers to delve deeper into Cognitive Engagement, to better understand how they can help patients stay focused on a task during therapy, which can get boring since most of the therapy tasks are repetitive.

New rehabilitation technologies include game-like elements such as entertaining graphics, automated difficulty adaptation, and in-game feedback mechanism to improve engagement and increase the intensity of therapy sessions. These games also help therapists support patient motivation and gather quantitative measures on their progression.

1.1 History of Neurorehabilitation

The neuroscience community has for very long has had a virtually axiomatic belief that our nervous system was hardwired and fixed. This was based on the work of Louis Broca in the 1850s, popularized by Ramon y Cajal. It was believed that the immature nervous system exhibited plasticity, but as time progressed, and mammals matured, the plasticity in our CNS began to degrade. However, in the last decade or so, evidence has surfaced that our plasticity persists, throughout our lifespan.

The process of change is exemplified throughout the history of neurological physical therapy. Medical practitioners in the early 20th century used forms of muscle re-education and corrective exercise, the former involving exercises directed at individual

muscles, with consideration of the roles of synergistic muscles. The knowledge that clinicians applied in their practice reflected an early focus on structural anatomy and principles of exercise as understood at the time Carr and Shepherd [3].
As time progressed, there was a major conceptual shift in neurological physical therapy, as the focus shifted from muscle to non-muscle elements. Researchers began focusing on our central nervous system (CNS). Major influences were the work of the Bobath in Bobath Therapy or Neurodevelopmental Therapy (NDT), and of Kabat, Knott and Voss, whose methods of movement facilitation were referred to as Proprioceptive Neuromuscular Facilitation (PNF). Other therapists also developed their ideas for therapy around this time, including Rood, Ayres, and Brunnstrom Carr and Shepherd [3]. These methods dominated the second half of the 20th century and are still popular. As time progressed, clinicians sought to bring/transfer these scientific findings into clinics. They took advantage of development in experimental work on movement, motor learning Carr and Shepherd [4] Carr and Shepherd [5], muscle adaptability Rose and Rothstein [6] Gossman et al. [7], muscle biology and psychology.

The development of neurological rehabilitation started following a more deductive process because of the increase in clinically relevant research findings related to movement. This lead to the development of newer clinical methods.

1.2 Importance and Motivation

While neurorehabilitation does help patients recover from injuries, it has some challenging hurdles it must overcome to be able to deliver results. They are:

1. Intensive Training:

   Patients need intensive training to benefit from neuroplastic effects, even in the presence of pharmaceutical factors.

2. Demographic Shift:

   As countries develop, we move from a pre-industrial economic system, one that has high birth and death rates, to an industrial economic system, which has lower birth and death rates. This means that the number of patients will increase given life expectancy increases.

3. Shortage of Personnel:

   As with the advancement of any technology or science, neurorehabilitation is advancing at a much quicker pace than the personnel and staff required at clinics. The process of training personnel is much slower, which combined with long, intensive training leads to a shortage of staff.

A solution for the above problems is the application of robotics in this field. Robots can be easily designed to perform intensive repetitive tasks, can be used for prolonged periods, require shorter training and can be replicated easily.
This also allows us to have a better look at the rehabilitation process to make it more directed and effective. This is where Cognitive Engagement comes into the picture. While robotics eliminates the challenges of a clinician, we also need to consider the patient. One of the primary drawbacks of automating therapy is keeping the patient cognitively engaged for therapeutic benefits.
Hence, we look to build an adaptive serious game that can assess Cognitive Engagement to help us better understand how to improve a therapeutic session.

1.3 Outline

- Chapter 2 describes what the neural foundations of rehabilitation are, why we need Serious Games, how we can achieve Cognitive Engagement through Adaptability and the role of Electroencephalogram.

- In Chapter 3, we discuss the game design which includes the idea behind the game, the concepts involved, the hardware and software specifications, the algorithms implemented and the events and triggers captured.

- Chapter 4 gives us plots and results from the data collected while the game was played, including game statistics, Go/No-Go, Reaction Time and Adaptability vs. Non-Adaptability.

- Chapter 5 attempts to delve into a discussion of the results obtained.

Chapter 2

Theory

In this chapter, we give a brief overview of the various concepts in Rehabilitation we have used to design our game. We also delve into the concept of serious games, cognitive engagement, and adaptability through cognitive engagement.

2.1 Neural foundations of Rehabilitation

2.1.1 Neuroplasticity

Luft et al. [8] define Neuroplasticity as the ability of the central nervous system (CNS) to undergo persistent or lasting modifications to the function or structure of its elements. Neuroplasticity is a CNS mechanism that enables successful learning. It is also the mechanism by which recovery after CNS lesioning takes place.

While the mechanism for learning in the healthy brain and a lesioned brain may not be the same, on the cellular level, they appear to be similar. One of the primary methods of enabling neuroplasticity is via motor learning.

Motor Learning

Motor learning is a general term that encompasses many different processes. It is described as an improvement of motor skills through practice, which is associated with long-lasting neuronal changes. They rely primarily on the primary motor cortex, premotor and supplementary motor cortices, cerebellum, thalamus, and striatal areas Karni et al. [9].

Motor learning can also be driven by feedback, either positive in the form of reward-based learning or negative in the form of avoidance learning. These learning processes can occur on short or long time scales depending on the type and complexity of the movement. Motor skills can also be learned via implicit reinforcement processes. Small improvements after repeating a unique movement, are often not obvious or consciously perceived. Unconscious rewarding feedback may play a role. The conscious reward typically comes late and temporally unrelated to the movement. Thus, implicit motor learning may be mediated through use-dependent or Hebbian-like plasticity rather than reinforcement mechanisms.

All forms of motor learning are dependent on cellular mechanisms of plasticity including long-term potentiation (LTP) and long- term depression (LTD). Learning of a motor skill requires gene expression in the primary motor cortex (M1) [11 , 12]. Gene and subsequent protein expression is a common requirement of various learning processes [13 , 14] as well as for cellular equivalents of learning, i.e., the changes in neuronal structure [15] and synaptic strength in the form of LTP and LTD.

LTP and LTD

Long term potentiation (LTP) and Long term depression (LTD) are seen as cellular equivalents of the brain's learning abilities [22]. Either by repetitive stimulation, regarded as the equivalent to repetitive training, or by synchronizing two signals that converge at one neuron, potentially reflecting associative learning phenomena, an increase in synaptic strength is induced that lasts from hours to days, known as LTP [23]. LTD is induced by low-frequency stimulation and leads to a lasting reduction in synaptic strength [22]. The observation that the ability of primary motor cortex (M1) neurons to undergo LTP and LTD is reduced in trained animals provides indirect evidence for the hypothesis that the primary motor cortex LTP/LTD is involved in motor skill learning [25]. However, the role of LTP and LTD in the context of recovery after brain or spinal cord injury is unclear.

2.1.2 Principles of Rehabilitation

Over the past decade, rehabilitation approaches have incorporated technological innovations that can provide more cost-effective means of achieving higher intensity practice over longer periods. These computer-based and robotic technologies have been shown to match or even exceed the efficacy of traditional therapy in promoting improvements in motor performance. Based on Sainburg and Mutha [10] rehabilitation can be defined by the following principles:

Principle 1: Optimal Control

A systematic identification of which movements should be practiced is often lacking. This is partly because the question of what defines a desirable movement has yielded no clear answer.

Traditionally, movements are made more normal. Thus, the goal is to develop movement patterns that are similar to those exhibited by non-impaired individuals. The role of sensory feedback mechanisms in these models is simply to correct deviations from the planned or desired trajectory, regardless of whether these deviations resist or assist in task completion. The output of feedback circuits is not incorporated in the optimization phase. Optimal feedback control scheme yields task-specific cost functions that often represent a hybrid mix of explicit task-level variables that relate to performance goals, such as movement precision, as well as implicit mechanically related costs that correspond to muscle force or effort. It is important to recognize that damage to the CNS from stroke and the associated secondary changes in the musculoskeletal system could induce changes in the set of possible solutions as well as the costs associated with any given task. Therefore, patients may arrive at solutions to a motor task that may not look normal, but may be optimal given physiological and biomechanical pathologies.

Principle 2: Impedance Control

Optimal feedback control theory emphasizes that the derivation of the optimal control signal incorporates knowledge about the state of the body and the environment.

However, these control strategies change due to external/random perturbation. According to the principle of minimal intervention proposed by optimal feedback control, the central nervous system intervenes only when errors are detrimental to goal achievement. This can build simple feedback circuits which can be modulated based on task demands. Feedback circuits such as reflexes can be modulated in accord with task goals through implicit mechanisms. Modulation of reflexes appears to be a fundamental mechanism that our nervous system employs to control limb impedance and thus resist perturbations.

Under conditions in which the movements were not mechanically perturbed, no changes in EMG or joint torque occurred at reflex latency relative to movements made with mechanical perturbations. Limb impedance is controlled without interfering with optimal coordination, by selectively modulating the expression of short- and long-latency reflex responses. The central nervous system invokes at least two aspects of control to achieve coordinated movements. First, the commands have specified that result in optimal coordination patterns that satisfy both costs associated with task performance and energetic costs.

Also, the nervous system appears to set control policies that modulate sensorimotor circuits such as reflexes, to account for perturbations from unexpected changes in environmental or internal conditions. The importance of recognizing both of these features of control in clinical environments is fundamentally important because brain damage due to stroke can have differential effects on these two aspects of coordination. While this type of practice is critical for improving coordination and voluntary control, focusing on repetitive movements under consistent environmental conditions should only be the first step in rehabilitation training.

Principle 3: Motor Lateralization

Optimal control and impedance control are component mechanisms of underlying control of voluntary movements. They are lateralized to the left and right brain hemispheres, respectively. Distributing different neural processes across the hemispheres was a natural consequence of developing complex functions during evolution.

The dynamic-dominance model proposes that the left hemisphere, in right-handers, is specialized for predictive processes that specify smooth and efficient movement trajectories under mechanically stable environmental circumstances, while the right hemisphere is specialized for impedance control mechanisms that confer robustness to movements performed under unpredictable and mechanically unstable environmental conditions. The left hemisphere appears specialized for control of well-established patterns of behavior, under ordinary and familiar circumstances, the right hemisphere is designed for detecting and responding to unexpected stimuli in the environment. Both hemispheres are recruited for their complementary contributions to integrated functional activities. Patients with left-hemisphere damage made movements that were very curved but were accurate in the final position. In contrast, patients with right-hemisphere damage made straight movements with poor final position accuracies. Thus, motor lateralization leads to deficits that depend on the side of the stroke and can lead to significant deficits. This is an important area for future research in rehabilitation intervention for stroke patients.

Principle 4: Motor Learning

Rehabilitation itself rests on the assumption that patients can relearn such control with repeated practice. Knowledge of how motor learning occurs, how it is retained, and how it generalizes to other conditions that have not been practiced is central to the development of effective rehabilitation strategies. Motor learning is used as an umbrella term to incorporate any practice-related improvement in motor performance.
Multiple mechanisms, presumably dependent on distinct neural substrates, contribute to an improvement in motor performance with practice. Loss of a particular component process because of focal lesions in different regions of the brain, therefore, does not automatically imply a complete loss of learning capacity.

Optimal rehabilitation protocols can be designed using a framework based on computational motor learning principles. Sensorimotor rehabilitation is one such example, as seen in Figure 2.1

2.1.3 MIT Manus

Robots for neurorehabilitation have been designed principally to automate repetitive, labor-intensive training and to support therapists and patients during different stages

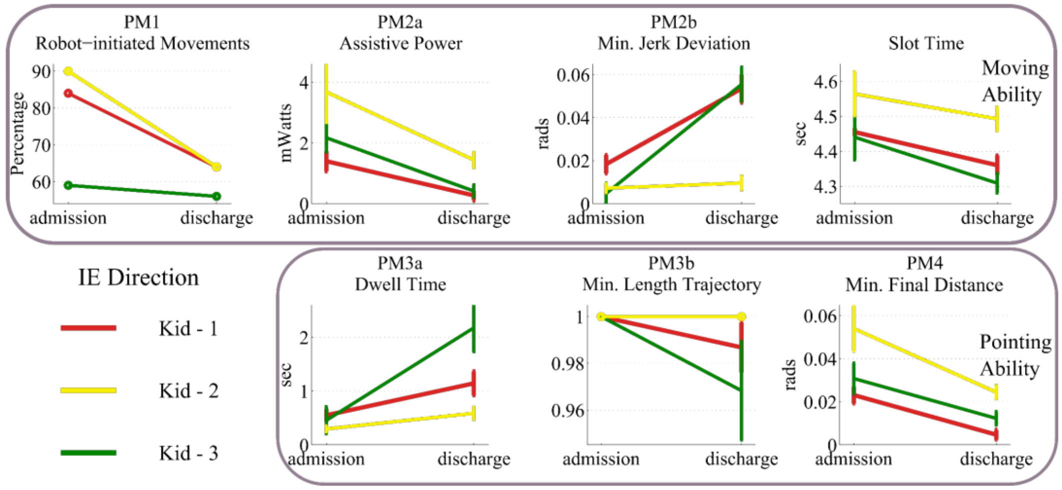


Figure 2.1: Robot therapy induces explicit motor learning. Michmizos et al. [2]
Performance metrics for assessment of moving (upper row) and pointing abilities (bottom row) for the three kids that received robotic therapy in DP direction. Metrics were estimated from the therapeutic sessions (44 movements). Error bars correspond to 95% confidence intervals.

of rehabilitation. The use of robotic technology to assist recovery after neurological injury has proven to be safe, feasible, and effective, at least in some forms (e.g., upper extremity) and for some patient populations (e.g., stroke).

The MIT Manus, which derives its name from MIT's motto 'Mens et maus', was developed around twenty-eight years ago by Professor Neville Hogan.

2.2 Serious Games in Rehabilitation

2.2.1 Serious Games

Serious games are broadly defined as games designed for a primary purpose other than pure entertainment Susi et al. [11]. While the term gains more popularity, there is no current single definition for this notion. The first formal description of the term was given by Abt [12] which defined serious games as "We are concerned with serious games in the sense that these games have an explicit and carefully thought-out educational purpose and are not intended to be played primarily for amusement.". Zyda [13] defines the same as "a mental contest, played with a computer following specific rules, which uses entertainment to further government or corporate training, education, health, public policy, and strategic communication objectives." The focus is on how we

Figure 2.2: The clinical version of MIT Manus, developed by Bionik

define the term "serious" in serious games, as this context can change how we define serious games.

While serious games have been usually played on a screen using a console, the use of games not for entertainment date as far back as the 7^{th} Century India, to a game called Chaturanga which is a precursor to chess, which teaches military strategies using a board game Parlett [14]. Apart from games in military context, pre-digital games have also been used to enact social change and government application of games for serious purposes. For instance, the Landlord's Game (1902) was designed to illustrate the dangers of capitalist approaches to land taxes and property renting Wilkinson [15].

From here on, we can trace the use of serious games throughout history to Army Battlezone (designed by Atari in 1980), and to America's Army (2002). Serious games have been applied to many diverse areas such as health, military training, education, corporate and cultural training Rego et al. [16]. Serious Games have had quite an impact on society. Some of the more popular games are:

- Microsoft Flight Simulator (1982)

The Microsoft Flight Simulator, developed in 1982, is one of the most popular and successful commercial flight simulators. Flight Simulators have been around for quite a while, hence given the tag 'grandfathers of serious games'. The MS Flight Simulator is one of the few non-combat flight simulators ever made.

- Tiltfactor Laboratory (2003)

  Tiltfactor Laboratory, a serious game research center established in 2003, saw success in the last few years with their innovative card games. Their motto is "Game Design for Social Change," and they have designed learning games like Pox and Awkward Moment, which teaches players about vital topics like the impact of the ant-vaccination movement and avoiding social stereotypes.

- A Force More Powerful (2006)

  Based on a serious documentary about non-violent resistance 'A Force More Powerful' released by PBS in 1999, Breakaway Games developed this video game in collaboration with one of the leaders of Serbia's Otpor! Movement. The purpose of the game is to inculcate nonviolent methods for waging conflict using player-built scenarios.

- Darfur is Dying (2006)

  One of the more popular serious games, Darfur is Dying attracted over 800,000 players in its opening months, from its launch in April 2006. Aimed at exposing the truth on the humanitarian disaster due to the war in Darfur, the game attracted quite the attention for a serious game.

- PeaceMaker (2007)

  A serious game that simulates a working government, PeaceMaker focuses on the Israeli-Palestine conflict. With the aim of promoting peace, the video game was originally designed as a university project. In this game, the player needs to represent a side of the government and make political, social and military decisions. The consequences of these decisions teach the player about the outcomes of their choices and how they can influence them.

- Superbetter (2012)

  Finally, Superbetter, which was originally known as the Concussion-Slayer is a game designed by Jane McGonigal to treat her condition of feeling depressed and suicidal. The game is designed to treat symptoms as well as keep the participant occupied by helping people achieve goals and overcome obstacles.

A major application of these games is in rehabilitation, which we shall discuss next.

2.2.2 Role of Serious Games in Rehabilitation

Rehabilitation is used for patients to recover from disabilities and impairments. It involves repetitive goal-based tasks aimed at improving a patient's function. The problem with this is the lack of patient interest in performing repetitive tasks and in ensuring that they finish the treatment program Burke et al. [17]. This is what makes the game boring for the patients. Hence, serious games can be used to augment physical and cognitive rehabilitation as a new form of therapy. Games require cognitive and motor activity so they can engage a person's attention Krichevets et al. [18]. They also allow us to introduce difficulties which can be adapted to a patient's abilities to make the game more challenging to them. We shall discuss these in further chapters. Another important aspect of these games is that they work very well as distraction, in case the patient is suffering from pain, and as such can be used to manage or influence it Burke et al. [17], Krichevets et al. [18].

2.2.3 Elements of a Serious Game

Based on literature surveyed we can break down the components of a serious game into the following parts:

- Application area:

  This defines the domain/area the serious game is going to be used in. The domains can be broadly categorized as military, rehabilitation, medical, education. They can even be specifically categorized into areas such as Cognitive Rehabilitation or Motor/Physical Rehabilitation.

- Adaptability:

  Adaptability defines if the game can change its difficulty based on a participant's performance.

- Game technology:

  The game technology defines the relationship of the game with the technology used. They can evaluate movement, or simulate an environment (for example)

- Number of players:

  This defines the number of participants playing the game. It can be a single or multiplayer game.

- Performance feedback:

  Does the game provide active feedback on the participant's interaction with the game?

- Game interface:

  How does the game interact with the participant? What periphery devices does it use to let the participants play on it? Examples include robotic arms, consoles, virtual reality, and others.

- Game portability:

  Is the system capable of being used at home, or does it require a specific environment?

Once our serious game is defined, we would need to modify it to adapt for Cognitive Engagement.

2.3 Cognitive Engagement

Cognitive Engagement is defined as "The act of beginning and carrying on of activity with a sense of emotional involvement or commitment and the deliberate application of effort. Therefore, the concept of 'cognitive engagement in rehabilitation' is operationally defined here as a deliberate effort and commitment to working toward the goals

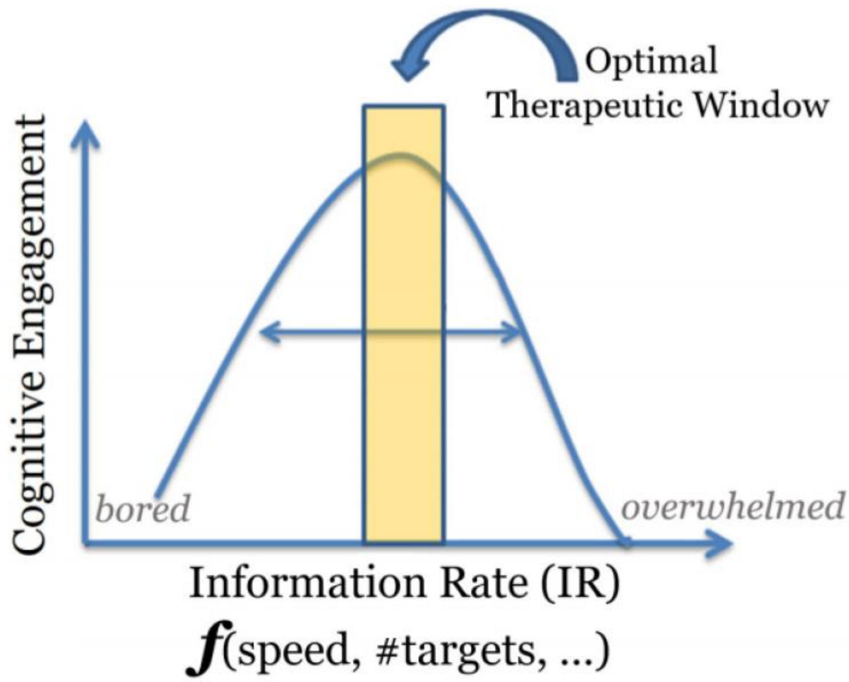


Figure 2.3: Cognitive Engagement Graph

of rehabilitation interventions, typically demonstrated through active, effort-full participation in therapy and cooperation with treatment providers" Lequerica and Kortte [1].

Cognitive Engagement is an integral chunk of neurorehabilitation, as it describes how engaged a patient is in a therapy session. As described above, neurorehabilitation therapy involves intensive repetitive tasks, which can make the patient uninterested and bored. This adversely affects the therapy, as lower cognitive engagement signifies lower brain activity, which means lower healing. As we can see in figure 2.3, the optimal therapeutic window is tiny. Hence, we need to assess how engaged the patient is and improve it if necessary.

Therapists and Clinicians were aware of lower cognitive engagement and looked at published research to fix the problem. However, these heuristic solutions also have their downside. These were:

- Self Reports:

  Self-reports are self-reported evaluations the patient does on their performance which the therapist uses to tweak the game. These are subjective and biased by the patient and hence not accurate.

- Physiological Signals:

  Physiological signals are readings that can be obtained from the patient via devices. Apart from having noisy data, they tend to be prone to sensory misplacement.

- Robot-derived Motor Performance Metrics:

  While robot-derived metrics come closest to what is happening, the data is usually compromised by the disease itself. Ex. If a patient suffers from impaired movement, the metrics derived from the robot itself would be insufficient in providing a clear picture of cognitive engagement.

Figure 2.4: Downside of heuristic solutions

2.4 Achieving Cognitive Engagement through Adaptability

Adaptability by certain parameters in a serious game can be used to assess and achieve cognitive engagement.

2.4.1 Accuracy

A measure of accuracy gives us a direct relationship to cognitive engagement Appleton et al. [19]. Simply put, the higher the accuracy, the better the patient is performing, hence more engaged. However, if the patient performs too well, it may be because the level of difficulty is low. Hence we need to increase the same, to make sure the patient is cognitively engaged. Similarly, if the patient performs too poorly, they may find the game too difficult, and we must reduce the difficulty level to ensure the engagement is high. In our game, we use accuracy to control the number of dots on the screen.

2.4.2 Reaction Time

Reaction time is another indicator of the patient's performance on cognitive engagement Barber et al. [20]. A patient's high reaction time is indicative of them requiring more time to make decisions. Hence, we would have to lower the difficulty of the game to compensate for the same. Lower reaction time, on the other hand, indicates the patient is quick to react to stimuli. Hence we would need to increase the difficulty to match the response. In our game, we use reaction time to control the speed of the dots.

2.4.3 Minimum Jerk

The minimum jerk profile is a derivative of acceleration that describes the movement pattern a patient ideally follows. The standard curve described by the profile can be used as a baseline to ensure that patients are cognitively engaged. The curve ideally has one peak, and initially increases up to the peak, and then gradually decreases as the patient reaches their target. If the patient follows any other form of movement, we know the patient is having difficulty performing their task. A higher minimum jerk profile indicates the patient can reach their goal quite easily, while a lower jerk profile, on the other hand, indicates they have difficulty reaching their target. Hence, we can accordingly increase or decrease the size of the target to ensure the patient has a standard minimum jerk profile.

Chapter 3

Game Design

In this chapter, we discuss the methodology behind the implementation of our serious game, including the basic concept of the game, robot infrastructure and how we can integrate or use it, game structure, the algorithms involved and the data and events captured.

3.1 Go No-Go Paradigm

The Go No-Go Paradigm is a method that is used to measure a component of cognitive control known as response inhibition.

3.1.1 Response Inhibition

Inhibition plays a central role in describing human cognition. Inhibition refers to the suppression of thoughts, actions, and emotions and is often regarded as a key component of executive control (e.g., Aron et al. [21] Miyake et al. [22] Logan [23]). Researchers have used this concept to explain several phenomena in clinical and cognitive psychology, neuropsychology and development. While the role of inhibitory processes is still debated (Macleod et al. [24]), researchers believe that some kind of inhibition is involved in deliberately stopping a prepared motor response (Logan and Cowan [25], Poldrack [26], Stuphorn and Schall [27])

Response inhibition is a primary process of executive control Criaud and Boulinguez [28]. It is pretty challenging to measure response inhibition, given its purpose is to suppress overt measurable behavior. However, because of its importance in cognitive neuroscience, scientists have been looking for a way to measure/study it. The Go No-Go paradigm and the Two Choice Experiments are the more popular choices with the stop-signal task to achieve the same. Thanks to its apparent simplicity, the go/no-go paradigm is supposed to ensure a reliable probing of response inhibition mechanisms. The basic underlying principle is that subjects respond when they are given the 'Go' stimuli and resist responding when the 'No-Go' stimuli are provided. The basic theoretical assumption is that inhibitory processes are phasic reactive mechanisms triggered by the external stimulus one must refrain from reacting to. Criaud and Boulinguez [28]

3.1.2 Go No-Go in our game

In this paradigm, participants are continuously provided with a stimulus which can be Go or No-go, and they have to respond accordingly. If the stimulus is Go, the participant responds, and if it is no-go, the participant withholds their response. This paradigm was first applied by Gordon and Caramazza [29] to a lexical decision task, where they claimed it gave better performance and less noisy data as compared to the two choice experiments.

In our game, we have implemented this paradigm using tracking and target dots. We shall explain this in more detail in the Game Structure section. The game has a Go stimulus if one of the tracking dots turns out to be a target dot, and a no-go stimulus if the target dot was not a tracking dot.

We have implemented this paradigm by introducing a Multiple Object Tracking (MOT) task which requires subjects to split their attention into multiple foci of attention. MOT is explained below.

3.2 Multiple Object Tracking (MOT)

Multiple-object tracking involves simultaneously tracking positions of some target-items as they move among distractors Trick et al. [30]. As described by Trick et al. [30], a classic multiple objects tracking task involves the following steps:

- Participants start with some identical visual items on a screen.
- Next, some of these items flash to indicate they are targets. This is usually a

subset (less than half) of the total number of items. The remaining items can be labeled as distractors.

- Once the flashing stops, the targets become identical in appearance to the distractors.

- All items are now set to random, independent motion, for a fixed time.

- The participants are now required to identify the items that were earlier targets.

- This process can happen in an iteration, with the number of targets to be tracked manipulated, while we measure the accuracy in every round. Accuracy is defined as the number of targets that were correctly identified.

It is an accepted fact that humans can focus selectively only to one region in the visual field at any instance. This comes from psychophysical and neurophysiological studies (e.g., Posner et al. 1978; Hoffman, 1979; Schulman et al. 1979; Posner, 1980; Jonides, 1983; Prinzmetal and Banks, 1983; Tsal, 1983; Eriksen and Yeh, 1985; Jolicouer et al. 1985). The first detailed study was conducted by Pylyshyn and Storm [31] and their results indicate young adults can track four to five items accurately, on average. This lead to coining of Fingers of Instantiation (FINSTs) which is a mental reference token, which allows items to be perceived as distinct from one another as well as distractors, and associate properties with them even when the move and change properties. The number of reference tokens is limited since it makes sense to focus only on a few items, instead of everything. Hence, FINSTs are used to focus on a few items for deeper processing. Consequently, there are corresponding limits to the number of items that can be individuated and tracked at once (Pylyshyn [32]). This is thought to be fundamental to visual-motor coordination and creating and maintaining short-term episodic representations of all the properties for selected individual objects within a visual scene. (Treisman, 1993). This has been further verified by a variety of techniques (e.g., Bahrami, 2003; Culham et al., 1998; Scholl and Pylyshyn, 1999; Sears and Pylyshyn, 2000; Yantis, 1992), although specialized trained adult populations have exhibited differences (Allen, McGeorge, Pearson, and Milne, 2004).

3.2.1 MOT Performance Metrics

Based on a literature survey, Bernardin and Stiefelhagen [33] defined performance metrics for multiple object tracking as:

1. Multiple Object Tracking Precision (MOTP):

$$MOTP = \frac{\sum_{i,t} d_t^i}{\sum_t c_t} \tag{3.1}$$

   It is the total error in the matches made, averaged by the total number of matches. It shows the ability of the participant to estimate precise object positions, independent of their skill at recognizing object configurations and keeping consistent trajectories.

2. Multiple Object Tracking Accuracy (MOTA):

$$MOTA = 1 - \frac{\sum_t (m_t + \mathcal{F}p_t + mme_t)}{\sum_t g_t} \tag{3.2}$$

   where m_t is the number of misses, $\mathcal{F}p_t$ is the number of false positives and mme_t is the number of mismatches. It is derived from three error ratios:

   - The ratio of misses, computed over the total number of items in all rounds.
   - Ratio of false positives.
   - Ratio of mismatches.

   Summing up all of the above gives us the total error rate E_t and $1 - E_t$ gives us the tracking accuracy. MOTA is similar to other popular metrics such as word error rate (WER) used in speech recognition.

The metrics give us a very intuitive measure of the participant's performance at detecting items and keeping their trajectories.

3.3 Robot Specifications and Integration

3.3.1 InMotion Robot

The Bionik InMotion 2 ARM robot is a 2-degree-of-freedom planar shoulder/elbow robot specifically designed for neurorehabilitation and enables clinicians to efficiently deliver intensive motor therapy to help patients regain motor function following a neurological condition or injury.

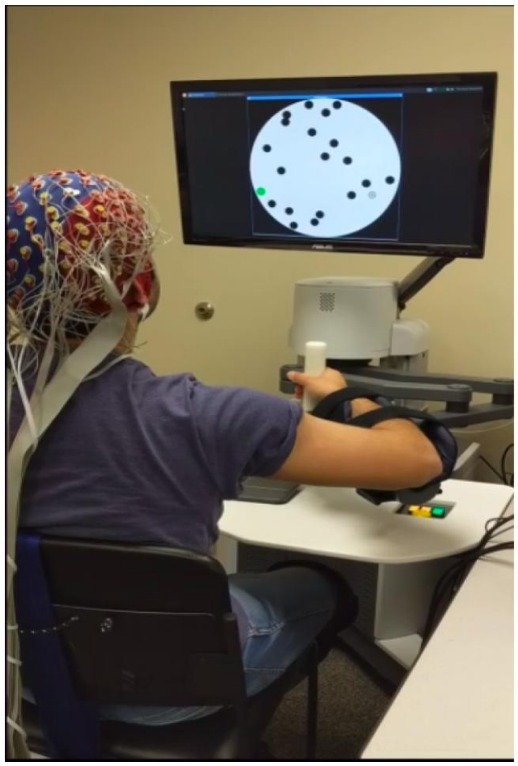


Figure 3.1: Participant playing our serious game on the robot.

Robot Hardware

The InMotion 2 robot consists of the following hardware components:

- Robot Arm
- Control Panel
- Junction Box

- CPU and Monitor
- Cabling
- Workstation Table

The planar robot is designed on the analogy of a human arm. It is not a prosthetic replacement for a human arm, but a special computer-controlled therapy/exercise machine. The robot arm has two links, corresponding to a person's upper arm and forearm. The upper arm link and its joint are together called the shoulder, the forearm link, and it's joint are the elbow. The two motors sit where the person's body would be, each motor controlling one of the links. At the wrist/hand endpoint of the planar robot, we have a grasping joystick attached along with support to strap a user's forearm.
The robot has two degrees of freedom, one for the shoulder and one for the elbow. This degree of freedom permits the handle to travel freely in the horizontal plane. The top motor controls the shoulder link, while the bottom controls the elbow link.

Interfacing Software

The robot has two back-drivable motors, encoders for sensing (x,y) position, and a force transducer for sensing forces. The hardware components are controlled through a data acquisition (DAQ) board in the CPU, which reads and writes data onto the analog to digital (a2d) and digital to analog (d2a) channels on the DAQ board. The InMotion 2 C programs perform the above actions, allowing us to change the control systems to suit our needs.
The robot software system runs on an Ubuntu distribution running a Linux 2.6 kernel, augmented with Xenomai real-time framework. Xenomai provides Linux with low-latency for interrupts and other real-time requirements, giving the programmer powerful tools to access raw robot metrics. The Linux kernel is run as a subordinate task under a tiny microkernel, hence providing just the near-minimum amount of software that can provide the mechanisms needed to implement an operating system.

Control Loop

Xenomai runs as a set of Linux Kernel Modules or LKMs which are real-time-enabled user-mode processes. The control loop runs as a daemon, which is a program that runs as a service, without actually being connected to a periphery device. A UI must communicate with the control loop through a client program. The InMotion2 robot performs the following tasks within each control loop:

- Read data from robot sensors
- Read data from reference sources
- Calculate controls based on input data
- Write control data to robot motors
- Write data to log channels

The control loop is written in C, as it is the language of the Linux kernel and it suits the deterministic requirements of real-time systems.

I/O and Data Structures

Programs that we design use shared memory buffers to access data processed in the robot control loop. Hence, we do not directly access robot control loop data, instead of reading from shared memory (SHM) to perform the necessary functions.

The robot has a data structure to describe the physical structures of the InMotion 2 system. They store data related to attributes of the two motors (input encoder angle, input tachometer velocity, and output torque) along with detailed values for each of the attributes. The robot handles this tree structured data as pairs, to circumvent object-orientedness.

File-oriented per-sample data, like logs and references, are sent over real-time pipes (rtpipes). Occasional data, like a request to tell the control loop to start or stop sampling, are sent using shared memory buffers (shm). Per sample data that is not being filed, like x/y position of the handle, used by a GUI, may be passed through either interface.

For the game design, user interface and logging, we decided to use Python, given its ease of usage and power. In particular, we used pygame to design the functionalities.

3.3.2 pygame

pygame is a Free and Open Source python programming language library for making multimedia applications like games built on top of the excellent SDL library. Like SDL, pygame is highly portable and runs on nearly every platform and operating system.

Why Pygame?

Pygame was the preferred library because:

- Does not require OpenGL
- Multi-core CPUs can be used easily
- Uses optimized C and Assembly code for functions
- Portable, easy to use
- Uses a small amount of code to perform the necessary task

3.3.3 Robot Pygame Integration

As mentioned above, the robot interface for accessing shared memory files is written in C. We need our game, designed in pygame to be able to access this shared memory. To achieve this, we wrote a simple, lightweight C program to access the required values from the shared memory buffers. We then wrote a service in python to access this C program to obtain real-time robot parameter values. We tested to ensure there is no significant lag/delay in the relay of this information.

3.4 Game Structure

The game consists of 120 rounds, with each round either being a go or no-go task. Each round can be broadly divided into two phases, Cognitive Task, and Motor Task.

3.4.1 Cognitive Task

The cognitive task encompasses the first phase of the round, wherein the participant observes a set of activities on the screen and decides the Motor Task. The game has a large white circle in the center, in which the following steps take place:

1. Display n black dots for 1 second.
2. A subset of n black dots turns blue. These blue dots can be labeled as Tracking dots. The tracking dots remain blue for 2 seconds and turn black again.
3. The dots move around for 10 seconds.
4. One of the dots, randomly chosen, turns green. This green dot is labeled as a Target dot.

The shape the dots move around in is a circle as the motion of the dots is kept as simplified as possible. Any other shape would have involved corners, which would have involved angles at the borders which would have made the motion of the dots complicated when they collided with the surface. We also ensure each dot is moving at an identical speed, to ensure all dots are identical.

The collision is simplified so that the participant does not have any difficulty in tracking the dots.

To ensure that the time intervals are not predictable, we introduce randomized jitter to keep the user focused on the task. The jitter introduces slight variation (200ms) for each time interval with varied values over each round.

Once the target dot appears the round moves to the next phase.

3.4.2 Motor Task

The motor task involves the participant moving the robot arm which controls a circular cursor on the screen. The participant has to move the cursor to the target dot if it was previously a tracking dot. If the target dot was not previously a tracking dot, the participant does not move. While the rounds are randomized 60-40% for go no-go,

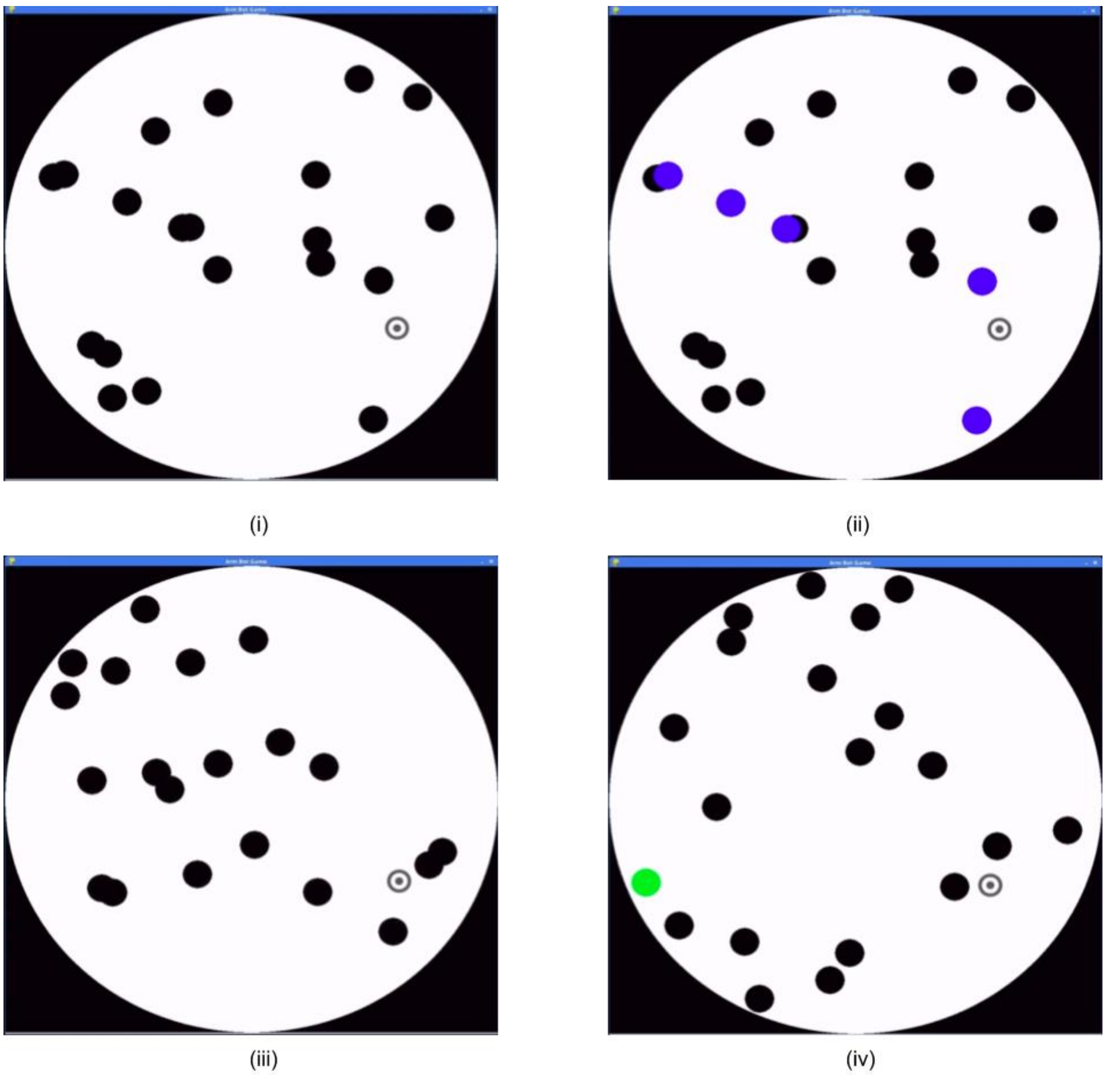


Figure 3.2: Game snapshots in during different stages of the game. (i) Displaying n black dots. (ii) Turning a subset of n black dots blue. (iii) Turning all the dots black, and independently moving them around. (iv) Turning the target dot green.

the order of each round is the same for every participant. The jitter values are also consistent among different participants.

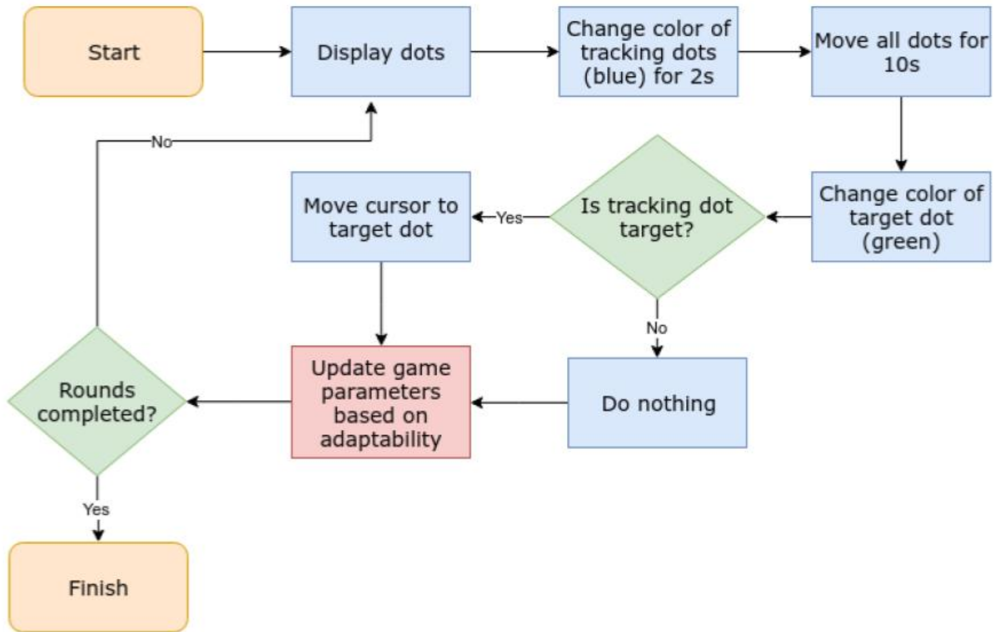


Figure 3.3: Game Flowchart

3.4.3 Game Adaptability

We have also included certain in-game adaptability measures. This includes actively using game statistics from each round to modify game configurations to adapt to a participant's performance. As discussed above, we have used accuracy to adapt the number of dots and reaction time to adapt speed.

Accuracy

Accuracy is defined as the number of Go and No-Go rounds the participant got correct, measured against the total number of rounds they have played for. We have a fixed interval, after which we check the accuracy to adjust the number of dots of the screen. We parametrized and limited the number we can change, ensuring the adaptability is controlled and subtle. We also fixed the maximum number of dots possible on the screen to ensure the same.

Currently, the game checks the accuracy every ten rounds, with an average accuracy of 70%. That means that if the accuracy at the end of 10 rounds is above 70%, we know the participant is playing well, and we would need to make the rounds more difficult by adding up-to two dots. However, if the score is below 70%, we know they are performing poorly, and we try and make the rounds easier by removing up-to two dots.

Reaction Time

Reaction Time is defined as the time duration between when the stimuli appear on the screen and when the participant begins to move. We begin by recording the reaction time for the initial few rounds to establish a baseline. We then use this baseline distribution's median to fix our desired reaction time. We then record the reaction time for a fixed interval and compare that distribution's median against our baseline. The percent change is how we increase/decrease each dot's speed, fixed by an incremental limit as well as boundary limits.

We initially check the reaction times for the first 20 rounds. Then at the end of every ten rounds, we look at the median reaction time of all the rounds excluding the last 10 and compare it to the median of the last ten rounds. We have an ordered bracket of different speeds, and we change brackets according to the percent change in reaction times.

3.5 Algorithms

The game has several concepts and designs implemented to achieve the necessary functions. They are:

3.5.1 Main Game Loop

Algorithm 1: Main Game Loop

```
Initialize game and pygame variables;
Build dots and pointer image;
while number-of-rounds > current-round do
    set jitter, pygame clock (time);
    increment current-round;
    while running do
        define CONTROL-BLOCK;
        draw outer circle;
        if time < 1 second then
            draw all dots previously built;
        else if 1 second ≤ time < 3 seconds then
            turn tracking dots blue;
        else if 3 second ≤ time < 8 seconds then
            turn all dots black;
            move-dots;
        else if 8 second ≤ time < 9 seconds then
            keep all dots stationary;
        else if 9 second ≤ time < 14 seconds then
            turn target dot green;
            check cursor movement;
            if cursor reached target then
                running = False;
            end
        else
            running = False;
        end
    end
end
```

3.5.2 Collision

Algorithm 2: Move each dot

```
Result: Move each visible dot in the large circle
for each visible dot do
    change dot by dx,dy;
    while check-dot-outside-large-circle do
        move dot back a pixel;
        switch dx, dy since normal reflection;
        change dot by dx,dy;
    end
end
```

3.5.3 Accuracy Adaptability

Algorithm 3: Change number of dots on screen

```
Result: Returns number of dots to be shown on the screen
difference = score - AVERAGE-SCORE;
if difference > 0 then
    inc-number-of-dots = ceiling(difference × MAX-CIRCLE-INC ÷
      (NO-OF-ADAPTING-ROUNDS - AVERAGE-SCORE));
    ensure number of dots isn't more than total number of dots;
else if difference < 0 then
    dec-number-of-dots = ceiling((1 - (score ÷ AVERAGE-SCORE)) ×
      MAX-CIRCLE-DEC);
    ensure number of dots isn't less than minimum number of dots;
```

3.5.4 Reaction Time Adaptability

Algorithm 4: Main Game Loop

```
Result: Write here the result
initialization;
while While condition do
    instructions;
    if condition then
        instructions1;
        instructions2;
    else
        instructions3;
    end
end
```

3.6 Events, Triggers and Logging

3.6.1 Game Events

Movement triggers are fired when value above set thresholds.

3.6.2 Logging

The game writes two types of logs capturing different information. They are:

1. Game Log

   The game log captures information at the end of every round. It stores the following information about each round, in a tab separated format:

   - Round Number
   - 1 if the trial was Go, 0 if the trial was No-Go
   - Integer, containing the number of dots on the screen for that round
   - Integer, containing the number of tracking dots for that round
   - Score for that round

Table 3.1: List of events and their corresponding trigger values

Event	**Trigger Number**	**Trigger Value**
Start of the game	1	0b00000001
Start of the trial	2	0b00000010
Start of tracking dots turning blue	3	0b00000011
End of tracking dots turning blue	4	0b00000100
Start of dots moving	5	0b00000101
End of dots moving	6	0b00000110
Target dot turning green	7	0b00000111
Target dot was blue	8	0b00001000
Start of moving towards the target (Go Scenario)	9	0b00001001
Start of moving towards the target (No-Go Scenario)	10	0b00001010
End of the trial (Not reaching the target)	11	0b00001011
End of the trial (Reaching target)	12	0b00001100
Start of break	13	0b00001101
End of break	14	0b00001110
End of the game	15	0b00001111

- Score so far, including the score for that round
- Distance moved by the cursor from the start of the trail until the end of the trial
- Distance moved by the cursor when the dot turns green until the end of the trial
- Reaction time

2. Robot Log

   The robot log captures robot kinematics every 16 microseconds along with trigger data, to give us which event previously occurred. It stores the following information about each instance, in a tab separated format:

   - Counter
   - Robot Arm x coordinate
   - Robot Arm y coordinate
   - Robot Arm x velocity value

- Robot Arm y velocity value
- Last fired trigger value

Chapter 4

Results

In this chapter, we plot the distribution of the game statistics as well as the confusion matrix for Go No-Go.

4.1 Plots of Distribution of Game statistics

4.1.1 Average plots of game statistics

We averaged the values for each round across all participants and plotted the same.

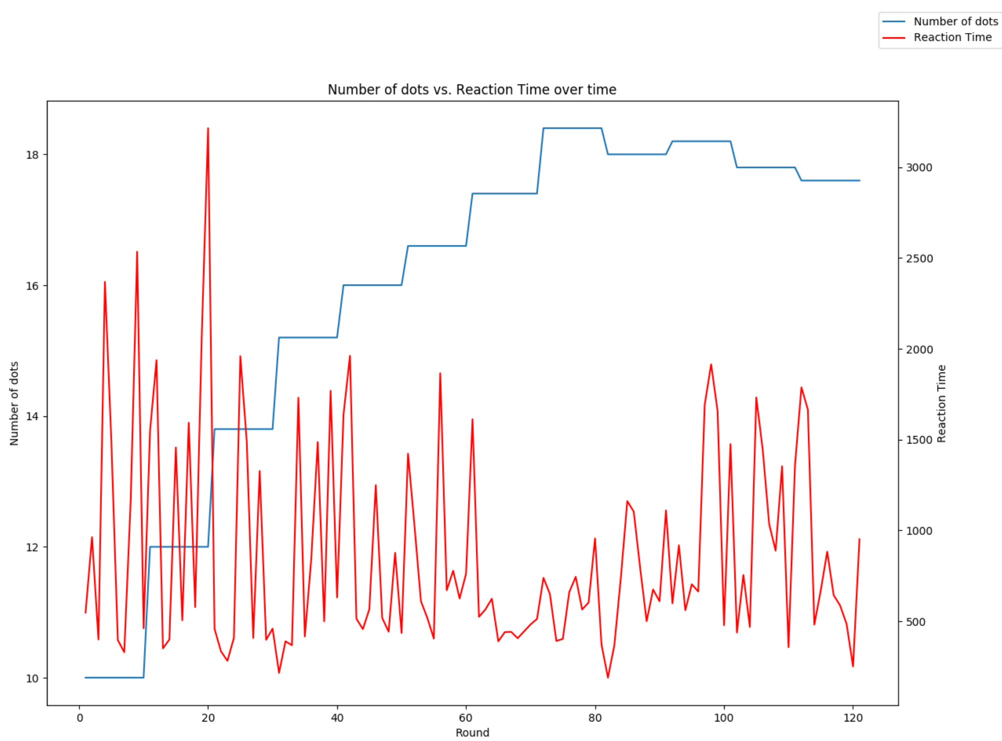


Figure 4.1: Plot of Number of Dots vs Reaction Time over Number of Rounds

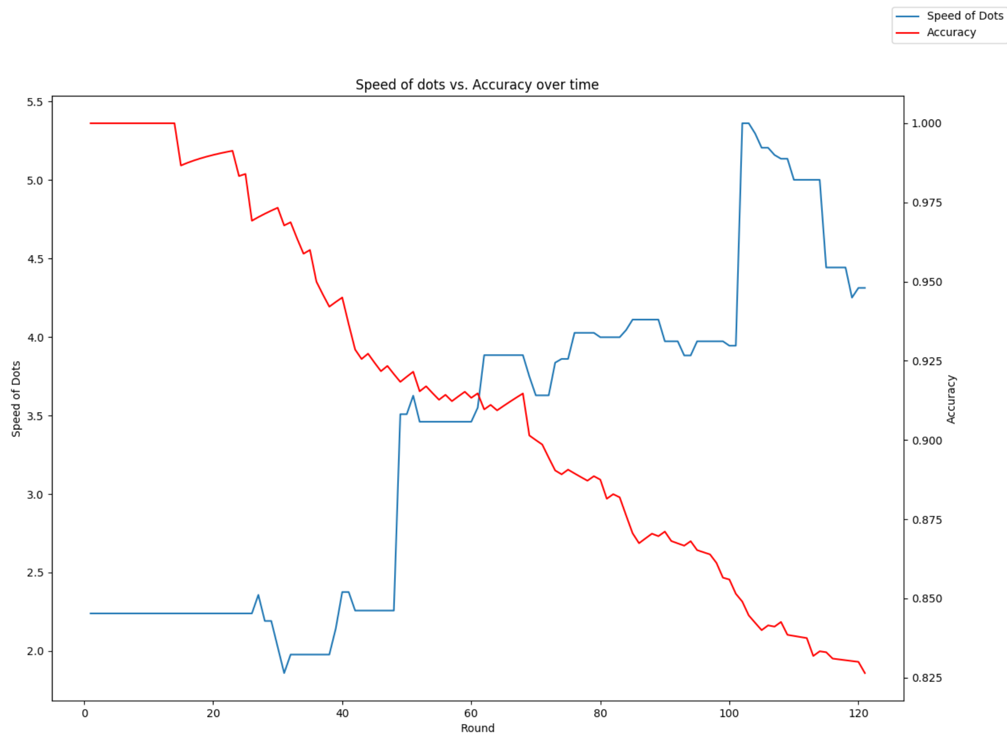


Figure 4.2: Plot of Speed of Dots vs Accuracy over Number of Rounds

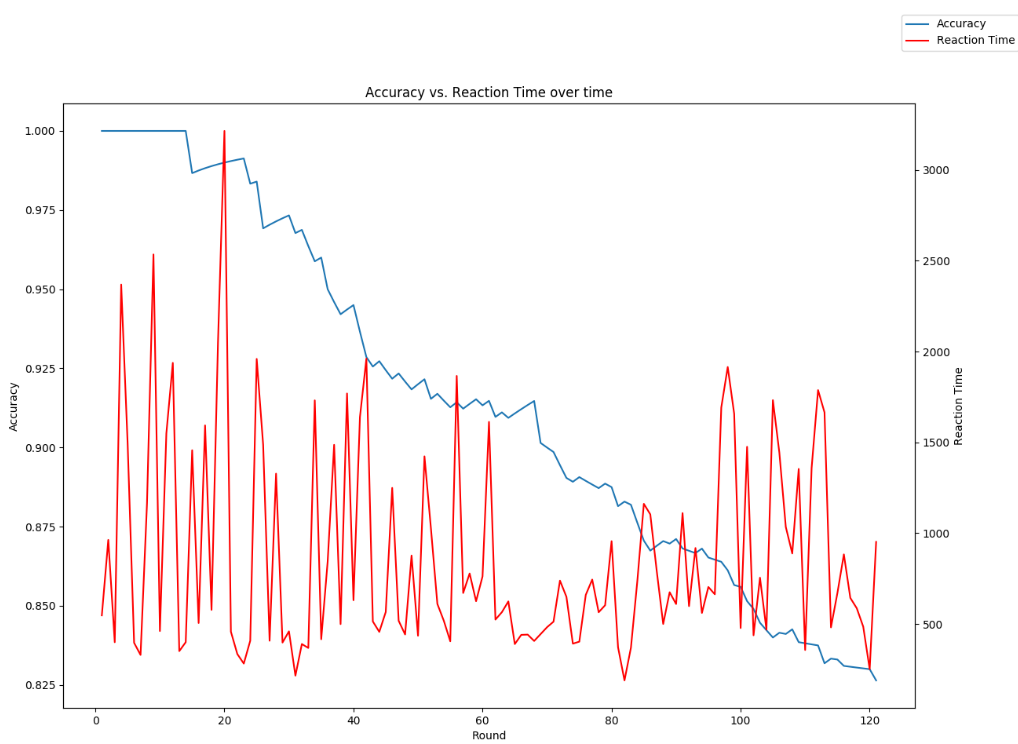


Figure 4.3: Plot of Accuracy vs Reaction Time over Number of Rounds

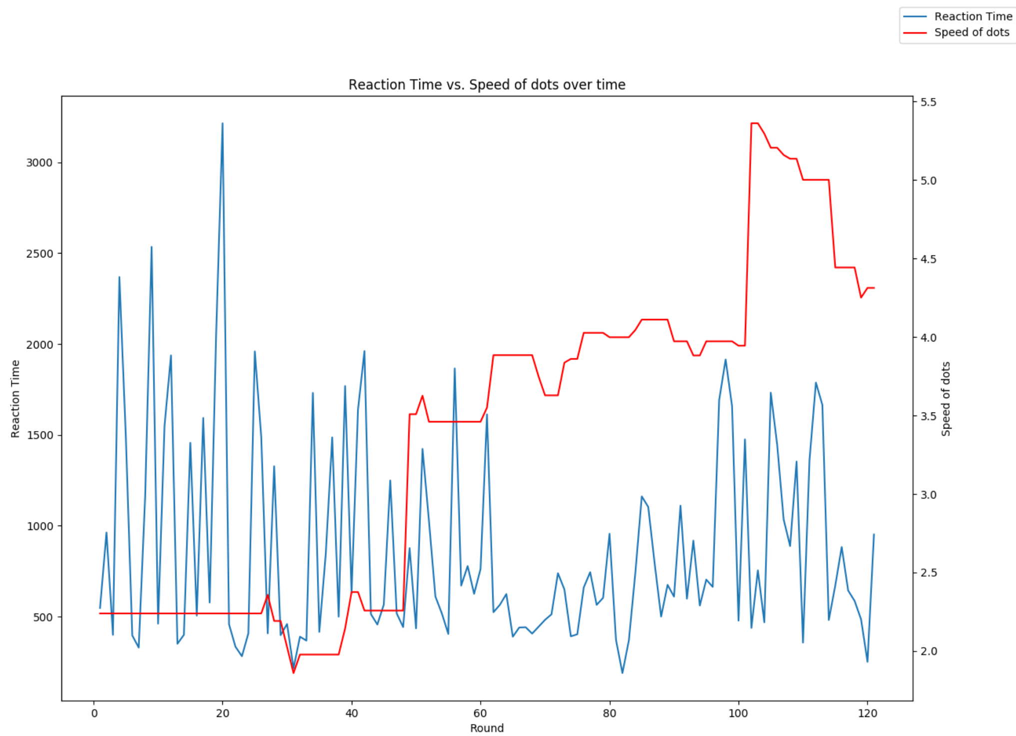


Figure 4.4: Plot of Reaction Time vs Speed over Number of Rounds

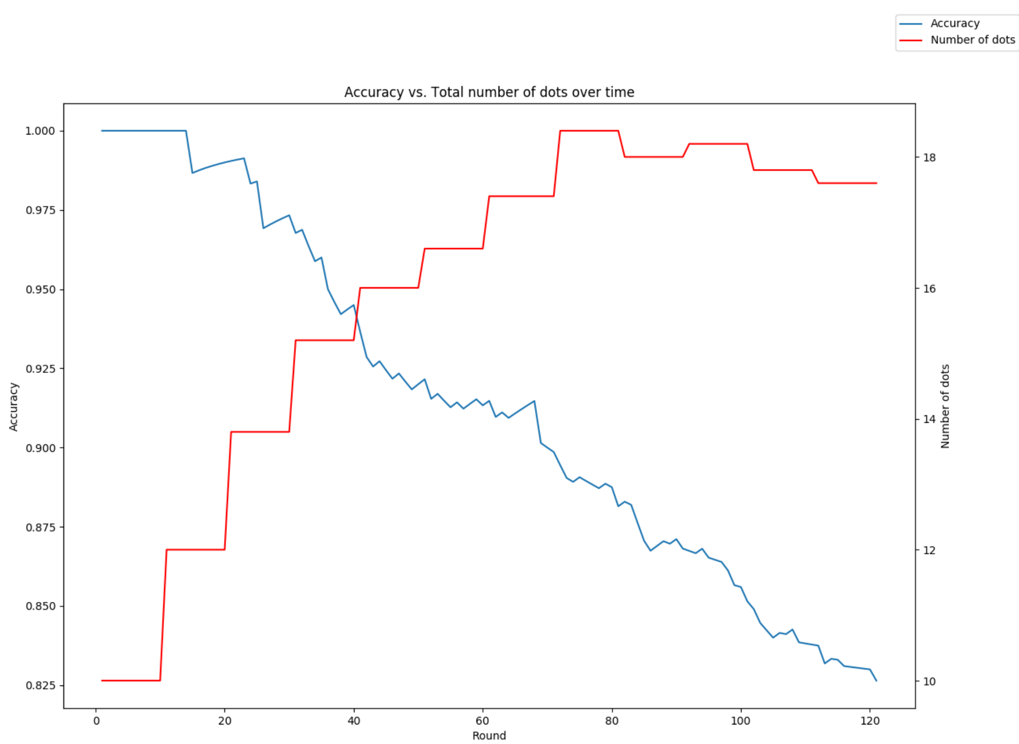


Figure 4.5: Plot of Accuracy vs Number of Dots over Number of Rounds

4.1.2 Distribution of Reaction Time

In this figure, we have plotted the distribution of reaction time, which is the frequency of the reaction time of each of the participant.

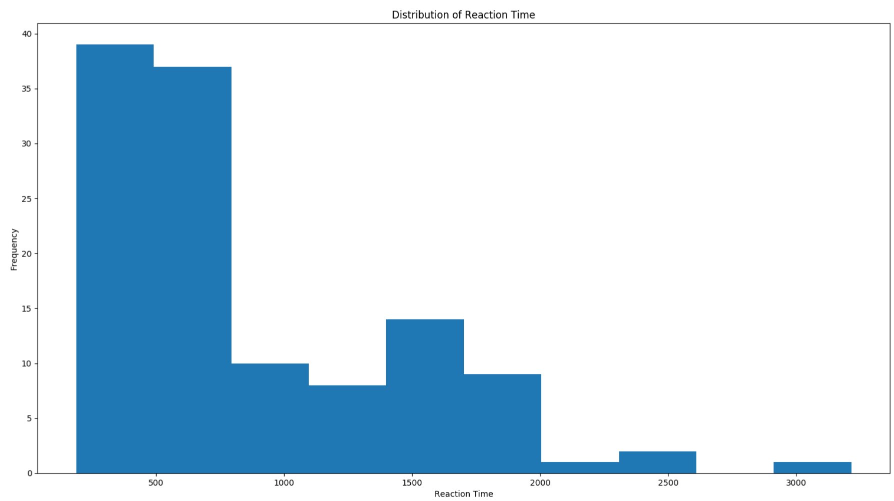
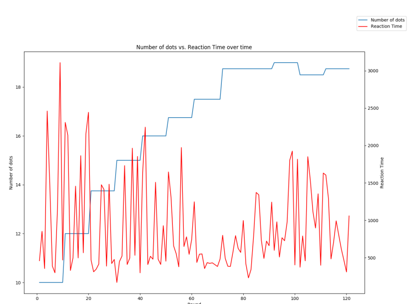


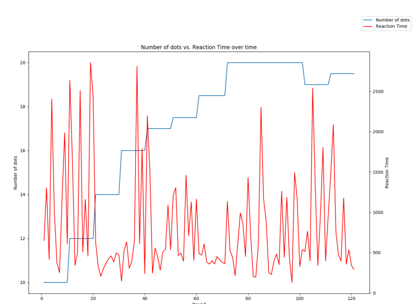
Figure 4.6: Distribution of Reaction Time

4.1.3 Individual Plots of game statistics

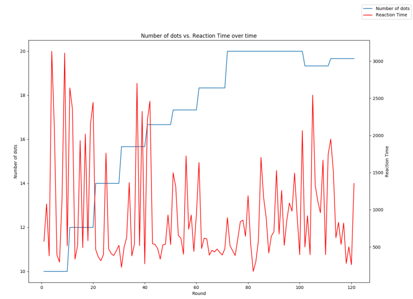
Here we have plotted the 5 comparisons similar to Section 4.1.1 but for each participant instead of an aggregate.



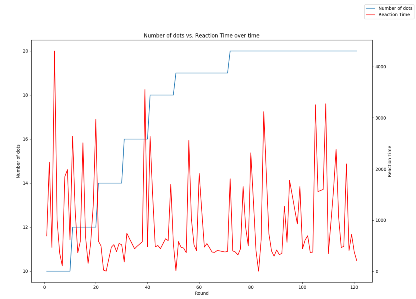
(a) 1a



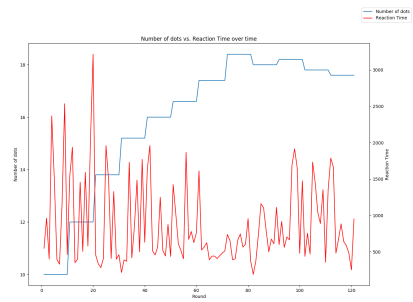
(b) 1b



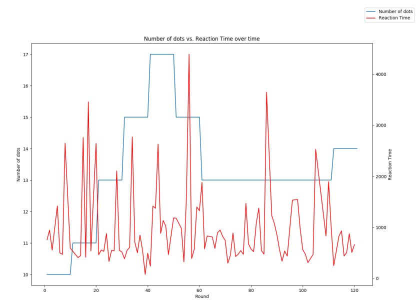
(a) 1c



(b) 1d

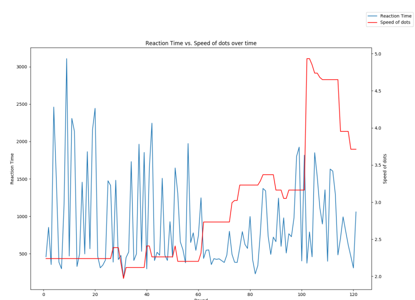


(a) 1e

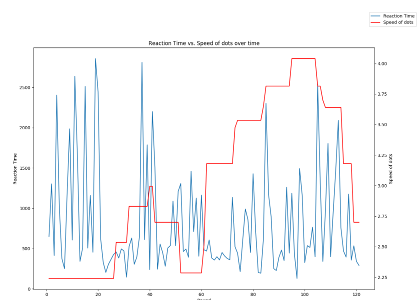


(b) 1f

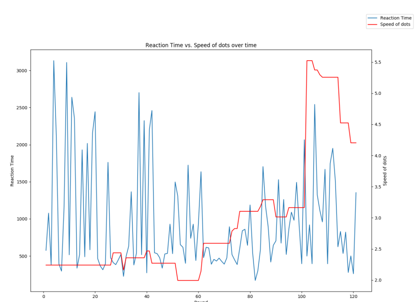
Figure 4.9: Figures of Number of Dots vs Reaction Time over Number of Rounds for all participants



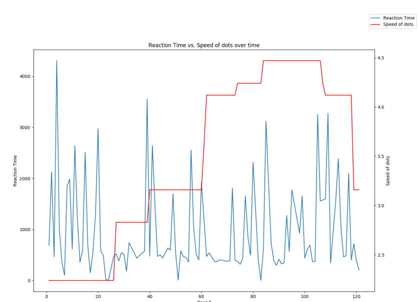
(a) 2a



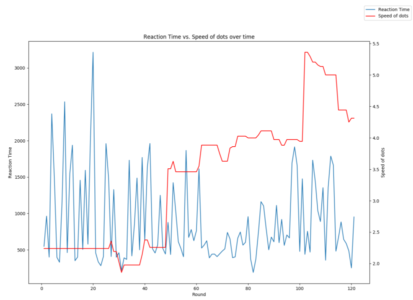
(b) 2b



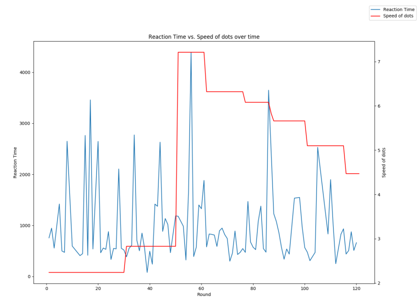
(a) 2c



(b) 2d

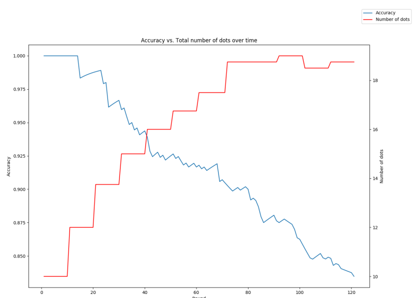


(a) 2e

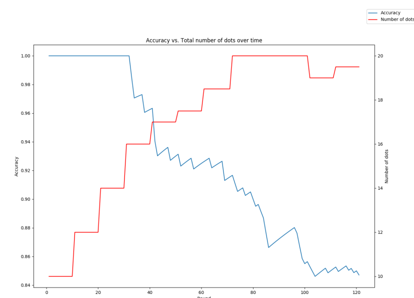


(b) 2f

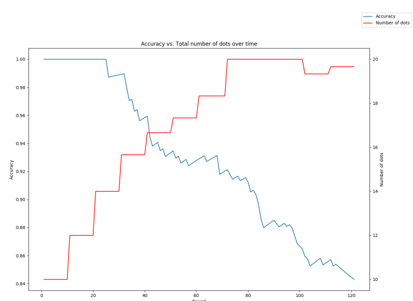
Figure 4.12: Figures of Reaction Time vs Speed of the Dots over Number of Rounds for all participants



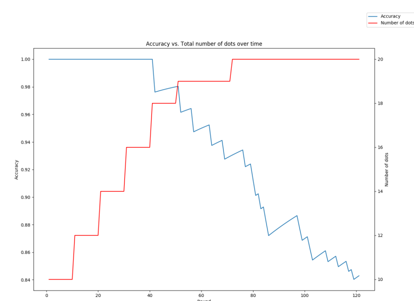
(a) 3a



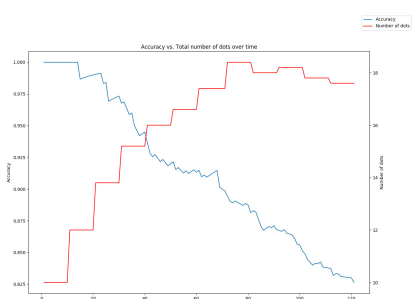
(b) 3b



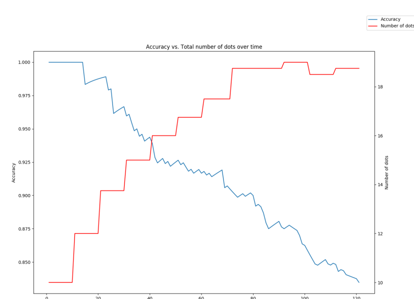
(a) 3c



(b) 3d

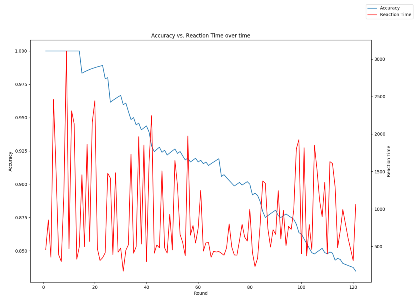


(a) 3e

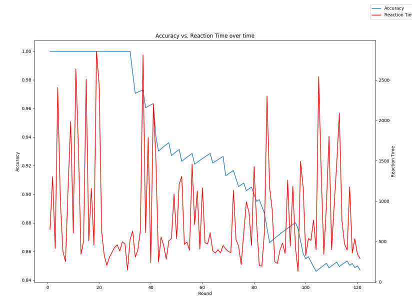


(b) 3f

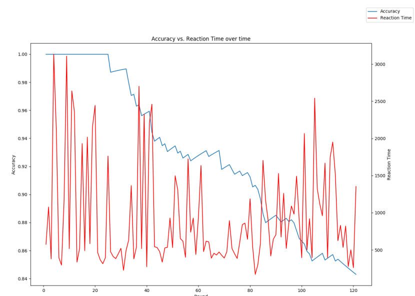
Figure 4.15: Figures of Accuracy vs Number of the Dots over Number of Rounds for all participants



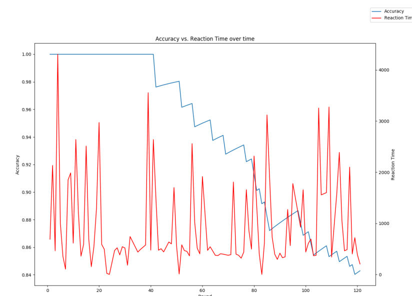
(a) 4a



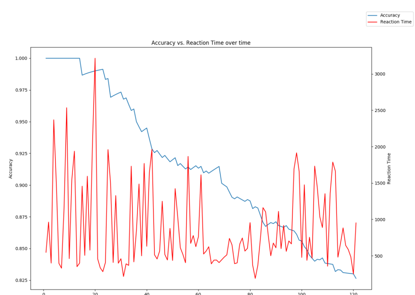
(b) 4b



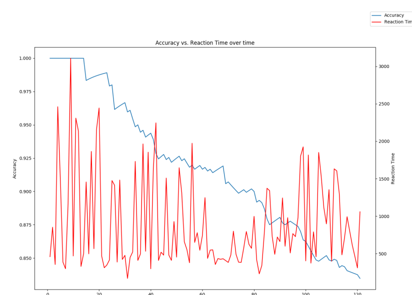
(a) 4c



(b) 4d

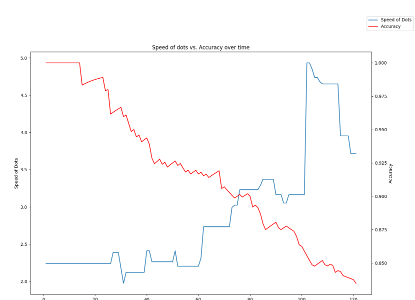


(a) 4e

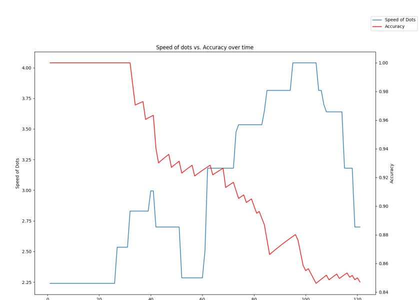


(b) 4f

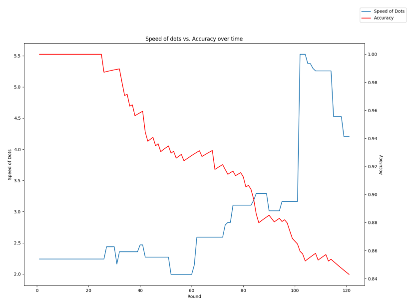
Figure 4.18: Figures of Accuracy vs Reaction Time over Number of Rounds for all participants



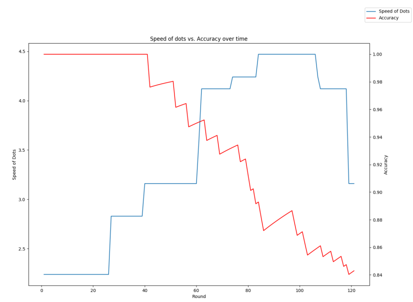
(a) 5a



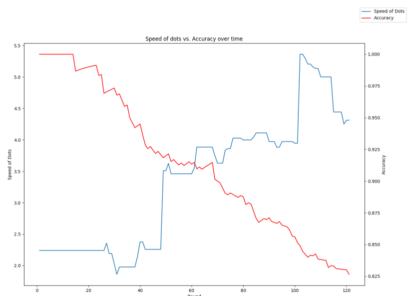
(b) 5b



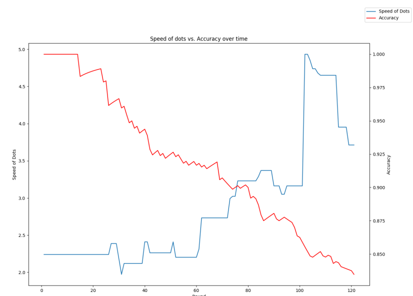
(a) 5c



(b) 5d



(a) 5e



(b) 5f

Figure 4.21: Figures of Speed vs Accuracy over Number of Rounds for all participants

4.2 Confusion Matrix

Here we plot the confusion matrix for data collected over all the participants for every round.

original choice

actual choice	Go	No-Go	total
Go	TP 381	FN 50	431
No-Go	FP 75	TN 220	295
total	456	270	

1. True Positive Rate or Sensitivity

$$TPR = \frac{TP}{TP + FN} = \frac{381}{381 + 50} = 88.39\%$$

2. True Negative Rate or Specificity

$$TNR = \frac{TN}{TN + FP} = \frac{220}{295} = 74.57\%$$

4.3 Player Performance

Player performance gives us details about how each participant performed during the experiment.

Table 4.1: Data on each player's performance

Player	**Total Score**	**Maximum Dot Speed (pixels per second)**	**Maximum Dot Count**	**Average Go Reaction Time (ms)**
Player 1	98	3.16	16	540.8
Player 2	101	7.21	17	727.39
Player 3	103	3.61	20	432.1
Player 4	101	8.49	20	655.68
Player 5	102	4.47	20	643.2
Player 6	96	7.21	17	584.47

Chapter 5

Discussion of Results and Conclusion

5.1 Discussion

5.1.1 Distribution of Reaction Time

From the plot in Figure 4.6, we see that the reaction time has a stereotypical distribution called ex Gaussian (Matzke [34]). Here, as expected, the reaction time peaks for values from 200 to 500 milliseconds, and gradually decreases as the time increases. This is because the reaction times are ideally between 200ms to 700ms, while the other values around it are noisy data and misfires. The curve is not as smooth as expected because we are trying to fit the curve on raw data without any pre-processing (removing noise).

5.1.2 Speed vs. Accuracy Tradeoff

From Figure 4.5 and 4.21 5a - 5f we see that the trend followed is similar to a popular concept of Speed-Accuracy Trade-Off, which describes that in any activity or game if we try to gain on either speed or accuracy, we compensate for it by reducing the other (Bogacz [35]). While in the traditional sense, the speed-accuracy trade-off occurs on the object that the participant controls in the game, here we see that the speed of the game affects the accuracy of the participant. For example, in our game, we can achieve higher accuracy by reducing speed. Alternatively, increasing speed will lead to lower accuracy. A general conclusion for this is that increasing speed makes it harder for patients to focus and aim at the dots, and they end up losing accuracy for the same.

5.1.3 Confusion Matrix

From the confusion matrix we see that, as expected, the diagonal values (top left and bottom right) are very high, while the other two are low.

Sensitivity, also known as true positive rate measures the portion of actual positives that are correctly identified. Hence, a high sensitivity of 88.39% signifies that on average, participants were able to successfully identify the 'Go' stimuli.

Specificity, also known as true negative rate measures the proportion of actual negatives that are correctly identified as such. Hence, high specificity of 74.57% signifies that participants were able to identify the 'No-Go' stimuli. However, since specificity is lower than sensitivity, we can also see that participants were able to identify the 'Go' stimuli better than the 'No-Go' stimuli, which is expected, since response inhibition is difficult for the participant to achieve, as they have to work harder for it.

5.1.4 Reaction Time vs Speed

While speed and reaction time should be inversely proportional, we notice that (Figure 4.4) the speed tends to be slower for a high fluctuation in reaction time. We may need to further process reaction time to obtain a better co-relation, perhaps applying median filtering and removing noise.

5.1.5 Accuracy vs. Number of Dots

For a comparison between accuracy and number of dots as seen in Figure 4.5 we have, as the number of dots increases, accuracy decreases, which is expected, as a higher number of dots would indicate a higher difficulty, leading to lower accuracy.

5.1.6 Mental Fatigue

Another noticeable trend from Figure 4.1 and Figure 4.3 is that as time progresses, reaction time gets smoother, and the number of dots begins to drop as well. The accuracy also seems to drop steeply, indicating that the participants may be encountering mental fatigue, leading to lowering of concentration.

5.1.7 Accuracy vs. Reaction Time

The traditional speed-accuracy trade-off, the graph should ideally show a decreasing accuracy as the game progresses, and a corresponding increasing reaction time. However, what we see is a very gradual increase in reaction times with many spikes. The spikes could be attributed to mental fatigue, as well as

5.2 Conclusion

The observations are based on data collected from healthy individuals so that we can establish a baseline. This can then be used in the future when this methodology is extended to patients and their therapy sessions. Hence, our main goal here was to implement robust adaptive strategies and monitor its outcome on therapy sessions.
Overall, our approach aims to elucidate the underlying neurophysiological mechanisms of cognitive engagement during motor learning and inform the design of new Neurorehabilitation Robots, with built-in adaptability. Further, this adaptability is expected to optimally drive therapeutic robots as they interact with brain dysfunction to steer it towards normalcy.

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