Continuous Monitor of Decision Processing to Measure Changes of Mind

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ABSTRACT

Perceptual decision-making is a huge part of everyday life; every time a stimulus is sensed, be that seen, heard, smelt, felt or tasted, and categorised as to what it is, a perceptual decision is being made. Despite this being a very common occurrence, not much is known about the mechanisms underlying how these decisions are made.

This project aimed to develop and validate a novel method of user response for use in decision-making trials. Previously, response systems were limited to binary responses in button presses. With recent investigations into response dynamics recording more response information, such as mouse cursor position to reveal more about decision processing, a continuous force measurement response could provide more information into the process. This would allow for the unfolding decision to be recorded and analysed on a single trial basis, maintaining artefacts such as changes of minds that would get lost with trial averaging, as is done with electroencephalogram (EEG) analysis. This motivated the development of the dual load cell system for this project .

A novel system was developed using two load cells to record participant responses during perceptual decision trials. The experimental program was run using Matlab and Psychtoolbox. It showed the participant two grating patterns angled in different directions at different brightness levels. The participant had to determine the brighter pattern and log their response by putting more force on the load cell. Trial conditions consisted of a high contrast difference, a low contrast difference, a low contrast difference with a temporary reduction in the higher brightness level,

a low contrast difference with a temporary increase in the lower brightness level and a low contrast brightness swap.

These conditions were selected as it was theorised they could cause changes of mind. Trails were run with seven people (two female), each taking part in a practice session and then a trial session where they did ten blocks of 60 trials, giving information on 4200 trials. During these trials, an electromyogram (EMG) was recorded of the first dorsal interosseous muscle (FDI) that could be used to provide more information about the response dynamics.

Trials where changes of mind were present were detected using this system, demonstrating the ability of the load cell to capture single trial occurrences that could be used for improved EEG analysis. The stimulus conditions were shown to affect response time, accuracy and the rate of changes of mind. The most changes of mind were detected in the brightness swap condition.

Future work for this project includes analysing the EMG signals in tandem with the force signals to improve the understanding of response dynamics and running trials while recording EEG. This would provide unique insight into the processes behind decision-making and help us understand how they work.

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LIST OF ACRONYMS

ANOVA Analysis of Variance. 30, 37

BCI Brain-Computer Interface. 3

CCP Centroparietal-Positiveity. 11

DAQ Data Acquisition. 20

DSNP Discriminative Spatial Network Pattern. 12, 13

EEG Electroelcephelogram. 3, 11, 12, 17

EEG Electroelcephelogram. 47

EMG Electromyogram. 5, 8, 13, 27, 28, 29

EMG Electromyogram. 25, 46, 47

ERP Event Related Potential. 11, 12

FDI First Dorsal Interosseous Muscle. 27, 28

LDA Linear Discriminate Analysis. 13

LHB Left Hemisphere Beta-band Signal. 11

LIP Lateral Interperenial Area. 10

MVC Maximum Voluntary Contraction. 25, 28

RT Response Time. 2

SNR Signal to Noise Ratio. 14

SSVEP Steady State Visually Evoked Potential. 19

CHAPTER

ONE

INTRODUCTION

1.1 Background

Every time we see, hear, smell, taste or feel something and identify it, we are decision-making. Every time we consciously move, we are decision-making. Every time we do something seemingly in the spur of the moment, we are decision-making. Decision-making is a massive part of everyday life, but the mechanisms that govern it are still relatively unknown (Merfeld et al. 2016). Perceptual decisions are those where sensory evidence is used to discern what is being sensed. Broadly, their processing can be looked at in three stages: sensory evidence accumulation, evidence integration or processing, and action response. While not outwardly something that might seem very important, understanding the inner workings of how decisions are processed has wide applications in understanding an array of neurological conditions. Understanding what differences in processing can lead to people making "risky" or "incorrect" decisions can help us in treating these conditions (Koop & Johnson 2011).

Models are developed to better grasp how people's behaviour correlates with the neural activity we measure. The most widely accepted theory behind decision-making in two-choice discrimination tasks is the drift-diffusion model, visualised

in 1.1; this theorises that sensory evidence is accumulated as a decision variable until it has reached a certain acceptance threshold. The speed at which evidence is accumulated, called the drift rate, provides the mean for the standard deviation of the response times (RT)(Ratcliff & McKoon 2008).

A standard method of user response when investigation decision processing is a

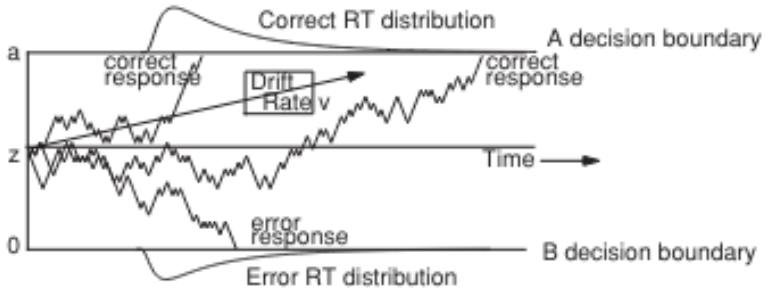

Figure 1.1: Drift Diffusion Model (Ratcliff & McKoon 2008)

button press input, such as Grogan, Rys, Kelly & O'Connell (2023). Still, there has been a recent trend in looking at new response systems that account more for the evolving decision, such as was used in Koop & Johnson (2011), which tracked mouse cursor movement as a decision was being made, or Scherbaum et al. (2010) which tracked cursor movement of a Wii controller.

There is potential to get more information about the mechanisms behind decision-making by tracking the dynamics of the process of deliberation throughout said deliberation (Koop & Johnson 2011). With this in mind, this project aims to develop a method to analyse evolving decision-formation dynamics on a single trial basis.

1.2 Motivation

This project aims to help better understand decision processing in the brain. People suffering from neurological disorders that affect maladaptive risk-taking behaviour as described in Yechiam, Busemeyer, Stout & Bechara (2005) could benefit from a greater understanding of how decisions are processed.

More specifically, the motivation is to get a new insight into decision processing.

The standard methods of continuously recording the processes governing decision processing, implanted electrodes, and electroencephalogram (EEG) do not provide enough information. In the case of implanted electrodes, although there is increased resolution, only a relatively small collection of neurons is recorded. EEG can measure many more neurons but has to be averaged across similar trials to reduce the noise. These characteristics mean that multiple models can explain the resulting measurements, but there is no way to know which ones, if any, are correct.

When a response is collected with a button press, there is potential insight into the evolving decision that is not collected. Developing a response system that can continuously measure a discrete response as it evolves in a single trial, without the need for averaging, would allow for more insight and, therefore, more accurate models for decision analysis.

This progression of the field of neuroscience further helps UN Sustainability Goal Three to ensure healthy lives and promote well-being for all ages. Aside from the help that a more in-depth understanding of decision processing can provide to people with conditions affecting that, a better understanding of the mechanisms behind the brain allows for better coverage with brain-computer interfaces (BCI). BCIs help improve the lives and health of people suffering from many conditions(Haselager et al. 2009, McFarland et al. 2017, Värbu et al. 2022), the more unknown workings of the brain that are revealed and explainable, but greater the potential of BCIs to help people.

The possible contribution to the field of neuroscience is also partially motivated by UN Sustainability Goal Nine, which is to build resilient infrastructure, promote inclusive and sustainable industrialisation and foster innovation. The system sought to be developed with this project would help foster further innovation in the field of neuroscience (*THE 17 GOALS | Sustainable Development* n.d.).

1.3 Overall Aim

This project aims to develop and test a novel user response system for perceptual decision-processing trials. This system will record the evolution of the participant's response over the course of a single and provide new insight into the mechanisms behind decision-making that were not previously available in the dynamics of the participant's response.

1.4 Specific Objectives

The objectives of the project are:

1. To develop software to record continuous user response using a dual load cell system.

   This would be done using Matlab object-oriented programming to create an object to account for the load cell information. This object would have associated methods allowing calibration values to be set manually or collected using a calibration protocol. The program would always require minimum force to be placed and maintained on the sensor to begin the trial. This would solve a flaw with Koop & Johnson (2011)'s response system; there could have been a flooring effect on the response data when the mouse is not in motion.

2. To develop a Matlab Psychtoolbox program to display decision-processing trials.

   This would display two grating patterns of different contrast and orientation to the participant, who would have to discern the brighter and respond using the developed system. Object-oriented programming would be used to show different stimuli based on input values. In a given trial, one of five possible conditions could be shown.

3. To record Electromyogram (EMG) data for the participants.

   This would be collected using a Delsys Trigno EMG recording system to measure the left and right index finger flexion muscle activation energy.

4. To test the system's viability to provide trial-specific decision-making information, such as the occurrence of changes of mind.

   This would be done in Matlab, where each trial would be saved into a data structure. This structure would contain the demographic data, load cell and EMG recording, and the trial information for each specific run. This would be used to determine if a change of mind had been detected and to assess the ability of this new system to provide trial-specific feedback.

CHAPTER

TWO

LITERATURE REVIEW

2.1 Introduction

2.2 How do we Model Decision Making?

Decision-making is a common occurrence in everyday life; perceptual decisions can be looked at in three processing stages: the sensory evidence is analysed, a decision is made, and the response is triggered (Sternberg 1969, Kelly & O'Connell 2015). There is interest in applying a model to understand the connection between behaviour and the cognitive processing that informs it.

Gold & Shadlen (2007) describes some of the basic understandings of how decisions are processed in the brain. It discusses the Signal Detection Theory for decision-making. This theory, first discussed in Green & Swets (1966), assumes that the evidence for a brain making a certain decision could be measured as the activity of a neuron or a group of neurons. If this evidence is informative about the evolving decision, then it can be seen that it varies with a different stimulus. This theory states that this evidence variable is subject to noise and, therefore, can be viewed as a stochastic distribution about a mean dependent on the stimulus

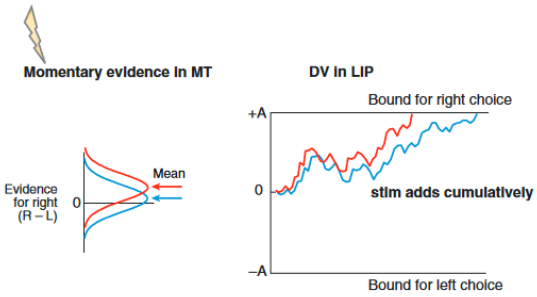

Figure 2.1: Demonstration of the Diffusion Decision Model from Gold & Shadlen (2007)

(Kingdom & Prins 2016). This theory provides a good framework for forced-choice decision-making processing by viewing the probability of correct choice as a function depending on the stimulus. This has wide applications across many fields, not just perceptual decision-making (Lynn & Barrett 2014). Macmillan & Creelman (1991) discusses the sensitivity and bias of a certain decision based on a given stimulus and how this can be used to inform decision modelling. In modelling decision processing, however, it is imperfect and fails to account for a point when enough evidence has been collected to make a decision. Wald & Wolfowitz (1950) introduced this idea by theorising about the minimum amount of observations needed for a certain decision to be made, which accounted for this shortcoming, giving bounds to the model.

This led to the development of sequential analysis, which built upon the signal detection theory of Green & Swets (1966) and the sequential analysis method of statistical inference by Wald (2004). This allows for a decision variable that can change through time as subsequent samples are collected (Gold & Shadlen 2007). This theory informed Ratcliff's diffusion models of decision processing, which were modelled specifically as random walk diffusion models (Ratcliff 1978, Ratcliff & Rouder 1998, Ratcliff & McKoon 2008). Random walk refers to the stochastic method that the accumulated evidence diffuses towards the acceptance boundary (Masuda, Porter & Lambiotte 2017). In this model, the evidence that drives the decision is accumulated until it reaches a high enough level of certainty to illicit a response. This model conflates certainty with the drift rate of the decision variable, with a faster move towards the boundary corresponding to a clearer difference

between possible stimuli. This accounts for any the relationship between task difficulty and reaction time (Ratcliff 1978).

Further continuation of the drift-diffusion model in Dendauw, Evans, Logan, Haffen, Bennabi, Gajdos & Servant (2024) sees the inclusion of EMG recordings to account for the role of muscle preparation and activation in decision processing. This model theorised that the sensory evidence was continuously transmitted to the muscles that would react once a "gate" or threshold level had been exceeded. This allows for EMG analysis to be used during decision-making trials.

The forced choice nature of the Signal detection theory means that it is only applicable to specific scenarios. The drift-diffusion models are suitable for two-factor perceptual decisions but do not work as well in more complex scenarios and decision-making trials, Ratcliff, Smith, Brown & McKoon (2016) says that multivariate decision models utilise racing accumulators and do not account for response competition as is accounted for in the two choice diffusion models. It should be noted that while there are many models for decision processing, uncertainty with the measurement systems of neural activity means that there is not enough evidence to rank one over another.

2.3 How is Decision Making Measured?

2.3.1 Experiments with Animals

Perceptual decision-making trials have been carried out on both animals and humans, with each providing valuable insight into how the brain works. Hanks & Summerfield (2017) provides a review of trials done with rodents, monkeys and humans in the field of perceptual decision neuroscience. It explores the previous trials that have been carried out and looks at emerging trends in them.

Rodents, while dissimilar to humans, have recently been used to provide critical insights into many aspects of the decision-making process. Hanks, Kopec, Brunton, Duan, Erlich & Brody (2015) used rodents to monitor the evolving decision variable in the posterior parietal cortex and prefrontal cortex. Recording

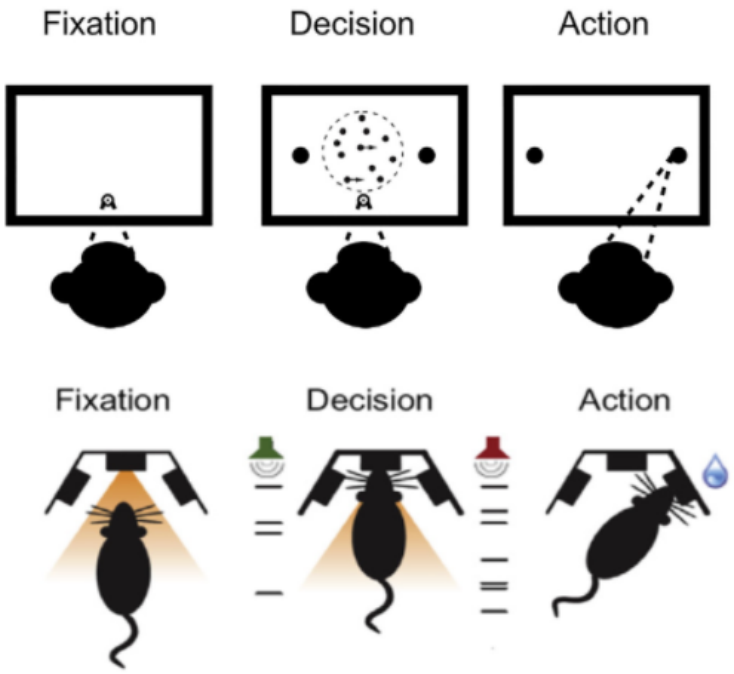

Figure 2.2: Animal Decision Processing Trials - Dot Motion Coherence Task for Monkeys - Auditory Detection Task for Rodents (Hanks & Summerfield 2017)

of the rodents was carried out using platinum-iridium tetrodes in nine rodents, and eighteen of them were used for optogenetic inactivation. Optogenetics is a method that utilises both optical and genetic techniques to inhibit specific cells of living tissue in animals(Deisseroth 2015). Rodents are well suited to cutting-edge technologies like optogenetics and their use in measuring decision processing reveals aspects that are unmeasurable in humans or larger animals. Earlier animal decision processing was carried out on monkeys, as it was in Pare (n.d.). This trial, informed by previous research (Maunsell & Newsome 1987), explored the brains of rhesus monkeys for visual processing information. The experiment sought to discover the effect of lesions on the middle temporal visual area of the brain by placing such lesions on two rhesus monkeys' brains and having them carry out decision-making tasks. There were two types of tasks in this experiment: a motion coherence task and a contrast differentiation task. The monkeys were recorded using an implanted magnetic search coil for eye movement, based on Judge, Richmond & Chu (1980) and a stainless steel microelectrode, as was used

in Evarts (1968). The study found that, while it had been widely theorised that the middle temporal visual area was responsible for motion information to inform eye movements, this paper found that it affected the perception of motion overall, with it having little to no effect on the contrast differentiation trails. The stimuli used in this paper and the method of recording the brain signals are used in a lot of decision-processing experiments, even though this paper was not concerned with the actual decision-processing.

Huk & Shadlen (2005) used a similar technique as in Pare (n.d.) for neural monitoring in an implanted eye coil and a glass-coated titanium electrode recording cylinder. The purpose of this experiment, however, was to investigate whether or not the lateral interperenial area (LIP) was responsible for processing sensory evidence in decision-making. Again, two rhesus monkeys were examined while a random dot motion discrimination trial was carried out. Recordings were made from the lateral bank of the intraparietal sulcus in a region corresponding to ventral LIP; this decision was informed by Lewis & Van Essen (2000). Extra difficulty was added to the task by adding pulses to the background. In one-third of cases, there was no pulse, but the background modulated like static noise. The other two-thirds of cases had pulses, which meant that the background would move for 100ms in or away from the direction of the dot motion. Each of these occurred in equal amounts, meaning that one-third of trials had "positive pulses" and one-third had "negative pulses".

The results of this paper showed that there was some relationship between the LIP neurons and sensory integration for decisions. It is noted, however, that it is unclear if this means that the sensory integration occurs in the LIP neurons that were examined or if they were relays for this information, although, if they were relays, they are likely to be accurate as the recorded signals were very similar to standard decision processing signals. There was also an interesting result found in this paper, that the pulses, although only present for a relatively short time, affected on the LIP could be detected for up to about 575ms after the onset of the stimulus. The method used in animal trials to detect neuron activity has a high

spatial resolution with the trade-off of the amount of area covered.

2.3.2 Experiments with Humans

EEG Recording - Averaging like Trials

EEG is a method of recording neural activity by measuring the wave activity of the nerve cells in the brain. The measured signal is the result of the summation of the firing neurons from the cerebral cortex(Elul 1972, Britton, Frey, Hopp, Korb, Koubeissi, Lievens, Pestana-Knight & St. Louis 2016).In human trials, a surface EEG is used to record the brain activity across a much wider area, albeit in a lot less detail. The resulting signal is quite noisy, and the large number of neurons that it measures means that there is uncertainty about what is causing each artefact. This fact means that EEG signals of similar conditions are averaged in order to reduce the effects of these artefacts; this process is shown in 2.3. O'Connell & Kelly (2021) reviewed uses of EEG in decision processing trials and how it can generate models for cognitive processing. There is still valuable information to be learned from EEG. For example, experiments have found the centroparietal positivity (CCP) and left hemisphere beta band signal (LHB) build with accumulated sensory evidence when decision processing, finding these to be related to the decision variable in the brain (O'Connell, Dockree & Kelly 2012). Even still, EEG is not ideal to help understand cognitive events that occur in single trials.

Singel Trial Analysis of EEG

Vidal (1977) provides an early look at the use of EEG to measure evoked potentials and event releated potentials (ERP) in the signal in real time. These are points in the signal that are triggered by processing within the brain. These potentials are small in amplitude in comparison to the rest of the EEG signal and are only viewable through averaging over multiple trials. ERPs can triggered by sensory

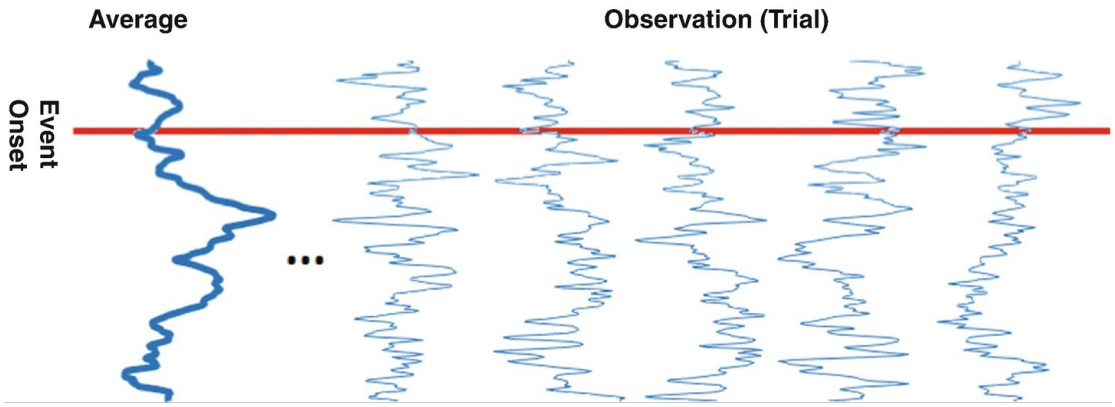

Figure 2.3: Effect of Averaging EEG Events (Kubben et al. 2019)

stimuli or voluntary motor movement. This paper discusses a method of detecting ERPs in real time using discriminant analysis. It reiterates a big problem with using this signal for decision processing trials, and that is averaging. When similar trials are averaged together, there is information lost on a trial-to-trial basis, such as changes of mind.

Work on single decision-making trial EEG analysis is vital to understanding the finer mechanisms of the brain and to categorise things that vary between trials. A recent method of single-trial EEG collection was developed by Si, Li, Duan, Tao, Li, Cao, Zhang, Biswal, Li, Yao & Xu (2020). It mentions Blankertz, Lemm, Treder, Haufe & Müller (2011), which proposes a new method of single-trial EEG, looking at the spatiotemporal patterns with filters to improve the linear estimation of the ERPs, with the drawback that it is dependent on the accuracy of an estimation of the covariant matrix, which is difficult for high dimensional space. Si, Li, Duan, Tao, Li, Cao, Zhang, Biswal, Li, Yao & Xu (2020) carried out ultimatum game trials, which consisted of the participants being shown a sum of money and a proposed method of splitting it with another person. If they accepted the offer and the other person accepted it, they would both get that sum, but if one of them rejected, they would not; rejection or acceptance was determined through a button press. They would receive 90 offers that were randomly selected, and EEG was recorded during the decision-making process to attempt to predict their decision. This prediction was made using a novel supervised machine learning approach to extract the discriminative spatial network pattern (DSNP) of the

brain and provide features for a linear discriminate analysis(LDA). The DSNP was trained on half of a participant's trials and tested on the other half. It found that this system of prediction had an accuracy that was dependent across subjects, ranging from 66% to 100%. It was found that the prediction accuracy was over 80% in 28 of the 34 subjects involved in the trial. Overall, this paper was engaging and provided a possible method of measuring the single-trial variability of decision processing. While the trials here do not examine perceptual decisions, with complex processing having to go into each decision, they do provide a new method of discerning the various processing that can occur in the brain. This method used recorded EEG signals to determine the evolving decision and predict the endpoint. Still, a continuous response method would allow for the evolving decision to be compared to any processing that had been recorded with the EEG and provide more information into the mechanisms of the decision.

Single Trial EMG Analysis

EMG is a method of recording the electrical energy that is generated during muscle contractions(Asif, Waris, Gilani, Jamil, Ashraf, Shafique & Niazi 2020). Surface EMG is done using electrodes placed on the surface of the skin above the muscle that is of interest. Servant, White, Montagnini & Burle (2015) carried out decision-making trials in which participants were tasked with identifying the middle letter in an array of letters, their response would be recorded using a button press and EMG was recorded during this experiment. Electrodes were placed upon the flexor pollicis brevis of both hands, which would record the medial rotation of the thumbs. It is mentioned that the signal of the EMG is noise and did require some manual assistance to ensure the detected markers were correct but the EMG recording did provide more constraints to help discern models that fully account for decision processing. On that topic, Dendauw, Evans, Logan, Haffen, Bennabi, Gajdos & Servant (2024) found that the decision variable is measurable with the EMG and that it appeared to be gated there until it reached a certain threshold to illicit an action response.

Single Trial Cursor Position Recording

Continuous response methods are used in decision-processing trials to allow for a cleaner signal that can reflect the deliberation. Scherbaum, Dshemuchadse, Fischer & Goschke (2010) demonstrate the use of a computer mouse as a response method. This allows for a constant measure of the decision variable in a signal with a desirable signal-to-noise ratio (SNR).

Scherbaum, Dshemuchadse, Fischer & Goschke (2010) uses this response method to investigate the effect of congruency on the participant's trial performance, known as the Simon effect(Simon 1969). Recording the use of the mouse trajectories had been used before in such trials but this study used this continuous response to carry out a detailed analysis of the signal over time in the trials. Two experiments were carried out. In the first experiment, trials were initiated by the participant clicking into a red box at the bottom of the screen then the task would begin. The task would entail two white boxes and an arrow being displayed on the screen indicating which box is to be selected. The participant then would have two seconds to select the relevant box. The computer mouse trajectory was recorded during the deliberation process. This display is shown in 2.4.

Previous trials examining the Simon effect found similar results to the first

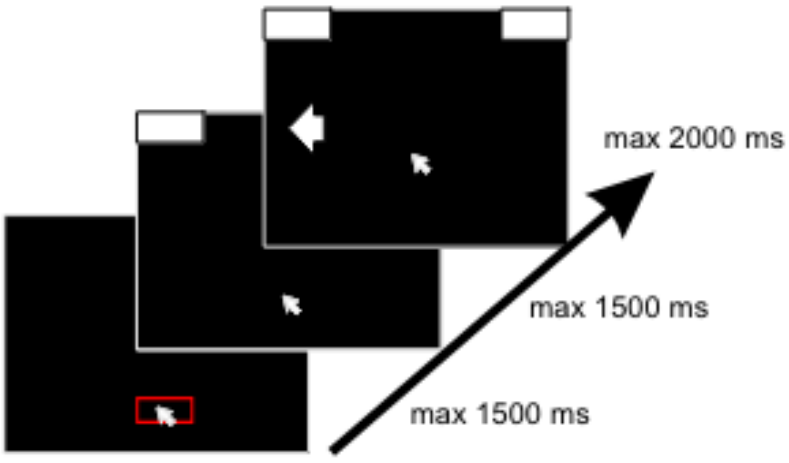

Figure 2.4: Visual Display for Scherbaum et al. (2010) Experiment

experiment, validating the continuous mouse trajectory measure as a response method(Burle, Possamaï, Vidal, Bonnet & Hasbroucq 2002). A second experiment

was carried out to investigate the effect of the stimulus of the Simon effect, where instead of an arrow that could point in one of two directions, the stimulus was replaced by a number that would have been greater or less than 5, and therefore reducing the amount of congruency in the stimuli. The second experiment showed similar results to the first, showing that the effects of repeated stimuli did not affect decision processing in a meaningful way. The continuous measure of the mouse trajectory was able to reveal time-varying patterns in the decision process that had not been seen previously. The use of a computer mouse provides information about how the decision is made, but if it is not in motion, there is a flooring effect on the available information.

Koop & Johnson (2011) uses a similar response method for decision-making experiments, recording the cursor position on the screen but using a Wii remote instead of a mouse. The use of this device means that the muscles must be constantly activated to maintain the cursor position on the screen. This would negate any flooring effect seen in the mouse tracking response system. The trials in this study use the Iowa gambling task, first described in Bechara, Damasio, Damasio & Anderson (1994); participants started with $2000, which would correspond to $4 in real money. They were shown four decks of cards, like in 2.5, which have different win and lose rates as well as different amounts for wins and losses. Generally, there are two 'bad' decks that have higher payouts higher losses and a higher likelihood of losing, there are also two 'good' decks that have lower rewards, but also lower and more infrequent punishments. The participants are not aware of this and must discern which deck is the best to bet on throughout 100 trials. The participant would begin a trial in the start area and select a deck; the outcome would be displayed, and the next trial's decks would be shown. This paper found that response dynam cs, or the recording and analysis of the user response, was able to open up new insights into the decision-making process.

With response dynamics, new information is made available to help understand the decision-making process and assess various models. This paper found that in the case of these trials, a dual system model would explain the results well, showing that an intuition-based system explained early responses until there was

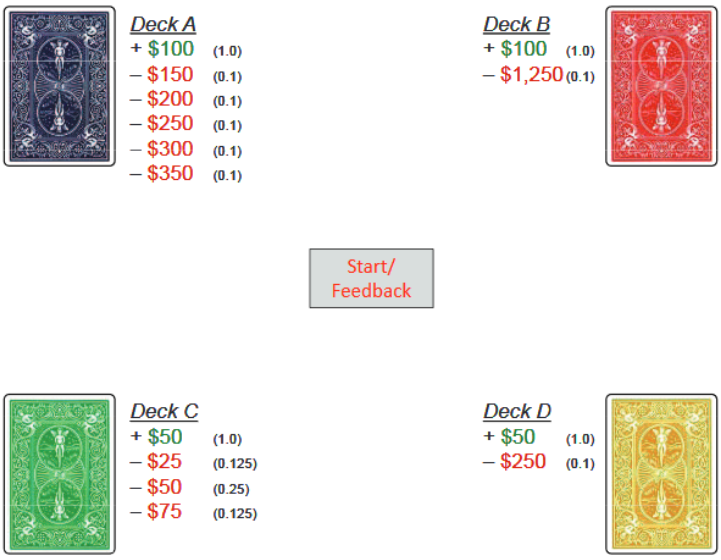

Figure 2.5: Visual Display for Koop & Johnson (2011) Experiment

enough information for a deliberate system to take over. It is suggested that further research in this field could incorporate an eye tracker to use participant attention to better assess if a sequential sampling model or a dual system model provides a better explanation. The complex processing done to make decisions in this trial is distinct from perceptual decisions, but the idea of response dynamics could provide more information into how decisions, in general, are formulated. It should be noted that in both of these studies, the only information recorded during these trials was the mouse trajectory. The recording of another signal, such as EEG, could provide more insight into how the decision is processed, more than just the physical result of the decision.

Single Trial Eye Motion Recording

Another method of continuous recording that can further inform the evolution of a decision is the use of eye trackers. Animal trials use a combination of electrodes and an implated eye coil to respond during decision-making. In humans, a noninvasive video-based technique that can be recorded and analysed is used. Brunyé & Gardony (2017) used this technology to investigate how it can be used

to measure uncertainty in perceptual decisions. In this study, participants were shown a square image that was either a face or a house that had varying levels of clarity, shown in 2.6.

Forty images of faces and the same number of houses were selected to be

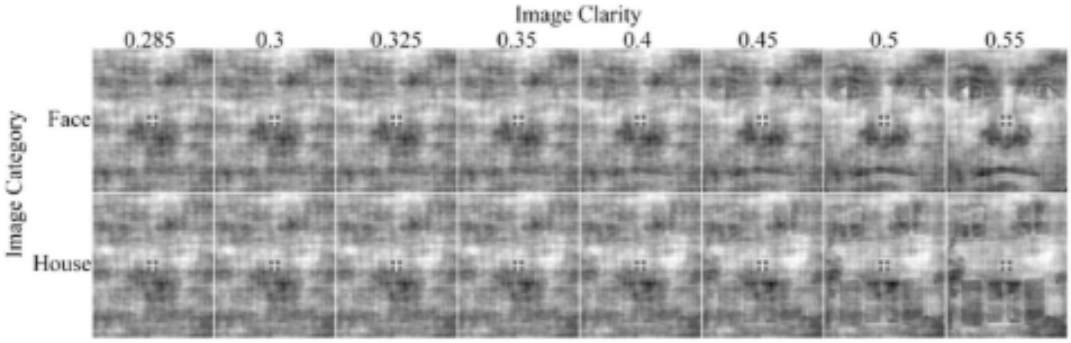

Figure 2.6: Stimuli Displayed in Brunyé & Gardony (2017) Experiment

used as the stimulus, and they were obscured at eight different levels; because of this, participants were shown a total of 640 images during the experiment. Each trial would consist of displaying an image for three seconds against a black background, then the options 'House' or 'Face' would be shown on the screen, with the participant looking at which option they believe to be the answer. They then would rate their certainty on a scale from one to seven. In addition to their performance and certainty levels, the results of this study looked at the participants' eye fixations, when their eyes pause in a certain location, saccades, the movements between fixations, blinks, and pupil diameter. The results of this trial suggest that there is a relationship between oculomotor behaviour and decision uncertainty. Critical information was found when analysing the pupil diameter, allowing the difference between exploration and exploitation of the image to gather as much information as possible from it. This study uses eye motion not only to provide data for analysis but also as the response method for the system. This could provide issues if it were to be used in conjunction with EEG recording unless specifically planned against, as eye motion and blinks can have a significant effect on the EEG signal(Plöchl, Ossandón & König 2012). Nonetheless, the use of recording eye motion does provide a new avenue to determine what is happening during the decision-processing stages. This study also mentions that the sampling

rate of the eye tracker, 60Hz, if increased, could provide more details about the temporal pupil dilations and the saccades.

2.4 Stimulus Types in Two Factor Forced Choice Perceptual Decision-Making Trials

2.4.1 Random Dot Motion Coherence

Random Dot Motion Coherence is a stimulus type in which a series of dots are shown on a screen moving in random directions. At a specified time, some of the dots will move in the same direction with coherence; the level of coherence is determined by the number of dots that change direction and stop acting stochastically. This is demonstrated in 2.7. Britten, Shadlen, Newsome & Movshon (1992) ran experiments using this stimulus to explore the effect of psychophysical decision processing on the neurons in the brain. The stimulus for this trial was based on work from Morgan & Ward (1980). This trial was run using monkeys and found that the neurons in the MT had played a role in motor perception. This stimulus type provides information about how motion is encoded in the brain during decision processing.

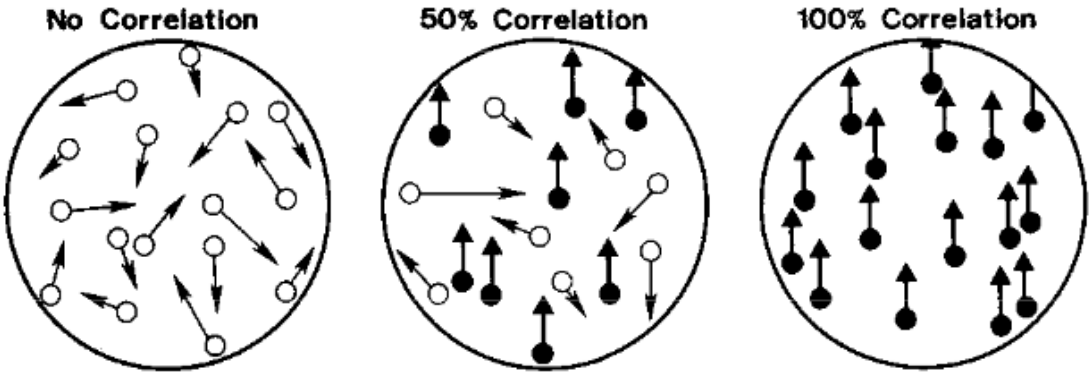

Figure 2.7: Random Dot Coherence Stimulus (Britten et al. 1992)

2.4.2 Contrast Discrimination

Many studies discuss using contrast discrimination stimuli in decision-making trials, with various alterations made to them. Steinemann, O'Connell & Kelly (2018), explores the effects of speed pressure on decision-making using a novel contrast-comparison trial method. The task of the trials used in this experiment was to determine in which direction the brighter of two flickering grating stimuli, oriented in different directions and flickering at two different frequencies, the resulting image resembles 2.8. The different frequency stimuli were able to be observed in the EEG by looking at steady state visually evoked potentials(SSVEP). These potentials are used to quantify the sensory processing by comparing the relative amplitudes of the flickers at the frequencies of each stimulus. This allowed for easy identification of the sensory processing of each factor. An eye tracker was used to determine extra factors such as pupil size. Overall, this study finds that sensory information is differently encoded when under speed pressure. This implied different methods of SSVEP modulation depending on pressure levels that corrected the negative effects that reduced time may have had on the accuracy. A possible issue with the stimuli in this study is that the different flicker rates for each stimulus could affect their perceived brightness(Magnussen & Glad 1975).

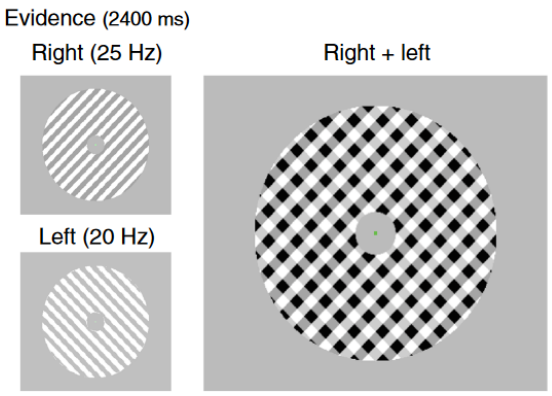

Figure 2.8: Steinemann et al. (2018) Contrast Discrimination Stimulus

CHAPTER

THREE

METHODOLOGY

3.1 Introduction

The response system, experimental program, and running experiments were developed over the year. The system was created using Matlab in conjunction with Psychtoolbox. The UCD School of Electrical and Electronic Engineering technical staff connected the load cells to amplifiers and a National Instruments 'USB-6001 USB Multifunctional I/O Device'. Load Cell Calibration After receiving the load cells apparatus from the electrical workshop in the UCD Engineering building, the generation of Matlab programs would begin. The nationak=l instruments driver software and the Matlab Data acquisition (DAQ) toolbox were used to read the force values. This would be used in the experiments to determine participant responses. They would have to place a minimum amount of pressure on the sensor to begin the trial, and in order to select an answer, they would have to elevate their pressure to a desired level on the relevant sensor. The initial testing apparatus is shown in 3.1.

It was decided that the load cells would be calibrated for each person to ensure participants' comfort and allow for increased comparability. This was informed by an informal poll, which found that some people's comfortable maximum pressure

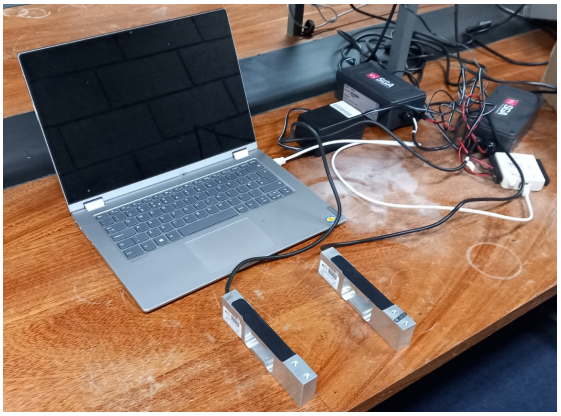

Figure 3.1: Load Cell Set up with DAQ and Laptop

overlapped with others' comfortable baseline. With this information, a Matlab object type called a loadCell was created that would be used in the experimental program.

3.2 Experimental Program Architecture

A Matlab Psychtoolbox program was provided to be amended for running experiments. In order to streamline the layout of it and make it easier to understand, it was restructured to utilise Matlab objects.

An object is a data structure that can have certain properties that are defined in its class definition file. These properties are callable as they would be from a data structure in Matlab. They have the extra benefit of being able to have functions associated with them, called methods, that will use their properties as the variables of the function.

The initial program consisted of one file with a for loop for each frame and many if statements to trigger the stimuli at different stages of the experiment. This was found to be very difficult to change and led to large areas of repeated code that was not user-friendly to edit. The plan to recreate the code was to have it consist of one experimental file that would read in objects that would correspond to different parts of the experiment that would have individual methods that would trigger when needed. This redesign would make the code easier to read and edit.

The main file was comprised of setters for each object type and a for loop to iterate between each trial. Switch and case statements were used to display different stimuli for different stages of the trial as well as to categorise the user responses.

3.3 Stimulus

The stimuli that would be shown to participants would be one of 5 conditions:

1. 1) High contrast - The difference between the higher and lower brightness levels was large. This was the easiest difficulty level
2. 2) Low contrast - The difference between the higher and lower brightness levels was small. This was an increased difficulty level.
3. 3) High perturbations - There was a low contrast difference maintained, with a perturbation that was a reduction in the higher brightness level added after 200ms and lasting 150ms
4. 4) Low perturbation - a low contrast difference maintained, with a perturbation of the lower brightness level increasing at the same times as condition 3).
5. 5) Brightness swap - low contrast level with both brightness levels swapping after 200ms and remaining so for the rest of the trial. This condition was added to encourage changes of mind. In order to prevent participants from being made aware of the false evidence being displayed, feedback was only provided to them after every ten trials.

The Stimulus would consist of two flickering grating patterns angled at 90 degrees to each other. They would be shown on the screen for one frame as is shown in 3.2, and they would be superimposed over each other from the point of view of the observer.

Figure 3.2: Frame cycle of Stimulus

3.4 Timing

The timing of each stage of the trial was dependent on values that were set in the parameters object. The trial featured different phases at which it would show different stimuli. A hold time duration was set as the length of time that the participant would have to maintain the force level above the threshold in order to start each trial and move it from the initial stage to the trial stages. this is shown in 3.3

1. Initial stage - display force level guides once the force level has been removed and maintained within the beginning window for a specified time (until started by the user).

2. Fixation stage - display white fixation point for the participant to focus on (100ms)

3. Baseline stage - display contrast gratings at the same brightness level with a white fixation point (600ms).

4. Cue stage - display contrast gratings at the same brightness level with yellow fixation point to signal evidence was about to occur (600ms).

5. Evidence stage - display contrast gratings with increased or decreased brightness levels with a yellow fixation point (200ms).

6. Perturbation Stage - depending on the trial condition, maintain grating contrast difference, temporarily decrease contrast difference in a certain direction, or swap contrast levels for the remainder of the trial (150ms).

7. Final stage - display the original evidence of perturbation condition; otherwise, maintain the Stimulus from the previous stage (4200ms).

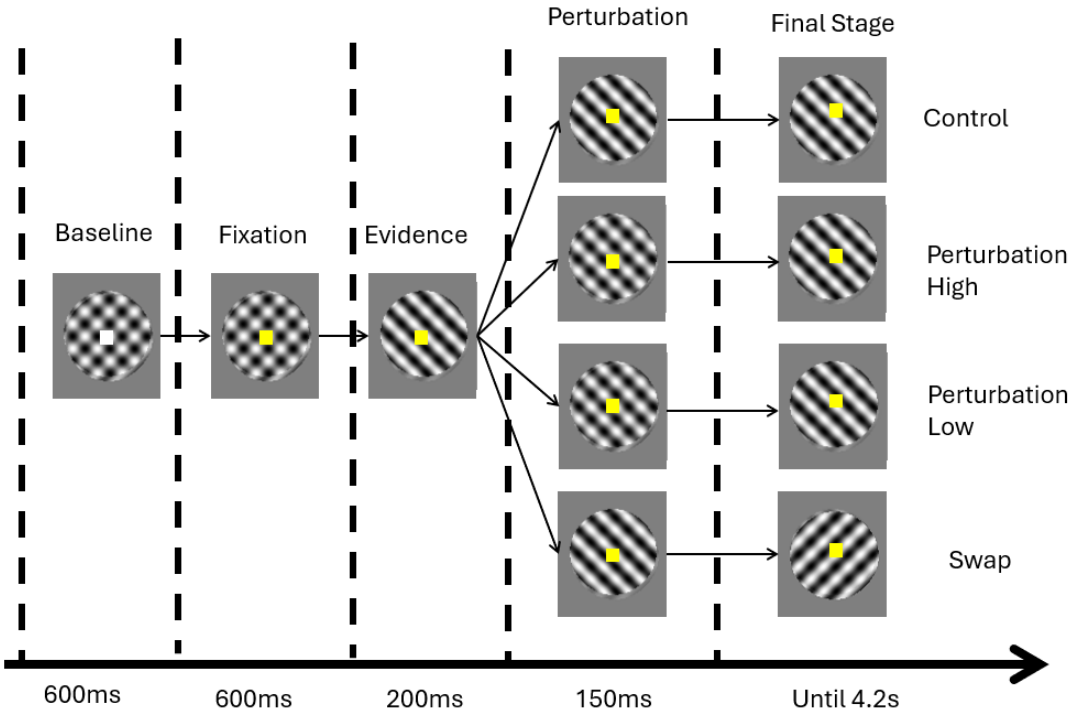

Figure 3.3: Timings of Trial with representation of Conditons

3.5 Objects Created

Several objects were created for this program. The most complex ones were called loadCell and displayInfo.

3.5.1 loadCell Object

In the creation of the loadCell object, the key properties in loadCell were:

1. d - the DAQ object that would be used to read the data
2. leftCh and rightCh - the left and right channels of the daq, corresponding to each load cell, set up as single-ended channels.

3. maxCal and minCal - the maximum and minimum calibration values that the recorded forces would be scaled by, corresponding to 1 and 0, respectively

4. MVCs - the maximum voluntary contraction, as measured on the force sensor as the EMG MVC was recorded, it was used to create maxCal and minCal

5. maxScale - a portion of the MVC that would correspond to the maxCal. It was set to 0.2 for the experiments but could be altered to increase or decrease resistance without recalibrating

6. left and right - numbers, either 1 or 2, that were manually changed and identified which load cell corresponded to which channel on the DAQ

The key methods of loadCell were

1. loadCell() - initialises the load cell with the DAQ, setting up the channels.

2. readCalForces() - reads the forces from the load cells and scales them from zero to one on a scale of maxCal to minCal

3. calibrateLC() - begins a calibration procedure on the load cells, using the displayInfo to display commands to the participant. This method would check if this was the first block in a session; if it were not, then it would inherit the calibration values from that trial.

3.5.2 displayInfo

This object is used to show commands, different stimuli and the participant's force values. The important properties of it were:

1. BLcontrast - the baseline level of contrast that was shown before evidence began.

2. highContrast and lowContrast- the higher and lower contrast difference levels corresponded to the amount above and below the baseline contrast that the two levels would be when evidence was shown

3. contrastChange - this was the size of the perturbations that would occur in the

4. fixColor - the colour of the fixation point, set to white

5. cueColor - the colour of the fixation point during evidence cue, set to yellow

6. textColor - the colour of the text that is being displayed, set to white

7. bgColor - the background colour, set to grey

The key methods associated with displayInfo were:

1. displayInfo() - initialised the displayInfo object, using the parameters object and the loadCells object.

2. showGuides() - this would display guides for the levels of force cells, using the 1x2 output of the loadCell's readForceCals() and a flip condition that, if set to false, would allow for two things to be displayed.

3. showBLGrating(), showCueGrating(), showEvGrating(), showPertGrating() - would all show different grating types, baseline, cue, evidence, perturbed. The showEvGrating was used to show the trial condition, informed by logic in the main program.

3.6 Other Objects

1. parameters - this stored all the trial-specific information, such as the participant ID, the recorded loadCell values, the loadCell triggers, the timing information, the number of trials and whether or not this was a practice. This also recorded which booth the trial was taking place in, and the gamma function and parallel port address were selected accordingly.

2. EMGTriggers - this was initialised with the parallel port address, it would be able to send a one, a zero or a spike to the EMG system via the parallel port.

3.7 Experiment Overview

The experiment took place in the cognitive neuroscience lab in the UCD Engineering Building. There was a trial computer that displayed contrast identification tasks. This consisted of 2 grating shapes of different brightness levels and orientations that alternated on the screen. The participant had to identify the direction of the brighter grating and select that option. This option was selected using a novel load cell response system, where the participant had to put pressure over a certain threshold and maintain it for a specified duration. There were five different trial types, with two different possible answers that were shown in a random order to the participants.

3.7.1 Muscle Selection

The first dorsal interosseous muscle (FDI) was selected for these trials. It is responsible for index finger flexion.

3.7.2 EMG System

The EMG readings were recorded for offline analysis. This was done using a Trigno Centro System with 'EMGWorks' software. This produced .hpf files that were converted to .mat format using 'Delsys File Utility'. Two Trigno Mini Sensors were used to record the EMG signal for each hand, and a Trigno Analog Input Adaptor was used to record triggers from the computer's parallel port.

3.8 Software Development

3.8.1 Structure

The class diagram shows the structure of the software used to run the trial code.

3.9 Experimental Methodology

3.9.1 Subjects

The experiments were carried out on a cohort of seven participants (5 male, 2 female); their mean age was 26.1 years old. All had normal or corrected to normal vision and were fluent in English; they were made aware of what the trials would entail and signed an informed consent form. They took part in the experiment in two sessions. The initial session was a training session, where they were shown the different conditions (excluding the switch condition, which they were not aware of) and took part in practice runs of 10 trials per block. The second session featured them carrying out ten blocks of sixty trials, with all fice conditions randomly arranged, recording the load cell readings and the EMG of the FDI. Participants were paid twenty euros for taking part in both sessions.

3.10 Results Analysis

3.10.1 Recorded Data

The demographic data, age and sex, was collected from the participants, with their names pseudonymised. The trial parameters and load cell readings were saved in the parameters object, the load cell calibration settings were saved in the loadCell object, and the contrast levels were saved in the displayInfo object. The EMG and load cell recordings were split into each trial which was then saved as a new object called trialData, which stored the user performance, the load cell recordings, the EMG recordings, and the trial information. This was used in the results analysis.

3.10.2 Data Pre-Processing

The results were split into individual trials and stored in an object called trialInfo, this held the left and right load cell and EMG recordings as well as the MVC for

that participant, the sampling rates, the response time, the trial conditions and the participant's performance.

The performance and conditions were used to gather information about the difficulty of the trials and the accuracy of each condition. The recorded EMG and force outputs were used to analyse participant response on a trial-to-trial basis.

3.10.3 EMG Pre-processing

The EMG would be pre-processed by first passing it through a band pass filter, this was a 5 - 500 Hz fifth-order Butterworth filter. The signal was then rectified and passed through a 2 Hz fort-order Butterworth low pass filter. This provided the envelopes that would show the average amplitude.

3.10.4 Results Collation

The recorded results were split into each trial. This also included the load cell force output recordings for each hand. There was an issue with splitting the EMG recordings from the saved files into individual trials; there was a timing issue that resulted in the EMG data lagging behind the muscle output. Several days were spent trying to rectify this, but in the interest of finishing the project, they were omitted from the results analysis.

There was also a bug in a version of the trial code which caused timed-out responses not to send triggers to the Delsys system. This was corrected, but it meant that for some trials, a combination of the EMG and load cell triggers would have to be used to divide the EMG recordings.

There was an instance during the eighth block of participant 'e's' second session, which resulted in three trials being discounted from EMG analysis; the other trials were all suitable for this. If it were to have been used, the EMG pre-processing would have been carried out as a method of the trialInfo object.

CHAPTER

FOUR

RESULTS

4.1 Stimulus Effects

The effects of the stimulus on the outcomes of a given trial were computed by looking at the correct answer rate and the response time. Analyses of variance(ANOVA) were used to understand the effect on the response time, and Fisher's exact tests were used to determine any impact on performance. All plots and graphics were generated using Matlab. A 5% level of significance was selected for the analysis.

4.1.1 Overall Conditions

Effect on Response Time

4.1 is a box chart of the effect that the conditions had on the response times of each trial. It was noted that there seemed to be little effect from the perturbations or brightness switch conditions. A one-way ANOVA showed that there was a significant effect had by the condition on the response time ($P\text{-}value \approx 0$).

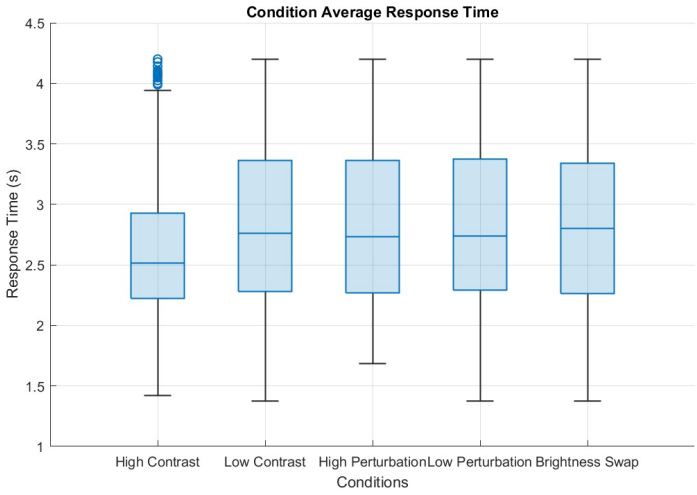

Figure 4.1: Distribution of response times for each trial condition.
0

Effect on Performance

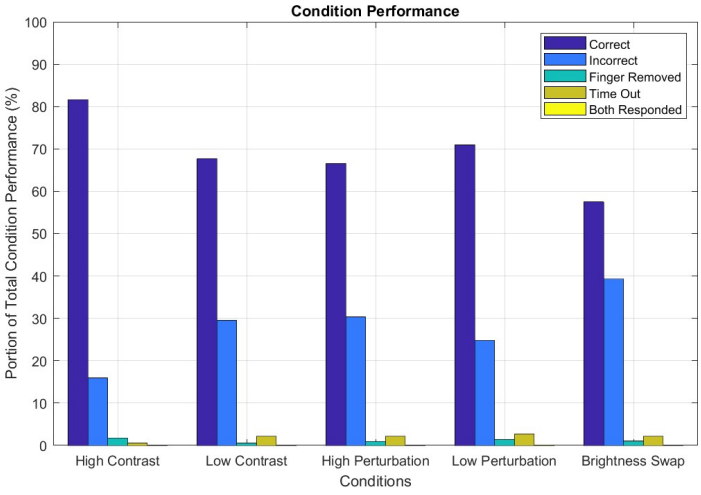

Figure 4.2: Distribution of performance for each trial condition

4.2 shows a histogram of the performance of the responses recorded for the various trial conditions.

4.1.2 Contrast

Effect on Response Time

The contrast effect on response time was compared between the high contrast and low contrast trials (without perturbation or swaps), and the effect was significant($P\text{-}value \approx 0$). 4.3 visually represents the difference between groups.

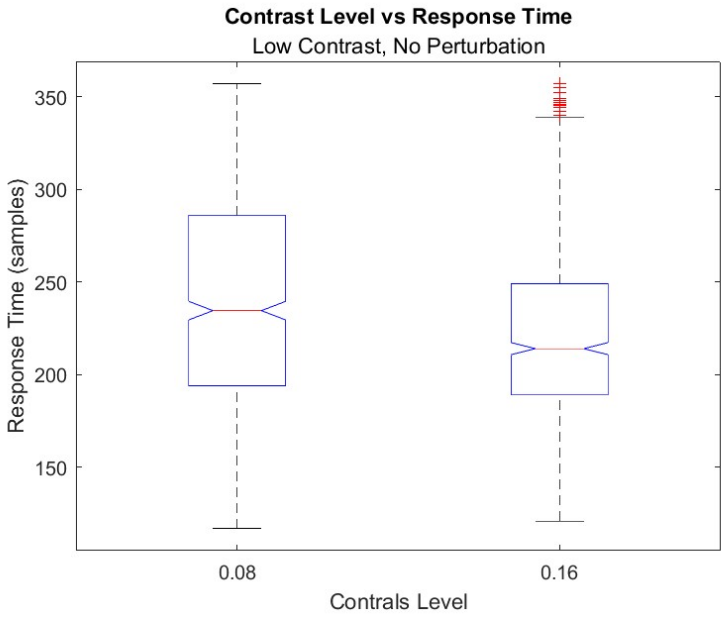

Figure 4.3: Distribution of response times for contrast level of stimulus

Effect on Performance

The effect of contrast on performance was significant ($P\text{-}value \approx 0$).

4.1.3 Perturbations

Effect on Response Time

The effect of perturbations on response time was analysed in several ways. The two different types of perturbations allowed for the effect of the direction of the perturbation on the response time to be determined.

When the three conditions were compared together, higher perturbation, lower perturbation, and no perturbation were provided. This was found to be significant (*P-Value = 0.002695*).

This looked at all recorded trials, when only the low contrast, non-swap condition trials were compared, that is, trials that only differed in presence and direction of perturbations, it produced 4.4 (where the perturbation level refers to the amount of perturbation present in the trial, 0.03, referring to an increase in the lower brightness lever and -0.03 referring to a decrease in the higher brightness level), finding no significant difference (*P-value = 0.98434*).

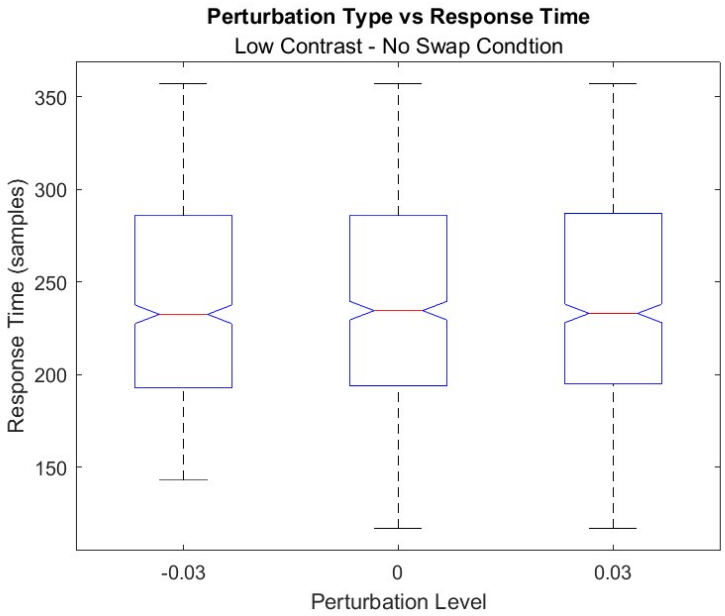

Figure 4.4: Distribution of response time for each perturbation type

The effect of the perturbation direction on the response time is provided 4.5. There was no significant difference between the groups detected (*P-value = 0.86029*).

The effect of the presence of any perturbation, when compared to no perturbation, was shown to be significant (*P-value = 0.00059196*). When only including the low contrast, no swap trials, the effect was found to be insignificant, however (*P-value = 0.98589*). This is shown in 4.6.

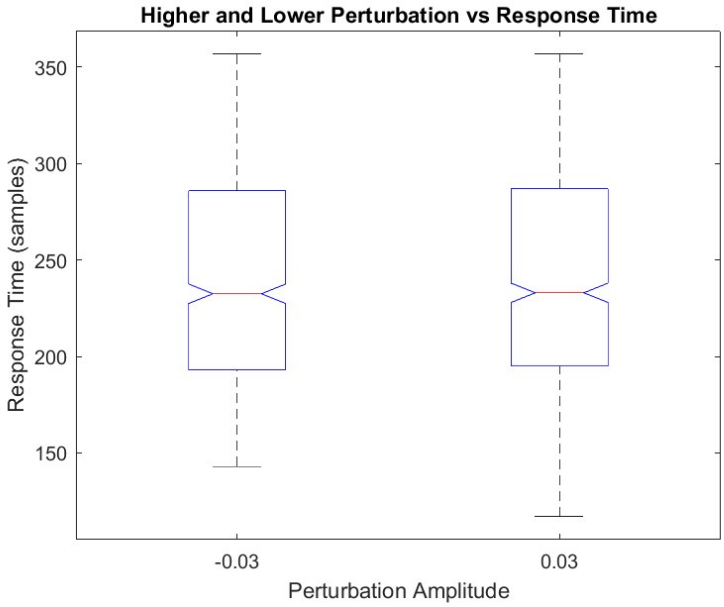

Figure 4.5: Distribution of response times for perturbation direction

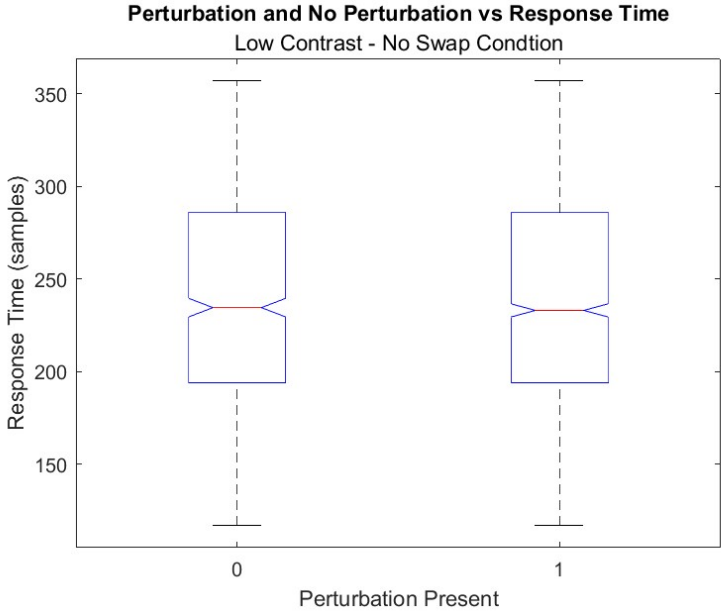

Figure 4.6: Distribution of response times for trials with perturbation versus without

Effect on Performance

The effect of the presence of a perturbation on the performance was found to be insignificant($P\text{-}value = 0.8919$). This included the high contrast and switch condition; when it was refined to compare the low contrast trials to the low contrast

with perturbations, it found that there was no significant difference (*P-value = 0.8918*). Similarly, the direction of the perturbation was found to not significantly affect the performance (*P-value = 0.0581*)

4.1.4 Brightness Swap

Effect on Response Time

The brightness swap condition was shown to have no significant effect on response times (*P-value = 0.12525*). When the response times of a brightness swap were just compared to the low contrast, no perturbation condition, the results were less significant(*P-value = 0.7116*). This can be seen in 4.7.

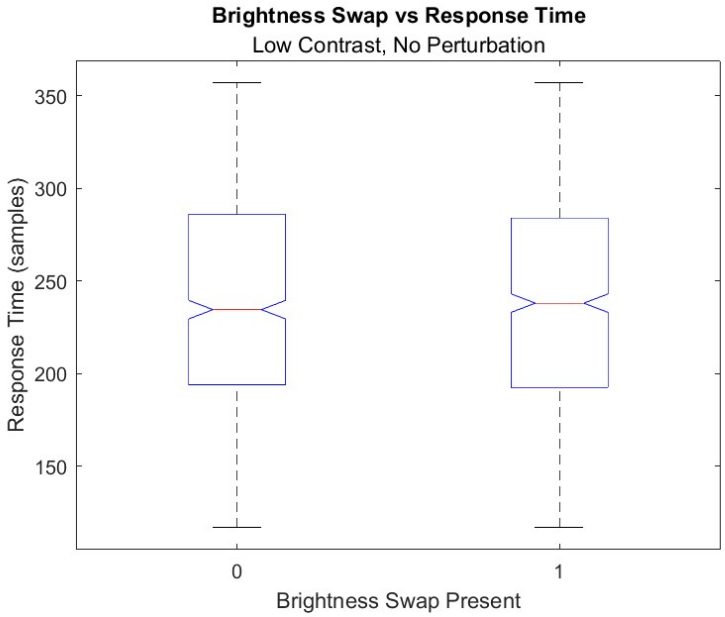

Figure 4.7: Distribution of response times when a brightness swap was present versus when not present

Effect on Performance

There was a significant effect on the trial performance (*P-value* $\approx$ *0*). The effect was still significant when the high contrast and perturbation condition trials were discounted (*P-value* $\approx$ *0*).

Condition	P -Value (Response Time)	P-Value (Performance)	Significance (Response Time)	Significance (Performance
Overall Conditions	0	-	Yes	-
Contrast Level	0	0	Yes	Yes
Brightness Swap	.12525	0	No	Yes
Perturbation Overall	0.98434	-	No	-
Perturbation Present	0.98589	0.6172	Yes	No
Perturbation Direction	0.86029	0.0581	No	Yes

Table 4.1: Table of Results for Conditions

4.2 Participant Variability

4.2.1 Response Time

The participant variability was found to be significant by means of ANOVA(P-$value \approx 0$). The resulting box chart is shown in 4.8.

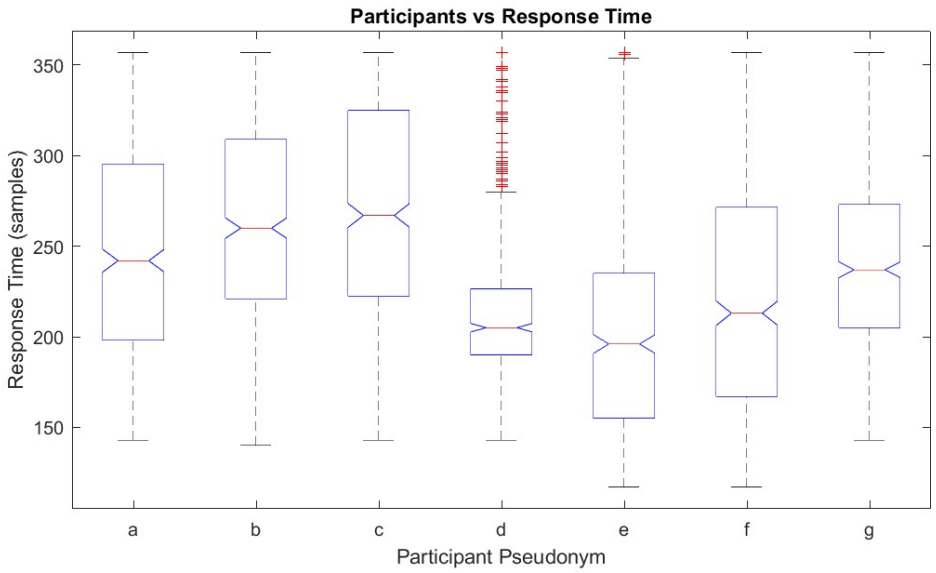

Figure 4.8: Distribution of response times for each participant

4.2.2 Performance

The performance between participants is shown in 4.9.

4.3 Changes of Mind

4.3.1 Categories

Changes of minds were detected using the recorded load cell data, they were detected in several ways. The first way was to record and detect the trials where

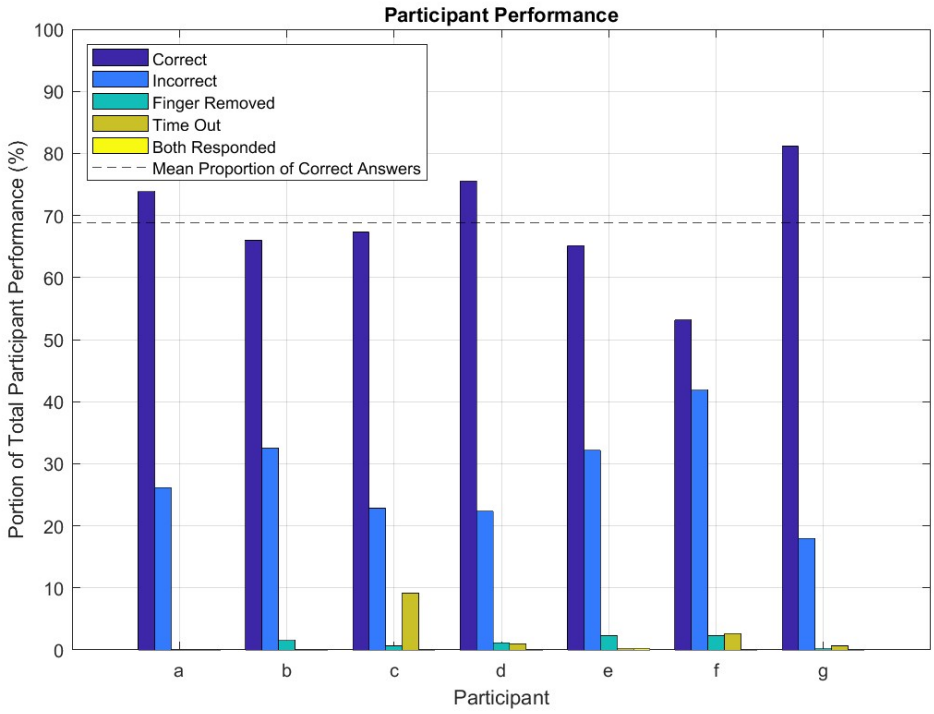

Figure 4.9: Distribution of trial performance for each participant

the acceptance threshold force had been exceeded with both hands, this would show a change of mind, with a chagne of answer. The second way was to capture changes of mind that had occurred too late, that is when the response had already been logged.

4.3.2 Prevalence

The first method was to record the trials where the participant had crossed the acceptane threshold with both hands, there were 46 such trials identified. Some secondary manual refining was carried out on these trials as if a participant that had started with more pressure on one side might not have changed their mind but still be recorded as such. After this had been done ther were 39 trials that fit the desired criteria.

The second method of detecting changes of mind looked at the second after the response had been logged for threshold crosses with the other hand. This occurred in one trial.

Conditions

The amount of changes of mind that were detected across the various conditions can be seen in 4.10.

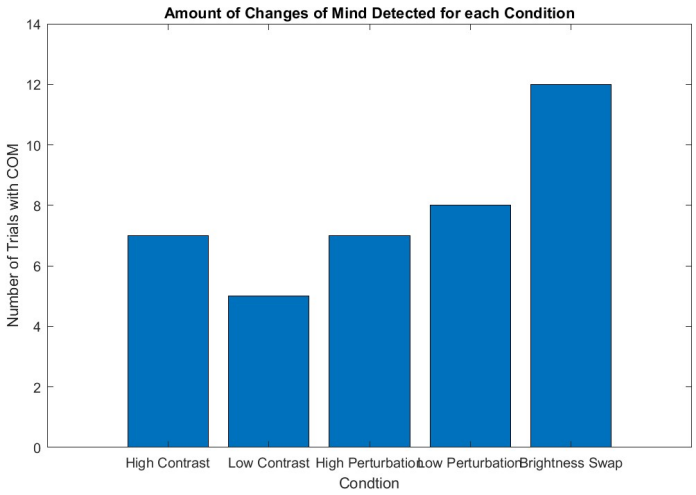

Figure 4.10: Number of changes of mind detected for each trial condition

Participants

The amount of changes of minds detected among participants is shown in 4.11

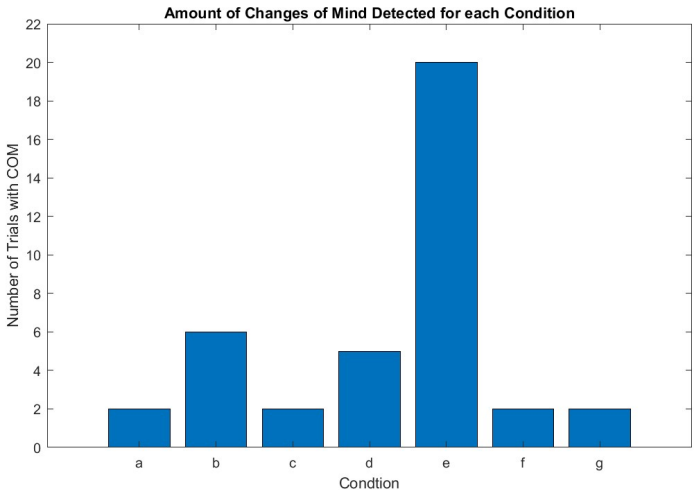

Figure 4.11: Number of changes of mind detected for each participant

4.4 Overall

A 3-way ANOVA was carried out to determine any significant interactions between participant, performance, response time and whether there was a change of mind present. With each variable on its own, there was only found to be a significant difference between participant and response time ($P\text{-}value \approx 0$).
There was no significant interaction between either participant and changes of mind ($P\text{-}value = 0.7125$) or performance and changes of mind($P\text{-}value = 0.9486$) and response time. There was a significant interaction between participant, performance and change of mind($P\text{-}value \approx 0$).

4.5 Notes

It was noted that repeated measures ANOVA would be more suitable for comparing the effects of the different conditions and participants on the trials; this would have been done if it had not been done under time constraints.

CHAPTER

FIVE

DUSCUSSION

5.1 Introduction

5.2 Stimulus Conditions

The overall results of the stimulus conditions provide interesting insight into how visual stimuli can affect perceptual decisions(4.1). Interesting effects were seen on both the response times and the trial performance for each condition.

5.2.1 Response Time

The response time results of each condition show that the only condition that led to a difference in response time was the contrast difference between the stimuli. This is interesting because the response time has been proposed to be proportional to the level of certainty (Ratcliff, Smith, Brown & McKoon 2016). These results imply that the perturbations or switch conditions has little effect on the participant's level of certainty. There was almost a significant difference detected with the brightness swap condition, possibly hinting that in some trials,

a reevaluation of the stimulus could have occurred, leading to increased response times in certain cases.

5.2.2 Performance

The stimulus conditions that were shown to have significant effects on trial performance were the contrast level and brightness swap. The contrast level is interesting as it elicited both an increase in response time and a reduction in performance this implies that the increased processing time was not enough to result in the same level of accuracy being maintained accoss diffiucuty levels.
The reduced accuracy for the brightness swap condition also provides interesting insight into how perceptual deliberation is processed, the reduced portion of correct answers shows that people still likely to stick with the initially perceived difference even when conflicting evidence was displayed for longer. This could imply that in these cases, once the initial decision was made the accumulation of evidence stopped.

5.3 Participant information

The participant information was useful to detect the differences between people. Response time distribution showed that the responses of the participants varied, with different means and standard deviations. The slowest average response was seen in participant 'c,' with the fastest seen in participant 'e.'
The performance between people also varied, with a mean of 68.88% correct answers. The highest number of average correct answers was found in participant 'g,' with 81.17% correct answers, and the lowest number of average correct answers was participant 'f,' with 53.17% accuracy.

5.4 Change of Mind Detection

5.4.1 Condtions

5.1 shows a sample trial that was categorised as a change of mind trial. The continuous response for the load cell meant that such trail specific changes of mind could be identified and used for decision making studies. This system could be used to determine more similar trials for ageraging, instead of using stimulus parameters.

The hypothesis of using the brightness swap and perturbation conditions to try encourage changes was successful in that regard, more changes of mind were detected in all 3 of these conditions compared to the low contrast difference, with each having. but interstingly, there was more chagnes of mind found when there

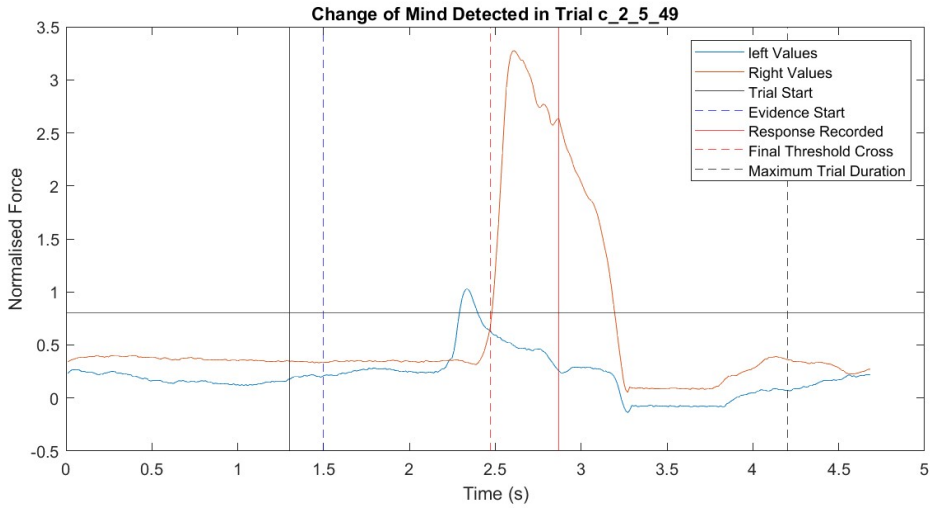

Figure 5.1: Example trial where a change of mind was detected

was a high contrast difference than a low contrast difference.

The sample size of the amount of change of mind trials was relatively now ($n = 39$), but it does imply that there stimulus does have some effect on the likelihood of a change of mind occurring.

5.4.2 Participants

Looking at the proportion of detected changes of mind for the participants, there was a much higher portion seen in participant 'e'. Interestingly, they had the fastest response time, implying that snap judgements were made, but then reevaluated, illiciting changes of mind. The distribution of chagnes of minds in 'e' trials, seen in 5.2, imply that the swap condition had no less effect on the decision reevaluation than the perturbations.

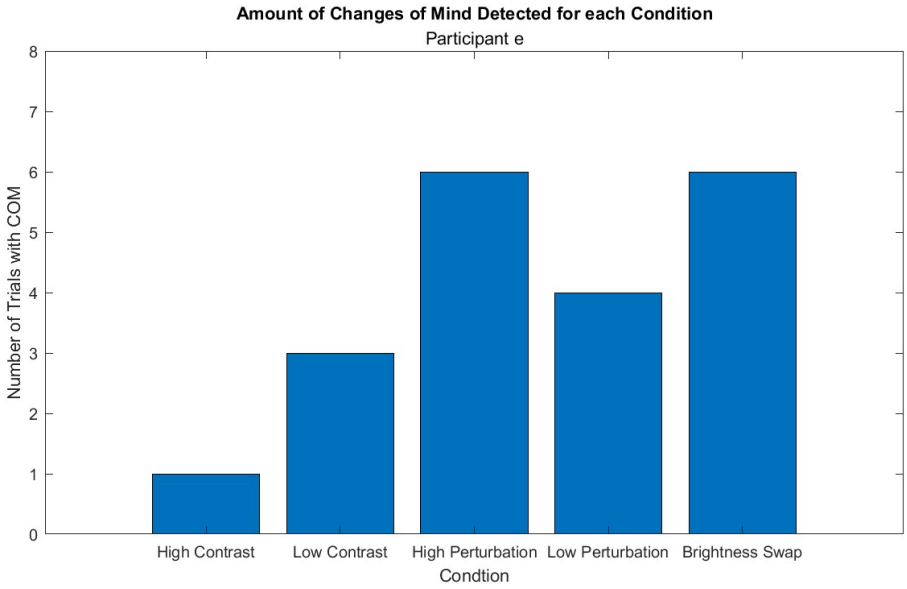

Figure 5.2: Changes of Minds detected for each condition of Participant 'e'

CHAPTER

SIX

CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

This project explores a new approach to investigating the process of perceptual decision-making. While it does not directly unveil new insights into the mechanisms underlying these decisions, it proposed a new methodology that proves a promising advancement for future decision-processing studies.

The novel dual load cell response system allows for a direct and continuous measure of the evolving decision in any given trial. Key events, such as changes of mind, can be detected with the recorded data.

The proposed stimulus conditions were effective at inspiring changes of mind in approximately 10% of trials. This shows the applications of this method in decision-processing trials moving forward.

The ability of this system to detect changes of mind demonstrates its potential to capture other such trial-specific occurrences. This provides a fresh avenue of information gathering for decision-processing trials that can help in the identification of the inner workings of the brain when deliberating.

The motivation to undertake this project was to provide a method to help better

understand decision processing in order to understand neurological conditions better. This system can do this; being able to analyse trial-specific events and identify key moments in decision-processing is a big step in garnering an in-depth understanding of how the brain works.
The UN Sustainability Goals Three and Nine, also motivators for this project, have been achieved with the validation of this new system. Its applications for understanding and aiding neurological conditions help ensure healthy lives for people, and the development of this novel method fosters further development in response dynamics analysis.

The overall aim was achieved, as well as the specific objectives. —It should be notes that although EMG was collected, due to technical difficulties, it was not analysed to provide insight to the actual decision processing.
Overall, the designed system here has the potential to provide valuable, not previously available, insights into the decision-making process and evolving decisions. The stimuli that were used have been shown to be more effective at eliciting changes of mind than would naturally occur. More important than that, though, is the ability to analyse individual trials, which opens up more opportunities for experiments. The minimum force requirement means that any floor effect that might have been seen has been negated.

6.2 Future Work

For future work on this project, there are a few avenues:

1. The object-oriented program code would allow for easy modification of trial-specific constants. This would be a great resource to keep using it, implementing more methods into the displayInfo object type or replacing the loadCell object with a different input type.

2. While the EMG was not analysed for this project, the analysis of those 4200 trials has the potential to shed new light on the results of this system and the decision processing that had occurred. It would be interesting to investigate if the decision variable could be decoded from this signal as was done in Dendauw et al. (2024).

3. There is also a great insight to be gained from using this system in conjunction with EEG. At a bare minimum, the extra information found during these trials could be used to carry out averaging of trials with similar events. This would maintain the decision artefacts in the EEG signals as well.

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Appendices

CHAPTER

SEVEN

SAFETY: RISK ASSESSMENTS FOR THESIS PROJECTS

BE/ME Biomedical Engineering Risk Assessment Form

The Following Details of the Proposed Project are Required.

1) **Student name:** Oisín Hogan

2) **E-Mail address (if any):** oisin.hogan1@ucdconnect.ie

3) **Project title:** A Continuous Measure of Decision Processing to Monitor Changes of Mind

4) **Project supervisor:** Elaine Corbette and Simon Kelly

5) **Description of proposed project activity and location of activity:**
Run experiments using MATLAB psychtoolbox, that would require participants to carry out perceptual decision-making tasks using a dual load cell input device, while collecting EEG and EMG recordings. The tasks would include contrast differentiation of two flickering diffusion gratings with different orientation. These trials would be run in the Kelly Lab in UCD.

6) **Identify who may be at risk from the activity:**
This may include you as a student working on the project, fellow students, workers, visitors, contractors and the public. The types of people may affect the risk controls needed and the location may affect the number of people at risk.

Persons at risk: Participants in the experimental trials

7) Identify hazards and control the risks.

1. An activity may be divided into tasks. For each task identify the hazards and associated risks. Also list the possible scenarios which could cause harm.
2. Determine controls necessary.
3. List existing risk controls and any additional controls that need to be implemented
4. Rate the risk once all controls are in place using the risk rating matrix below

Risk rating methodology and matrix		
Consequences	**Likelihood**	**Calculate Risk**
Consider: What type of harm could occur (minor, serious, death)? Is there anything that will influence the severity (e.g. proximity to hazard, person involved in task etc.). How many people are exposed to the hazard? Could one failure lead to other failures? Could a small event escalate?	Consider: How often is the task done? Has an accident happened before (here or at another workplace)? How long are people exposed? How effective are the control measures? Does the environment effect it (e.g. lighting/temperature/pace)? What are people's behaviours (e.g. stress, panic, deadlines) What people are exposed (e.g. disabled, young workers etc.)?	1.Take the consequences rating and select the correct column 2.Take the likelihood rating and select the correct row 3. Select the risk rating where the two ratings cross on the matrix below. **VH = Very high, H = High, M = Medium, L = Low**
5. **Severe**: death or permanent disability to one or more persons 4. **Major**: hospital admission required 3. **Moderate**: medical treatment required 2. **Minor**: first aid required 1. **Insignificant**: injuries not requiring first aid	**A. Almost certain:** expected to occur in most circumstances **B. Likely:** will probably occur in most circumstances **C. Possible:** might occur occasionally **D. Unlikely:** could happen at some time **E. Rare**: may happen only in exceptional circumstances	

		Consequences				
Likelihood		1	2	3	4	5
	A	M	H	H	VH	VH
	B	M	M	H	H	VH
	C	L	M	H	H	VH
	D	L	L	M	M	H
	E	L	L	M	M	M

Risk level	Required action
Very high	**Act immediately**: The proposed task or process activity must not proceed. Steps must be taken to lower the risk level to as low as reasonably practicable using the hierarchy of risk controls
High	**Act today:** The proposed activity can only proceed, provided that: (i) the risk level has been reduced to as low as reasonably practicable using the hierarchy of risk controls and (ii) the risk controls must include those identified in legislation, Australian Standards, Codes of Practice etc (iii) the document has been reviewed and approved by the Supervisor and (iv) a Safe Working Procedure or Safe Work Method has been prepared and (v) the supervisor must review and document the effectiveness of the implemented risk controls (ii) the supervisor must review and document the effectiveness of the
Medium	**Act this week**: The proposed task or process can proceed, provided that: (i) the risk level has been reduced to as low as reasonably practicable using the hierarchy of controls and (ii) the document has been reviewed and approved by the Supervisor and (iii) a Safe Working Procedure or Safe Work Method has been prepared.
Low	**Act this month:** Managed by local documented routine procedures which must include application of the hierarchy of controls.

Task/ Scenario	*Hazard*	*Associated harm*	*Existing controls*	*Any additional controls required?*	Consequences	Likelihood	Risk	*Cost of controls (in terms of time, effort, money)*	*Is this reasonably practicable* Y/N
Observing Stimuli	Flickering stimuli on screen	Possibility to cause epileptic seizures	Flicker rate is above epileptiform frequencies	Exclude participants with a sensitivity to flickering light	3	E	L	None	Y
Recording response	Uncomfortable position	Discomfort	Ergonomic cushions for participant in booth, Participants will be given breaks to move if wanted	None	1	D	L	None (Rests already owned)	Y
Data Analysis	Information leak	Invasion of privacy	Participants will be pseudonymised	None	2	E	L	None	Y
EMG	Silver	Allergic Reaction	Exclude participants with a silver allergy	None	2	E	L	None	Y
EMG	Tape	Irritation on skin	Carefully remove surgical tape	None	1	D	L	None	Y
EMG	Implanted electronic devices	Device malfunction	Exclude participants with implanted electronic devices	None	3	E	L		

SHADED GREY AREAS If you need to determine whether it's reasonably practicable to implement a control based on the risk, complete the shaded grey columns.
Feel free to resize the boxes to suit your situation/the amount of text you need to use.

7) **List emergency procedures and controls.** List emergency controls for how to deal with fires, spills or exposure to hazardous substances and/or emergency shutdown procedures.

8) **Review**

Are all control measures in place?	Yes
Are controls eliminating or minimising the risk?	Yes
Are there any new problems with the risk?	No
Review by: (Name)	Oisín Hogan

9) Declaration:

I declare that I have read and understand this risk management form.

Signed (Student): Oisín Hogan **Date**: 17/01/2024

Signed (Project supervisor): __Elaine Corbett_____ **Date**: ____17/01/24_____

This Risk Assessment Form must be completed and submitted together with the Project Plan in January and a copy emailed to your project supervisor. It should also be submitted as an appendix in the final thesis.

CHAPTER

EIGHT

APPENDIX1: LINK TO GOOGLE DRIVE WITH CODE AND RESULTS

Results

Program code