THE INFLUENCE OF MOVEMENT COSTS
ON SEARCH BEHAVIOUR

by

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Abstract

Humans regularly search their environment for an object to grasp through movements of the eye, head, and body. While search behaviour in humans has been well-studied, there has been little work which has investigated if the movement costs associated with searching influence where we search. While it has been shown that people attempt to minimize movement costs in other sensorimotor tasks, it is unclear to what extent people minimize these costs when making decisions of where to search for a target object. This thesis investigated whether people attempt to minimize both the biomechanical effort and time associated with searching for, and reaching to, target objects. The three studies contained in this thesis had participants search an environment for a target among distractors through either movements of the hand or eye. We manipulated the costs associated with searching, or reaching, by increasing the effort or time it took to search or reach to particular locations of the search environment. In the first study, we conducted a series of experiments to test the influence of movement effort and time on both visual and manual search. We found that visual search was influenced by time, but not effort associated with searching, with manual search being influenced by both time and effort costs. In the second study, we showed that participants are more influenced by movement time and effort costs during visual search when the costs are specified by visual information present
in the search space. In the third study, we showed that participants are capable of minimizing movement effort during manual search after learning to associate the effort involved in search to visual features of potential target objects. Together, these studies are the first to directly reveal the influence of movement costs on search behaviour, reinforcing the view of search as a complex sensorimotor behaviour.
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List of Abbreviations

ACC Anterior cingulate cortex

ACCd Dorsal anterior cingulate cortex

AI Anterior insula

ANOVA Analysis of variance

cm Centimeter

cm/s Centimeter per second

CI Confidence interval

DLPF Dorsolateral prefrontal cortex

fMRI Functional magnetic resonance imaging

F Force

FEF Frontal eye fields

FIT Feature integration theory

g Gram

xi
HMD  Head-mounted display

Hz  Hertz

kg  Kilogram

LIP  Lateral intraparietal cortex

m  Meter

M  Mean

mm  Millimeter

ms  Millisecond

MD  Movement distance

MT  Movement time

N  Newton

NHP  Non-human primate

N/m  Newton per meter

Ns/m  Newton second per meter

PD  Parkinson’s disorder

PFC  Prefrontal cortex

PMd  Dorsal premotor cortex

PPC  Posterior parietal cortex
r  Pearson correlation coefficient

rmANOVA  Repeated measures analysis of variance

RL  Reinforcement learning

s  Seconds

SC  Superior colliculus

SE  Standard error

SEF  Supplementary eye fields

SNC  Substantia nigra pars compacta

SNr  Substantia nigra pars reticulata

V  Velocity

VSL  Visual statistical learning

V1  Primary visual cortex
Chapter 1

General Introduction

1.1 Preamble

You’re getting ready to leave the house but can’t find your cell phone. Do you search for it by visually inspecting the entryway table, or the floor in case you dropped it? Do you walk upstairs to your bedroom to search, or stay on the main floor and search the kitchen? Each of these search options has a different cost associated with it, such as greater time or effort required when moving upstairs to search, but also associated benefits, such as a high probability of locating your phone in the bedroom. Throughout a typical day, people weigh these kinds of costs and benefits to make numerous decisions, often quickly, about where to search for items of interest.

In the above scenario, and in many cases of real-world search, movement is an integral aspect of the search task, whether through the physical exploration of an environment or the eventual need to reach and grasp an object once it is located. However, research on search has primarily used tasks that do not require manual actions or locomotion to either explore the search space or to act on a target object after it has been found. It is only in the last two decades that the traditionally separate
studies of visual cognition and sensorimotor neuroscience have been brought together
to understand how gaze is controlled during visually-guided behaviour (Hayhoe, 2017;
Hayhoe & Ballard, 2005). Evidence across a range of tasks suggest that the costs and
rewards associated with movement have a profound impact on sensorimotor decisions
and can even bias perceptual decisions, a bias which could extend to where we allocate
attention during search (Gallivan et al., 2018; Trommershäuser et al., 2008; Wolpert
& Landy, 2012).

The goal of the present study was to investigate whether movement-related costs
are capable of influencing search performance. This question was evaluated using
(1) search-then-act tasks in which targets are reached toward once found, and (2)
act-to-search tasks, in which hand actions are required to carry out the search. In
these tasks we manipulated two kinds of motor-related costs: the effort required to
move the hand and the time required to move it. We used the location of the eye
and hand as a measure of where participants allocated attention, examining whether
participants expressed a bias to searching in areas which were associated with lower
movement-related costs.

My approach in this introduction is an integrative one, seeking to unite separate
fields of study to better understand how gaze is influenced. In particular, I want to
document our current understanding of search behaviour at the computational level
(Marr, 1982; Marr & Poggio, 1976). That is, explaining what problems the brain has
to solve, and how it solves them, across a variety of search and action tasks.
1.2 Eye movements

In order to understand why we behave the way we do when we search for an object, it is instructive to first consider the limitations of our physical sensors and neural machinery. In this way, we can conceptualize our search behaviours as adaptations designed to overcome these limitations.

In humans and other mammals, much of our visual acuity comes from the fovea centralis on the surface of our eye’s retina, a small region consisting of less than 1% of the retina’s surface area (Rapaport & Stone, 1984). Despite its small retinal footprint, the fovea is represented in the primary visual cortex (V1) by around 8% of the available neurons (Azzopardi & Cowey, 1993). Away from the fovea, the lower density of cone photoreceptors lead to a gradual reduction in visual resolution (Wässle & Boycott, 1991). This lower resolution in the retinal periphery makes it more difficult to discriminate nearby objects viewed in peripheral vision, a phenomenon referred to as crowding (Rosenholtz, 2016; Strasburger et al., 2011).

To solve the issue of low spatial acuity in the retinal periphery, we reorient the fovea around three times a second through the use of rapid eye movements referred to as saccades, punctuated by periods of stability referred to as fixations (Henderson, 2003). Visual information is only acquired during fixations, owing to ‘saccadic suppression’ of the visual input. Interestingly, even animals without foveas engage in saccade-like behaviour, which functions to prevent motion blur on the retina during self-motion (Land, 1999). This behaviour allows us to maintain a high degree of visual acuity in our environment without the high metabolic costs that additional cortical area or movements of the head and body would entail.

Movements of the eye and attention are closely linked, but are still considered
separate processes. The distinction is often made between *covert* shifts of attention, where the eyes are fixed in place but there is preferential processing for a particular location in the visual field, and *overt* shifts of attention, where eye movements are used to place a location on the high resolution fovea and have it receive preferential processing (Posner, 1980). Nonetheless, there is often a tight linkage between attention and eye movements (Casarotti et al., 2012; Cavanagh et al., 2010; Rolfs et al., 2011; Zhao et al., 2012), even when search performance would not otherwise be impacted by the lack of eye movements (Klein & Farrell, 1989). As such, movements of the eye present a natural way to measure where attention is allocated during search.

### 1.3 Models of guided attention

The majority of the time we do not search by randomly inspecting objects until we have found our target, rather, attention appears to be guided in a strategic manner. In some cases, our gaze is drawn automatically to locations of our environment because they contain visual features which capture our attention. Models of guided attention have attempted to offer mechanisms for how these features are able to guide search behaviour.

The idea of a mechanism that guides attention has its roots in literature from the 1950s (Egeth et al., 1984; Green & Anderson, 1956; Hoffman, 1979; Wolfe et al., 1989). One of the more influential early models of attention is Treisman’s Feature Integration Theory (FIT) (1980), which attempted to provide an explanation for the observed differences in serial and pop-out type searches. Treisman suggests that features of objects, such as orientation, color, and shape, are first processed automatically and in
1.3. MODELS OF GUIDED ATTENTION

parallel across the visual field in an early preattentive stage, allowing for effortless pop-out search when a target differs from its distractors in only one feature dimension. For example, searching for a vertical line target among horizontal lines is not influenced by set size, the vertical line appears to ‘pop-out’ regardless of the number of distractors present. A second stage requires focused attention in order to correctly combine the multiple features back into a whole object. This second stage is necessary for performing serial search, when there is a conjunction of features between the target and its distractors (Treisman & Gelade, 1980). According to Treisman & Gelade (1980) attention provides the “glue” which combines features to form a single object.

Later models went on to suggest that features processed in a preattentive stage could be used to help guide attention during serial search. Wolfe’s (1994) guided search model, which has undergone revisions over the years (Wolfe et al., 2015; Wolfe, 2000, 2007), suggests that both the low-level salience of visual features in the display and knowledge of the target’s features are used to determine where attention is allocated. In the model, object features such as color and orientation are processed in parallel across the visual scene, and if an object’s feature, such as colour, is sufficiently different from that of the objects neighbouring it, that object’s location receives greater activation on a map which represents how much colour influences attention for each spatial location in the display (Wolfe, 1994). The model posits multiple maps corresponding to different low-level visual features (e.g., colour, orientation, etc.). These low-level features that ‘grab’ our attention are what are known as bottom-up influences on attention, aspects of the sensory input that shape where visual attention is allocated.
Over the years, there has been a substantial amount of interest into which low-level visual features are capable of influencing attention. In addition to the core guiding features such as colour, motion, orientation, and size (Wolfe & Horowitz, 2004), probable features have been identified such as stereoscopic depth (Nakayama & Silverman, 1986; O’Toole & Walker, 1997), luminance (Theeuwes & Kooi, 1994), and lighting direction (Enns & Rensink, 1990). More recently, axis of rotation for an object (Schill et al., 2020) and illusory motion (Thornton & Zdravković, 2020) have also been identified as features that can guide search.

Some models such as Itti & Koch (2000) focus exclusively on accurately capturing the bottom-up influences on attention. Their model attempts to simulate the properties of the early primate visual system, and they test the accuracy of their model through comparison to human search behaviour on photographic images. In their model, they find regions of an image high in visual salience by extracting the contrast, at many different spatial scales of the image, between a location and its surrounding across three different visual features: luminance, colour, and orientation. This method simulates the center-surround inhibitory architecture of the primate retina. Areas which are high in contrast are considered to also be higher in visual salience. The model then combines these contrasts into a single saliency map that, along with an inhibition of return mechanism, allocates attention in a scene based on which map locations have the highest contrast. The model was applied to searching through high-resolution images for a target, and it performed similar to and even better than human participants (Itti & Koch, 2000). While better than human performance is desirable in computer vision algorithms that want to maximize detection rate, models whose goal is to replicate human search behaviour ideally want to match
as closely to human performance as possible.

Contrasting with bottom-up influences are top-down influences on search behaviour, such as information from memory or higher cortical areas. For example, consider the task of searching for a rotated target “T” among distractors consisting of rotated “L”s, but with half of the “L”s being coloured purple and half being green. If we know that the target “T” we are looking for is also coloured green we can direct our search among the green stimuli only, reducing our search time in half (Egeth et al., 1984; Wolfe, 2020). In some cases, this can be thought of as cognitive control over the ‘spotlight’ of attention, voluntarily directing it to various locations.

In Wolfe’s model, top-down influences can bias attention by increasing feature map activity in a location where the feature matches that of the search target. Subsequently, these various feature maps are combined in a linear manner to form a global activation map, with attention directed to the location of highest activation on this map. A critical requirement of this model, and other similar models, is a mechanism to prevent the model from becoming “stuck” at the highest point of activation and never shifting attention to any other spatial location. To accomplish this, the model sets the activation of a location, once visited, to an arbitrarily small value (Wolfe, 1994). This produces similar behaviour to a phenomenon noted in real-world search known as inhibition of return, where once attention is shifted away from a location, there is a delay in subsequently returning attention to that location (Klein, 1988; Posner & Cohen, 1984). It has been proposed that inhibition of return is an adaptive mechanism that facilitates search by orienting us away from previously searched locations (Klein, 2000; Klein & MacInnes, 1999), although the purpose of the mechanism is still under debate (Berlucchi, 2006).
Whereas models such as Itti & Koch’s suggest that low-level visual features can be used to predict attention in various search tasks, other models additionally incorporate top-down influences to better predict fixation locations during search of realistic scenes (Torralba et al., 2006; Tsotsos, 2011). For example, a model proposed by Torralba et al. (2006) combines a saliency-based map of an image with a map that contains the probable location of the target based on a database of images for which the target location was known. In other words, the model was trained using knowledge of where objects tend to occur in similar images (Torralba et al., 2006). This in effect simulates people using contextual information present in a scene to guide search (Brockmole et al., 2006; Castelhano & Heaven, 2010; Henderson et al., 1999). In conclusion, incorporating top-down and other complex factors, in addition to bottom-up factors, has generally improved the ability of models to predict where people search in scenes.

Driven by findings of faster than expected searches of real-world scenes, visual search can be viewed as a dichotomy between selective and nonselective types of processing (Wolfe et al., 2011). The selective pathway contains a resource bottleneck, consistent with the attentive stage of Triesman’s FIT among other models, where attentional processing is spatially limited and has to be directed on the basis of top-down or bottom-up influences. The nonselective pathway is seen as responsible for extracting information rapidly from an entire scene, such as the mean and distribution from a range of visual features including size (Chong & Treisman, 2003), orientation (Parkes et al., 2001), and contrast (Chubb et al., 2007). These scene statistics allow people to categorize scenes quickly, and help direct the slower, selective search guidance.
In recent years, other successful search models have been proposed (Bylinskii et al., 2015; Grieben et al., 2020; Lleras et al., 2020; Tsotsos et al., 2015). In this section, I was only able to scratch the surface of these efforts. In the next section I will begin to review some of the top-down influences that have been shown to be pervasive in real-world search, with a focus on tasks using naturalistic scenes.

1.4 Guidance of attention in natural scenes

Since the early experiments of Buswell (1935) and Yarbus (1967) there has been a considerable amount of research into human gaze behaviour when viewing natural scenes. Yarbus had a participant view a painting, Ilya Repin’s *The Unexpected Visitor*, a depiction of a family at home, and captured eye movements through use of a suction cup mechanism attached to the eye. He found evidence that task instructions influenced the eye movements made, suggesting that cognitive goals influence where we look more than the visually salient areas of the scene. The increasing use of more naturalistic stimuli in search tasks, compared to the studies mentioned above that used simple geometric stimuli, has largely shown that bottom-up influence on attention cannot fully account for real-world search behaviour (Henderson et al., 2007, 2009; Underwood et al., 2009). That is, the extent to which an area of a scene is meaningful, informative, or recognizable is more likely to influence whether that area is looked at than whether the area is high in visual salience (Hayes & Henderson, 2019; Henderson & Hayes, 2017, 2018).

A great deal of work on scene perception has used eye movement recordings to study where attention is allocated within a scene; an approach that has been justified given the strong relationship between covert and overt forms of attention (Findlay,
2004). This approach has been aided by the increased availability of accurate, relatively inexpensive, and mobile eye trackers (Pelz et al., 2000). Research in this area has overwhelmingly revealed that we tend to look at locations in naturalistic scenes that contain information required to achieve the goals of our task, which may include search.

Task-related guidance involves the use of a learned strategy for directing fixations during search. For example, depending on whether the task is to locate an object or memorize the scene our pattern of fixations are very different (Castelhano et al., 2009; Henderson et al., 1999). Notable gaze strategies seem to be present across a variety of tasks, including reading (Rayner, 1998), driving (Land & Lee, 1994), and preparing tea (Land et al., 1999a). In a later section I will go into more detail on how gaze is influenced in the performance of various action tasks.

Natural scenes are likely to contain global information that aids a viewer in locating a target object. After spending our lifetime interacting within spaces such as kitchens, bedrooms, and garages we can recognize a scene as one of the above categories (also known as recognizing the scene’s *gist*) (Greene & Oliva, 2009; Oliva, 2005; Oliva & Torralba, 2001). Moreover, we can use knowledge of where objects are likely to be located in the scene to guide search (Castelhano & Heaven, 2011; Castelhano & Henderson, 2007; Pereira & Castelhano, 2019). For instance, when looking for a toaster in a kitchen scene, knowledge that toasters generally appear on countertops can guide search to that location. Additionally, knowledge of an object’s function can help guide search for it. Castelhano & Witherspoon (2016) had participants learn the function of a novel object. Participants were then shown pictures of a room where the object was placed, in either a location congruent or incongruent with its function.
When asked to search for the object, participants were faster to locate learned objects compared to novel objects whose function they had not learned. Additionally, they found that when an object was placed in a location congruent with its function, participants were more likely to search in the same region that the object was located in, suggesting that knowledge of a target’s function guides search strategy.

It has been argued that knowledge of how objects are likely arranged in a scene is in many ways similar to the knowledge of how words are arranged in language, creating a scene grammar that has rules for where objects are likely to occur (Henderson & Ferreira, 2004; Vo & Wolfe, 2013). This grammar can be divided into scene semantics, where an object is likely to occur given its function and previous history, and scene syntax, where it is possible for objects to occur (e.g., a toaster could not be floating near the ceiling). Together, these properties aid in search and memory formation for novel environments (Draschkow & Vo, 2017).

Clearly, realistic scenes offer us incredibly rich information which we can extract to aid in search. In the next section, I will delve further in the direction of naturalistic search, by discussing the research that has largely shifted the perspective of search as a passive perceptual process, to an active one, where eye movements are often combined with body movements, to accomplish the goal of obtaining information relevant to our current behavioural goals (Eckstein, 2017; Hayhoe, 2017; Yang et al., 2016b).

1.5 Search as sensory-motor decision making

Inspired in part by ideas from sensorimotor neuroscience, search guidance is increasingly being viewed as a decision making process that factors in the costs and rewards
of eye movements, body movements, and the uncertainty of both incoming sensory information and outgoing movements (Hayhoe, 2017). Through applying statistical decision theory to the process of determining where to look, we can think of search as a series of decisions designed to maximize the likelihood of locating a target given prior knowledge of the world and accounting for visual and motor uncertainty (Maloney & Zhang, 2010; Trommershäuser et al., 2008; Wolpert & Landy, 2012).

It is instructive to think about how a system could successfully achieve high search performance in the face of uncertainty. The noise inherent to our nervous system (Faisal et al., 2008) and decay of memory means that we make decisions in the face of uncertainty about the state of our body and environment. To better understand how the brain deals with this uncertainty we can posit the scenario of an ideal observer, a theoretical actor that performs a perceptual task in an optimal manner given the information available to them (Geisler, 2003, 2011). In the Bayesian framework, an ideal observer can optimally infer the state of their environment by using Bayes’ rule. That is, the probability that the environment is in a particular state (e.g., there being a target in the location currently fixated) given some uncertain sensory information (e.g., target-like object projected onto my retina) can be determined solely on the basis of the incoming sensory information received (i.e., what is the probability of receiving this sensory information given that the target is actually there) and an internal model of the environment and the sensory system (i.e., the probability that the target is actually there, and the probability of receiving this information, based on what I know about this environment and my sensory system, Yang et al., 2016b).

Recent work has found that people perform sensorimotor tasks in near-optimal ways, consistent with properties of the ideal observer (e.g., Najemnik & Geisler, 2008;
1.6 Vision is used to collect task-relevant information and control movement

Given the limitations of our sensory system and the unpredictable nature of the outside world, there is inherent uncertainty in the state of our environment. This poses a problem when we want to determine the optimal action to take during complex sensorimotor behaviour, such as searching for an object (Hayhoe, 2017; Sprague et al., 2007). Gaze is not always directed towards a location in a scene in which the target is most likely to occur, rather, in many cases gaze is directed to locations that maximize the gathering of information, reducing uncertainty, and ultimately maximizing reward in the long-term (Najemnik & Geisler, 2005; Renninger et al., 2007; Yang et al., 2016b).

Najemnik & Geisler (2005, 2008) showed that human search performance is very similar to that of an ideal observer, in that it utilizes both knowledge of the statistical properties of the search environment and the properties of the visual system (i.e., it factors in the lower acuity of visual information in the periphery of the retina), to maximize the information gathered for each fixation made. Interestingly, the authors
find that information is poorly retained across fixations, but that little task benefit emerges from retaining this information (although see De Vries et al., 2014 for evidence that multiple saccades are planned in advance).

Further evidence for the crucial role that information gathering plays in directing gaze comes from studies of action tasks (Sullivan et al., 2012; Tong et al., 2017). In Sullivan et al. (2012) participants drove a car in a driving simulator and had to maintain a constant speed. When the experimenters increased the amount of uncertainty associated with the car’s speedometer it resulted in participants looking more frequently at its location, suggesting that participants adjusted their gaze strategy to maintain task performance. As we learn a task our gaze strategies also improve to maximize information gathering, with participants learning to extract more information from each fixation (Holm et al., 2012) and selecting locations to fixate that are Bayesian optimal at maximizing information (Peterson & Eckstein, 2014). Our efficient performance of everyday tasks such as sandwich making and driving comes from having learned what objects are relevant to fixate and where they are likely to occur (Hayhoe & Ballard, 2005; Land et al., 1999a; Land & Hayhoe, 2001; Land & Lee, 1994).

The information we gather through vision is often highly optimized to control ongoing action, such as fixating the spout of a teapot to best control the flow of liquid into our cup (Land et al., 1999b). Indeed, there is a tight linkage between eye movements and body movements across a number of tasks, such as during object lifting, where we fixate a point on an object just before we grasp it (Johansson et al., 2001). In a time-constrained reaching task, people optimally balance viewing time
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and movement time, factoring in the quality of information received and the speed-accuracy tradeoff of their movement to maximize reaching accuracy (Battaglia & Schrater, 2007; Faisal & Wolpert, 2009). These studies show that gaze information is also gathered in a manner which supports the control of movements.

In many instances we can predict where we need to look to maximize information gathering. In a well-known study, Land & McLeod (2000) studied where cricket batsmen fixate as they prepare to hit a pitched ball. Skilled batsmen tended to fixate at the bounce point earlier than novice players, and prior to fixating there look at the ball as it leaves the pitcher’s hand. This suggests that players had an internal model for the dynamics of the ball that they combined with sensory information to predict the location of the bounce point and hence their next fixation. Thus, various factors influence where we look and are often adaptive measures to maximize information in a task-dependent manner.

1.7 The influence of costs and reward on sensorimotor behaviour

The movements we make on a daily basis carry the potential for rewarding outcomes. When it comes to visual search the reward could be associated with the object we locate, such as locating a food item for consumption, or simply the pleasure in finding what we are looking for, such as when a bird watcher successfully locates a rare bird. At the same time movements carry with them costs in the form of movement time and metabolic energy. Both neuroimaging and neurophysiological studies have shown that the costs and rewards associated with movement are represented in the brain across a range of areas involved in decision making and motor control. In this section I will examine some of the evidence which indicates that reward-related activity is
ultimately responsible for driving our behaviour across a variety of sensorimotor tasks.

As noted in the previous section, after experience with a sensorimotor task we learn to direct gaze to areas high in task-relevant information. Thus, there must be some mechanism within the brain that supports this learning. Reinforcement learning (RL) is one such mechanism, where actions that lead to reward are more likely to be selected in the future. Many areas of the brain show activity that is consistent with RL models (Glimcher, 2011; Lee et al., 2012; Schultz, 2000). Many of these areas contain dopaminergic neurons which support learning by signalling for expected reward, such as those located in the substantia nigra pars compacta (SNC) of the basal ganglia (Montague et al., 2004; Schultz, 2000).

The basal ganglia has been implicated in the learning associated with eye and body movements through its connections to cortical areas associated with the planning of eye movements, such as the lateral intraparietal cortex (LIP), frontal eye fields (FEF), and dorsolateral prefrontal cortex (DLPF). These areas all project onto the caudate within the basal ganglia, forming a circuit along with the superior colliculus (SC) that controls eye movement (Shires et al., 2010). Eye movements are influenced through GABAergic projections onto SC from the substantia nigra pars reticulata (SNr), the SNC’s neighbouring region, whose activity controls the release of saccades (Hikosaka et al., 2006, 2000). Clearly, due to connectivity to structures of the basal ganglia, eye-movement planning areas are influenced by dopaminergic activity in the brain, and correspondingly reward-based signals.

In many non-human primate (NHP) studies of cue-based learning and decision making, reward comes in the form of juice given to the animal as a consequence of successfully responding to some visual cue, usually a target location that must be
reached or saccaded to. These studies have found considerable evidence that neurons in eye movement planning areas are sensitive to reward. The LIP has been shown to code for both the expected reward and probability of reward prior to the execution of a saccade and the subjective value of potential movement targets (Dorris & Glimcher, 2004; Gottlieb, 2012; Kable & Glimcher, 2009; Platt & Glimcher, 1999; Sugrue et al., 2004; Trommershäuser et al., 2009). Activity in the supplementary eye fields (SEF) has also been linked to reward-related outcomes of saccades (Stuphorn et al., 2000) with the SC found to represent planning activity for an upcoming eye movement (McPeek & Keller, 2002).

Outside of the neural areas that are directly involved in eye movements, reward-related activity has been found in several other cortical and subcortical areas of the brain. The striatum has been found to encode for the value of upcoming actions (Lau & Glimcher, 2008; Samejima et al., 2005), with evidence that neurons in one part of the striatum, the caudate nucleus, represent the target of an upcoming saccade and the reward expected from it (Hikosaka et al., 2006). Kennerley et al. (2009, 2006) have found that the anterior cingulate cortex (ACC) may be a part of a circuit for learning and maintaining the value of potential actions. Both fMRI studies in humans (Hare et al., 2008; Plassmann et al., 2007; Valentin et al., 2007) and NHP neurophysiology studies (Padoa-Schioppa, 2009; Padoa-Schioppa & Assad, 2006, 2008; Wallis & Miller, 2003) have implicated the prefrontal cortex (PFC) in processing of stimulus value.

Sensorimotor decisions also carry with them costs in the form of effort or time needed before reward can be earned. Neuroimaging studies have found that reward and effort may be processed in separate areas of the brain. Croxson et al. (2009) found that activity in the ventral striatum and midbrain was linked to the value of an
upcoming action, while activity in the dorsal ACC (ACCd) represented the tradeoff between reward and effort costs. Skvortsova et al. (2014) found similar results with effort related activity in a network including the posterior parietal cortex (PPC), anterior insula (AI), and dorsal ACC.

The effort and costs of movement have also been shown to influence how we look. In eye movements, it has been found that saccades to a highly rewarding stimulus are faster, with a shorter duration (Xu-Wilson et al., 2009). This makes sense if reward is discounted as a function of time. That is, people devalue reward the longer it takes to receive (Green et al., 1997) and so a faster movement to obtain reward can be subjectively more rewarding. Indeed, it was found that the vigor with which people saccaded to targets was dependent on individual differences in reward discounting, with participants showing greater saccade vigor the more they discounted reward as a function of time (Choi et al., 2014). At the neural level, saccadic vigor is associated with the activity of cells in the SC and basal ganglia (Ikeda & Hikosaka, 2007), with greater vigor associated with a decrease in activity in the SNr (Sato & Hikosaka, 2002).

Furthermore, there is evidence to suggest that both covert and overt shifts of attention are directed to locations that are rewarding. Attention seems to be covertly guided to features that have been associated with reward (Anderson et al., 2011, 2013). Overt shifts of attention, in the form of eye movement are likewise influenced, with saccadic trajectories influenced by reward-associated distractors (Bourgeois et al., 2016; Hickey & van Zoest, 2012; McCoy & Theeuwes, 2016) and biased to regions associated with reward (Bourgeois et al., 2018). Saccades also factor in both the information and reward received from locations in a manner consistent with
a Bayesian ideal observer (Navalpakkam et al., 2010).

Evidence from other action tasks, such as reaching and locomotion also reveal the influence of reward and effort. In a reaching task to a target with overlapping penalty and reward regions, participants factor in their own motor variability to select reach locations that maximize reward (Trommershäuser et al., 2005, 2006). During walking, participants adjust their gaze so as to maintain an energetically efficient and stable gait (Domínguez-Zamora & Marigold, 2019; Matthijs et al., 2018). Therefore it seems that reward and effort influence a wide range of sensorimotor behaviours.

If movement rewards and costs factor so much into our decision making can we predict behaviour based on their influence? Computational models of decision making across a variety of tasks which incorporate the reward and costs associated with movement outcomes have successfully predicted human behaviour across a variety of tasks. A model where the utility of movement is a function of the rewards and costs associated with it, both discounted in time, successfully predicted behaviour in both human and animal studies (Shadmehr et al., 2016). These models have led to better understanding of how the brain balances the cost of time and reward in both healthy and pathological motor control (Berret & Jean, 2016; Rigoux & Guigon, 2012).

Furthermore, movement costs are an integral component of many models of arm movements. These models often incorporate movement-related cost functions, which attempt to minimize costs associated with reaching such as energy (Nelson, 1983) or jerk (Flash & Hogan, 1985). A recent and influential model, optimal feedback control, includes a penalty for effort which scales with the magnitude of the control signal (Todorov & Jordan, 2002). Clearly, people value reaching with relatively low effort, a prerequisite for there to be any influence of movement cost on search behaviour.
In this section, I’ve provided an overview of the neurological underpinnings to how eye movements can be influenced by the rewards and costs associated with them. This reward machinery is present throughout the brain, and influences everything from reaching movements to locomotion. In many ways reward may be the “ultimate” motivation for why and where we move, encouraging us to react and orient to stimuli that differ widely in their visual features, but all share the common feature of association with reward (Schultz, 2015).

1.8 The influence of memory on gaze behaviour

It only takes experiencing the frustration of locating an item in the grocery store after they rearrange their aisles to appreciate the integral role memory plays in aiding search. When we perform search and other visually guided behaviours we rely heavily on different types of memory, both episodic and semantic. Episodic memory that aids in search could be memory for where you put down a glass of water in the room, aiding in refixating the glass’s location once you look away (Henderson, 2003). Semantic memory could be longer-term memory for the location of fixed objects, such as where you expect to find objects in a kitchen. However, our memory is not infallible, it often degrades over time and has a limited capacity in the short-term, and as our environment changes it becomes out of date. How our brain balances the use of novel visual information and memory to perform visually guided behaviour is an important topic.

There is substantial evidence that memory influences gaze when viewing naturalistic scenes (Brockmole et al., 2006; Hollingworth, 2009; Vô & Henderson, 2010). After repeatedly searching a scene, both subsequent searches for a target previously
located and for objects that were previously distractors, speed up (Võ & Wolfe, 2012). Even the brief presentation of a scene in a non-search context later speeds up search within it (Hollingworth, 2012). As I reviewed in the earlier section on the guidance of attention in natural scenes, memory for objects and their functions also play an outsized role in guiding search (Castelhano & Witherspoon, 2016).

When searching in 3D environments, there is reason to believe that memory may play an even bigger role. Li et al. (2018) suggest that in 3D environments, where movements of the body and head are often involved, the greater reliance on spatial memory for where objects are located may be useful in that it minimizes the amount of movement, and therefore effort and time, needed to locate a target object. The fact that saccades can be used to locate any object in a standard 2D search task, presented on a nearby computer monitor, reduces the effort associated with searching and may reduce the reliance on memory for search. Indeed, evidence from naturalistic action tasks suggests that memory is relied on more in 3D search tasks (Li et al., 2016) and is often traded-off against effort-related costs (Li et al., 2018).

For example, Kit et al. (2014) showed that memory can be used to speed up search in a realistic 3D environment. They had participants search a virtual apartment containing multiple rooms for various objects on consecutive days. The authors reported a decrease in the number of fixations needed to locate items on day two in comparison to day one. In a follow up study, Li et al. (2018) had participants search for various items in a virtual apartment across blocks of trials. On the second to last block of trials, they changed the location the items were in. Despite this, participants maintained a rapid search time during that block, attributed to the fact that participants learn the structure of the room and where items are likely to appear. In larger-scale
outdoor environments, the use of whole-body movements and memory for features of the environment allow people to encode locations in both allocentric and egocentric reference frames, improving their ability to navigate and recall object locations (Jiang et al., 2014).

Although we exploit memory to improve search and navigation, there is also evidence that we prefer to limit our memory usage when possible (Horowitz & Wolfe, 1998; Woodman et al., 2001). In a task where participants had to arrange a set of blocks to match a visible model (show the desired arrangement), participants made frequent saccades between the model and the set of blocks indicating that they did not memorize as much of the pattern at once as would be predicted given the capacity limits of short-term memory (Ballard et al., 1995). However, when experimenters modified the experiment such that large head movements were required to shift gaze between the model and the block set, participants made few saccades, indicating they committed more of the model pattern to memory (Ballard et al., 1995). This latter finding suggests that participants trade-off memory and movement costs.

Other studies have shown that participants are selective in what they commit to memory. For example, it has been shown that participants do not notice changes in the colour or size of objects they lifted and interacted with when those features were not relevant to their current task goals (Droll & Hayhoe, 2005; Triesch et al., 2003). Interestingly, when the number of object features relevant to the task increased, leading to increased uncertainty about the object’s features, participants directed gaze more often to the object to collect information on it (Droll & Hayhoe, 2005). Together, these studies suggest that we only use memory for tasks when it is necessary and prefer to rely on short-term memory and gaze to update information critical for
task completion.

In real life, it is rare for environments and the objects in them to remain stable. For instance, when we revisit a friend’s house a given item of interest may have changed location or have been removed. As we reach for a remembered object, how does our brain balance the memory of its location with updated visual information? Work by Brouwer & Knill (2007, 2009) examined reaching to a target after its previous location was shifted. They found that early on in the reach, more weight was given to the target’s remembered location, but as the hand moved closer to the target, more weight was given to the updated sensory (i.e., visual) information. This weighting was found to be optimal based on a Bayesian model. This shows that people factor in both memory and visual information when planning reaches. Overall, it appears that memory is used frequently in a variety of visually guided behaviours, although we often limit its usage if possible and weigh its reliability against updated visual information.

1.9 Conclusions

Search is a complex sensorimotor behaviour, likely governed by a number of distinct areas of the brain. In this introduction I’ve attempted to explain why we need to engage in a relatively methodical search given the processing limitations of the brain and its sensors. I’ve outlined the numerous factors that influence our behaviour during search: the value of information gained through eye movements, the rewards from completing a task, the costs of movement needed to do so, and finally the use of memory to aid in search. While I attempted to provide a reasonable overview of the search literature, there are several related topics which I have skimmed over,
including the extensive literature related to foraging behaviour and optimal foraging
theory (Charnov, 1976; Stephens & Krebs, 1987). My goal was to provide context for
the chapters which follow and an appreciation for the complexity of everyday search
behaviour.

1.10 Outline of experiments

This thesis consists of three studies of search behaviour in healthy adults. Our primary
goal across all of these studies was to better understand the role that movement-
related costs play in influencing search behaviour. Different experiments focus on
two movement-related costs: the effort required to move and the time associated
with moving. These costs are present in search tasks via one of two ways: 1) Costs
incurred after a target object has been located through visual search, during the
reach to the object. 2) Costs incurred during the search for a target object, from
movements of the hand required to locate the target. Respectively, we refer to these
as 1) visual search or search-then-act tasks, 2) manual search or act-to-search tasks.
Eye and hand movements are used, respectively, to measure search behaviour in these
two tasks.

In all of these studies participants grasped the handle of a robotic device to interact
with virtual objects, using it to reach a target object once visually located, or moving
it over objects to reveal their identity as target or distractor. In some cases the robot
applied forces to the hand to manipulate the effort associated with moving.

In the work described in chapter two, we conducted an initial series of experiments
to test whether we could find any influence of movement cost in both visual and man-
ual search tasks. Given the greater duration and distance of movements associated
with manual search tasks as compared to visual ones, we were fairly confident that we would see some influence of costs for manual search tasks. Indeed, we found that both time and effort-based costs influence manual search, but the influence of effort costs were weak. For visual search tasks, we found it challenging to find any influence of movement costs, both for time and effort. Therefore, the third and fourth chapters featured experiments designed to make movement costs more salient to our participants in the hope it would have greater influence on their search behaviour.

In the study described in chapter three, we tried to find any influence of movement costs for visual search. By placing an obstacle in the environment we increased the movement duration and distance for reaching a subset of the objects in the display. We found that this manipulation influenced participants to search among objects located on the side of the obstacle associated with lower movement duration and distance, suggesting that participants attempted to minimize movement costs associated with searching.

In chapter four, we again investigated the influence of effort costs on manual search behaviour. We tested whether participants could learn to associate effort with the properties of objects in their search environment and use that information to minimize effort by searching among objects associated with less effort. Again, we found a small, but significant influence of movement effort on participant search behaviour.

1.11 References


1.11. REFERENCES


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Chapter 2

Time and effort-based movement costs differentially bias visual and manual search

2.1 Abstract

Movement is often a component of real-world search tasks, either when locating a search target or acting on a target once it has been found. Here we investigated whether movement-related costs influence search behaviour in two kinds of search tasks. In our visual search tasks, participants made saccades to find a target object among distractors and then moved a cursor, controlled by the handle of a robotic manipulandum, to the target. In our manual search tasks, participants moved the cursor around the environment to search, placing it onto concealed objects to reveal their identity as either target or distractor. In different experiments we manipulated either the effort or time costs associated with movements in particular regions of the search space. Effort was varied by applying different resistive forces to the handle and time costs were varied by altering the speed of the cursor. Analysis of both cursor and eye movements during manual and visual search suggested that movement effort has a small but significant influence on manual but not visual search, whereas
movement time influenced both visual and manual guided search. Overall our results demonstrate that movement-related factors can influence search behaviour, suggesting that search be viewed as a result of an interaction between sensory, motor, and cognitive systems.

2.2 Introduction

Visual search behaviour in humans has been studied extensively, with evidence suggesting that search is driven by both bottom-up (i.e., stimulus-driven) and top-down (i.e., goal-oriented) influences on attention (Corbetta & Shulman, 2002; Desimone & Duncan, 1995; Wolfe & Horowitz, 2017). Bottom-up attention refers to attention being guided involuntarily to objects in the environment because of the salience of their features, whereas top-down attention comprises voluntary guidance of attention to certain features or locations in a space. Recent work has found that visual search in natural scenes is guided less by bottom-up attention and more by prior knowledge of the scene and its structure, such as where particular objects are likely to be located (Castelhano & Henderson, 2007; Draschkow & Võ, 2017; Henderson & Hollingworth, 1999).

Movement is often a component of real-world search behaviour, whether it is moving within and acting on the environment in order to search—for example, moving around the kitchen and opening drawers in search of a can opener—or acting on a target object once it has been successfully located—for example, reaching for the nicest apple one could find in a bushel. Despite this, most studies of search behaviour involve producing only a small movement, typically a button press, once a target is located, and few studies have examined search tasks that require limb movements in
order to search. Thus, it is unclear to what extent movement influences and guides search behaviour.

While the advent of mobile eye-tracking has led to the study of gaze in more naturalistic action tasks (Land & Hayhoe, 2001; Land et al., 1999; for a review see Hayhoe, 2017) there has been little work investigating search in a more realistic manner, where movements of the head and body are needed to locate and reach objects (Gilchrist et al., 2001; Kit et al., 2014; Li et al., 2016, 2018; Smith et al., 2008; Solman & Kingstone, 2014). Partly accounting for this lack of research is an assumption, built into traditional studies of visual search, that the factors that influence where we search are largely independent from the factors that influence movement planning. Accepting this assumption, search proceeds in a serial manner, with decisions of where to look followed by planning the movements needed to arrive there; either to act on a located object or to determine whether an object is a target. However, this serial view has been challenged by converging neurophysiological and behavioral evidence suggesting that cognitive, perceptual, and motor processes occur in parallel and share neural circuitry (Cisek, 2007; Cisek & Kalaska, 2010; Song & Nakayama, 2009). The view that behaviour is a product of multiple interacting brain areas supports the idea that properties of movements themselves can influence decisions traditionally seen as occurring purely in the cognitive domain, and prior to movement planning and execution.

Properties of movements such as variability, duration, and effort are likely candidates for influencing decision making behaviour. Indeed, movement decisions have been shown to be sensitive to costs across a variety of sensorimotor tasks (Gallivan
2.2. INTRODUCTION

et al., 2018; Hayhoe, 2017; Hayhoe & Ballard, 2005). Studies of target-directed reaching have found that people can rapidly estimate their motor variability when making strategic decisions about where to reach (Diamond et al., 2017; Trommershäuser et al., 2008). Additionally, knowledge of variability is incorporated when making explicit task decisions, such as selecting among possible targets to aim towards (Moskowitz et al., 2020b; Trommershäuser et al., 2005). In tasks which trade-off viewing time and movement time, participants factor in the duration of their movements to maximize reaching accuracy (Battaglia & Schrater, 2007; Faisal & Wolpert, 2009). Decision making across a range of tasks reflects the goal of minimizing effort expended. In a task where participants could freely choose between two possible reach targets, participants preferred movements to the target associated with less biomechanical effort (Cos et al., 2011, 2014, 2012). During locomotion, people select footholds which minimize energetic costs through maintenance of a stable gait (Domínguez-Zamora & Marigold, 2019; Matthis et al., 2018). Despite the above work, it remains unclear whether the cost of search-related movements also have the capability to bias where we search.

Recent work from Mary Hayhoe’s group suggests that effort associated with movement has the potential to direct gaze during search (Hayhoe & Matthis, 2018). When given the chance to visually and physically explore a virtual 3D environment, people tend to form long-term memories for the location of objects in the space, and make use of this spatial memory to speed up search (Kit et al., 2014; Li et al., 2016, 2018). The authors suggest that in 3D environments, where body and head movements are involved in search, relying on spatial memory may be beneficial for minimizing movement, and the energetic cost associated with it (Li et al., 2018).
Recently, it was shown that the movement costs associated with responding are capable of biasing decision making in a perceptual judgement task (Hagura et al., 2017; Marcos et al., 2015). Hagura et al. (2017) asked participants to report whether they saw dots in a display moving coherently either to the left or right, by reaching with the left or right hand, respectively. When the effort associated with reaching for one hand was increased, participants reported seeing dot motion associated with the response of the opposite, unloaded hand. In a similar experiment, participants reported the direction of dot motion by reaching to left or right target locations (Burk et al., 2014). After initiating the reach participants sometimes changed their mind, and reversed their reach direction, based on visual evidence obtained after the initial decision to move. It was found that the likelihood that a participant would change their mind, based on this evidence, was mediated by the movement effort required, with fewer changes of mind occurring the further away from each other the two target locations were placed, and hence the greater effort required to correct the movement. These studies suggest that movement effort has the ability to bias decisions made on the basis of incoming sensory information, a scenario similar to that faced when making decisions related to search.

While the above work establishes that movement costs can influence decisions about movement selection (Cos et al., 2011, 2014, 2012) and can also influence perceptual processes (Burk et al., 2014; Hagura et al., 2017), there has been little research that has directly examined whether visual or manual search is influenced by movement costs associated with reaching towards or locating a target object. To investigate this issue, we designed a series of experiments where participants searched a display containing target and distractor objects and incurred movement costs either as a result
of reaching a target object once located (visual search), or in the act of searching itself (manual search). These costs were always on a spatial gradient, such that some locations in the search space were associated with either a high or low movement-related cost. Each search trial always had multiple potential targets objects that were randomly distributed in the display, meaning that participants would still have a high probability of successfully locating a target object regardless of whether they searched in a high or low movement cost location. If people factor in the costs of movement into their search decisions, we expected to see a shift in participant search behaviour, towards locations that consistently reduce the movement effort or duration associated with their search.

In Exp. 1 we tested whether movement effort influences visual search by having two participant groups perform different conditions of a “search-and-then-reach” task in which participants are asked to visually search for a target object among distractors, and then reach for the target using a cursor controlled by the handle of a robotic manipulandum. Participants were required to locate one of two targets, and move a cursor from the center of the display onto the target object. The target and distractor objects were chosen such that identifying the target object required fixating on, or close to, its location. Therefore, recorded eye movements could be used to determine where a participant was searching for the target.

During a test phase, we manipulated the effort associated with reaching the target by applying a large resistive, viscous (i.e., velocity-dependent) force to the handle for movement on either the left or right side of the search space. We predicted that during this test phase, participants would avoid searching the side of space associated with greater movement costs (i.e., greater viscosity). The test phase was
preceded by a phase of baseline trials which we included so that we could establish, for each participant, any baseline bias in their search behaviour. After comparing search behaviour between baseline and test phases, we found that this application of a resistive force, and hence greater reach effort, to a particular side of the space had no discernible effect on participants’ search behaviour relative to baseline.

In Exp. 2 we tested whether movement effort influenced search behaviour during an “act-to-search” task in which hand movements were required to perform the search. We anticipated that in this manual search task, which required greater movement overall when compared to our visual search task, it would be more likely that movement costs would influence search behaviour. Participants used the same apparatus as Exp. 1, but with an expanded search space containing more target and distractor objects. Participants had to move the cursor and hold it over an object’s location to reveal its identity. If the revealed object was a target, the trial ended, otherwise participants had to continue their search. We manipulated the effort associated with exploring the environment by applying an elastic force to the handle that was proportional to its distance from the start position, resulting in greater effort being required to identify objects farther from the start. Across blocks of trials, participants searched for a target object with the elastic force turned either on or off. Through analysis of the locations of objects visited, we found a small, but significant effect of effort, with participants visiting objects closer to the start location when the elastic force was on.

In Exp. 3 and 4 we tested whether time-based movement costs influenced both manual and visual search. In Exp. 3 participants performed a manual search task similar to Exp. 2 (using the same number of targets and distractors) but in the
absence of an elastic force applied to the handle. Cursor movement was controlled by the handle of the robotic manipulandum, which acted as a ‘joystick’ which could be moved from its start position to control the speed and direction of cursor movement. The joystick was easy to move and had a limited range of motion. Thus little effort was required to control the joystick. We manipulated the time required to move in different regions of the search space by modifying the speed of the cursor based on its radial angle from the start position, with the cursor moving faster when it was located on either the left or right side of the search space (counterbalanced across blocks). Exp. 3 revealed a significant influence of movement time on search behaviour, with participants visiting targets more often on the side of space associated with faster cursor speeds, and hence lower movement time costs.

In Exp. 4 we followed up these results by partially replicating the results of Exp. 3 and subsequently having participants perform a visual search version of the same task. Participants completed a block of manual search trials where they learned that the cursor moved slowly on one side of the search space. They then completed a block of visual search trials—with the same cursor motion—in which they visually searched the display of objects and, once a target was located, moved the cursor to the target. We predicted that participants would learn the properties of their search environment in the manual search trials replicating the results of Exp. 3, and then go on to show biases in the visual search trials, as revealed by the location of object fixations. We found that search in both the manual search task and the coupled visual search task was biased to the side associated with faster cursor movements, and hence lower movement time costs.
2.3  Experiment 1

In Exp. 1 we tested the novel hypothesis that the physical effort associated with reaching a target object can influence visual search behaviour, as measured by gaze. We applied a large resistive force when participants reached towards the left or right side of the search space during a test phase, and predicted participants would quickly learn to associate effort and reach direction across trials, and adopt a bias to search the lower-effort side. The display viewed by participants always contained 30 objects with 15 on either side of midline. Two of these objects were targets and these were randomly located such that at least one target was located on a given side on 75 percent of the trials. Thus, in principle, participants could reduce the effort required to perform by first searching the lower-effort side of space.

Participants were randomly assigned to perform one of two experimental conditions. In the spatial load condition the forces, and thus movement costs, were applied to the handle of the manipulandum when the participant moved the cursor to the target on either the left or right side of the search space (counterbalanced across participants). In the object load condition, rather than move the cursor to the target to end the trial as in the spatial load condition, participants had to “pick up” the target object by moving the cursor on top of it (locking the target’s location to the cursor) and dragging it back to the center of the display. Forces were applied to the handle during the return movement from either the left or right side of the search space (counterbalanced across participants). We included both of these conditions as we were uncertain which association—i.e., between force and the environment in general, or between force and particular objects in the environment—might be easier to learn.
2.3. EXPERIMENT 1

2.3.1 Methods

The methods for the spatial load condition and the object load condition were identical, unless otherwise noted.

Participants

Eleven participants (8 female) between the ages of 18 and 22 years old (M = 19.6) were recruited to take part in the spatial load condition. Thirteen separate participants (10 female) between 18 and 33 years of age (M = 20.8) were recruited to take part in the object load condition. One additional participant from each condition was excluded after analysis revealed poor eye tracking data (the number of trials with greater than 1 second of gaze loss was 2.5 standard deviations above the mean for that condition). Participants were required to be right handed, and have normal vision or corrected-to-normal vision while wearing contacts. These sample sizes are in line with those typically used in studies of human motor learning and visual search. All participants were compensated $15 or 1.0 course credits for their participation. Participants provided written informed consent, and after the conclusion of the experiment they were debriefed. The experiment was approved by the Queen’s General Research Ethics Board and complied with the Declaration of Helsinki.
Figure 2.1: Experimental set up and an exemplar trial. **A**, Participants moved a cursor to target objects located on a vertical screen by moving the grasped handle of a robotic manipulandum in the horizontal plane. The manipulandum was programmed to apply forces to the hand. Gaze was recorded with an infrared video-based eye tracker. **B**, In each trial 30 objects were presented on the screen, with 15 on either side of midline positioned in a 3 x 5 grid. The object position within each grid cell was randomly jittered. The 30 objects include two target objects (pink on the right side), and 28 distractor objects (pink on the left side). The gray dashed line shows an exemplar gaze path starting from the origin and ending at the target object on the left side of the screen. Solid black trace was the hand path taken to the target object. **C**, Time varying X and Y gaze locations, as well as the X position of the cursor for the same exemplar trial as B.
2.3. EXPERIMENT 1

Apparatus and stimuli

Seated participants used their dominant hand to grasp the handle of a planar robotic manipulandum (Fig. 2.1A; Kinarm End-Point Lab, Kinarm, Kingston, ON, Canada) and viewed the visual stimuli—including the target objects, distractor objects, and a cursor controlled by handle movement—on a vertical monitor positioned directly in front of them (Fig. 2.1B). The position of the cursor (filled white circle, radius 3 mm) on the monitor was linked to the position of the handle in a horizontal plane. The direction mapping between handle movement and cursor movement was the same as a standard computer mouse, such that forward and backward movements of the handle moved the cursor up and down, and right and left handle movements moved the cursor right and left. When the cursor was in the center of the screen, the handle was located 20 cm in front of the participant’s chest and in the mid-sagittal plane. There was a 1 to 1 correspondence between the distance moved by the handle in the horizontal plane and the distance moved by the cursor on the screen. The position of the handle, its velocity, and force commanded to it was recorded at 1000 Hz. Gaze data were collected at a rate of 500 Hz using an infrared eye tracker (Eyelink 1000, SR Research, Ottawa, ON, Canada) mounted just below the display monitor. A chin rest (not shown in Fig. 2.1A) was used to limit head motion during the experiment. Black boards were placed on either side of the display and room lights were turned off to limit reflection interference.

At the beginning of each trial, a start position (empty green circle, radius 5 mm) appeared at the vertical and horizontal center of the monitor. Once participants moved the cursor to this location, it filled solid green, and after a delay of 750 ms, a fixation cross appeared over it in the center of the screen (filled white, width 1.4 cm).
Participants were instructed to fixate the cross until the target and distractor objects appeared. The fixation cross was displayed for a constant time of 1000 ms. After this period, the target objects and distractor objects were presented on the monitor and participants attempted to find one of the two target objects and complete a reaching movement to it (i.e., move the cursor so that it overlaps with the target). The target was considered reached after the cursor was within 3 mm of the target for 100 ms. In the object load condition, when the cursor reached the target, it ‘locked’ to it, and participants had to drag the target object back to within 3 mm of the start position and hold it there for 100 ms to complete the trial.

A movement time criterion was imposed such that if participants took longer than 2 s to reach the target once they initiated a movement, they would be presented with the phrase “TOO SLOW” and an ‘incorrect’ tone (5 Hz, 100 ms) in the center of the display. In the object load condition, this movement time criterion was instead applied to the return movement, when participants dragged the target object back to the start position. The movement time criterion was required so that participants were able to consistently experience the velocity-dependent forces imposed by the handle. There was also a reasonable limit put on search time such that if the target was not reached in 10 seconds, participants would be presented with the phrase “TIMEOUT” and the same incorrect tone. This time limit was very seldom reached, consisting of a total of 1% of all participants’ trials. Otherwise, if search and movement time criteria were met, participants were presented with the phrase “TARGET FOUND” and a ‘correct’ tone (5000 Hz, 100 ms).

In each search trial, a total of 30 objects were presented on the screen, with 15 objects on each side located in cells of a 3 x 5 grid (Fig. 2.1B). There were a total of
28 distractors and 2 target objects on each trial. The size of each cell of the grid was 4 x 4 cm and the position of each object within the cell was randomly jittered. The objects were 1.2 cm wide squares (subtending 1.9° of visual angle when in the center of the monitor) with one half coloured pink and the other blue. The target objects had the opposite colour arrangement to the distractor objects. The locations of the targets (i.e., the cells in which the targets appeared) were pseudo-randomized such that, over the course of the experiment, both targets were on the left side in 25% of the trials, both targets were on the right side in 25% of the trials, and there was one target on either side in 50% of the trials.

**Procedure**

Participants in each condition were assigned to either experiencing a large resistive force on the right or left side of the search space (counterbalanced across participants). Prior to beginning the experiment we ran participants through an eye-tracking calibration. Participants first completed a block of five practice trials, followed by 30 baseline trials. In all of these trials, a small viscous (i.e. velocity-dependent), resistive force of 10 Ns/m applied to the handle when reaching to targets on either the left or right side. Specifically, the relationship between force (F) and velocity (V), defined as vectors, is described by equation 2.1 below:

\[
\begin{bmatrix}
F_x \\
F_y
\end{bmatrix} = b \begin{bmatrix}
-1 & 0 \\
0 & -1
\end{bmatrix} \begin{bmatrix}
\dot{x} \\
\dot{y}
\end{bmatrix}
\] (2.1)

where the viscosity \( b = 10 \) Ns/m. By including these baseline trials, we could measure any preexisting bias in participants’ search behaviour.
2.3. EXPERIMENT 1

Figure 2.2: A, The peak recorded velocity and B, peak commanded force of the handle when either reaching to the target object (spatial load) or returning the object to the center (object load) during the test phase. Reaches were grouped by condition and side reached to. Force minimum side reaches are always associated with low effort (10 Ns/m), while reaches to the force maximum side were associated with high effort (30 or 80 Ns/m for spatial and object load respectively). Error bars indicate ±1 standard error.

Following the baseline trials, participants completed 180 test trials and could take a short rest every 60 trials. In the spatial load condition five of the eleven participants experienced increased forces when reaching to the right side, while the other six experienced increased forces when reaching to the left side. In the object load condition six out of thirteen participants experienced increased forces when returning a target located on the right side, while the other seven experienced increased forces when returning a target located on the left side. We set the viscosity of the field on the higher effort side (or force maximum side) to 30 Ns/m in the spatial condition, and 80 Ns/m in the object load condition, while keeping the low effort side (or force
minimum side) at the baseline value of 10 Ns/m.

We selected these viscosities because we anticipated, based on pilot testing, that peak handle velocities would be smaller for return movements in the object load condition than for outward movements in the spatial load condition, as was indeed the case (Fig. 2.2A). As a consequence, participants in the spatial and object load conditions experienced roughly similar forces on the handle during the test phase (Fig. 2.2B). Note that although peak handle velocity was smaller for movements to the force maximum side in both the spatial (\(t_{10} = 5.82, p < .001\)) and object load conditions (\(t_{12} = 8.79, p < .001\)), peak forces were far greater for the force maximum side in both conditions (spatial: \(t_{10} = 22.56, p < .001\); object: \(t_{12} = 24.53, p < .001\)).

After the test phase, participants performed an additional block of 30 baseline trials, with viscosity returning to 10 Ns/m on both sides, which we refer to as the washout phase. We included this phase to measure whether any induced search bias would disappear once the effort associated with reaching either the left or right side returned to baseline values.

After all trials had been completed, we asked participants about their search strategy. We first asked for any general thoughts on the experiment and then asked if they had a search strategy that they could describe, if they noticed any changes during the experiment, if they noticed a resistance, and then if they noticed any patterns in the placement of the targets.

**Data analysis**

After eliminating blinks the raw gaze signal was smoothed using a second-order, zero-phase lag Butterworth filter with a cutoff frequency of 50 Hz. We then extracted the
2.3. EXPERIMENT 1

fixation locations for each trial from the time of search object onset until reach onset (i.e., hand movement speed exceeding 5 cm/s), excluding the first fixation location as it was centered on the fixation cross. To examine the number of objects fixated on each trial we attempted to assign each fixation location on each trial to an object location. We assigned each fixation to the closest object, as long as it was no more than 2 cm in distance from the center of that object. We then removed non-unique fixations (if the same object within a trial was fixated twice, we dropped the second fixation from our analysis) and fixations that could not be assigned to any object.

2.3.2 Results

Figure 2.1B shows the gaze and cursor paths for an exemplar trial in the spatial load condition and Figure 2.1C shows the x and y gaze positions, and the x cursor position, as a function of time for the same trial. In this trial, the search time (from the onset of the search stimuli to the onset of the reaching movement) was 3.8 seconds, during which 10 objects, including the target, were fixated. The average trial search times in the spatial and object conditions were 2.8 (SE = .09) and 3.3 s (SE = .12) and the corresponding average numbers of objects fixated were 5.8 (SE = .3) and 6.3 (SE = .3) respectively.

Gaze behaviour

We were primarily interested in which side of the search space participants directed their gaze during search. Therefore, for each trial, we first computed the average x-location of each fixation prior to reach onset, where the x-location of the center of the search space is zero (Fig. 2.1B). We then signed this location as positive or
negative depending on whether it was on the force minimum side or force maximum side, respectively, and multiplied it by the duration of the fixation. We then summed up these values, across the fixations in the trial and divided by the total fixation duration in the trial. We refer to this measure as the weighted location of gaze, with positive values indicating that gaze was biased towards that side requiring less effort in the test phase. Note that when computing the weighted location of gaze in baseline trials, we used the force minimum and maximum sides from the subsequent test phase experienced by the participant, allowing us to remove baseline bias. Similar measures to evaluate gaze bias, such as the proportion of fixations on the force minimum side or relative time spent fixating the force minimum side (a very similar measure), were tested. Because all of these measures revealed very similar patterns of results, we opted to only report the results of the weighted fixation location measure.
Figure 2.3: Weighted fixation locations of all participants in the spatial and object load conditions. Baseline weighted fixations are plotted against test weighted fixations, where higher numbers represent weighted fixations towards the force minimum side of the screen. Arrows indicate the hypothesized direction of the effect. Participants above the line increased their fixations on the force minimum side during test trials as compared to baseline. Each participant is plotted with ±1 standard error in both directions showing error in baseline horizontally and error in test vertically. Closed circle participants experienced maximum handle forces on the left side of space, whereas open circle participants experienced maximum handle forces on the right side of space.
Figure 2.3 shows the relationship, across participants, between the average weighted fixation location in baseline and test trials. Each circle represents a single participant and, as noted above, positive values indicate a bias to searching on the force minimum side. Participants above the unity line (i.e., $x=y$) searched more on the force minimum side during test trials as compared to baseline trials, as our hypothesis would predict. Participants along the line did not change their search behaviour from baseline to the test phase, and participants below the line were more biased towards the force maximum side during test trials. It appears that most participants are clustered around the unity line, and after combining participants for both conditions, baseline location significantly correlated with test locations, $r = .80$, $p < .001$. This indicates that the direction bias in baseline was predictive of the direction bias during test trials, indicating that despite the introduction of a large resistive force during test trials, participants largely did not change their search behaviour from baseline to test phases.
Figure 2.4: A, Mean weighted fixation locations for the spatial load and object load conditions across each phase of the experiment. For filled bars, where more effort was required to reach on the left, negative values indicate fixations on the left side. For open bars, where more effort was required to reach on the right, positive values indicate fixations on the left side. B, Difference score of fixation location between baseline and test phase. Positive values indicate an increase in fixations on the force minimum side during the test phase as compared to baseline. Error bars indicate ±1 standard error.

Figure 2.4A shows the mean weighted fixation location, averaged across participants, during the baseline, test and washout phases. Separate bars are shown for the spatial and object load conditions and, for each condition, whether the force maximum side was on the left or right side. Overall a clear left bias was observed such that when the force maximum side was the right (open bars), gaze tended to be on the left, and when the force maximum side was on the left (filled bars), gaze tended to be on the left as well. Figure 2.4B shows the difference in weighted fixation location from baseline to test for the same four groups of participants. A positive difference score would have indicated increased searching on the force minimum side during test trials, which would be predicted by our hypothesis. With respect to the data in Figure 2.4A, a 3 (Phase: baseline, test, washout) x 2 (Condition: spatial load, object load) x 2 (Side: force max left, force max right) mixed model analysis of variance (ANOVA) failed to reveal an effect of either phase, $F_{2,40} = .112, p = .894$, or condition, $F_{1,20} = .602, p = .447$, on weighted fixation location. There was a significant effect of side, $F_{1,20} = 6.82, p = .017, \eta^2 = .254$, reflecting the consistent left side bias noted above. There were no significant interactions: phase x side, $F_{2,40} = .185, p = .832$; phase x condition, $F_{2,40} = .003, p = .997$; side x condition, $F_{1,20} = 1.55, p = .228$; or phase x condition x side $F_{2,40} = .389, p = .680$. Note that the main hypothesis predicted that there would be an effect of phase, and possibly a side x phase interaction, but
Finally, we looked at the proportion of search trials in which participants’ gaze switched sides at least once. This provides a measure of how often participants searched just a single side of the space. If participants exhaustively searched the side they began their search on, they should have switched about 25% of the time. Instead, we found that switches occurred in the spatial load condition in 51% of baseline trials and 44% of test trials, and in the object load condition 47% of baseline trials and 40% of test trials. The rate of switching we observed during both baseline and test trials suggests that participants were not biased to picking a single side to search within a trial.

Figure 2.5: The proportion of reaches to the side associated with less reach effort during trials where there was one target on both sides of the screen. For the open bars the force maximum side was on the right, and for the filled bars the force maximum side was on the left. Error bars indicate ±1 standard error.
2.3. EXPERIMENT 1

Reaching behaviour

The proportion of reaches to the force minimum side was calculated during the trials where there was one target object on either side of the screen (i.e. half of all trials in a given phase). Figure 2.5 shows the proportion of reaches to the force minimum side in each phase (i.e., baseline, test, washout) of the experiment. Separate bars are shown for the spatial and object load conditions and, for each condition, whether the force maximum side was on the left or right side. It can be seen that for all conditions and different locations of the force maximum side, the proportion of reaches did not change over the phases of the experiment. However, reaches tended to be biased towards the left side of space (above or close to 0.5 when the force maximum side was on the right and below 0.5 for the force maximum side was on the left), consistent with the fixation bias towards the left side. A 3 (Phase: baseline, test, washout) x 2 (Condition: spatial load, object load) x 2 (Side: force max left, force max right) mixed model ANOVA was conducted. The analysis failed to reveal a significant main effect of phase, $F_{2,40} = .074$, $p = .929$, side, $F_{1,20} = 2.627$, $p = .121$, or condition, $F_{1,20} = .811$, $p = .379$, and no interactions were significant, $p > .05$.

Questionnaire results

After the search task had ended, participants were asked a series of questions to gauge their understanding of the forces and their search behaviour. In the spatial load condition, 10 participants noticed the forces and 1 did not. Of the 10 who noticed the forces, 6 of them were able to accurately describe the force bias in the test phase (i.e., more effort when reaching on the left or right side). In the object load condition, all 13 participants noticed the forces, and 10 of them could accurately
describe the force bias in the test phase. A commonly reported strategy was to
start on the left side and scan from top to bottom, or to start in the middle and go
outwards. Another reported strategy was that if several trials in a row always had
a target on one particular side, then they would switch and search the other side.
Based on these qualitative findings, it does not seem to be the case that our failure
to demonstrate movement cost influences on search can be attributed to a failure to
appreciate, at the level of verbal report, that forces were acting and that they were
dependent on the direction reached.

2.3.3 Discussion

In this experiment we asked participants to search a display consisting of target and
distractor objects and, once a target object was located, reach for it using the handle
of a robotic manipulandum. We manipulated the physical effort of that reach during
a test phase by applying a large velocity dependent resistive force to the handle when
it was moved on either the left or right side of the search environment. We predicted
that during the test phase, participants would bias their search to the opposite, lower
effort side, and thereby reduce the overall amount of movement effort incurred in the
task.

In both the spatial and object load versions of the experiment, similar results were
found which showed that participants did not tend to alter their search behaviour after
forces were introduced. While it is possible that some participants were not aware
of the increase in effort, both post-experiment questionnaires, and the magnitude of
the forces recorded on the handle (see Fig. 2.2B), indicate to us that participants
likely experienced substantially greater forces when the handle moved on the side
associated with greater reach effort.

It is possible that due to the binary nature of the task, some participants tended to pick a side early on during baseline and did not deviate from this strategy. However, many participants did not have a strong bias towards any given side as can be seen from the individual plots in Figure 2.3. In our task, the movement costs participants experienced when reaching a located target were at a significant temporal delay from the decision of where to search for the target. Participants may have discounted effort as a function of time, not factoring in those later experienced costs into the decision of where to search. Such an observation is consistent with several computational models of sensorimotor decision making in which both effort and reward are discounted by time (Berret & Jean, 2016; Rigoux & Guigon, 2012; Shadmehr et al., 2010). It is also possible that despite experiencing larger forces on the handle, that participants simply did not find the load experienced on the handle adverse enough to modify their behaviour. Future work will be needed to explore whether there is some threshold of effort that must be met before these types of costs can bias search. In summary, we found no evidence for an influence of movement effort on visual search behaviour.

2.4 Experiment 2

Experiment 1 assessed movement costs associated with reaching after a target was located in a visual search task. The aim of Exp. 2 was to test whether movement costs experienced during a manual search task influence search behaviour. We had participants manually search a display for a target object using a cursor controlled by the handle of the robotic manipulandum. In alternating blocks of trials, participants experienced two different load conditions. In force-on trials, a large elastic load was
applied to the handle of the manipulandum as participants moved it to search the
display, whereas in force-off trials, no such load was applied. We anticipated that
application of this load in force-on trials would cause participants to keep the handle
closer to the start position than in force-off trials, thereby reducing effort expended
during search. Participants alternated between block types, such that all participants
experienced two force-on blocks and two force-off blocks. The block structure allowed
us to compare search performance between early (block 1 and 2) and late (blocks
3 and 4) trials. It is possible that participants needed a full block of force-on trials
before they learned that the force on the handle scaled with its distance from the start
position, knowledge which they could then apply to their search behaviour during late
force-on trials by searching locations closer to the start.

There are several reasons to believe that movement effort costs might have a
greater influence on search behaviour in manual search in comparison to visual search.
First, in our manual search task, effort is expended, often for a fairly sustained period
of time, during search and not simply when reaching after search has been completed.
Second, whereas in visual search effort costs are delayed, in manual search they are
experienced during search. Third, in our manual search task, participants typically
have to make a sequence of decisions about which object (and potential target) to
move to next, giving a greater number of decision points per trial in which an influence
of effort might be observed.
2.4. EXPERIMENT 2

2.4.1 Methods

Participants

Sixteen participants (5 female) between the ages of 18 and 24 years old (M = 19.5) were recruited for this experiment. Participants were required to be right handed, and have normal or corrected-to-normal vision while wearing contacts. This sample size is in line with those typically used in studies of human motor learning and visual search. All participants were compensated $15 for their participation. Participants provided written informed consent, and after the conclusion of the experiment they were debriefed. The experiment was approved by the Queen’s General Research Ethics Board and complied with the Declaration of Helsinki.

Apparatus & Stimuli

Participants used the same apparatus described in Exp. 1, with the cursor being controlled via movement of a robotic manipulandum (Kinarm End-Point Lab, Kinarm, Kingston, ON, Canada) with a 1 to 1 correspondence (as in Exp. 1). The position of the handle, its velocity, and force commanded to it were recorded at 1000 Hz. However, eye tracking was not carried out.

The target and distractor objects in this experiment were the same size as in Exp. 1 and were located in a circular shape, with a radius of 14 cm around the horizontal and vertical center of the monitor (see Figure 2.6A). Within this circle, the 60 search objects were arranged by aligning them to a grid which contained 61 cells, with the extra cell containing the start position (see below). The size of each cell of the grid was 3.5 x 3.5 cm and the position of each object within the cell was randomly jittered, with the exception of the start position which always appeared in the same central
location.

The start positions for the first 61 trials were selected by shuffling an array containing all 61 possible target positions. The start positions for the last 39 trials were selected by random sampling without replacement from an identical array of all 61 target positions. This process ensured that each start position was used at least once. For each trial, we randomly sampled without replacement 4 target locations from the 60 possible target locations (excluding the already selected start position).

As in Exp. 1, participants had to hold the cursor at the start position and were asked to fixate the cross that appeared over it. Once the cursor was held in the start position for 750 ms, 60 gray search objects appeared on the screen. In order to identify whether a given gray search object was a target or a distractor, participants had to bring the cursor to a stop at the object. Specifically, they needed to keep the center of the cursor within 5 mm of the center of the object for 500 ms, after which the search object changed color. If the object was a target, it turned pink, the text “TARGET FOUND” was displayed in the center of the display, a ‘correct’ tone (5000 Hz, 100 ms) sounded, and the trial ended. If the object was a distractor, it turned blue, and participants had to continue searching for one of the targets. Once a search object changed color, it remained that way for the duration of the trial. If participants could not locate a target object within 30 s, “TIMEOUT” was displayed on the screen, an incorrect tone (5 Hz, 100 ms) sounded, and the trial ended.

Procedure

Participants were informed prior to beginning that there were a total of four search targets on each trial and that their location was determined through randomization.
The experimenter demonstrated a trial to familiarize them with the task. Participants completed four blocks of 50 trials each starting with either a force-on or force-off block (counterbalanced across participants) and then alternating between block types, such that all participants experienced two force-on blocks and two force-off blocks. In force-on trials, the manipulandum applied an elastic force to the handle with the force increasing linearly with the distance of the cursor from the start position multiplied by the spring constant $k = 80 \text{ N/m}$, described by formula 2.2:

$$
\begin{bmatrix}
F_x \\
F_y
\end{bmatrix}
= -k \begin{bmatrix}
\Delta x \\
\Delta y
\end{bmatrix}
$$

(2.2)

With the application of this elastic load, the further an object was from the start position, the more effort participants needed to expend to visit it. In force-off trials, no external force was applied to the handle (i.e., $k$ was set to zero).

**Data Analysis**

The location of search objects visited was recorded across trials. For each trial, we calculated the euclidean distance from the objects visited to the start location as a measure of how far from the start participants searched. As the location of the start position varied across trials, we chose not to analyze any directional biases in search as in many trials participants were limited in the direction they could move, particularly when the start location was assigned to a location on the perimeter of the search space.
2.4. EXPERIMENT 2

2.4.2 Results

Figure 2.6: A, In each trial 60 objects were presented on the screen, positioned in a circular grid. The object position within each grid cell was randomly jittered. The 60 objects include unvisited objects in gray, visited distractors in blue, and the location of four hidden target objects (shown in pink for illustrative purposes). The black line shows an example cursor path starting from the origin and ending at the target object at the bottom of the screen. Inset shows the commanded force on the manipulandum handle as a function of time in the trial. The time at which search objects 1-18 were visited is labelled. B, Average distance from origin of objects visited across trials for blocks with the elastic force on, and blocks without. Individuals shown in gray traces. Error bars indicate ±1 standard error.

An exemplar trial can be seen in Figure 2.6A, showing the cursor’s path, the objects visited, and the locations of the four targets (the three unvisited targets shown in pink only for illustrative purposes). On average the search time across participants was 14.9 s (SE = .4) in force-off trials, and 15.3 s (SE = .3) in force-on trials. In force-off trials participants visited an average of 11.9 (SE = .3) objects before locating the search target, with the average for force-on trials being 11.7 (SE = .2). As expected, there was no significant difference between force-on and force-off trials in terms of search time, \( t_{15} = .809, p = .431 \), or the number of objects visited to locate a search target, \( t_{15} = .433, p = .671 \).
2.4. EXPERIMENT 2

Distance of Objects Visited

We reasoned that if applying an elastic load were to have an influence on participants’ search behaviour, it would presumably be expressed by how far away from the start location participants searched, given that force (and hence effort) was proportional to the distance of the cursor from the start. We predicted that participants would, on average, visit object locations closer to the start position in force-on trials in comparison to force-off trials. To assess this prediction, for each trial, we determined the mean distance of the objects visited (including the target) from the start position. We then computed, for each participant, the mean average distance across all force-on trials and all force-off trials. Figure 2.6B shows the group means of this average distance for force-on and force-off trials. We found that participants in force-off trials visited objects that were, on average, .73 cm (SE = .19) further away from the start position than in force-on trials. Additionally, we were interested in whether there were differences between early (blocks 1 and 2) vs late (blocks 3 and 4) trials. Participants may have needed to first experience early force-on trials in order to learn to associate more distant handle movements with greater effort. To investigate both the effect of the load and whether any learning occurred over the course of the experiment we ran a 2 (block type: force-on, force-off) x 2 (time: early, late) repeated measures analysis of variance (rmANOVA) with average handle distance as our dependent variable, which revealed a significant effect of block type, $F_{1,15} = 14.08, p = .002, \eta^2 = .484$. There was no significant effect of time, $F_{1,15} = .985, p = .337$, or interaction between block type and time, $F_{1,15} = .778, p = .392$. These results suggest that participants searched closer to the start position in force-on trials, and that this behaviour was consistent for both early and late trials.
2.4. EXPERIMENT 2

2.4.3 Discussion

In Exp. 2 we asked participants to manually search a space containing both target and distractor objects, which required moving a cursor to objects in order to uncover their identities (i.e., target or distractor). In different trial blocks, participants either experienced an elastic force on the handle that was proportional to the cursor’s distance from the start position (force-on trials), or no force at all (force-off trials). We predicted that in the force-on trials, participants would reduce the effort associated with searching by choosing to search for the target among objects closer to the start position compared to force-off blocks. Indeed, we found a significant influence of effort, with participants visiting objects closer to the start position in force-on trials compared to force-off ones.

There may be a number of factors that contributed to seeing a small, but significant, influence of effort on search behaviour in Exp. 2 but not in Exp. 1. One, participants generally experienced higher forces on the handle of the manipulandum, and for longer, in Exp. 2 compared to Exp. 1. On average, in a given trial, participants in Exp. 2 experienced a peak commanded force of 21 N (SE = .4) on the handle whereas the average peaks in Exp. 1’s spatial and object load conditions were 12 N (SE = .5) and 14 N (SE = .5), respectively. Two, whereas participants in Exp. 1 experienced forces during a short duration point to point movement, participants in Exp. 2 experienced these forces continuously during an extended period when they were visiting and holding the cursor over objects. Three, in Exp. 1 movement costs are experienced after search occurs, whereas in Exp. 2 the costs are experienced during the search process itself, thereby reducing any temporal discounting of costs (Berret & Jean, 2016; Rigoux & Guigon, 2012; Shadmehr et al., 2010). Four, the
larger amount of effort to search in Exp. 2 when compared to Exp. 1 may have led to participants becoming increasingly fatigued and it has been shown in other tasks that increased fatigue can bias movement decisions toward lower effort options (Iodice et al., 2017a, 2017b).

2.5 Experiment 3

The previous experiments examined whether movement effort has the capacity to influence search behaviour during performance of visual and manual search tasks. Given that movement time costs have been found to influence choice behaviour in humans (Berret & Jean, 2016; Rigoux & Guigon, 2012) we wanted to investigate whether this type of movement cost also influences search behaviour. In Exp. 3 we used a manual search task to investigate whether people are sensitive to movement time related costs when searching for a target object. Using a very similar procedure as Exp. 2 we had participants search a grid containing a total of 60 target and distractor objects. To reveal the identity of objects as either target or distractor participants had to hold a cursor over their location. In this task participants controlled the speed and direction (i.e., velocity) of cursor motion using a virtual joystick simulated with a robot handle. To manipulate the cost of time, the cursor’s maximum speed was a function of the location of the cursor in the search space. More specifically, the maximum speed depended on the angle of the cursor relative to the center of the search space. By looking at the location of objects visited, we investigated whether participants were biased towards the side of space associated with higher cursor speeds, and hence, lower time costs.

In slow-left trials, the maximum speed was greatest when the cursor was located
to the right of center (0 degrees) and slowest when the cursor was located to the left of center (180 degrees), and these directions were flipped in slow-right trials. This in effect made search generally slower on one side of the search space. Four of the objects on each trial were targets and these were randomly located such that there was a high probability at least one target was located on a given side in each trial. Thus, participants could reduce the time required to locate a target object by searching the side of space associated with faster cursor movements.

Participants experienced alternating blocks of slow-left and slow-right trials (with the starting block counterbalanced across participants), such that all participants experienced two slow-left blocks and two slow-right blocks. It is possible that participants required a full block of slow-left or slow-right trials to learn the relationship between the angle of the cursor and its speed, knowledge which could then be incorporated into their search behaviour by biasing search to the side of space with higher cursor speeds. The block structure we used allowed us to test this possibility by comparing search performance between early (block 1 and 2) and late (blocks 3 and 4) trials.

2.5.1 Methods

Participants

Twelve participants (6 female) between the ages of 18 and 21 years old (M = 18.9) were recruited for this experiment. Participants were required to be right handed, and have normal or corrected-to-normal vision while wearing contacts. This sample size is in line with those typically used in studies of human motor learning and visual search. All participants were compensated $15 for their participation. Participants
provided written informed consent, and after the conclusion of the experiment they were debriefed. The experiment was approved by the Queen’s General Research Ethics Board and complied with the Declaration of Helsinki.

Apparatus & Stimuli

Participants used an apparatus identical to that described in Exp. 1. The position of the cursor and its velocity were recorded at 1000 Hz. Eye tracking was not carried out. The target and distractor objects in this experiment were the same size and appearance as in Exp. 2. The arrangement of those objects was also identical, placed within a 14 cm circle around the center of the monitor and aligned to a grid containing 61 cells. The method for selecting target locations on each trial was the same as that described in Exp. 2, except rather than randomly varying the cursor’s start location on each trial, the start location was always in the cell located in the center of the search grid.

At the beginning of each trial, the handle of the manipulandum still controlled the cursor with a 1 to 1 correspondence as in previous experiments. Participants had to move the cursor to the joystick start position (empty green circle, radius 5 mm) which was located 9 cm below the center of the display. Once held at this position for 750 ms, the handle cursor was removed from the screen, and replaced with a search cursor, which appeared in the center of the search space, coinciding with the appearance of the search objects.

To create a virtual joystick, we simulated, using a very stiff spring (6000 Ns/m stiffness, -4 N/m damping), a circular barrier around the joystick start position with a radius of 1 cm. Thus, handle travel was limited to 1 cm in any direction. Additionally,
we used a weak spring (300 Ns/m stiffness, -1 N/m damping) that brought the handle back to its start location if no forces were applied to the handle by the participant. These two springs allowed the handle of the manipulandum to effectively function as a joystick.

The cursor’s speed depended on the distance and direction of the joystick from its central start position and the current angular location of the cursor, described by formula 2.3:

$$\begin{bmatrix} V_x \\ V_y \end{bmatrix} = \begin{bmatrix} J_x \\ J_y \end{bmatrix} \left( (\cos(\theta) + 1) \cdot 1.25 + 1.5 \text{s}^{-1} \right) \quad (2.3)$$

where $V_x$ and $V_y$ are the x and y cursor velocities in cm/s, $J_x$ and $J_y$ are the x and y joystick positions in cm, and $\theta$ is the angular position of the cursor. We applied a cosine function to the cursor’s angle in order to allow for a gradual change in cursor speed between the 0 and 180 degree positions (see gray regions in Figure 2.7A). At the 180 degree position the cursor had a maximum speed of 1.5 cm/s, and at the 0 degree position the cursor had a maximum speed of 4 cm/s (counterbalanced across blocks). Participants could slow the cursor down below the maximum speed by bringing the handle back to its start position, aided by the weak spring. Overall, the above parameters used to control cursor movement allowed participants to accurately control the cursor with little to no training required.

As in Exp. 2, participants had to locate one of the four search targets after search objects appeared. The criteria for successfully revealing the identity of a search object was slightly changed from Exp. 2. Here participants had to move the search cursor within 5 mm of the object and hold it there for 300 ms, with an additional criteria
that the cursor’s speed had to be below 1 cm/s after the hold period to reveal the object’s identity. The same feedback as Exp. 2 was given for either successfully locating the target object, or timing out, with the search time allotted remaining at 30s.

**Procedure**

After the task was explained to them, participants completed four blocks of 25 trials starting with either a block of slow-right trials or slow-left trials, counterbalanced across participants. Participants alternated block types, such that by the end of the experiment participants completed two blocks of trials where the cursor moved slowly on the left and two blocks where it moved slowly on the right.

Prior to beginning each block, participants completed a single practice trial, where they had to visit each search object location and reveal its identity with the cursor. On this trial, cursor behaviour was the same as in the upcoming block. Additionally, all search objects were set as distractors, so the experimenter ended the trial once all object locations had been visited. Participants were informed that the practice trials were an opportunity to learn how to accurately control their cursor on the upcoming block, with the same joystick-to-cursor mapping applied to trials within the upcoming block.

**2.5.2 Results**

The average search time across participants was 18.9 s (SE = .6) in slow-left trials, and 18.5 s (SE = .4) in slow-right trials. The average number of objects visited across participants was 9.8 (SE = .3) in slow-left trials, and 9.9 (SE = .3) in slow-right trials.
There was no significant difference between slow-left and slow-right trials in terms of search time, $t(11) = .726$, $p = .483$, or the number of objects visited, $t(11) = .112$, $p = .913$.

Figure 2.7: **A**, Polar plot indicating the relationship between cursor angle and its maximum speed for one block. Edge of the gray shaded area indicates the maximum speed of the cursor for that angle, for this block the cursor is slowest at 180 degrees (1.5 cm/s) and fastest at 0 degrees (4 cm/s). **B**, Polar plot showing the probability density of the cursor visiting search objects at each angular location. Note the large difference in density for the different block types, with participants tending to visit objects at angles close to 180 degrees when the cursor is fastest there, and preferring to visit objects at angles close to 0 degrees in blocks when it is fastest there. **C**, Average x-location of objects visited by the cursor across block types. Positive values indicate locations to the right of midline. Individuals shown in gray traces. Error bars indicate $\pm 1$ standard error.

**Location of objects visited**

To investigate the influence of movement time on participants’ search behaviour we looked at both the angle and x-location of objects visited across block types. In trials where the cursor was slow at angles near 0 degrees (i.e., slow-right trials) we predicted that participants would minimize the time associated with searching by visiting objects at angles near 180 degrees (i.e. on the faster, left side), with the
opposite pattern expected for blocks where the cursor was slow at angles near 180 degrees. Figure 2.6B depicts a polar probability density plot for the location of objects visited for each block type. It can be seen that participants tended to visit objects on the side associated with faster cursor movements, with most of the visited objects located within 60 degrees of the angle associated with the fastest cursor speed (i.e., a region where the maximum cursor speed was 84% of the fastest cursor speed in the entire search space).

To quantify these effects we computed the average x-location of objects visited for each block type in order to determine if participants had a significant bias towards searching the side associated with faster cursor movements. Figure 2.7C shows the average x-location of objects visited for both slow-left and slow-right trials, with participants visiting objects an average of 3.4 cm (SE = .8) to the right of midline for slow-left trials, and 4.0 cm (SE = .7) to the left of midline for slow-right trials. These directional biases can be visualized by examining the arrangement of search objects shown in Fig 2.6A.

We conducted a 2 (block type: slow-left, slow-right) x 2 (time: early, late) rmANOVA, with the average x-location of objects visited as our dependent variable, to investigate both the influence of the cursor speed and whether any learning occurred over the course of the experiment. The analysis found a significant effect of block type, $F_{1,11} = 27.93, p < .001, \eta^2 = .717$, consistent with the difference in participant search location between block types noted above, and a significant interaction between block and time, $F_{1,11} = 11.10, p = .007, \eta^2 = .502$, suggesting that participants search bias changed as they learned the task. There was no significant effect of time, $F_{1,11} = .44, p = .519$. The significant interaction was driven by a larger
difference between block types (i.e., slow-left vs. slow-right trials) in late trials (8.65 cm) compared to early trials (6.05 cm), suggesting that participants’ bias towards searching the faster side became more pronounced as they gained experience with the task. Follow up paired t-tests revealed significant differences between both early blocks ($t_{11} = 4.81, p = .001$) and both late blocks ($t_{11} = 5.37, p < .001$), which remain significant when corrected with the Holm-Bonferroni method. The results suggest that participants searched in areas associated with higher cursor speed, and hence, lower time costs, and that this bias only increased as participants became more familiar with their search environment.

**Participants bias in search location reduces search time**

If participants are in fact biasing their search strategy due to the influence of time costs, it would follow that when participants visited objects on the side associated with higher cursor speed they actually shortened their search times by moving the cursor faster. In principle, participants did not have to move the cursor faster on the side associated with higher cursor speed. For instance, it is possible that increasing the cursor speed would lead to greater inaccuracy in their movements and contribute to longer search times. To examine the speed at which participants searched, we calculated the average duration, across participants, for cursor movements between search objects that were both on the fast or slow side of the search space (we ignored any movements between objects that crossed the midline). Movement durations were significantly shorter for cursor movements between fast side objects ($M = 1.09$ s, SE = .02) than slow side objects ($M = 1.69$ s, SE = .06), $t_{11} = 10.09, p < .001$, suggesting that participants did in fact reduce search times by moving the cursor faster when
2.5. EXPERIMENT 3

given the opportunity to do so.

2.5.3 Discussion

In Exp. 3 we asked participants to manually search a space using a virtual joystick to control the speed and direction of the cursor. Across alternating blocks, the speed of the cursor was slower on either the left or right side of the search space. We predicted that participants would reduce the time associated with searching by preferring to visit objects that were on the side associated with faster cursor movements. We found that participants’ search behaviour underwent a large shift across blocks, with participants expressing a preference for searching the side associated with faster cursor speeds. The ‘fast’ side alternated across blocks, indicating that participants deliberately chose to search in a location that resulted in lower time costs and not simply a particular side of the display.

The bias to searching the side with faster cursor speeds was more pronounced in the second half of the experiment after participants had gained experience with the task. We also found that when participants searched on the faster side they had significantly faster movement times. The results of this experiment are consistent with previous work that has found people incorporate kinematic factors such as movement time, effort, and object size and distance when deciding between movement options (Cos et al., 2011, 2014, 2012; Diamond et al., 2017; Michalski et al., 2020), suggesting that the influence of these factors extend to decisions traditionally seen as more cognitive in nature, such as deciding where to search for a target object.
2.6 Experiment 4

The results of Exp. 3 suggest that movement time costs have the ability to influence behaviour in a manual search task. In Exp. 4, we wanted to test whether movement time costs also have the ability to influence visual search behaviour. The findings from Exp. 3 suggest that after experience searching in early trials, participants search bias towards the side associated with lower movement times is more pronounced. We attribute this increase in bias to participants having learned more about the costs associated with searching in the first half of the experiment, and subsequently applying that knowledge in the second half. Additionally, our failure to find any significant effects of movement costs in Exp. 1 may have been due to participants’ limited opportunity to learn about the relationship between handle movement direction and effort experienced. Therefore, before testing participants on a visual search task that incorporated movement time costs, we wanted to train them on a manual search version of the task, so that they had both greater exposure to, and the opportunity to fully learn about, the costs associated with searching.

In Exp. 4, we trained participants first on a manual version of the search task (identical to the one used in Exp. 3) prior to having them perform any visual search trials. We had participants first complete a block of manual search trials, where the identity of search objects as either target or distractor was revealed by holding a cursor over their location. In these trials participants controlled the speed and direction (i.e., velocity) of cursor motion using a virtual joystick simulated with a robot handle. To manipulate the cost of time, the cursor’s maximum speed was a function of the cursor’s location, either slow on the left side (slow-left trials), or slow on the right side (slow-right trials) of the search space.
After completing a block of manual search trials, participants completed a block of visual search trials. In these visual search trials, search objects were split-color squares, similar in appearance to the stimuli used as target and distractors in Exp. 1, and participants could identify an object as target or distractor by foveating its location. Once located, participants moved the cursor to the target object using the handle as a virtual joystick to control it, in the same manner as the manual search trials.

In each block of visual search trials the cursor’s speed had the same mapping as in the previous block of manual search trials, so the relationship between the cursor location and its speed was already known to participants, and this was made explicitly clear to them by the experimenters. For example, if a manual search block consisted of slow-left trials, the subsequent visual search block also consisted of slow-left trials. Participants first completed a pair of manual and visual search blocks consisting of trials that were all either slow-left or slow-right (counterbalanced across participants), followed by another pair of manual and visual blocks with the opposite cursor speed mapping (e.g., blocks 3 and 4 would consist of slow-left trials if blocks 1 and 2 consisted of slow-right trials). In both manual and visual search trials there was a high probability of locating the search target on a given side in each trial, and therefore, participants could shorten their overall search time by either manually or visually searching the side of space associated with fast cursor movements.

We predicted that participants would learn the relationship between cursor speed and angle during the manual search trials, and subsequently demonstrate a bias towards searching the side of space associated with faster cursor speeds in visual search trials. We tested for the influence of cursor speed by comparing search behaviour
between slow-left and slow-right blocks. For each manual search block, we computed the average x-location of objects visited for each participant. While for visual search trials, we compared the average x-location of objects fixated for each participant.

2.6.1 Methods

Participants

Twelve participants (8 female) between the ages of 18 and 22 years old (M = 19.8) were recruited for this experiment. Participants were required to be right handed, and have normal or corrected-to-normal vision while wearing contacts. This sample size is in line with those typically used in studies of human motor learning and visual search. All participants were compensated $15 for their participation. Participants provided written informed consent, and after the conclusion of the experiment they were debriefed. The experiment was approved by the Queen’s General Research Ethics Board and complied with the Declaration of Helsinki.

Apparatus & Stimuli

Participants used an apparatus identical to that depicted in Fig 2.1A and described in the methods for Exp. 1. Search objects in the manual search trials were gray squares which participants had to identify as either target or distractor by holding their cursor over their location. Objects in the visual search trials were split color squares with one half pink and the other half blue. The target objects had the opposite colour arrangement to the distractor objects. The position of the cursor and its velocity were recorded at 1000 Hz. Gaze data was collected at a rate of 500 Hz using an infrared eye tracker (Eyelink 1000, SR Research, Ottawa, ON, Canada) during the
entire experiment, but only data for visual search trials was analyzed.

The target and distractor objects in this experiment had slightly modified size and arrangement compared to Exp. 3. Here the object width was reduced to 1 cm (about 1.6 degrees visual angle) and the grid radius was 11.4 cm around the horizontal and vertical center of the monitor (see Figure 2.8A). Within this circle, we arranged 32 search objects by aligning them to a grid containing 33 cells, with the extra cell containing the start position at the center. The size of each cell of the grid was 3.8 x 3.8 cm. We used a smaller search grid and object size to allow us to accurately perform eye tracking in the search space. There were a total of four search targets and the method for selecting target locations was the same as that described in Exp. 2, except the start position was not randomly selected, and always appeared in the cell located in the center of the search grid.

Manual search trials proceeded in the same manner as described in Exp. 3. For visual search trials, participants were instructed that once the search objects appeared that they should hold the search cursor in the start position (by not moving the manipulandum handle) until they visually located the target object. Upon locating the target object, participants were instructed to move the cursor to the target and hold it over its location to end the trial. The hold criteria for the target in visual search trials was identical to the hold criteria for revealing a search object’s identity in the manual trials, which was fully described in the methods for Exp. 3. When moving, the search cursor behaved in an identical manner to manual search trials, with it having a 4 cm/s maximum speed at either the 0 (slow-right trials) or 180 degree positions (slow-left trials). The feedback given for successfully locating the target object, or timing out, was the same as in Exp. 2 and 3, however we modified
the maximum search time for both manual and visual search trials, extending it to 60 s before participants timed out.

**Procedure**

Prior to beginning the experiment we ran participants through an eye-tracking calibration. After being explained the task participants completed four blocks of 25 trials each starting with a pair of manual and visual search blocks consisting of slow-left trials, followed by another pair of manual and visual blocks consisting of slow-right trials. This was counterbalanced such that for half of participants, the first pair of manual-visual search blocks consisted of slow-right trials.

Prior to beginning each manual search block, participants completed a practice trial, like in Exp. 3, where the cursor’s behaviour was the same as in the upcoming block of trials. We modified this trial slightly from the previous experiment, reducing the number of objects participants had to visit to 16, with the objects equally spaced out in a square grid that had a width and height of 22.8 cm, equal to the diameter of the circular search grid. This gave participants a chance to learn the relationship between the cursor’s location and its speed in locations they might encounter objects during manual and visual search trials. Participants were informed that the practice trials were an opportunity to learn how to control their cursor on the upcoming block. After completing a block of manual search trials, we explained to participants that the relationship between the cursor’s location and its speed would be the same on the subsequent block of visual search trials.
2.6. EXPERIMENT 4

Data Analysis

Similar to Exp. 3 we examined the location of objects visited in manual search trials to examine if participants expressed a spatial bias when searching. For visual search trials, after eliminating blinks and low-pass filtering the raw gaze signal, we extracted the fixation locations for each trial from the time of search object onset until the cursor was more than 5 cm from the start position. For each participant we assigned each fixation (except the first) on each trial to the closest search object and used the location of those objects as a measure of where participants searched. This allowed us to make a direct comparison between where participants searched in visual and manual search trials.

2.6.2 Results

For manual search blocks, there was no significant difference in search time, across participants, between slow-right (M = 15.6 s, SE = .9) and slow-left (M = 15.8 s, SE = .7) trials, t(11) = .161, p = .875. For visual search blocks, there was also no significant difference in search time, across participants, between slow-right (M = 5.8 s, SE = .2) and slow-left (M = 6.1 s, SE = .2) trials, t(11) = 1.34, p = .207. Looking at the average number of objects visited before locating the search target for manual search trials, we also found no significant difference between slow-right (M = 6.4, SE = .3) and slow-left (M = 6.5, SE = .3) trials, t(11) = .503, p = .625.
2.6. EXPERIMENT 4

Figure 2.8: A, In each trial 32 objects were presented on the screen located in cells, each 3.8 x 3.8 cm in size. The object position within each cell was randomly jittered. The 32 objects include four target objects (pink on the right side), and 28 distractor objects (pink on the left side). The gray dashed line shows an example gaze path for a slow-left visual search trial starting from the origin and ending at the target object on the right side of the screen. Solid black trace was the cursor path taken to the target object. B, Average x-location of objects visited by the cursor (for manual search trials), or fixated (for visual search trials). Positive values indicate locations to the right of midline. Individuals shown in gray traces. Error bars indicate ±1 standard error.

Location of Objects Visited

We examined, for each participant, the average x-location of objects visited for manual search trials, or fixated, for visual search trials. We anticipated that when participants were given the opportunity to learn more about the movement costs associated with searching by initially completing manual search trials, they would bring forward knowledge of the movement time costs into the next block’s subsequent visual search trials, and demonstrate a similar bias to visually searching the side of space associated with faster cursor movements, and hence, lower movement time costs.

To examine the influence of cursor speed on participant behaviour we conducted a 2 (block type: slow-left, slow-right) x 2 (search type: manual, visual) rmANOVA.
The analysis found a significant effect of block type, $F_{1,11} = 14.70$, $p = .003$, $\eta^2 = .572$. There was no significant effect of search type, $F_{1,11} = 4.06$, $p = .069$, while the interaction between search type and block type approached significance, $F_{1,11} = 4.61$, $p = .055$. Follow up paired t-tests revealed significant differences between block types for both manual (slow-left vs. slow-right: $t_{11} = 4.08$, $p = .002$) and visual (slow-left vs. slow-right: $t_{11} = 2.37$, $p = .037$) search trials which remained significant when corrected with the Holm-Bonferroni method. The results suggest that participants searched in areas associated with higher cursor speeds during manual search trials, successfully replicating the results of Exp. 3. We also found that in visual search trials participants maintained the bias towards searching the side associated with faster cursor speeds that they learned in the previous manual search block.

2.6.3 Discussion

In Exp. 4 we replicated and extended the results of Exp. 3, showing that participants avoided manually searching areas that are associated with slower movement speeds, and hence larger time costs. We also found that participants maintained this bias towards searching the same side in subsequent visual search trials, as revealed by the location of objects fixated.

2.7 General Discussion

Converging evidence from a number of studies suggests that movement costs (i.e. undesirable consequences of movement, such as large amounts of effort or time expended) influence the decisions we make during the performance of action tasks (Cos et al., 2011, 2014, 2012; Diamond et al., 2017; Michalski et al., 2020). In this paper
we examined how movement costs incurred either in the act of searching (manual search), or as a result of reaching a target once located (visual search), influence search behaviour. Across four different experiments we attempted to bias where participants searched for a target object by introducing either large effort or time costs to particular areas of their search environment. We wanted to know if participants would take into account these costs, and minimize them, through modifying their search behaviour over time to search in areas that reduced the movement effort or duration associated with searching.

In Exp. 1 we asked participants to visually search a display for a target object among distractors, and, once located, reach for it using a cursor controlled by the handle of a robotic manipulandum. After a baseline measure of participant search bias, we manipulated the effort associated with reaching to either the left or right side of the search space by applying a resistive, viscous force to the handle. By analyzing participant fixation locations across trials, we found that the application of the resistive force had little influence on participant search behaviour, with participants not deviating from their initial search behaviour during baseline trials, and with most participants expressing a strong leftward search bias throughout the experiment.

In Exp. 2 we had participants manually search for a target object. We predicted that in manual search, which requires greater movement overall when compared to visual search, that we would observe a greater influence of effort costs on participant search behaviour. In this task, participants had to visit objects using the cursor, controlled by the handle of a robotic manipulandum, to reveal their identity as target or distractor. We manipulated the effort associated with searching by applying an elastic force to the handle that was proportional to the cursor’s distance from its start...
location. Across blocks of trials, the elastic force was turned on or off. We found a small, but significant influence of effort, with participants visiting target locations that were closer to the start location when the elastic force was applied, thereby minimizing the effort of locating the search target.

Exp. 3 and 4 investigated the role of movement time costs in influencing search behaviour. Given that time costs have been noted to influence choice behaviour (Berret & Jean, 2016; Rigoux & Guigon, 2012; Shadmehr et al., 2010) we anticipated that these costs would significantly influence participant search behaviour. Exp. 3 had participants again manually search for a target object among distractors, by controlling a cursor using a joystick. The cursor’s movement speed was a function of its angle relative to the center of the search grid, with the cursor moving slower on the left or right side of the search space. We found that participants consistently visited search objects that were on the side of the search space associated with faster cursor movement. This was not simply a bias to searching a particular side of space, as the side associated with faster cursor speeds changed across blocks. Additionally, we found that participants became more biased to searching the fast side as the experiment progressed, as evidenced by the larger difference between the x-location of objects visited by participants in blocks 3 and 4 when compared to blocks 1 and 2. This suggests that as participants gained experience with the task in early trials, they learned the relationship between the cursor’s speed and its location, and applied that knowledge when searching in late trials.

Exp. 4 investigated whether movement time costs also were capable of influencing visual search behaviour. Given the noted increase in search bias across early vs. late blocks observed in Exp. 3, we decided to first train participants in a manual search
task. After completing a block of manual search trials, participants completed a block of visual search trials, visually searching for a target object and once located, moving the cursor to it using the same virtual joystick as in the manual search trials. Each manual-visual block pair had an identical movement cost gradient, with the cursor moving slowly on either the left or right side of the search space. Through analysis of the x-location of targets visited in manual search trials, we found that Exp. 4 replicated the spatial bias seen in Exp. 3, with participants searching areas associated with faster cursor movement. We also found that the bias towards searching the side associated with faster cursor movement in manual search trials was maintained in trials of the subsequent visual search block. The results suggest that after learning about the costs of manually searching an environment, participants were capable of applying that knowledge when visually searching the same environment in order to minimize movement time.

Overall, the current study shows that movement time and movement effort costs affect human search behaviour to different extents. We demonstrated that effort-based costs have an overall weak influence on human search behaviour, with a small but significant influence on manual search behaviour but none on visual search behaviour. Whereas time-based costs seem to have a large influence on manual search, and a small but significant influence on visual search behaviour. In the latter case, these costs are learned by searching the environment manually first. Taken together, these experiments support the idea that human search behaviour is influenced by movement costs associated with searching for and reaching to target objects.

Previous work has shown that movement costs are factored into human decision making across a variety of tasks including hand (Bakker et al., 2017) and target
selection (Cos et al., 2014, 2012; Diamond et al., 2017; Morel et al., 2017), gaze orienting (Kit et al., 2014; Li et al., 2016, 2018), and perceptual judgement tasks (Burk et al., 2014; Hagura et al., 2017). The novel contribution of the current work is showing that these costs can influence both gaze and hand movements in the real-world scenario of searching for, and reaching to, an object in nearby space.

While our work doesn’t address which areas of the brain represent movement costs, previous work suggests that they may be represented in the same sensorimotor areas responsible for planning eye or hand movements that occur during search (Michalski et al., 2020). Indeed, there is now substantial evidence that neural circuitry responsible for triggering and specifying arm and eye movements also represents decision variables about where to move and look (for a review see Andersen & Cui, 2009; Cisek & Kalaska, 2010; Gold & Shadlen, 2007). Areas found to code for decision-related variables include the lateral intraparietal area (LIP) (Bennur & Gold, 2011; Gold & Shadlen, 2000; Huk & Shadlen, 2005; Platt & Glimcher, 1999; Roitman & Shadlen, 2002), superior colliculus (SC) (McPeek & Keller, 2002), posterior parietal cortex (PPC) (Andersen & Cui, 2009; Christopoulos et al., 2015; Cui & Andersen, 2007; Klaes et al., 2011; Scherberger & Andersen, 2007), and dorsal premotor cortex (PMd) (Cisek & Kalaska, 2005; Pastor-Bernier & Cisek, 2011; Pesaran et al., 2008; Thura & Cisek, 2014; Westendorff et al., 2010). Both LIP and SC have been implicated in triggering target-directed saccades (Colby et al., 1996; Lee et al., 1988; Munoz & Wurtz, 1993; Wardak et al., 2002), with PPC and PMd involved in target selection for reaching (Cisek & Kalaska, 2005), as well as arm selection and specifying hand actions (i.e., grasp vs. reach) (Gallivan et al., 2013). However, how these areas interact, at the whole-brain level, to influence complex behaviour such as search remains
2.7. GENERAL DISCUSSION

less understood (Gallivan et al., 2018). Neuroimaging studies are a promising direction for better understanding how different brain systems interact to produce search behaviour, supporting a move away from a serial model of search-related processing.

While we propose that participant behaviour in our tasks was largely motivated by the minimization of biomechanical effort, or movement time, there may be other factors that could have influenced participant behaviour. One type of movement cost that may have played a role in influencing search behaviour is metabolic fatigue. In Exp. 1 we failed to note any significant influence of the resistive force on search behaviour, despite previous work which found that such forces have the capacity to bias perceptual decision making (Hagura et al., 2017). One possible source of this discrepancy could be the amount of fatigue participants experienced through exposure to forces. When compared to the test phase of Exp. 1, participants in Hagura et al. (2017) completed nearly five times as many trials in a similar phase of their experiment. It is possible that in their experiment, participants had become fatigued, and that is what drove their response bias. The significant influence of effort on search behaviour we noted in Exp. 2 could have also resulted from fatigue, owing to the larger and greater duration of those forces, when compared to Exp. 1. As participants become more metabolically fatigued from reaching, there might be a corresponding increase in the penalty of effort costs, leading to a greater influence of expected effort on movement decisions (Iodice et al., 2017a).

Another possible driver of participant behaviour is the history of prior target locations. Indeed, evidence suggests that there is a bias to search locations which previously contained target locations (Talcott & Gaspelin, 2020). We designed our experiments so that there was a high probability of locating a target on either side
of the search space. However, there were still some trials in which participants could not successfully locate a target object in areas associated with a low movement cost (25% of trials in Exp. 1, and in less than 10% of trials in our later experiments). In these trials, the behaviour of searching high cost areas was reinforced by the successful location of the target object. It is possible that trial-to-trial fluctuations in search success could have contributed to participant decisions on where to search, although based on the verbal reports of participants in Exp. 1, there was no indication that participants engaged in the strategy of searching locations where targets were previously located.

It is likely that well-learned search behaviour, such as in everyday search tasks, is more strongly influenced by movement costs than in our tasks, which participants had no previous experience with, and had limited time to learn the cost structure of their search environment. A cost function that trades off potential reward and effort fit to one movement task was not able to predict subject behaviour in a different one, suggesting that sensitivity to movement costs may not be the same across all tasks (Berniker et al., 2013). In our tasks, the forces we applied to the handle of the manipulandum, or the speed of the cursor, were quite artificial manipulations of movement effort and movement time respectively. It is possible that in a more ecological task, where movement costs are manipulated in a less artificial manner, that we would see a larger influence of movement costs on participant behaviour. We followed up with such a study to test whether the presence of a haptic obstacle in the environment, whose presence divides the search space into areas associated with low and high movement cost, biases search behaviour (Moskowitz et al., 2020a). Given the presence of obstacles in our everyday environment—e.g., a large vase on a table
obstructing an object we wish to locate—it is likely that participants have experience searching in areas containing obstacles, and understand the movement costs they impose on the environment.

The current findings show the importance of factoring in movement costs into our understanding of real-world search behaviour. Future studies would benefit from more closely examining the relationship between reward, costs, and memory limitations that factor into real-world search and other action tasks. Our study adds to the growing body of evidence that sensory, motor, and cognitive systems interact to produce complex human behaviour.

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Chapter 3

Gaze behaviour when visually searching for targets to be reached toward is influenced by movement-related costs imposed by obstacles

3.1 Abstract

Real-world action tasks often involve operating in a cluttered environment, in which we search for a target object among distractors. In many cases, these environments contain obstacles that constrain our movements and increase the movement costs associated with reaching the located target, such as avoiding a fragile wine glass when reaching for a cup at the back of a cupboard. While it is well established that people are sensitive to movement costs when selecting between potential movements, it is unclear whether movement costs likewise influence visual search behaviour. Here we tested whether visual search behaviour, as measured by gaze, is biased by the movement costs associated with acting on a target object. In each trial, an obstacle was briefly displayed and then a set of 36 objects, including 4 targets and 32 distractors, were displayed. The length, location, and orientation of the obstacle and the locations
3.2. INTRODUCTION

of the target objects were randomly varied. The task was to locate a target and then reach for it using a cursor controlled by the handle of a robotic manipulandum. The handle could apply forces simulating any contact between the cursor and the unseen obstacle. The cursor start position was in the center of the display and the objects in a given trial were either on the ‘near’ or ‘far’ side of the obstacle. We found that search, and hence target selection, was biased towards the near side of the obstacle, thus reducing the time and energy costs associated with reaching. This result suggests that humans can readily incorporate the movement costs of an environment when forming visual search strategies.

3.2 Introduction

Many of the actions we take on a daily basis require us to search for an object and, once it is located, perform a movement towards it. For example, when preparing a cup of tea, we might locate a teapot by orienting our body towards a countertop, visually search for it using gaze, and then reach and grasp the pot once it is located (Land & Hayhoe, 2001; Land et al., 1999). When searching for an object in a familiar scene, such as a kitchen, it has been shown that people make use of stored representations of how such scenes are structured to guide search (Brockmole et al., 2006; Henderson & Hollingworth, 1999). Knowledge of a scene’s structure guides search to locations consistent with an object’s function (Castelhano & Heaven, 2011; Castelhano & Witherspoon, 2016). For example, when searching for a teapot in a kitchen, gaze is often directed towards locations it is likely to be found, such as on a countertop, rather than on other surfaces such as the top of a fridge or on the floor. While these studies suggest that knowledge about the properties of a search target,
such as its function, influence where we search, it is unclear whether other properties
associated with objects in the environment, such as the costs associated with reaching
them, could likewise influence where we search.

In the real world, visual search often ends with a reaching movement to grasp
a located object. In most studies of visual search, participants search for a target
object and respond, typically with a button press, once they find a target object.
The lack of reaching movements in many traditional search studies can be partly
attributed to both technology limitations and simplicity of design, but also to an
implicit assumption: that factors associated with reaching to a target are unlikely to
influence the prior search for it. The aim of this study is to test the hypothesis that
movement related costs can, in fact, influence search strategies for reach objects.

Properties of movements, such as their variability (Diamond et al., 2017; Moskowitz
et al., 2020b; Trommershäuser et al., 2005, 2008), duration (Battaglia & Schrater,
2007; Faisal & Wolpert, 2009), and effort (Bakker et al., 2017; Cos et al., 2011,
2014) have all been shown to influence sensorimotor decisions. Recent evidence has
emerged that the costs associated with movement have some influence on perceptual
and search processes. Studies that involve participants physically walking around an
environment to locate target objects have found that people form long-term memories
for the location of objects in the space to speed up search (Gilchrist et al., 2001; Kit
et al., 2014; Li et al., 2016, 2018). It has been proposed that reliance on this spatial
memory is beneficial for minimizing movement associated with search, and hence, the
lowering of energetic costs (Li et al., 2018; Solman & Kingstone, 2014). In perceptual
discrimination tasks, movement costs associated with responding have been shown to
bias responses (Burk et al., 2014; Hagura et al., 2017; Marcos et al., 2015). However,
this work does not directly address the question of whether movement related time or effort costs in a visual search task influence where people search.

We recently investigated this question using a task in which participants made saccades to find a target object and then moved a cursor, controlled by the handle of a robotic manipulandum, to the target (Moskowitz et al., 2020a). In two separate experiments, we manipulated either the movement effort or time required to move in different regions of the search space. In the first experiment, participants experienced a larger resistive force on the manipulandum’s handle, increasing movement effort, when reaching to targets on one side of the display. In the second experiment, participants experienced a decrease in the cursor’s movement speed, increasing movement duration, when reaching to targets on one side of the display. In both experiments, we made use of multiple target objects, such that there was a high likelihood of participants locating a target regardless of which side of the display they searched. In the first experiment, we failed to find an influence of effort on search behaviour, whereas in the second experiment we found only a weak bias towards searching the side of space associated with lower movement time costs.

A main feature of the current task, which distinguishes it from the above experiments, is that participants are provided—prior to search onset—with visual information about the scene, in the form of an obstacle’s location, that specifies movement time and energy costs associated with reaching to different regions of the search space. In contrast, the manipulations of resistive force or cursor speed in the previous task are only apparent once the reaching movement commences. There are many real-world examples in which visual information about the scene effectively specifies movement-related costs. For example, consider searching for a particular book in a
tall bookshelf where you visually appreciate that you cannot reach the top shelf without getting a stool to stand on. The specific, two-part, hypothesis being tested in the current study is that participants can (1) quickly appreciate the mapping between space and movement cost based on visual information about the search environment, and (2) use this knowledge to bias search towards lower cost regions of the search space.

To test this specific hypothesis, we designed a novel task in which participants visually searched for one of 4 target objects among 32 distractors and, once a target was located, reached towards it using a cursor controlled by the handle of a robotic manipulandum. The design of target and distractor objects was such that identifying the target object required fixation at, or close to, its location. Therefore, we extracted fixation locations on each trial to identify where a participant was searching.

On each trial we manipulated the movement cost associated with reaching certain areas of the display by inserting an obstacle in the environment on each trial. The obstacle’s location is shown to participants at the start of each trial, prior to search onset, and upon target and distractor presentation, the obstacle’s location is hidden. Forces applied to the handle of the manipulandum simulated contact between the cursor and the unseen obstacle. We anticipated that participants would quickly appreciate the movement time and energy costs specified by the obstacle. Indeed, previous work has shown that humans rapidly factor in the presence of obstacles in their environment, altering both the speed and trajectory of movement to avoid them (Biegstraaten et al., 2003; Garzorz et al., 2018; Nashed et al., 2012).

We randomly varied the length, location, and orientation of the obstacle on each trial, along with the locations target objects would appear. Participants started with
their cursor in the center of the display, and search objects were either on the ‘near’ or ‘far’ side of the obstacle. If participants wanted to reach a target object located on the far (or obstructed) side of the obstacle, they were required to perform a larger movement to navigate the cursor around the obstacle, incurring greater movement time and effort costs relative to reaches on the near (or open) side of the obstacle. We predicted that participants rapidly integrate an obstacle’s location into their search strategy, by preferentially searching for the target object on the near side of the obstacle and thereby avoiding potentially high movement costs incurred from locating, and reaching to, target objects on the far side.

3.3 Methods

3.3.1 Participants

Twelve participants (6 female) between the ages of 18 and 19 years old (M = 18.7) were recruited for this experiment. Participants were required to be right handed and have normal or corrected-to-normal vision while wearing contacts. These sample sizes are in line with those typically used in studies of human motor learning and visual search. All participants were compensated $15 or 1.0 course credits for their participation. Participants provided written informed consent, and after the conclusion of the experiment they were debriefed. The experiment was approved by the Queen’s General Research Ethics Board and complied with the Declaration of Helsinki.
3.3. METHODS

Figure 3.1: A, Participants moved a cursor to target objects located on a vertical screen by moving the grasped handle of a robotic manipulandum in the horizontal plane. The manipulandum was programmed to apply forces to the hand. Gaze was recorded with an infrared video-based eye tracker. B, Object locations, obstacle location, gaze and hand position all taken from an exemplar trial. In each trial 36 objects were presented on the screen, arranged in a circular grid. The object position is randomly jittered on each trial. The 36 objects include 4 target objects (pink on the left side), and 32 distractor objects (pink on the right side). Black trace indicates raw gaze position, with fixations highlighted in blue and numbered. Dashed gray trace indicates hand position.

3.3.2 Apparatus & Stimuli

Seated participants viewed the visual stimuli—including the target and distractor objects, and a cursor controlled by hand movement—on a vertical monitor positioned directly in front of them (Figure 3.1A and 3.1B). Participants controlled the cursor by grasping the handle of a planar robotic manipulandum (Kinarm End-Point Lab, Kinarm, Kingston, ON, Canada). The position of the cursor on the monitor was linked to the position of the handle grasped by the participant, and moved in a
horizontal plane.

The direction mapping between handle movement and cursor movement was the same as a standard computer mouse, such that forward and backward movements of the handle moved the cursor up and down, and right and left handle movements moved the cursor right and left. When the cursor was in the center of the screen, the handle was located about 20 cm in front of the participant’s chest and in the mid-sagittal plane. There was a 1 to 1 correspondence between the distance moved by the handle in the horizontal plane and the distance moved by the cursor on the screen.

The position of the handle was recorded at 1000 Hz. Gaze data was collected at a rate of 500 Hz using an infrared eye tracker (Eyelink 1000, SR Research, Ottawa, ON, Canada) mounted just below the display monitor. A chin rest (not shown in Fig. 3.1A) was used to limit head motion during the experiment. Black boards were placed on either side of the display and room lights were turned off to limit reflection interference.

In each search trial, a total of 4 target and 32 distractor objects were presented on the screen, located within the confines of a circle with a radius of 11.4 cm around the start location (Fig 3.1B). Within this circle, the 36 search objects were arranged by aligning them to a grid which contained 36 cells. The size of each cell of the grid was 3.8 x 3.8 cm and the position of each object within the cell was jittered using a random shift in the x and y location drawn from a continuous distribution between ± 0.7 cm in order to create unique object locations across trials. Both target and distractor objects were 1 cm wide squares (subtending 1.6 degrees of visual angle when in the center of the monitor) split vertically down the middle with one half colored pink
and the other half blue. The target objects had the opposite colour arrangement to the distractor objects. We chose these stimuli as identifying an object as target or distractor required fixating on, or close to, its location (Moskowitz et al., 2020a).

The start position (empty green circle, radius 5 mm) appeared at the vertical and horizontal center of the monitor. The obstacle could have one of four possible angles relative to the start location, appearing either above, left, right, or below it. The obstacle was oriented vertically when positioned to the left or right, and horizontally when positioned above or below the start location. The obstacle could also be located at one of two positions from the start location; either far or close with the near edge of the obstacle being 5.3 or 1.5 cm from the center of the start location. Finally, the obstacle could be one of two lengths, either long (20 cm in length) or short (5 cm in length). This made for a total of sixteen possible obstacle configurations that could appear on a given trial. The use of multiple obstacle configurations allowed us to control for any possible directional biases in gaze and investigate the influence of both obstacle distance (from the start) and obstacle length on gaze behaviour. The edges of the obstacle were modelled as a very stiff spring (6000 N/m) with damping (-4 Ns/m) that prevented the handle of the manipulandum from crossing the outer edges of the obstacle, simulating a physical barrier placed in the search space.

To select target locations, we randomly sampled without replacement 4 target locations from the 36 possible target locations. To select the obstacle configurations, for each block of 16 experimental trials, we randomly permuted all 16 possible obstacle configurations and assigned those configurations to that block of trials. This ensured that participants would experience each obstacle configuration at regular intervals throughout the experiment, and ensured that each obstacle configuration was used in
3.3. METHODS

an identical number of trials. With the exception of one participant, all participants experienced the same order of obstacle configurations and target locations.

3.3.3 Procedure

At the beginning of each trial, participants moved the cursor (filled white circle, radius 3 mm) to the start position in the center of the monitor, the start position filled solid green, and after a delay of 750 ms, a fixation cross appeared over it in the center of the screen (white, width 1.4 cm). Participants were instructed to fixate the cross until an obstacle appeared. The fixation cross was displayed for a constant duration of 500 ms. After this period, participants were shown the location of the obstacle on the monitor, appearing as a filled orange rectangle (width: 0.8 cm). After 1000 ms the visual location of the obstacle was removed prior to target and distractor onset, but the forces simulating the obstacle’s presence remained throughout the trial. Removal of the obstacle’s visual location was done to prevent the possibility that participant gaze would be drawn to the obstacle’s location during the trial.

The target and distractor objects were presented on the monitor following removal of the obstacle’s visual location, and participants attempted to locate one of four target objects and complete a reaching movement to it (i.e., move the cursor so that it overlaps with the target). The target was considered reached after the cursor was within 3 mm of the target for 100 ms. There was no movement time criterion but participants were instructed to leave the cursor at the start location until they located a target object. A limit was put on search time such that if the target was not reached within 30 seconds after object presentation participants would be presented with the phrase “TIMEOUT” and an incorrect tone (5 Hz, 100 ms). If participants reached a
target object they were presented with the phrase “TARGET FOUND” and a correct tone (5000 Hz, 100 ms). Feedback remained on the screen for 1500 ms before the next trial began.

Prior to beginning the experiment we ran participants through an eye-tracking calibration. Participants were informed prior to beginning that there were a total of four search targets on each trial and that their location, in addition to the location of the obstacle, was determined through randomization. After being instructed on the task participants completed a total of 4 practice trials. In these practice trials the obstacle was visually left on the screen for the duration of the trial, in order to give participants a chance to move the cursor against the obstacle to appreciate that the obstacle acted as a physical barrier to the manipulandum handle. Participants completed a total of 208 search trials, with a short rest inserted every 30 trials.

3.3.4 Data Analysis

After eliminating blinks the raw gaze signal was smoothed using a second-order, zero-phase lag Butterworth filter with a cutoff frequency of 50 Hz. We then extracted fixation locations for each trial from the time of target and distractor onset until the time that the target was reached by the cursor. We further processed the gaze data to remove drift. In each trial, we identified the fixation of the start position and the fixation of the target during the reach and computed the average offset, in x and y, between these fixations and the corresponding positions. These average offsets were then applied to the gaze data in that trial. Figure 3.1B shows the drift-corrected gaze signal for an exemplar trial with fixation locations highlighted in blue and numbered.

For each trial, we attempted to assign each fixation location to an object location.
3.3. METHODS

For the first fixation only we checked if it was within 2 cm of the start location and if so, did not attempt to assign it to an object. We otherwise assigned each fixation to the closest object, as long as it was no more than 1.5 cm in distance from the center of an object’s location. After removing non-unique fixations (if the same object within a trial was fixated twice, we dropped the second fixation from our analysis) and fixations that could not be assigned to an object, we analysed the position of the objects fixated by participants during each trial.

In our analysis we focused on the effects of obstacle position (far vs close) and length (short vs. long) on search and reach behaviour, collapsing across obstacle angle (above, left, right, or below the start). This was done by rotating the fixation and object locations to a common coordinate frame with the obstacle always on the left side of space (as shown in Figure 3.3A-D). We then defined any objects/fixations to the right of the obstacle as being in “open” space, and objects/fixations to the left of the obstacle as being in “obstructed” space. While it is true that for short obstacles, unlike long ones, participants could reach some of the objects in the first column to the left of the obstacle without deviating their reach from a straight line, our initial data analysis showed that these objects were fixated with similar frequencies in the short and long obstacle conditions, suggesting that participants treated these objects as being on the obstructed side of the obstacle.

To analyze movement duration and distance we defined the movement window as starting from the time that hand speed exceeded 5 cm/s, or if the hand did not reach that speed, when the cursor exceeded a distance of 1 cm from the start location, and ending when the target was reached.
3.4 Results

3.4.1 Reaching to the obstructed side increases movement time

Our hypothesis, that participants prefer to visually search the open side of the display, presumes that movement time (MT) and movement distance (MD) would be greater for reaches to the obstructed side. To test this assumption, while controlling for the displacement from the start position to the target, we compared, for each obstacle condition (i.e., long & far, long & close, short & far, short & close), reaches to targets on the obstructed side with reaches to targets located within the matched (i.e., mirrored) region on the open side. For example, in long & far obstacle trials (as depicted in Figure 3.3A), we compared the MT and MD of obstructed side reaches (i.e. reaches to targets in the two leftmost columns) to reaches that were to targets in the two rightmost columns.

Figures 3.2C and 3.2D show, for each obstacle condition, cumulative distributions of MTs and MDs for all trials from all participants. What can be immediately appreciated is that MT and MD are closely linked, with near identical distributions for both variables. Reaches to the matched open side were quite similar in MT and MD for all obstacle conditions. In all conditions, reaches to the obstructed side had greater MT and MD compared to open side reaches, however, there are clear effects of obstacle length and position, with MT and MD being greater for the long and far obstacles.

Separate 2 (obstacle length: long, short) x 2 (obstacle position: far, close) x 2 (side reached: matched open side, obstructed side) rmANOVAs were conducted, one examining MT, and the other MD, using the average MT and average MD for each participant, for each obstacle condition. As MT and MD are closely linked, we found
that the rmANOVAs produced similar results for both measures, and so we chose to report results for the MT rmANOVA only.

For MT, we found a significant effect of side reached, $F_{1,11} = 292.99, p < .001, \eta^2 = .964$, with reaches to the obstructed side ($M = 2.0$ s, $SE = .09$) taking longer than reaches to the matched open side ($M = .9$ s, $SE = .06$), confirming our presumption that the obstacle increased the MT and MD to targets on the obstructed side. We also found a significant effect of obstacle length, $F_{1,11} = 66.40, p < .001, \eta^2 = .858$, with reaches when the obstacle was long ($M = 1.7$ s, $SE = .07$) taking longer than reaches when the obstacle was short ($M = 1.3$ s, $SE = .06$). Additionally, we found a significant effect of obstacle position, $F_{1,11} = 9.52, p = .01, \eta^2 = .464$, with reaches when the obstacle was far to the start ($M = 1.5$ s, $SE = .07$) taking longer than reaches when obstacle was close to the start ($M = 1.4$, $SE = .07$), which likely reflects the fact that the location of reach objects in the far obstacle conditions were farther from the center, on average, when compared to the location of reach objects in the close obstacle conditions.

There was also a significant two-way interaction between obstacle length and side reached, $F_{1,11} = 106.01, p < .001, \eta^2 = .906$, with reaches to the obstructed side being greatly affected by obstacle length (short: $M = 1.6$ s, $SE = .08$; long: $M = 2.4$ s, $SE = .11$) whereas reaches to the matched open side were, unsurprisingly, not (short: $M = .9$ s, $SE = .07$; long: $M = .9$ s, $SE = .05$). All other 2 and 3-way interactions failed to reach significance ($p > .05$ in all three cases).
3.4. RESULTS

Figure 3.2: Cumulative proportion of A, movement times and B, movement distances for both matched open side (blue and magenta color), and obstructed side (dark blue and dark magenta color) reaches for all obstacle conditions. Relative proportion of C, distance between objects visited and D, number of objects fixated, for all trials in each obstacle condition.
3.4.2 Participants prefer to reach to targets on the open side

To initially examine participant search preferences we looked at, across obstacle conditions, the proportion of reaches to obstructed side targets compared to open side targets. There was on average, nearly four times the number of reaches to the open side of space, with participants reaching to the obstructed side 19.2% of the time (SE = 2.1%) with a 95% confidence interval of [14.7%, 23.8%]. Note that there was at least one target on the open side in all but a handful of trials. Of the total of 208 trials there was a total of 3 trials (1.44%) in which all targets were on the obstructed side, thereby forcing participants to reach to that side. Thus, although participants were strongly biased to the open side they nevertheless selected and moved to targets on the obstructed side far more often than necessary. In close obstacle trials 91% of the time at least one target was located on the obstructed side, with this being the case in 75% of far obstacle trials. Therefore, there was still a very high probability of participants locating a target on the obstructed side if they searched there.

An issue with using reach frequencies to both the open and obstructed sides as a measure of search preference is that there are more objects, and therefore more targets, on the open side and, on average, these objects are closer to the start position. If participants were merely searching at random for a target object we would expect that participants would reach to a target on the open side more often than the obstructed side, simply due to chance alone. To address this issue, we compared the rate at which participants reached to the obstructed side, to the rate which would be observed had they been searching for a target completely at random and reached to the first one located. To make this comparison we simulated 10,000 search trials, with the four target locations on each of those simulated trials obtained by randomly
3.4. RESULTS

sampling a trial of the actual experiment and obtaining the target locations used in that trial. In addition, half of the 10,000 were far obstacle trials, with the other half close obstacle trials. For each of the simulated trials, we randomly selected one of the search target locations, and noted whether it fell on the open or obstructed side of the search space. We found that the selected target was on the obstructed side an average of 32.7% of the time across the 10,000 simulated trials, which falls well outside of the 95% CI for the experimental data, suggesting that the bias participants showed to searching the open side cannot be attributed to participants engaging in a wholly random search strategy.

To investigate whether there was any influence of obstacle condition on reach location we conducted a 2 (obstacle length: long, short) x 2 (obstacle position: far, close) rmANOVA on the proportion of reaches to the obstructed side. We found a main effect of obstacle position, $F_{1,11} = 10.64, p = .008, \eta^2 = .492$, with participants reaching to the obstructed side significantly less in far obstacle trials ($M = .15, SE = .02$) compared to close obstacle trials ($M = .23, SE = .03$). Both the effect of obstacle length and the interaction between length and position were not significant ($p > .05$ in both cases).

3.4.3 Participant saccade and fixation behaviour

To investigate participants’ visual search strategy, we examined two different measures of search behaviour. We first examined saccade amplitudes, or the distance between sequential object fixations. For each obstacle condition, we calculated the distance between objects that participants sequentially fixated on each trial, and visualized the proportion of each distance (Figure 3.2C). As can be seen, there were near identical
saccade amplitudes across conditions, with the largest peak around 3.8 cm, which approximates the distance objects were placed apart from each other. The smaller peaks at each multiple of this distance indicate when participants made saccades to objects two or three away from the current object fixated. These data suggest that participants mostly fixated neighboring objects when searching. We also examined the number of objects participants fixated before locating a target object (Figure 3.2D). We found that participants fixated a median of 4 unique objects before locating the search target. On average, participants re-fixated less than a single object per trial (M = .7, SE = .1). Given that both measures showcased similar results for all obstacle conditions, we calculated the average distance between object fixations (M = 5.5 cm, SE = .1) and the average number of objects fixated (M = 5.6, SE = .2) across all trials.
Figure 3.3: Object-centered fixation locations across all trials and participants for A,
far & long, B, close & long, C, far & short, D, and short & close obstacle conditions. Fixations more than 1.5 cm away from the center of a search object were removed, and remaining fixations were assigned to the closest search object and fixation location was then shifted by the amount of jitter applied to that assigned object. Fixation and obstacle locations were rotated to a common reference frame with the obstacle on the left side of the search grid. Numbers above each column indicate the average number of fixations per object in that column. E, Relative proportion of fixations per object for each column of the search grid across all participants and trials. Shown in the thin traces is the data for the undirected search model for each obstacle condition. Error bars indicate standard error of the mean across participants.

3.4.4 Participants prefer visually searching on the open side

We examined the location of participant fixations across trials to determine whether there was a bias to visually searching the open side of the search space. Figures 3.3A-D show the locations of all fixations, across all participants and trials, in each obstacle condition. Note that fixations associated with the four different obstacle angles are shown in a common space with the obstacle on the left side of the start location. To create this visualization, we took all fixations that were successfully assigned to an object location (i.e., those within 1.5 cm of an object) and then, for each fixation, adjusted its location to compensate for the random shift applied to the object it was assigned to on that trial. In this way, we were able to plot fixations across trials aligned to a common, object-centered grid.

What can be quickly appreciated is the clear asymmetry in fixation density between the obstructed and open sides across all four obstacle conditions, with a higher density of fixations on the open side (Figure 3.3A-D). In each panel of the figure the number above each column is a normalized count of fixations per object (the total number of fixations in that column divided by the number of objects in that column). These numbers indicate that participants consistently had the fewest number
of fixations on objects located in obstructed columns compared to the corresponding columns on the open side.

To further examine the density of fixations per column, we plotted, in Figure 3.3E, the average number of fixations per object per column for all four obstacle conditions. We defined the center column containing the start location as 0, with the columns to the right of it being assigned positive integer values, and the columns to the left being assigned negative integer values. We refer to the magnitude of these integers as the column’s eccentricity (i.e., distance from the center). To investigate the influence of the obstacle on search behaviour we conducted a 2 (obstacle position: far, close) x 2 (side: left, right) x 3 (eccentricity: 1, 2, 3) rmANOVA on the avg. number of fixations per object in each column. We did not include the center column as a level of eccentricity as we are mainly interested in testing whether participants showed a bias towards a side of the search space. We chose to leave out obstacle length as a factor in this analysis since it did not appreciably impact fixation density.

Critically, we found a main effect of side, $F_{1,11} = 13.61, p = .004, \eta^2 = .553$, with participants fixating more than twice as often on the side without an obstacle ($M = .18, SE = .02$) when compared to the side of the display where the obstacle was located ($M = .08, SE = .01$). We also found an effect of eccentricity, $F_{1,11} = 27.41, p < .001, \eta^2 = .714$, indicating participants made less fixations to columns as they increased in eccentricity ($\pm 1: M = .18, \pm 2: M = .13, \pm 3: M = .09, \text{all SEs} = .01$).

There was also a significant three-way interaction between position, side, and eccentricity, $F_{1,11} = 8.73, p = .002, \eta^2 = .442$, which was likely driven by the difference in fixation density in the -1 eccentricity column between close ($M = .10, SE = .01$) and far obstacle trials ($M = .15, SE = .02$). Finally, we observed a significant effect
of position, $F_{1,11} = 29.52$, $p < .001$, $\eta^2 = .729$, with participants fixating overall more in far obstacle trials ($M = .14$, $SE = .01$) than in close obstacle trials ($M = .13$, $SE = .01$). No other two-way interactions were significant ($p > .05$ in all three cases).

We also observed a clear asymmetry between the -1 and +1 eccentricity columns in terms of fixation density, even in far obstacle trials, in which both of these columns are located on the open side of the display. This suggests that participants tended to move away from the obstacle during search, even when targets located between the start position and the obstacle were unobstructed and could therefore be easily reached.

As in our analysis for reach locations, we wanted to compare the rate at which participants fixated different locations to the rate that would be expected had participants not factored into account the obstacle when searching. Therefore, we designed a simple model that included random decision making about where to search, while keeping saccade amplitude as small as possible and not allowing re-fixations, consistent with participants’ observed search behaviour (as described above). Starting at the central fixation point, the model randomly selected one of the eight adjacent objects that were one step away; i.e., objects located in cells located one column, one row, or one row and one column away. This selection process continued, iteratively, while excluding previously visited objects. If there were no unvisited objects one step away, the model then selected, at random, among objects that were two steps away, and so on.

We ran a total of 10,000 simulated trials (2,500 for each obstacle condition) with the four target locations on each trial obtained by randomly sampling a trial of the actual experiment. Using the output of the model, we were able to calculate
the average number of “unbiased” fixations for each object in each column of the simulated trials. These simulation results are shown as thin traces in Fig 3.3E. As expected, the model’s distribution of search locations is symmetrical, suggesting that a random search strategy would not have led to a bias towards fixating objects on the open or obstructed sides, and therefore participant behaviour cannot be attributed to searching for a target at random locations. Additionally, we found that the model fixated a median of 6 unique objects before it located the target. That the model took more fixations than our participants to locate a target is unsurprising, given the high likelihood that parafoveal vision aided participants in locating a search target.

3.5 Discussion

The goal of the current study was to address whether visual search strategy is influenced by the costs associated with reaching a located target object. We investigated this by having participants search a vertical display consisting of target and distractor objects. Participants moved a cursor, controlled by the handle of a robotic manipulandum, to a target object once located. On each trial we placed an obstacle in the scene that the handle could not pass through, and whose location was briefly shown to participants at the beginning of each trial. The obstacle split the search space up into two sides, an open side, which contained objects that could be easily reached, and an obstructed side, which contained objects requiring an increased movement time and distance in order to reach, and hence, greater movement costs when reaching to objects on that side. We first confirmed that reaching to target objects on the obstructed side of the display led to greater movement time and distance than reaching to the open side. We found that, on average, obstructed side reaches took
over twice as long as reaches to the open side, and that obstacle condition moderated this relationship, with larger movement times to the obstructed side in long obstacle and far obstacle trials, when compared to short obstacle and near obstacle trials.

Given the greater movement times and distances found for obstructed side reaches, we predicted that participants would more often search the open side of the display for target objects. We tested this prediction by analyzing both the location of the object participants reached to on each trial, as well as the location of gaze over the course of each trial. We found that participants reached targets located on the open side of the display nearly four times as often as the obstructed side, with fewer reaches occurring on the obstructed side in far obstacle trials. Through randomly selecting a search target in simulated trials, we found that the proportion of reaches to the obstructed side was much less than what would be expected had participants simply searched for the target at random.

Finally, by examining the proportion of fixations per object across columns of search objects, we found that participants fixated objects on the side which did not contain the obstacle more than twice as often as the side containing the obstacle. Participants primarily fixated the objects near the center of the display, with fewer fixations observed on more eccentric objects. We then compared participant performance to a model that randomly selected nearby, unvisited objects during search. Whereas the location of objects fixated by the model were symmetrical about the center of the display, participant fixations were notably asymmetrical, with significantly fewer objects fixated on the side of the display containing the obstacle.

Studies that have examined three-dimensional reaching movements in the presence of obstacles have found that people factor the obstacle's presence into their movement
trajectory, taking into account both the visual uncertainty of the obstacle’s location and proprioceptive uncertainty of the hand (Cohen et al., 2010; Sabes & Jordan, 1997; Sabes et al., 1998). In our study, there may have been greater uncertainty of the obstacle’s location due to the fact that participants had to hold its location in memory during search. This uncertainty over the obstacle location could have encouraged participants to take more biomechanically costly trajectories to keep the handle as far from the obstacle as possible when reaching to targets on the obstructed side, so as to avoid any possible contact with the obstacle. Therefore, the uncertainty present in our study may have further incentivized participants to reach to objects on the open side if participants were taking more costly trajectories than necessary to the obstructed side.

Several different parameters of a possible upcoming movement have been found to influence movement selection, such as biomechanical effort (Cos et al., 2011, 2014, 2012), perceived effort (Morel et al., 2017), cost of control (Manohar et al., 2015), and target size and distance (Diamond et al., 2017; Michalski et al., 2020). In this study, we showed that visual search behaviour is influenced by movement time and effort costs. It is unclear whether the effects we saw were more due to the cost of time or cost of effort associated with these reaches. Previous work by our group found that participants seem to be more sensitive to time-based costs, as opposed to effort during visual search (Moskowitz et al., 2020a). Future studies will have to disentangle whether movement effort or time is the more significant motivator, whether they have an additive effect, or can operate independently to drive search behaviour.

The results of the current task suggest that visual search behaviour is influenced by movement time and effort costs, in contrast to previous work by our group that
found no influence of movement effort on visual search (Moskowitz et al., 2020a). In our previous work participants only became aware of the manipulation of effort once their reaching commenced, and had to learn the relationship between reach direction and effort over the course of many trials. In contrast, in the current task, we provided participants with visual information (the location of an obstacle) prior to searching which clearly specified the movement costs associated with reaching. We predicted that participants would quickly understand the movement costs specified by the obstacle and use that knowledge to form a bias to search low movement cost regions of the search space. The results of our experiment suggest that participants do benefit from receiving visual information specifying movement costs, and that such information may be crucial to the formation of an effort-minimizing search strategy.

In many action tasks, gaze is often directed in such a way as to minimize movement cost. For example, in a realistic search task, participants learned the layout of an environment to minimize the cost associated with moving within it to locate a search target (Li et al., 2018). In a task where participants were asked to copy a pattern of blocks, participants make frequent saccades to and from the pattern, rather than holding its contents in memory. As the head movements required to view the pattern increased in magnitude, participants relied more on memory to complete the task (Ballard et al., 1995). Whereas these two studies specifically investigated tradeoffs between spatial memory and movement costs, we show that independent of memory costs, people prefer to visually search areas of a space that are associated with lower movement costs.

Memory may play a greater role in manual search so as to avoid revisiting locations already searched (Gilchrist et al., 2001; Smith et al., 2008). This is perhaps
unsurprising, given that in manual search, when large movements of the body may be
required to reinspect a search location, the movement cost associated with revisiting
search locations is greater than in visual search tasks, where only small movements
of the eye are needed to do so.

Movement costs may be represented at the neural level in the same structures
used to plan and shape upcoming eye and hand movements. There is now substantial
evidence that neural circuitry responsible for eye and hand planning is also involved
in deciding between saccade or reach targets (for a review see Andersen & Cui, 2009;
Cisek & Kalaska, 2010; Gold & Shadlen, 2007). In our task, the movement cost of
reaching appeared to influence the earlier decision of where to move the eyes. How
these costs are represented or shared among structures responsible for eye and hand
movements remains unclear.

Our findings show a strong influence of movement costs on gaze even for a visual
search task using relatively simple stimuli. One limitation of the current study may be
that the search task itself is quite artificial compared to several of the more naturalistic
tasks and 3D environments and stimuli used in many recent studies of visual search.
Indeed, the strong influence of scene context on search behaviour has been noted
across many different studies (Castelhano & Henderson, 2007; Draschkow & Võ, 2017;
Henderson & Hollingworth, 1999). To what extent movement costs influence gaze
in a real-world scene remains to be determined. Given recent advances in virtual
reality display and robotic technologies there is now the potential for future studies to
examine how movement costs influence search using large scale virtual environments
where body movements and stimuli can be tightly controlled.
3.6 References


Chapter 4

People minimize effort during search by learning the movement costs of objects in their environment

4.1 Abstract

In real-world search tasks, physical exploration of an environment is often required to locate a target object, such as opening kitchen cupboard doors in search of a cup. In such tasks substantial movement-related time and effort costs may be associated with search. The aim of the current study was to test the hypothesis that participants factor into account movement-related energy costs when making search decisions. Using a novel 3D robotic device and head-mounted display system, we developed a task in which participants searched by lifting objects and effort was manipulated by varying object weight. On each trial, participants viewed a 4 x 4 grid of 16 objects, two of which were target objects. To reveal whether an object was a target or a distractor, the participant had to lift and replace it. Half of the objects weighted 0.1 kg and the other half weighed 1.1 kg. Separate participant groups completed one of
two conditions of the task, one where the object weight was tied to its brightness (light or dark), and one where weight was tied to location in the environment (left or right side of the grid). We found that participants were able to associate the brightness of an object to its weight and use that information to reduce search effort by favouring lighter objects. In contrast, participants did not appear to learn the association between weight and spatial location. Participants in both conditions exhibited a bias to lift objects closer to the body and thus requiring less effort to lift. Our results suggest that participants use knowledge of energy costs associated with movement to guide search.

4.2 Introduction

Most research on search behaviour has focused on visual search tasks in which participants scan a visual scene, often using eye movements, in an attempt to locate a target object. However, many everyday search tasks involve moving through, and acting on the environment. For example, when preparing a cup of tea in an unfamiliar kitchen, we may search for a cup by walking from cupboard to cupboard and using our hands to open each one. While the factors underlying purely visual search have received considerable attention (Wolfe, 2020; Wolfe & Horowitz, 2017), relatively little research has focused on search tasks that involve acting on the environment.

Recent work has shown that when performing search tasks that involve moving around an environment, in comparison to traditional visual search tasks, participants make greater use of memory of the environment (Hayhoe, 2017). In a task where participants moved around a virtual apartment to locate a target object, participants use spatial memory of the environment to speed search (Kit et al., 2014; Li et al.,
2016, 2018). In a large-scale search task where participants had to visit containers spread out on a floor and open them to locate a target object, participants tended to revisit already inspected locations much less when compared to visual search tasks with comparable stimulus sizes, suggesting a greater role for memory in manual search (Gilchrist & Harvey, 2000; Gilchrist et al., 2001). As emphasized by the authors of these studies, the increased reliance on memory in these tasks may be attributed to the increased cost of movements when exploring large spaces. This finding is consistent with work showing that when large head movements (as opposed to eye movements only) are used to acquire task-relevant information, people tend to rely more on spatial memory (Ballard et al., 1995; Hardiess et al., 2008; Solman & Kingstone, 2014).

Further evidence that movement costs can influence movement selection comes from studies of sensorimotor decision making (Gallivan et al., 2018; Wolpert & Landy, 2012). In tasks where participants are given the choice to reach to one of two target locations, participants consistently move to the target associated with less biomechanical effort (Cos et al., 2011, 2014, 2012). Several other movement-related factors including target size and distance (Diamond et al., 2017; Michalski et al., 2020), controllability (Manohar et al., 2015), and perceived effort (Morel et al., 2017) have been found to influence the selection of an upcoming movement.

We recently investigated the influence of movement effort and time in manual search tasks in which participants are presented with multiple objects on a screen and must determine whether a given object is a target or a distractor by moving a cursor, controlled by the handle of a planar robotic manipulandum, to that object (Moskowitz et al., 2020a, 2020b). We found that search behaviour was strongly influenced by movement time costs (see also Morel et al., 2017), but only weakly
influenced by movement effort costs. We manipulated effort costs associated with exploring the environment by adding an elastic force that constantly pulled the handle towards its starting location, which increased the effort associated with searching as the hand moved further away from the start. In that experiment, we found a small, but significant influence of the elastic force, with participants tending to visiting objects closer to the start when compared to trials without any force applied to the handle.

The weak effect we observed in the above study may have been due to the rather arbitrary nature of the resistive force applied to the hand. Specifically, participants may have had difficulty learning or appreciating the relationship between hand position and effort, or connecting knowledge of this relationship to search decisions. The aim of the current study was to revisit the question, asked by the above study, of whether effort costs can influence search behaviour, but extend the results using a task in which variation in effort might be more easily ascertained. An example of a task where people naturally incorporate information related to movement effort is when lifting objects of various weights. It is well established that when lifting objects, people predict their weights so that they can appropriately scale lifting forces (Johansson & Flanagan, 2009). When asked, people can accurately report the weights of objects, indicating that they are explicitly aware of these weights (Flanagan & Bandomir, 2000). Based on these observations, we designed a search task which required participants to lift and replace objects of two distinct weights in order to ‘uncover’ the location of a target object.

In the current study participants viewed a grid of 16 virtual objects rendered stereoscopically in 3D using an Oculus Rift head-mounted display. These objects
were placed on a flat surface. On each trial, two of the sixteen objects were randomly selected as targets. To determine whether an object was a target, participants moved a virtual suction cup, controlled by the handle of a three dimensional robotic manipulandum, onto an object and lifted and replaced it. The manipulandum applied forces to simulate contact between the suction cup and object, the weight and inertia of the object as it was lifted, and contact between the object and the surface when the object was replaced. Participants were free to choose any object to lift, and continued lifting and replacing objects until one of the target objects was found.

In separate experiments, we associated object weight with either the appearance of the objects (feature condition) or their locations (spatial condition). In both conditions, half of the objects weighed 0.1 kg and the other half weighed 1.1 kg. In the feature condition, object weight was linked to its brightness (light or dark), and in the spatial condition, object weight was linked to its location in the environment (left or right side of the grid).

We predicted that participants would learn the association between brightness and weight or location and weight, and use that information to minimize the effort associated with searching by initially lifting the lighter objects in search of a target. Critically, there was a 77% chance that a target could be found after only lifting lighter weight objects, thus ensuring participants could engage in a strategy that minimized effort while also maintaining a high probability of locating a target.

We also expected that participants would exhibit an overall bias towards lifting near objects before far objects, because the near objects were closer to the hand’s start position and required smaller shoulder torque when lifting. Ultimately, we attempted
to answer two complementary questions. Can participants learn to associate an object’s visual or spatial properties with weight, and if so, do they use that knowledge to bias their search so as to minimize effort?

4.3 Methods

4.3.1 Participants

Twelve participants (9 female) between the ages of 18 and 21 years old (M = 19.3) were recruited to take part in the feature condition. Twelve separate participants (7 female) between the ages of 18 and 21 (M = 19.2) were recruited to take part in the spatial condition. Participants were required to be right handed, and have normal or corrected-to-normal vision while wearing contacts. These sample sizes are in line with those typically used in studies of human motor learning and visual search. All participants were compensated $15 or 1.0 course credits for their participation. Participants provided written informed consent, and after the conclusion of the experiment they were debriefed. The experiment was approved by the Queen’s General Research Ethics Board and complied with the Declaration of Helsinki.

4.3.2 Apparatus

Participants were seated in front of a custom three dimensional robotic manipulandum (3BOT) with an integrated head-mounted display (HMD) (Oculus Rift DK2) (Fig. 4.1A). The HMD had a resolution of 960 x 1080 pixels per eye, with a refresh rate of 75 Hz, and a response time of 2 ms. Participants grasped the handle of the manipulandum with their dominant hand. The manipulandum, driven by DC motors, could apply forces to the handle to offset the weight of the robot’s arm and simulate
the weight and inertial properties of virtual objects. High-resolution encoders allowed the handle’s position to be recorded at 1000 Hz, and the programmed forces on the handle were recorded at the same frequency.

4.3.3 Stimuli

At the beginning of each trial participants viewed, through the head-mounted display, a grid of 16 cylindrical objects (height: 5 cm, radius: 2 cm) placed onto a wooden tabletop (Figure 4.1B). The vertical position of the tabletop was roughly in line with the participant’s waist, when seated, and the front row of objects was located around 30 cm in front of the participant’s chest and in the mid-sagittal plane. The objects were arranged in a 16 cm x 16 cm grid and spaced, on average, 5.3 cm apart from each other in both the x (left to right) and y (front to back) directions. However, on each trial, the object locations were jittered using a random shift in both the horizontal and vertical direction by a value drawn randomly from a uniform distribution between ± 0.17 cm.

The participant could view using the HMD a white suction cup, the position and orientation of which was controlled by the handle of the manipulandum. When the suction cup was lowered onto, and contacted, the top surface of an object, it attached to it, with the connection between the suction cup and object modelled as a stiff (0.3 N/m) spring with damping (0.0003 Ns/m). When the participant lifted the suction cup the manipulandum simulated the weight and inertia of the lifting forces associated with the object it was attached to. Once the object was lifted a minimum of 2 cm, participants could return the suction cup down, releasing the object once it made contact with the tabletop.
On each trial, half of the objects were assigned a weight of 100 g with the other half being 1100 g. In the feature condition, in which object brightness was indicative of its weight, the 1100 g objects were dark green with the 100 g objects being bright green or vice versa (counterbalanced across participants), and the locations of bright and dark objects were randomized across trials. In the spatial condition, in which an object’s location was indicative of its weight, objects were a uniform bright green, but the weight of each object was tied to its left-right location. The two leftmost columns contained the 100 g objects and the two rightmost columns contained the 1100 g objects or vice versa (counterbalanced across participants).

4.3.4 Procedure

Prior to beginning the experiment participants were instructed that the goal of the task was to locate one of two target objects on each trial. Participants were instructed to locate the target by lifting and replacing the virtual objects using the suction cup controlled by the manipulandum’s handle, and they were free to select any object to lift. An auditory beep sounded when the suction cup made contact with the object (880 Hz, 50 ms) and when the object made contact with the surface on replacement (440 Hz, 50 ms). Participants were instructed to keep the handle in a vertical position, avoiding any pitch or roll in its orientation.

Once an object was replaced it would change to the colour grey if it was a non-target. The trial continued until participants lifted and replaced one of the two target objects, at which point both target objects turned red and the trial ended. We showed both target objects at the end of each trial as a constant reminder to the participant that there were two targets. For each trial, we randomly sampled without replacement
the two target locations from the 16 possible target locations.

Participants completed a total of 90 trials, with a rest inserted every 30. The first 3 trials were discarded as practice trials to allow for participants to familiarize themselves with the task. Participants were not explicitly told anything about the association between brightness and weight or location and weight, or even that objects had different weights. At the end of the experiment participants were asked if they noticed any weight differences and if so, did they notice any particular pattern to the weights, and did this influence how they searched.

Figure 4.1: **A**, Participants held onto the physical handle of a robotic manipulandum (3BOT), which was capable of movement in three dimensions. The handle controlled the position of a suction cup location seen through the head-mounted display (HMD) and was programmed to apply forces to the hand. **B**, In each trial, 16 cylindrical objects were presented through the visual reality headset along with a white suction cup. Shown here is the feature condition where object weight is mapped to brightness.
To find out if an object is a target, participants moved the virtual suction cup, controlled by the handle of the 3BOT, onto the object, and then lifted and replaced it. When the object is replaced it either turned red if it was a target or grey if not. C, A top-down view of an exemplar trial, with the hand path shown in black, and the 1st and 12th (last) lift indicated. D, The time varying x, y, and z positions of the handle location during this same trial with lift number indicated.

4.3.5 Data Analysis

Data from each trial was analyzed to extract the location and weight of each object lifted. The position of the handle was recorded during the object lift-off to touch-down period for the x, y, and z axes. To assess whether participants biased their search to minimize lift weight, we calculated, for each participant, the proportion of lifts across all trials where they lifted a lighter (100 g) object. One sample t-tests, with a test value of 0.5, were used to determine if the proportion of lighter object lifts was significantly different from chance-level behaviour. To assess whether there was any spatial bias in lift behaviour we used chi-square goodness of fit tests for each participant separately using the number of lifts for each x and y location.

We calculated the peak height for each lift by taking the difference between the maximum z position and minimum z position of the handle during the lift period. An ANOVA assessed the effects of weight and condition on peak lift height. An alpha level of .05 was used for all analyses. Error bars used in figures show ±1 standard error of the mean.

4.4 Results

An exemplar trial is shown in Figure 4.1C with the hand’s x and y location shown in black, with the first and last (12) object lifted numbered. The time varying x, y,
and z positions of the handle are shown in Figure 4.1D. The search duration for each trial was calculated as the time from stimulus onset to the time when a target object was placed back down. The average search times in the feature and spatial conditions were 9.5 s (SE = .5 s) and 8.5 s (SE = .4 s), respectively. The average number of lifts it took to locate the target object in the feature and spatial conditions were 5.4 (SE = .1) and 5.7 (SE = .1). Few trials (< 14%) contained greater than 10 lifts.

![Figure 4.2](image-url)

Figure 4.2: A, Boxplots of the proportion of light object lifts for both the spatial and feature conditions. Dashed line (0.5) indicates chance-level behaviour. Individual participant data is shown in light or dark green filled circles. Error bars show ±1 standard error of the mean. * = p < .05, ** = p < .01, *** = p < .001, n.s. = not significant. B, Average proportion of light object lifts for each lift number with individual participant traces shown. Dashed line indicates the chance-level probability for lifting a light object for each lift number. Percentages correspond to the percent of trials containing the lift number indicated on the x-axis. Data shown only for feature condition participants.
4.4. RESULTS

4.4.1 Object weight predicts lift choices in the feature but not the spatial condition

To determine if participants demonstrated a bias towards lifting the lighter objects on each trial, for each participant we looked at all lifts across all trials, and calculated the proportion of lifts for the lightweight objects (see Figure 4.2A). Had participants lifted objects completely at random, we would expect the proportion of light object lifts to be 0.5, or chance-level. A one sample t-test against 0.5 showed that participants in the feature condition lifted lighter objects significantly more ($M = .57, SE = .02$) than would be expected due to chance alone, $t_{11} = 3.20$, $p = .008$. In the spatial condition, participants lifted lighter objects more ($M = .56, SE = .03$), but this difference did not quite reach significance, $t_{11} = 2.09$, $p = .060$.

Given the significant bias in the feature condition, we performed an additional analysis on data from feature condition participants to look at how their lift preferences evolved within a trial. For each participant, we calculated the proportion of lightweight object lifts for each lift number across all trials. Figure 4.2B shows the mean proportion of lightweight object lifts based on lift number, with individual traces shown in light grey. The dashed-line shows the average proportion of lightweight objects remaining after each lift and therefore represents the evolving, average proportion of lightweight object lifts that would be expected by chance. As participants lifted more lightweight than heavyweight objects, the probability of lifting a lightweight object at random decreased, resulting in the negative slope for the dashed line. We observed that participants had a consistent preference for lifting lighter objects at greater than chance levels throughout a trial.
4.4. RESULTS

Figure 4.3: Proportion of lifts for each object row and column location. Dashed horizontal line (0.25) indicates chance-level behaviour. Y (row) location of where participants preferred to search in the A, feature condition and B, spatial condition. Negative values indicate rows that are closer to the body. X (column) location of where participants preferred to search in the C, feature condition and D, spatial condition. Negative values indicating columns that are on the left side.

4.4.2 Participants preferred to lift objects closer to the body

We also considered the possibility that participants preferred to lift objects closer to the body, in order to reduce energetic costs. To determine if there were any spatial biases in search behaviour we examined both the x and y-locations of lifted objects in both conditions, with negative y-location values corresponding to objects
closer to the body, and negative x-location values corresponding to objects in the two leftmost columns (see Figure 4.1C). We assigned each object to its non-jittered location such that there were 4 x-locations and 4 y-location values. We then looked at the proportion of lifts across all trials for each x location and each y-location (Fig. 4.3). The expected chance level proportion for each x or y location is 0.25.

As can be seen in Figure 4.3A and 4.3B, on average, we observed a bias to lifting objects closest to the participant (large negative y-location) in both the feature and spatial conditions, and the proportion of lifts decreased monotonically as the y position of the objects moved further away in both conditions. In Figure 4.3C we observed a center-right bias in the feature condition, with participants having the highest proportion of lifts for that column. Figure 4.3D indicates that participants in the spatial condition had a bias towards lifting objects on the side associated with lighter objects.

We conducted chi-square goodness of fit tests for each participant separately using the number of lifts for each x and y-location to test for evidence of bias in lift locations. A significant chi-square test for a participant would suggest that they had some preference for lifting objects in a particular x or y-location. We first examined the y-location of their lifts. In the feature condition, we found that 9 out of 12 participants had significant chi-square values of $p < .05$ when comparing the y-locations (see Figure 4.3A). In the spatial condition, we found that 10 out of 12 participants had significant chi-square values of $p < .001$ (see Figure 4.3B). These results suggest that across both conditions participants’ preference for the y-location of objects they lifted deviated from chance-level, with a preference to lift objects closer to the body.

We then examined the x-location of participant lifts to look for any leftward or
rightward bias in lifting behaviour. In the feature condition, we found that only 6 out of 12 participants had significant chi-square values of \( p < .05 \) when comparing the \( x \)-locations (see Figure 4.3C). Since the weight of each object was linked to its \( x \)-location in the spatial condition, we performed separate chi-square analyses for participants assigned to experiencing heavier objects on the left, and those assigned to experiencing heavier objects on the right. For participants that experienced heavier objects on the left, 5 out of 6 participants had significant chi-square values of \( p < .05 \). For those assigned to experiencing heavier objects on the right, 5 out of 6 participants had significant chi-square values of \( p < .05 \).

Overall, these results suggest that participants in the feature condition had a weak center-right bias. In contrast, most participants in the spatial condition expressed a bias towards searching the side associated with lighter objects (see Figure 4.3D). This differential bias we observed between the right objects lighter and left objects lighter subgroups is consistent with the results of our earlier analysis of light object lift rate for the spatial condition, showing a strong trend towards lifting the lighter objects that did not quite reach significance.
4.4. RESULTS

Figure 4.4: A, Average lift height for each condition and object weight across blocks (each block is 10 trials). After an initial adjustment in blocks 1 and 2, participants’ lift height becomes fairly consistent across blocks. B, Average lift height across all blocks for each condition and weight.

4.4.3 Lifting behaviour reveals poorer weight prediction in the spatial condition

Previous work has shown that people scale their vertical lifting, or load force, to predicted object weight (Johansson & Flanagan, 2009). This force scaling allows people to lift objects of varying, known weight to the same height in about the same time. Conversely, a failure to scale load force to object weight can lead to the object not lifting off at the expected time, and lifting to a height that is higher or lower than desired.

In our task, if participants learned the mapping between object brightness and
weight, or between location and weight, we would expect them to lift the lighter and heavier objects to a similar height. However, if participants did not learn to predict weight based on brightness or location, we might expect lighter objects to be lifted to a greater height than the heavier objects. By examining the average lift height for heavy vs. light objects in our task we assessed whether participants successfully associated brightness and weight, or location and weight.

We first examined the average lift height for light and heavy objects in both the feature and spatial conditions across successive blocks of 10 trials (Figure 4.4A). For both weights in both conditions, lift height decreases over the first two blocks and then becomes fairly consistent. This may reflect general learning of the task parameters (e.g., how high the objects need to be lifted on average). In the spatial condition, there was a large difference in lift height in the first few blocks and this difference persisted throughout the experiment, suggesting that participants in this condition struggled to accurately scale their lifting forces to the different object weights. In contrast, in the feature condition, lift height was similar for the two weights throughout. Even in the first block, the lift height was only a little higher for the light object, suggesting that participants very quickly learn the association between brightness and weight allowing them to accurately scale their lifting forces.

Figure 4.4B shows the average lift height across all blocks by condition and weight. A mixed ANOVA revealed a significant interaction between condition and object weight, $F_{1,22} = 10.81, p = .003, \eta^2 = .329$, with participants in the spatial condition generating higher lifts for light objects ($M = 7.85 \text{ cm}, SE = .5$) than heavy ones ($M = 5.5 \text{ cm}, SE = .3$). This result suggests that participants in the feature condition learned to associate weight and brightness, allowing them to scale load force to object
weight, whereas participants in the spatial condition did not learn to associate location and weight and were therefore unable to accurately scale their lifting forces.

4.4.4 Post-experiment debriefing

After the search task had ended, participants were asked a series of questions to gauge their understanding of the weight differences between objects and their search behaviour. In the feature condition, 11 out of 12 participants reported that they were aware that the brightness of the objects corresponded to their weight. Of the 11 who reported this, only 7 reported using this information to bias their lifts towards the lighter objects. In the spatial condition, 8 out of 12 participants reported that they were aware that the side the objects were on corresponded to their weight. Of the 8 who reported this, only 4 reported using this information to bias their lifts towards lighter objects.

Some participants reported using a strategy of searching for the target at random. Another reported strategy was to find a pattern in where the target was likely to appear, and search there. Based on these qualitative findings, it would appear that participants in the spatial condition had a more difficult time learning to associate location and weight when compared to participants learning of brightness and weight in the feature condition.

4.5 Discussion

Recently, our group investigated the influence of movement effort on search behaviour, and failed to find a strong influence of effort during performance of a manual search task (Moskowitz et al., 2020a). We wanted to revisit the question of whether effort can
influence search behaviour through a task in which participants could more readily appreciate variance in effort when searching for a target object.

In this study we had participants manually search an environment for a target object by lifting and replacing objects. We tested two groups of participants, one in which the brightness of each object was indicative of its weight (feature condition), and one in which the location of each object was indicative of its weight (spatial condition). We predicted that participants would learn the association between brightness and weight, or location and weight, and then make use of that information to reduce the physical effort involved in search by preferentially selecting lighter objects while searching for a target.

We found that participants in the feature condition preferred to lift the lighter objects more often than expected due to chance alone. In the spatial condition, while participants showed a tendency towards preferring to lift lighter weight objects, the effect was marginally significant. We also examined the spatial location of objects that participants lifted to determine if participants had a preference for lifting objects closer to the body or on either the left or right side. We found that the majority of participants in both conditions preferred to lift objects closest to the body at greater than chance levels. Half of the participants in the feature condition expressed some lateral bias, with a preference for lifting objects just right of center, while the majority of participants in the spatial condition expressed a bias towards lifting objects on the side associated with lower weight objects.

Analysis of object lifting height revealed that participants in the spatial condition did not accurately scale lifting or load forces to object weight, suggesting that
many participants in that condition failed to accurately associate weight and location in order to predict object weight. However, there is clear evidence that many participants in the spatial condition nonetheless expressed a bias towards searching the side associated with lightweight objects. The results of the chi-square analyses point to the majority of participants having a bias towards searching the side associated with lightweight objects and the majority of participants in the spatial condition reported being explicitly aware of the experimental manipulation based on their post-experiment debriefing responses. Our failure to find consistent effects for the spatial condition may have been the result of several factors.

One possibility is that the brightness of an object is a more salient reminder of object weight than its location, making it easier for participants in the feature condition to utilize knowledge of the experimental manipulation to guide decision making. Smith et al. (2010, 2009) showed that both the use of consistent search locations and a visual cue (much like the feature condition in our study) helped participants learn that their search environment was split into two halves with different search-relevant properties (in their case, the likelihood of the target being located was higher in one half of the environment). In the spatial version of our task, while search locations were kept consistent, participants still struggled to associate the left and right side of the search space with heavy and light objects. One possible explanation is that the attentional demands of the search task interfered with the arguably more difficult learning of the association between weight and location required in the spatial condition.

Findings from research on visual statistical learning (VSL) indicate that some level
of attention is required to learn patterns in stimuli over time (Baker et al., 2004; Turk-Browne et al., 2005). However, it is unclear whether the learning that took place in our task was typical of that found in VSL paradigms given that participants in both Smith et al. (2010) and our own study largely reported being aware of the experimental manipulation, which is unlike the implicit nature of the statistical learning seen in typical VSL paradigms.

Another possibility is that it is unusual for an object’s spatial location to dictate its physical properties. While there are environmental factors which can influence the dynamics of objects being manipulated (e.g., wind), people typically make use of an object’s visual cues, such as its size, texture, or identity to predict its weight (Gordon et al., 1991; Johansson & Westling, 1988). Although people have shown the ability to quickly update and maintain sensorimotor memory for objects with unexpected weight (Flanagan et al., 2008, 2001), in those tasks the physical properties of the objects still provided a cue as to the object’s true weight once it was learned.

Additionally, it has been shown that people make use of both egocentric and allocentric coordinate frames when forming spatial memories (Burgess, 2006). In small environments, such as a tabletop, it is more difficult for participants to generate an egocentric map of their search space (Jiang et al., 2013). In larger-scale environments, full body movement and environmental cues allow people to generate and flexibly use both egocentric and allocentric reference frames, supporting learning to guide visual search (Jiang et al., 2014). In our task, participants’ fixed view of the search environment and lack of environmental contextual cues may have inhibited the learning necessary to associate each object’s location with a weight.

While we observed that participants preferred to lift objects closest to the body,
it is unclear whether this behaviour was due to the objects’ proximity to the hand, or, an attempt to reduce shoulder torque when lifting, due to their proximity to the body. To distinguish between these two possibilities, a follow-up study could move the hand’s start position away from the front row of objects. In this scenario, if participants still exhibited a preference to lift objects closest to the body—and away from the location of the hand—then it could be concluded that the search strategy was an attempt to reduce shoulder torque during lifting. Furthermore, it is unclear how this preference to lift closer objects interacts with the competing preference to lifting lightweight objects. For instance, if participants prioritize lifting objects closest to the body, they might prefer to lift a heavier object that is closest, rather than a lighter one further away. It is possible that this competition across preferences could be responsible for weakening the influence of object weight on participant search strategy.

It is certainly the case that had we run a condition of the experiment where object weight was more intuitively linked to its physical feature, such as size, that we could have still addressed whether participants’ search behaviour is biased towards lighter objects. This would have also avoided the potential difficulties of having participants learn that an arbitrary feature of an object is associated with its weight. However, the associations we used, between weight and brightness or weight and location, were designed so as not to generate any difference in low-level salience between the objects (in the case of brightness, we applied a counterbalance to avoid any possible preference for brighter, more salient objects). For size, this would have been more challenging; had we properly counterbalanced the size and weight of objects it would require participants to potentially learn that smaller objects were heavier than large
ones, which could introduce issues due to violations in previously learned size-weight priors (Baugh et al., 2012) and complicate resulting patterns of effects.

Our results are consistent with recent work that has shown that people are sensitive to movement costs during both manual (Moskowitz et al., 2020a) and visual search behaviour (Moskowitz et al., 2020b). More broadly, our findings are also consistent with work showing that people factor movement costs into decisions related to action selection, such as biomechanical effort (Cos et al., 2011, 2014, 2012; Hagura et al., 2017), perceived effort (Manohar et al., 2015; Morel et al., 2017), and the size of, and distance between targets (Diamond et al., 2017; Michalski et al., 2020).

It is possible that these movement costs, which impact decisions related to reach movement selection, are represented in brain areas responsible for the planning and execution of reaching behaviour. Neurophysiological studies in non-human primates have found that the same neural circuits responsible for the planning of eye and arm movements also encode upcoming decisions related to the use of those movement effectors (for a review see Andersen & Cui, 2009; Cisek & Kalaska, 2010; Gold & Shadlen, 2007). For instance, activity in reach planning areas such as posterior parietal cortex (Andersen & Cui, 2009; Christopoulos et al., 2015; Cui & Andersen, 2007; Klaes et al., 2011; Scherberger & Andersen, 2007) and dorsal premotor cortex (PMd) (Cisek & Kalaska, 2005; Pastor-Bernier & Cisek, 2011; Pesaran et al., 2008; Thura & Cisek, 2014; Westendorff et al., 2010) have been found to represent the decision of where to reach for an upcoming movement. In addition, it has been shown that some of these areas represent the competition between action choices prior to target selection (Cisek & Kalaska, 2005) and, moreover, that this competition is influenced by the biomechanical factors associated with those choices, such as target distance
4.5. DISCUSSION

(Pastor-Bernier & Cisek, 2011). This latter finding is consistent with the idea that the activity in reach-related brain circuits may represent the biomechanical costs of prospective actions, which, in our task, could drive decisions of which objects to reach, lift, and replace during search.

The ventral striatum has also been implicated in the processing of reward for upcoming actions (Lau & Glimcher, 2008; Samejima et al., 2005). Recent work by Suzuki et al. (2020) found that ventral striatum activity also represents costs related to effort. In that study human participants underwent functional magnetic resonance imaging (fMRI) while they performed a maze-navigation task that required effort to navigate in the form of button-pressing. They found that both the anticipation of required effort and the initiation of effort were encoded by a dorsomedial region of ventral striatum (Suzuki et al., 2020).

During object lifting, areas including the cerebellum and supplementary motor areas are likely involved in the recruitment of internal models of an object’s dynamics (Bursztyn et al., 2006; Kawato et al., 2003), enabling prediction of the forces necessary for skillful object manipulation (Miall & Wolpert, 1996; Wolpert et al., 1998). In our task, it is likely that such models provide information on the weight of an object once it has been selected to be lifted, but it is unclear whether these same signals can also bias the selection of which object to lift. How different brain areas interact to produce a complex behaviour such as searching for a target via the lifting of multiple objects remains unclear, with neuroimaging studies providing a promising option to better understand whole-brain dynamics during search (Gallivan et al., 2018).

The current study provides further evidence that sensorimotor decisions, including decisions made in the context of search, such as deciding where to move when locating
a target object, are influenced by factors pertaining to the motor system. A greater understanding of human search behaviour is likely to come from incorporating factors such as movement cost, along with other factors, such as spatial memory, to more fully understand the interaction between various brain systems that are responsible for search-related decisions (Hayhoe, 2017).

4.6 References


4.6. REFERENCES


Moskowitz, J. B., Castelhano, M. S., Gallivan, J. P., & Flanagan, J. R. (2020b). Gaze behaviour when visually searching for targets to be reached toward is influenced by movement-related costs imposed by obstacles.


Search behaviour in humans has been a popular topic of study over the past few decades. From this research we have learned that search is a process governed by both bottom-up influences from external stimuli present in the environment and top-down influences from higher cortical areas (see Eckstein, 2017; Wolfe, 2020; Wolfe & Horowitz, 2017 for reviews). What we know about search behaviour has largely come from laboratory tasks, often requiring a small movement, such as a button press, upon detecting a target in a display. In contrast, many instances of real world search require moving within and acting on an environment in order to search. For example, moving to, opening, and looking within cupboards in a kitchen in search of an ingredient. As has been noted across a variety of sensorimotor tasks (Gallivan et al., 2018; Hayhoe & Ballard, 2005; Hayhoe, 2017), factors related to movement, such as the effort or time required to move, can influence human decision making behaviour. These findings support the idea that movement could likewise influence and guide search behaviour.

Studies of search behaviour in humans are now making use of virtual reality technology to import more naturalistic search tasks into the laboratory (Bourgeois et al.,
5.1. SUMMARY OF STUDIES AND PRINCIPLE FINDINGS

In this thesis, we leveraged both robotic devices capable of applying force to the hand, and virtual reality displays that indicated the location of the hand in space, to simulate searching for an object, and reaching to it, once located. Using variants of this task we discovered that movement costs, such as the effort or time associated either with searching, or reaching for an object once located, have the ability to bias where we search. Our work adds to the growing body of evidence that search behaviour, like sensorimotor decision making, is influenced by factors associated with movement.

5.1 Summary of studies and principle findings

In Chapter 2 I reported a series of experiments designed to test whether there is any influence of movement costs on human search behaviour. In these experiments we had participants search a display for a target among distractors either visually, using eye movements, or manually, using a cursor controlled by the handle of a robotic manipulandum. By applying forces to the handle of the robot or, by slowing the movement speed of the cursor, we were able to test the influence of movement effort and movement time on search behaviour. Specifically, greater movement effort or time was associated with searching a particular area of the display, and we predicted that participants would bias their search away from this area, as measured by either gaze or hand position. In the visual search tasks, participants had to foveate a target object in order to identify it as a target or distractor. In the manual search tasks, participants could not identify the target by foveating it, rather they searched using their cursor, positioning it over an object to reveal its identity as target or distractor.

Experiments 1 and 2 tested the influence of movement effort on search behaviour.
Experiment 1 found that movement effort did not significantly bias visual search behaviour, with Experiment 2 finding a weak, but significant effect of effort on manual search. Experiment 3 and 4 tested the influence of movement time. Experiment 3 found that movement time significantly biased manual search, with Experiment 4 replicating that result, and showing that after training in the manual search task, participants expressed a movement time bias in a subsequent visual search version of the same task.

In Chapter 3 we investigated whether participants’ visual search behaviour would be sensitive to the presence of an obstacle in their search environment, which obstructed participants’ ability to reach targets on one side of the display. We found that participants’ search behaviour, as measured by gaze, was significantly biased away from the obstructed area. We also compared participant behaviour to that of a model that searched at random within constraints that matched participant behaviour in several respects, and found that participants’ bias was not a result of them implementing a random search strategy.

In Chapter 4 we investigated how movement effort could bias manual search behaviour in a virtual reality environment. Participants viewed virtual objects placed on a tabletop which they could lift and replace using a robotic manipulandum. On each trial, participants searched for a target by lifting and replacing an object, to reveal its identity as target or distractor. The simulated weights of the objects were tied to either their brightness or spatial location in separate conditions. We tested whether participants could learn the association between brightness and weight, or location and weight, and bias their search by selecting to lift lighter objects. We found that participants learned to associate brightness, but not location, with weight, and
use that information to bias their search towards lighter objects, thus minimizing the effort incurred during search. Participants in both conditions also expressed a general bias towards lifting objects closer to the body.

5.2 Costs, reward, and memory

Consider again the search scenario I mentioned in the opening of the introduction to this thesis, looking for your cell phone as you’re about to leave your house. While the decision of where to search in this scenario has costs associated with it, such as the greater movement effort associated with deciding to climb the stairs to search your bedroom, there are clearly other factors at play that will influence your decision, even potentially to a greater extent than the influence of movement costs. For example, your memory for the phone’s location is likely to be a strong influence on where you search. If you remember leaving your phone in your bedroom, it may be the first place you look. Reward in the form of task goals and expectations also factors in. If you’re expecting an important call shortly, you are likely to search longer and more thoroughly than if not. In this scenario, both reward and memory play large roles in influencing how and where we search.

In our studies, there were key differences in when participants encountered movement costs. In the visual search paradigms reported in Chapter 2 movement costs are encountered in the future, i.e., after a participant has already located a target object. In contrast, in our manual search tasks, participants experience the costs associated with searching on an ongoing basis. A large delay between the decision of where to search and the encountering of movement costs, such as in our visual search tasks, could partly contribute to participants being less influenced by movement cost, due to
the temporal discounting of movement costs, i.e., people devalue costs in proportion to the time it will take to experience the costs. This is consistent with work that has found temporal discounting of both effort and reward for movements of the eye and hand (Shadmehr et al., 2016, 2010).

In one study, participants were given the decision to select between two different motor tasks that differed in the amount of effort required to carry out (Rosenbaum et al., 2014). Both tasks had participants walk towards and lift a weighted bucket, and carry it to a platform at the end of an alley. What differed between the two tasks was the distance of each bucket from the platform. In order to minimize physical effort participants could have selected the easier of the two tasks, in which the bucket was closer to the platform, allowing them to carry a load a shorter distance. Surprisingly, participants consistently did the opposite, electing to carry a load over a longer distance. This result seems to compete with the previous account of temporal discounting of motor costs. If participants in this study had discounted future costs, they would have judged the subtask of walking to the bucket as more effortful than the subtask of carrying the bucket to the platform. The authors attribute the behaviour they observed to a desire to reduce working memory load, which participants achieve by completing the subtask of walking to and lifting the bucket as soon as possible, but which results in a longer carrying time, and hence, greater overall effort expenditure.

In our studies, we equally incentivized searching regions of high and low movement cost by maintaining an equal probability of locating a target object across the search space. But what if searching a high cost region was associated with greater reward? There is some evidence to suggest that rewards can function to offset costs during
sensorimotor tasks. Manohar et al. (2015) had participants perform a target-directed saccade, and rewarded participants with variable amounts of money for successful performance. When given a high reward, they found that participants occasionally violated the typical speed-accuracy tradeoff that applies to movements of the eye. The authors suggest that there is a cognitive effort cost to this violation of the speed-accuracy tradeoff, and it is only when reward is high that participants are sufficiently motivated to engage in this practice. There is now substantial evidence that reward effectively modifies the speed for movements of both the eye and arm, incentivizing faster movements, and hence, greater energy expenditure (Opris et al., 2011; Reppert et al., 2015; Sackaloo et al., 2015; Shadmehr et al., 2010; Xu-Wilson et al., 2009).

These findings suggest that people may be willing to experience an increase in costs to facilitate earning reward. However, it is unclear whether this behaviour extends to tasks in which there are differential costs, e.g., when searching for a highly rewarding target in a search space divided into regions of high and low movement cost. It is certainly true that in some cases an increase in movement speed introduces risks that may outweigh any potential reward. For example, when walking over difficult terrain, where the risk of falling and injuring oneself increases with greater movement speed, people slow down to maintain a stable gait (Matthis et al., 2018) (although the authors of that study did not manipulate reward associated with task completion).

Further study of the interaction between reward and effort should factor in the reward assigned to task outcomes. Indeed, recent work has successfully identified the internal reward value assigned to actions taken in sensorimotor tasks (Rothkopf & Ballard, 2013; Tong et al., 2015). Such a framework could provide us with greater understanding of the interplay between costs and rewards in naturalistic tasks.
Finally, it is important to consider the impact of memory use on search behaviour. In our manual search tasks, visited objects were visually marked (e.g. turned grey) so as to reduce the working memory requirement associated with avoiding previously visited objects. That is, because visited objects were marked, participants did not have to use spatial memory resources to tag visited objects. It is possible that visually marking visited objects might speed up search by preventing revisits of objects. When developing our search tasks we noticed that when visited objects were not visually marked, participants seemed to use a more regimented search strategy—for example, searching row by row or column by column—presumably to aid in encoding visited objects. In some real world search tasks, people might use a strategy that involves visually marking visited locations. For example, they may leave checked drawers open. However, in other instances, previously visited locations or objects may not be visually marked and participants may develop different strategies for this situation; e.g., searching systematically from the leftmost to the rightmost drawer. In future work it would be interesting to examine and compare how movement-related costs influence search in these different scenarios. For example, the influence of movement costs may be reduced when visited locations are not marked and a systematic search strategy is advantageous.

Additionally, there is some evidence to suggest that holding information in memory has its own set of costs associated with it. Ballard et al. (1995) show that participants are willing to engage in greater movement to limit the amount of information held in memory. In their task, participants who had to copy a pattern of blocks tended to make frequent saccades to and from the pattern, rather than hold its contents in memory. However, when the pattern was moved further away from
5.2. COSTS, REWARD, AND MEMORY

the participant, requiring large head movements to fixate, participants shifted in the
direction of increasing memorization of the pattern.

Solman & Kingstone (2014) found similar results for a visual search task, where
they had participants either search a display that required movements of the eye
alone (eye-contingent) or a display that required movements of the head and eyes to
fixate targets (head-contingent). Critically, participants experience repeated displays
consisting of the same target-distractor configurations, allowing participants to use
memory for previous searches to speed up future ones. The authors found that for
the head-contingent search participants relied more on memory and exhibited greater
recall of previous target locations.

These results suggest that participants balance effort and memory costs. When
movement costs increase, such as when large movements of the head are required for
search, our reluctance to use memory to accomplish our task diminishes. It seems
likely that this scenario is prevalent in everyday search behaviour as much of our
real-world searches occur in large-scale environments where movements of the head
and body are required.

Ultimately, more precise measures of effort are needed to quantify the relationship
between costs, reward, and memory. One promising approach would be the use of
expired gas analysis as a measure of metabolic rate, an approach which has been
used to calculate effort in a variety of motor tasks including reaching (Huang et al.,
2012; Shadmehr et al., 2016). By clearly quantifying and manipulating costs, reward,
and memory we can better understand how these various factors influence search
behaviour.
5.3 Visual information facilitates learning of movement costs

In Chapter 3 we found a large influence of reach effort on participant visual search behaviour, in contrast to the results of the first experiment reported in Chapter 2, in which we found no clear influence of reach effort. We attributed the difference in results to the fact that participants in each study received very different information about the effort associated with searching their environment. In Chapter 2, Exp 1, participants experienced asymmetry in reach effort between the sides of the display, but received no visual indication as to which side was the high or low cost region.

In contrast, in Chapter 3 participants received visual information, prior to search onset, which specified the movement costs associated with reaching different regions of the search space. The information provided was very natural, in the form of an obstacle that clearly divided the search space into high and low cost regions. It is quite evident that people have the ability to quickly and effortlessly appreciate obstacles as they move around an environment (Biegstraaten et al., 2003; Garzorz et al., 2018; Nashed et al., 2012). We suggested that this inclusion of visual information allowed participants to more readily appreciate the upcoming movement costs associated with each search trial.

The results presented in Chapter 4 seem to support this conjecture. In that chapter, participants in the feature condition, where object weight was tied to brightness, exhibited a larger bias towards minimizing effort in manual search, when compared to participants in the spatial condition, where object weight was tied to its location.

In Chapter 2, Exp. 3, where we manipulated the cost of movement time during manual search, participants exhibited a large bias to searching in areas that reduced movement time. Participants in this experiment likewise received visual information
specifying the movement costs. Here, participants could visually appreciate that the
cursor’s movement speed changed as a function of its location in the search space.

Together, these results support the idea that visual information, such as the pre-
ence of an obstacle in the environment or the color of an object, enhances participants’
ability to learn and use knowledge of the movement costs associated with a search
space to bias search towards low cost regions.

5.4 Probabilistic reasoning and participant behaviour

A key aspect of all the studies contained in this thesis was that targets objects were
randomly selected from the full set of objects and thus participants were able to locate
a target object with equal probability, regardless of where they decided to search. In
addition, because multiple targets were used in each trial, participants had a good
chance of locating a target object if they committed to searching a particular region
of the search space (e.g., the left side of the search space). Across all experiments, the
probability of locating a target object in a region associated with either low, or high
costs, was at least 75%, and in some cases much higher. To observe any influence of
motor costs on participant behaviour it was important that participants understood
the consequence of these features; i.e., that they were likely to locate a target in a
region associated with lower motor costs and, critically, that target locations were
truly random.

While participants were briefed, prior to beginning each experiment, on the above
two features, it is possible that participants did not fully appreciate their impact when
it came to forming a search strategy. In many cases, people have incorrect intuitions
when it comes to probability and randomness (Kahneman & Tversky, 1972; Konold,
5.5. USE OF ARTIFICIAL DISPLAYS

For example, some participants reported engaging in what appeared to be a strategy consistent with the gambler’s fallacy. They believed that future probabilities of where a target would appear were affected by where it was on previous trials. Similarly, in experiments in which there were 4 targets in each trial, some participants reported that they thought the targets would be equally spread out in different regions of the search space on each trial. This type of behaviour can be found in many other examples of real-world decision making such as betting (Croson & Sundali, 2005; Huber et al., 2010). If participants believed that confining their search in one region of the space hurt their chances of locating a target, then it would be unlikely that movement costs would influence their search strategy. For example, in Chapter 4, one of our experimental conditions featured a spatial manipulation of movement costs by assigning objects on a given side of the search space to be either heavy or light. If a participant felt that they lowered their chances of locating a target object by confining their search to just one side of the search space, it seems unlikely that their search strategy would be consistent with one that attempts to reduce movement-related costs.

5.5 Use of artificial displays

Over the last couple of decades there have been increasing calls for researchers to study gaze behaviour using more naturalistic sensorimotor tasks (Hayhoe & Ballard, 2005; Kingstone et al., 2003; Tatler et al., 2011). In the current thesis we attempted to incorporate more naturalistic elements in the design of our search tasks; namely requiring participants to reach to an object once it was located or requiring them to move in order to search. Despite this, there are still some concerns about the
generalizability of our tasks to the real world. Particularly for the work in Chapters 2 and 3, there could be concern over the use of stimuli presented on a vertical display.

In tasks making use of a vertical monitor placed in front of participants, leftward gaze biases during viewing of photographs and line bisection tasks have been noted (Foulsham et al., 2013), with other studies suggesting that there is a strong tendency to fixate the center of the display (Tatler, 2007; Vincent et al., 2009). While we cannot eliminate the possibility that these biases influenced our participant behaviour, the fact that our experiments were designed to encourage participants to choose a particular side of the display to search may have reduced the impact of these biases.

Additionally, the stimuli used in many of our experiments, i.e., the split-colour squares, were not very natural representations of objects one would search for in the real world (although they allowed us to reduce the use of parafoveal vision during search). The objects used in our Chapter 4 study were more natural in some ways; although objects in the real world do not change colour when lifted, information can be revealed when lifting (e.g., when there is something underneath the object).

5.6 CLINICAL POPULATIONS

The results of our studies provide a measurement for how people normally factor effort into search-based decision making and could aid development of tools for the diagnosis and assessment of motor or cognitive dysfunction. It seems likely that impairments to areas of the brain involved in effort and reward processing could have notable effects on search behaviour, whether search is performed using eye movements or both eye and hand movements. Deficits in reward and effort processing have been tied to abnormal movement times observed in a variety of neurological disorders. For
example, it has been noted that among patients with cerebellar movement disorders
eye movements during search were slower (Veneri et al., 2014).

Abnormal movement times have been noted in other conditions as well. It is
known that individuals with Parkinson’s Disorder (PD) move more slowly, but recent
work by Mazzoni et al. (2007) has shown that it is not because these individuals
are incapable of making fast and accurate movements. Rather, the authors suggest
that the reasons for slower movement in patients with PD is a reduction in reward
sensitivity, with movement speeds in PD being accurately predicted by a model that
assigned low value to reward (Shadmehr et al., 2010). Indeed, it was found that PD
patients had reduced sensitivity to reward in a perceptual judgement task relative to
age-matched controls (Manohar et al., 2015).

Conversely, individuals with schizophrenia exhibit saccade velocities that are faster
than those observed in healthy individuals (Mahlberg et al., 2001). It has been
suggested that this behaviour could be the result of dysregulation in dopaminergic
pathways (Shadmehr et al., 2010), with greater dopamine synthesis in the striatum in
individuals with schizophrenia (Stone et al., 2007). Together, these findings suggest
that dopaminergic pathways may play a role in sensitivity to reward, influencing a
wide range of decision making behaviours.

5.7 Other types of search

In our studies, a target was always present on each trial and could be located on
the order of seconds. However, in many cases in the real world, search can take
on the order of minutes, hours, or even days, and can often fail to turn up the
target of our search (e.g., searching for a missing vessel in the ocean). This raises
the question of when it is optimal to stop looking, otherwise known as the optimal stopping problem (Chow et al., 1971). The optimal stopping problem is choosing the duration of how long to search, as opposed to selecting the location of where to sample information from in the environment. In perceptual tasks, peoples’ decision of how long to collect information prior to making a movement decision appears to be near optimal (Drugowitsch et al., 2015), and it has been shown that participants optimally trade-off viewing and movement time in a reaching task to maximize task performance (Battaglia & Schrater, 2007; Faisal & Wolpert, 2009).

More research is needed on how people perform in naturalistic search tasks where a decision may be made to stop search. Take again the example of searching for a missing vessel. The longer we search a particular patch of ocean for the missing ship, the more information we can gather as to its potential whereabouts, but we do so at the cost of missing out on searching other patches, which have the potential to contain the ship or information leading to its location. Framed in this manner, this type of search is better described as foraging behaviour, where the decision to leave a patch can be predicted using optimal foraging theory (Charnov, 1976; Stephens & Krebs, 1986).

Questions about when to stop search are also relevant for common searches that occur for extremely rare items. For example, it has been found that for airport security searches or medical cancer screenings, error rates are quite high, with people often stopping search before a target could be located (Mitroff & Biggs, 2014; Wolfe et al., 2013). People generally quit searching more quickly in these rare items searches, with searchers needing less evidence to convince themselves that a target is absent (Horowitz, 2017), although it appears people can improve their stopping behaviour.
with experience (Brams et al., 2019; Chun & Wolfe, 1996; Wolfe & Van Wert, 2010). Solman et al. (2014) suggested that the high error rates could be due to a lack of diligence during search, with participants during visual search tasks failing to inspect all the items, and in manual search, failing to adequately inspect individual items.

It would be of interest to study how the effort or reward associated with searching influences error rates in rare item searches. Consistent with other models of sensorimotor behaviour, it would follow that increasing reward could pay the cost of the increased cognitive resources expended during these types of search.

5.8 Conclusions

On a daily basis people move within and perform actions on their environment in order to locate objects. Given that these movements have costs associated with them, it is natural to want to study what influence these costs have on where we choose to search. The studies presented here offer a small, but significant advance, by showcasing that movement effort and time can influence decisions on where to search, as revealed through movements of the eye or hand. In doing so, my hope is that we have further contributed to viewing search as a complex sensorimotor behaviour, produced by our brains through the interaction between perceptual, motor, and cognitive systems.

5.9 References


Battaglia, P. W. & Schrater, P. R. (2007). Humans trade off viewing time and


Appendix
Research Ethics Approval

May 16, 2017

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GREB TRAQ #: 6003707
Title: "GPSYC-367-07 - Sensorimotor Control Processes Underlying Object Manipulation"

Dear Dr. Flanagan:

The General Research Ethics Board (GREB) has reviewed and cleared your request for renewal of ethics clearance for the above-named study. This renewal is valid for one year from May 28, 2017. Prior to the next renewal date you will be sent a reminder memo and the link to ROMEO to renew for another year. You are reminded of your obligation to submit an Annual Renewal/Closure Form prior to the annual renewal due date (access this form at http://www.queensu.ca/traq/signon.html; click on "Events"; under "Create New Event" click on "General Research Ethics Board Annual Renewal/Closure Form for Cleared Studies"). Please note that when your research project is completed, you need to submit an Annual Renewal/Completed Form in Romeo/traq indicating that the project is 'completed' so that the file can be closed. This should be submitted at the time of completion; there is no need to wait until the annual renewal due date.

You are reminded of your obligation to advise the GREB of any adverse event(s) that occur during this one year period. An adverse event includes, but is not limited to, a complaint, a change or unexpected event that alters the level of risk for the researcher or participants or situation that requires a substantial change in approach to a participant(s). You are also advised that all adverse events must be reported to the GREB within 48 hours. To submit an adverse event report, access the application at http://www.queensu.ca/traq/signon.html; click on "Events"; under "Create New Event" click on "General Research Ethics Board Adverse Event Form".

You are also reminded that all changes that might affect human participants must be cleared by the GREB. For example, you must report changes in study procedures or implementation of new aspects into the study procedures. Your request for protocol changes will be forwarded to the appropriate GREB reviewers and/or the GREB Chair. To submit an amendment form, access the application at http://www.queensu.ca/traq/signon.html; click on "Events"; under "Create New Event" click on "General Research Ethics Board Request for the Amendment of Approved Studies".

On behalf of the General Research Ethics Board, I wish you continued success in your research.

Yours sincerely,

John Freeman, Ph.D.
Chair, General Research Ethics Board

c.: Miss Taylor Jarvis, Miss Stephanie Clayton, Mr. Joshua Moskowitz, Miss Lauren Smail, and Mr. Mohammed Albaghdadi, Research Assistants
Dr. Leandre Fabrigar, Chair, Unit REB