RESOURCE FLEXIBILITY AND STRATEGY IN MULTIPLE OBJECT TRACKING

by

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A dissertation submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Psychology

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IN MULTIPLE OBJECT TRACKING

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ABSTRACT

Tracking capacity is typically defined by a limitation of 3-4 objects, suggesting that there may be a structural constraint on attentional resources for tracking (Pylyshyn & Storm, 1988). In this view, tracking capacity is item limited and the amount of resources allocated to each object is fixed. However, studies have found that tracking limits can be extended to 8 or more objects with appropriate reductions in velocity (Alvarez and Franconeri, 2007). Contrary to the discrete resource account, these findings suggest that tracking may depend on a continuous limited-capacity system in which a finite resource is divided among tracked objects in varying amounts, depending on tracking difficulty. The present set of experiments examined the nature of the resource limitations observed in multiple object tracking.

The continuous resource model posits that participants can only increase the number of objects tracked by reducing the amount of resource allocated to each tracked object with accompanying reductions in the spatial precision of tracking. This prediction was evaluated using a novel version of the MOT task in conjunction with a mixture model to obtain separate estimates of the number of objects tracked and tracking precision as the number of objects to-be-tracked was varied between 1 and 6. The results showed marked individual differences at high tracking loads, where half of the participants tracked only a few targets with high precision while the remaining half

tracked many targets with low precision. Experiment 2 explored whether these individual differences reflected fixed differences in the underlying tracking architecture or different strategies that could be freely adopted by any observer. Participants were instructed and incentivized to maximize the number of objects tracked at the expense of precision to determine whether tracking performance is flexible to strategy. Many but not all observers were able to flexibly trade off precision in favor of a larger number of tracked targets. These results are consistent with models that point to a limited resource whose allocation is flexibly determined by tracking demands.

The flexibility of attention allocation was further tested in Experiment 3 to examine whether resources can be endogenously varied between targets. High priority targets were tracked with greater precision than low priority targets, indicating that differential amounts of attention could be distributed between tracked objects. Experiment 4 examined whether tracking resources are hemifield specific or if a common pool is shared across visual fields. Although tracking two objects was just as precise as tracking a single object when they were presented bilaterally, distractors were more likely to be mistaken for tracked objects with increased set size regardless of spatial arrangement. The results support a bilateral advantage in tracking, but not independence. Experiment 5 investigated whether people attend to all tracked objects simultaneously or if each object is attended serially. ERPs were used to measure online processing of task-relevant probes on moving objects. Consistent with a parallel account, probes occurring on tracked objects were processed with no delay regardless of the number of objects tracked, while probes on distractor objects were processed with significant delays.

In summary, these results are consistent with continuous resource models that assume that tracking additional objects is accompanied by reductions in tracking precision. Allocation of this resource is subject to individual differences that depend partly on strategy but may also reflect differences in total capacity. Furthermore, people can flexibly allocate variable amount of tracking resources between targets. This resource appears to be largely hemifield specific and allocated in parallel to tracked objects.

Chapter 1

GENERAL INTRODUCTION

Our visual system provides us with a rich perception of the world, and our seemingly effortless experience and interaction with the external environment may lead us to believe that we have limitless visual capacity. Contrary to our rich conscious experience, there is in fact a stark limitation to how much our visual system can process at any given moment. Our environment provides an overwhelming amount of information to our visual system, but not all visual input is processed fully and equally. The visual system relies on visual attention to prioritize the processing of relevant information. Attentional selection is critical for many everyday activities such as keeping track of several simultaneously moving objects. Examples include driving through traffic and playing team sports. However, visual attention resources are finite and there is a limit to the number of items that can be concurrently attended. This processing limit is exemplified in the multiple object tracking task (MOT; shown in Fig. 1.1) introduced by Pylyshyn and Storm (1988). This task requires observers to track a set of target objects moving randomly among identical distractor objects. Results show that people can typically track around four or fewer objects with high accuracy, but performance drops precipitously with more objects (although see Alvarez & Franconeri, 2007).

One general account of this tracking limit is that tracked objects compete for a limited mental resource such as visual attention. Allocation of that resource can either be discrete or continuous. In discrete allocation, each object receives a fixed portion of the resource while continuous allocation allows different objects to receive different amounts of the resource. In the next two sections, I consider the evidence for each of these allocation policies.

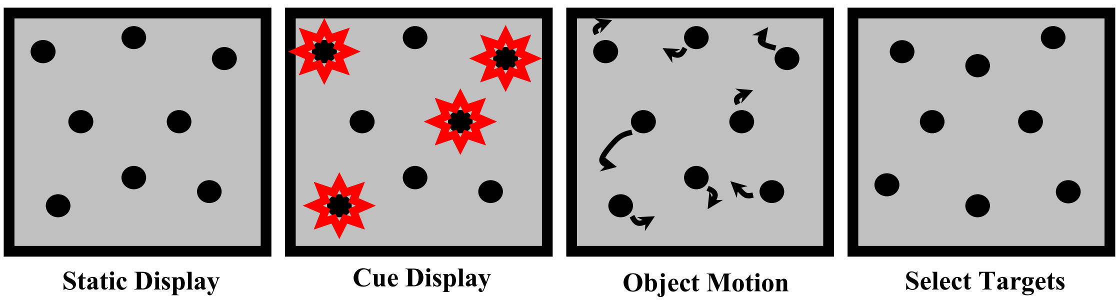


Figure 1.1: Sample trial sequence from a typical MOT experiment. A subset of stationary objects are cued at the start of a trial to designate them as targets to be tracked. All objects are identical and move in random motion during the tracking interval. Observers are instructed to select the targets at the end of each trial.

1.1 Discrete resource models of MOT

Visual attention can be thought of as an indivisible discrete resource that is directed to different objects in the visual field. Since it is unlikely that a single spotlight would encompass targets but not distractors, it would need to be serially shifted between the to-be-tracked objects (for a review, see Pylyshyn, Burkell, Fisher, Sears, Schmidt, & Trick, 1994). Pylyshyn and Storm (1988) challenged this model by showing that the predicted tracking performance of a serial spotlight mechanism with realistic switching speeds would be much lower than the performance achieved by human observers.

Instead, Pylyshyn (1989) argued that visual objects in the environment are tracked by assigning a set of discrete pointers or visual indexes to the tracked objects. This can be seen as a modification of the spotlight model in which attention is divided and allocated simultaneously to multiple objects. However, Pylyshyn maintained that visual attention is unitary and that indexes constitute a separate system that keeps track of objects without providing information about their properties or identities which was assumed to the province of attention. The number of objects that can be tracked is assumed to be constrained by the number of available indexes, which appears to be about three or four. This fixed number of indexes provides a straightforward explanation for the strict item limit observed in tracking.

This claim is disputed by recent evidence suggesting that there may not be any fixed limit in the number of items that can be tracked. For example, Alvarez and Franconeri (2007) showed that observers could track up to eight objects at slow speeds with suitable increases in the inter-object distance because close inter-object distances lead to spatial interference between attended objects (Franconeri, 2013; Franconeri, Alvarez, & Cavanagh, 2013). Many of the cortical regions in the brain that are implicated in tracking, such as the frontal eye fields (Culham, Cavanagh, & Kanwisher, 2001; Shim, Alvarez, Vickery, & Jiang, 2010), represent objects in a spatial map-like representation. There appears to be an inhibitory zone that surrounds each attended item on the map and interference occurs when two or more attended objects are close enough for their suppressive surrounds to overlap (Franconeri, 2013; Franconeri, Alvarez, & Cavanagh, 2013). Therefore, tracking capacity may not be limited by the capacity of an attentional mechanism but by competition for limited representational space.

However, the spatial interference model's claim that tracking limits are completely determined by spatial competition is challenged by a recent study by Holcombe, Chen, Piers, & Howe (2014) who found poorer performance in tracking two objects compared to one, even when inter-object separation was beyond the inhibitory or crowding zone. Crowding is known to affect a person's ability to individuate an object from neighboring stimuli due to spatial interference (Intriligator & Cavanagh, 2001). In their study, Holcombe et al. (2014) investigated whether there was a performance cost to tracking additional objects when the minimum distance between objects was well beyond the crowding range. The objects moved in concentric circular tracks each containing two objects, one of which could be a target. The maximum inter-object separation tested was 59 degrees at 66 degrees of eccentricity which is large enough to avoid crowding. Holcombe et al. still found a performance penalty for tracking an additional target even at this distance, which indicates that spatial crowding is not the sole cause of tracking limits.

1.2 Continuous resource model of MOT

Both the indexing and spatial interference models assume that each target is tracked with equal priority. These models do not provide any role for a dynamic, flexible top-down attention system that can favor one object over another. An alternative conception of MOT that does incorporate this kind of flexibility is the multifocal attention theory proposed by Alvarez and colleagues (Alvarez & Franconeri, 2007; Cavanagh & Alvarez, 2005). They challenged the claim that there is an item-limit on the capacity of attentional tracking resources, as proposed by the discrete resource account. This model assumes that visual attention can be subdivided into multiple spotlights that can be allocated in parallel to multiple objects. Therefore, tracking capacity depends on the availability of a limited visual attention resource that can be flexibly divided among targets. In this view, observers should be able to adjust the amount of attention allocated to different targets in response to changes in relative rewards and tracking difficulty.

The multifocal attention model predicts that tracking depends on a limited resource that can be allocated to different objects in a *continuous* fashion while indexing theory assumes a set of *discrete* resources (indexes) that are allocated to tracked objects in an all-or-none fashion. The continuous resource perspective assumes that when the number of objects to be tracked increases there is a diminishing amount of resources allocated to each object, resulting in a degraded spatial representation of each target's position. Tracking performance is commonly evaluated by measuring the number of objects correctly tracked, but this may not be the most sensitive method to detect a loss in target precision. For example, even if participants have a degraded representation of the target's location, it may still be precise enough to discriminate the target from surrounding distractors. A better approach would be to require participants to provide estimates of *target location*. In this case, the distance between the reported and actual positions of the target provides a continuous, fine grained measure of tracking precision. This approach, which was successfully applied in obtaining estimates of working memory capacity, is reviewed in the next section.

1.3 Parallels with VSTM models

The capacity of VSTM has been traditionally examined using the change detection paradigm which tests the observers' ability to identify a change in an array of items across a retention period. A typical finding in the VSTM literature is that observers can remember approximately four objects across a short retention interval (Luck & Vogel, 1997; Pashler, 1988). This is consistent with a discrete model of working memory which holds that there is a limited number of slots for holding items in VSTM and that all objects are represented with high precision (Luck & Vogel, 1997; Zhang & Luck, 2008). However, it is important to consider not just the quantity of representations that can be held in VSTM, but also their quality. Resource models propose that the capacity of VSTM can be characterized in terms of a limited continuous resource that is shared among objects in VSTM. The precision of representations is flexibly determined by the amount of resource devoted to each object, such that one could either store many objects with low precision or just a few with high precision. In contrast, a discrete resource model holds that there are a limited number of slots (discrete resources) for holding objects in VSTM and each object is represented with the same fixed precision.

Early tests of these predictions favored the discrete resource model. For example, Awh, Barton, and Vogel (2007) measured the capacity of working memory (‘Cowan’s k’, Cowan (2001)) for displays containing simple or complex objects. According to the continuous resource model, complex objects would require more processing resources than simple objects and should result in lower capacity estimates. However, they also noted that increasing complexity was confounded with greater similarity between the objects being stored. This increased similarity, in turn, would make the decision process more error prone when participants judged whether a test item matched an item in the original display. When they controlled for this similarity confound, they found no effect of complexity on estimated capacity (see also Barton, Ester, & Awh, 2009).

However, the change detection task might not be sensitive to small changes in resolution because small reductions in resolution might still be sufficient to judge the test object as being different from the corresponding memory representation. To estimate the precision with which items were encoded, Zhang and Luck (2008) used a continuous partial-report task (Wilken & Ma, 2004) requiring observers to mark the color of a remembered item on a color wheel. They fit a mixture model to the differences between the actual color and the observers’ response (response errors). According to the mixture model, the full set of response errors consists of a mixture of two kinds of trials: those in which the tested items is in memory and those in which it is not, requiring observers to guess. In-memory response errors were fit to a circular normal distribution (von Mises) centered on the correct color. Guess errors were assumed to be uniformly distributed over the full set of colors.

The mixture model provides estimates of the probability that a probed item was stored in VSTM, as well as the standard deviation (sd) of the von Mises distribution reflecting the precision with which the item was represented. The discrete and continuous models make different predictions about the effect of set size on these parameters. According to the discrete model, resolution should remain fixed across set sizes, because objects are stored in individual slots with fixed resolution. In addition, the likelihood of guessing should remain the same across set sizes that are less than the number of slots and increase rapidly for set sizes exceeding this number. In contrast, the continuous model predicts a gradual decline in resolution with increasing set size even for set sizes that exceed the typical limits cited for VSTM (3-4 objects) because a fixed resource is being shared between all the objects in the display (i.e., there is no item limit). For the same reason, the continuous model does not predict a sudden increase in guessing when set size exceeds 3-4 objects.

Zhang and Luck found that the guessing rate increased with set size, but more dramatically once the three-item maximum had been reached. Additionally, the standard deviation of the normal distribution increased with the first three items, but further increases were not observed for larger set sizes. They accounted for this decrement in precision in terms of the *slots+averaging* model which holds that an item can be independently stored in multiple slots whenever there are more available slots than memory items. These multiple independent representations can be averaged to provide greater precision for an item. This deviation from the classic slot model allows the slots + averaging model to make predictions that are similar to the continuous resource model, such as the flexible allocation of slots to a prioritized item (Zhang & Luck, 2008). The remaining critical distinction between these models is that the slots + averaging model predicts a fixed upper limit on the number of items that can be stored. The large increase in guessing and the plateau in the standard deviation of the normal distribution that occur with set sizes larger than three items were interpreted as evidence for an item limit in VSTM.

Accuracy in working memory tasks requires participants to maintain both the task-relevant *features* (e.g., color) as well as the *locations* of items in memory. Features and locations must be bound together during encoding for correct retrieval at test (Treisman, 1998; Treisman & Schmidt, 1982). Errors in the binding process would lead an observer to report the feature belonging to memory items other than the probed item. These binding errors, also known as swap errors, are unaccounted for by Zhang and Luck's mixture model. Bays, Catalao, and Husain (2009) addressed this issue by fitting the data from a color report task with a mixture model that separated the response distribution into three types of error: error for color belonging to the probed item (Gaussian distribution centered on the target color), error for color belonging to a non-probed item (swap error modelled as a Gaussian distribution centered on each noncued object), and error from random guessing (uniform distribution). With the inclusion of swap errors in the mixture model, the authors found that random guessing accounted for only a small proportion (around 14%) of the responses for the largest set size (six-item arrays). In contrast, the proportion of swap errors grew with increasing memory load and accounted for almost 30% of the responses in the largest set size (Bays et al., 2009). This finding challenged the item limit assumption on memory capacity as it appeared that variability in target recall together with swap errors accounted for most of the response distribution.

More recently, van den Berg, Shin, Chou, George, & Ma (2012) introduced an account of the continuous resource model known as the variable-precision model, which may be able to explain the increased guessing rate that accompanies increases in memory load without invoking an item limit. This model assumes that the precision with which an object is represented varies according to the amount of resources it receives, and this amount varies across items on each trial. Due to this variability in resource allocation, some items will, by chance, receive less resource resulting in large errors that will likely be grouped into the uniform guessing distribution. Therefore, increasing memory set size will increase the apparent guessing rate. Note that this apparent increase in the guessing rate actually reflects an increase in low precision representations. Furthermore, a Bayesian model comparison based on individual-trial data found that the log likelihood of the variable-precision model exceeded those of the classic slot model, the standard continuous resource model, and the slots+averaging model (van den Berg & Ma, 2014; van den Berg et al., 2012).

1.4 Current status of the MOT resource debate

In the realm of multiple object tracking, recent findings also appear to support a continuous resource model. Howard and Holcombe (2008) measured the spatial precision with which objects were tracked as a function of set size by instructing observers to click on the final position of tracked objects. They found that this response became less precise as tracking load increased. Horowitz and Cohen (2010) found this to be true for movement direction as well. Furthermore, the continuous resource account predicts an increase in spatial resolution for objects that are allocated a greater share of the attentional resources. Observers appear to increase their attention on a tracked object when it gets close to a distractor (Franconeri, Jonathan, & Scimeca, 2010; Tombu & Seiffert, 2008). Evidence suggests that increasing crowding is counteracted by a greater allocation of attention to the tracked object (Intriligator & Cavanagh, 2001; Tombu & Seiffert, 2008). For example, Iordanescu, Grabowecky, and Suzuki (2009) demonstrated that a target was localized with higher precision when a distractor approached within 3 degrees of visual angle (see also Srivastavja and Vul, 2015). Thus, it appears that attentional resources can be flexibly allocated to tracked objects depending on task difficulty (Tombu & Seiffert, 2008).

Has the debate between discrete versus continuous resource models been resolved and decided in favor of the resource model? Findings from a recent study examining the neural correlates of tracking load and precision (Shim, Alvarez, Vickery, & Jiang, 2010) suggest that each model alone may not be able to account for the evidence. In their study, observers tracked a target spoke in one or two pinwheels while the *attentional precision* needed for accurate tracking was adjusted by varying rotation speed (Alvarez & Franconeri, 2007; Holcombe & Chen, 2012). Set size was manipulated to identify brain regions responsive to the *number* of tracked targets. Using functional magnetic resonance imaging (fMRI), Shim et al. found that although activity in posterior parietal cortex was sensitive to the *number* of objects being tracked, it was not affected by manipulations of object *speed*. On the other hand, activity in the frontal eye fields (FEF), another region in the dorsal attention network thought to be involved in tracking, was affected by both the number of objects tracked and their velocity. These findings are consistent with a hybrid model of resource distribution (Zhang & Luck, 2008), in which the number of targets being tracked determines the number of independent spotlights or indexes being used, while the precision of individual spotlights is dependent on the amount of attention allocated to each object. It appears that mechanisms responsible for the indexing or individuation of targets reside in the posterior parietal cortex, while the amount of attention to be allocated to each target is determined by mechanisms in the FEF.

Current MOT findings thus appear to support either a continuous resource, or a hybrid resource account. However, one caveat in accepting this conclusion is that previous studies on target precision (Howard & Holcombe, 2008; Iordanescu, Grabowecky, & Suzuki, 2009) have not differentiated "guess" trials from trials in which targets were tracked. According to the slot model, guesses become more frequent with larger tracking loads that exceed the number of slots. In order to accurately address the resource question, it is important to measure the precision of tracking independent of guess trials.

1.5 Summary of Current Experiments

The current set of experiments addressed several fundamental questions regarding the nature of the limited resource that is important in MOT (continuous vs. discrete), flexibility in resource allocation, role of separate cerebral hemispheres, and whether objects are tracked serially or in parallel. In order to address these issues, I used a version of the Wilken and Ma's continuous report paradigm modified for MOT. The method used is illustrated in Fig. 2.1 which schematically shows a typical trial. To measure the spatial precision of tracked objects, observers were instructed to localize the position of tracked objects on a circular track after the objects have been removed from the visual display at the end of each trial. This continuous-response technique allows for a measure of precision based on the angular differences between the reported and actual target positions. The mixture model was used to decompose these errors into a mixture of three different trial types: *tracking trials* in which the object is tracked with a precision corresponding to a von Mises (circular normal) distribution centered on the correct target position, *guessing trials* in which the target wasn't tracked and participants have to guess its location, resulting in a uniform distribution, and *swap trials* in which the participant incorrectly tracks the distractor leading to errors that correspond to a von Mises distribution centered on the distractor location. The model provides parameters corresponding to the probability of each of these three trial types as well as an estimate of the standard deviation (1/precision) of the von Mises distribution.

The data showed marked individual differences in results at high tracking loads, where half of the participants tracked only a few targets with high precision while others tracked many targets with low precision. In a second follow-up experiment, it was shown that about half of the participants who tracked few objects were able to more than double the number of objects they were tracking when instructed to do so. Critically, there was an observed tradeoff between the quantity of objects tracked and the precision with which they were tracked. Moreover, this flexibility in attentional control applies to the amount of resources allocated to each target as well as demonstrated in Experiment 3. More resources could be applied to a high priority object, but this is done by withdrawing resources from another object. Experiment 4 examined whether tracking resources are hemifield specific or if a common pool is shared across visual fields. It was found that tracking precision for two objects was just as good as for a single object when objects were presented bilaterally. However, observers were more likely to mistake a distractor for a tracked object with increased set size, regardless of spatial arrangement. It appears that there's advantages to tracking objects bilaterally, but tracking resources are not completely independent. Experiment 5 tested whether tracking of multiple objects is performed serially or in parallel by utilizing ERP to measure online processing of task-relevant probes on moving objects. In support of the parallel tracking account, probes occurring on tracked objects were processed with no delay regardless of the number of objects tracked, while probes on distractor objects were processed with significant delays.

Chapter 2

EXPERIMENT 1

2.1 Introduction

In the present study, the mixture model approach (Bays et al., 2009; Zhang & Luck, 2008) was used to evaluate the nature of limited capacity resources in MOT. To this end, the Wilken and Ma continuous report paradigm was modified in order to apply it to MOT. Observers tracked objects moving on circular tracks and indicated their final positions when they disappeared at the end of the tracking period. The angular difference between the reported and actual target positions provides a continuous measure of tracking precision. The mixture model of Bays, Catalao, and Husain (2009) will be used to classify trials into three different types: *correct tracking trials* in which the target object is tracked with a precision corresponding to a von Mises (circular normal) distribution centered on the correct target position, *guessing trials* in which the target wasn't tracked and participants have to guess its location, resulting in a uniform distribution of location of location errors, and *swap trials* in which the participant incorrectly tracks a distractor leading to errors that correspond to a von Mises distribution centered on the distractor location. The model provides parameters corresponding to the probability of each of these three trial types as well as an estimate of the standard deviation of the von Mises distribution (the reciprocal of which provides a measure of precision).

In Experiment 1, observers tracked one, two, three, or six objects on each trial. Each tracked object was paired with a distractor moving along the same circular track (see Fig. 1). To anticipate the results, there were striking individual differences in tracking performance at the highest load (six objects). Some participants tracked just a few targets with high precision, while others tracked more targets but with lower precision.

2.2 Method

2.2.1 Participants

Participants were University of Delaware students (14 females and 8 males with a mean age = 18.7 years) who received monetary compensation at the rate of $10 per hour for their participation. They all reported normal or corrected-to-normal visual acuity and provided informed written consent. One female participant was excluded from analysis because the mixture model failed to converge on parameter estimates for her data. All experiments were approved by the University of Delaware IRB.

2.2.2 Apparatus

Observers were tested in a dimly lit and acoustically isolated room. Displays were presented on a SAMSUNG 2233RZ 22” LCD Monitor (Wang & Nikolic, 2011) having 1,680 x 1,050 pixel resolution and a 120-Hz refresh rate. Viewing distance was fixed at 70 cm using a chin rest. Experiments were controlled by a Dell 3.60 GHz computer. The experiment was programmed with Python version 2.7 (Python Software Foundation, http://www.python.org; van Rossum, 1995) using PsychoPy software extensions (Peirce, 2007; Peirce, 2009). Eye movements were monitored with an Eyelink 1000 eye tracker using the Eyelink Toolbox extensions (SR Research, Ontario Canada). Eye position was sampled at 500-Hz. An eye movement was defined as three consecutive eye samples that were more than 1.4 degrees of visual angle (dva) from fixation.

2.2.3 Stimuli and Procedure

A sample visual display is shown in Fig. 2.1. On each trial observers tracked one, two, three, or six objects (radius = 0.2 dva) that moved on circular tracks (radius = 2 dva) that were positioned along an imaginary circle with a radius of 5.5 dva centered on the fixation point. The track centers were fixed at 0, 30, 90, 150, 210, and

270 degrees on the imaginary circle. Two objects were placed on each track. Thirty-

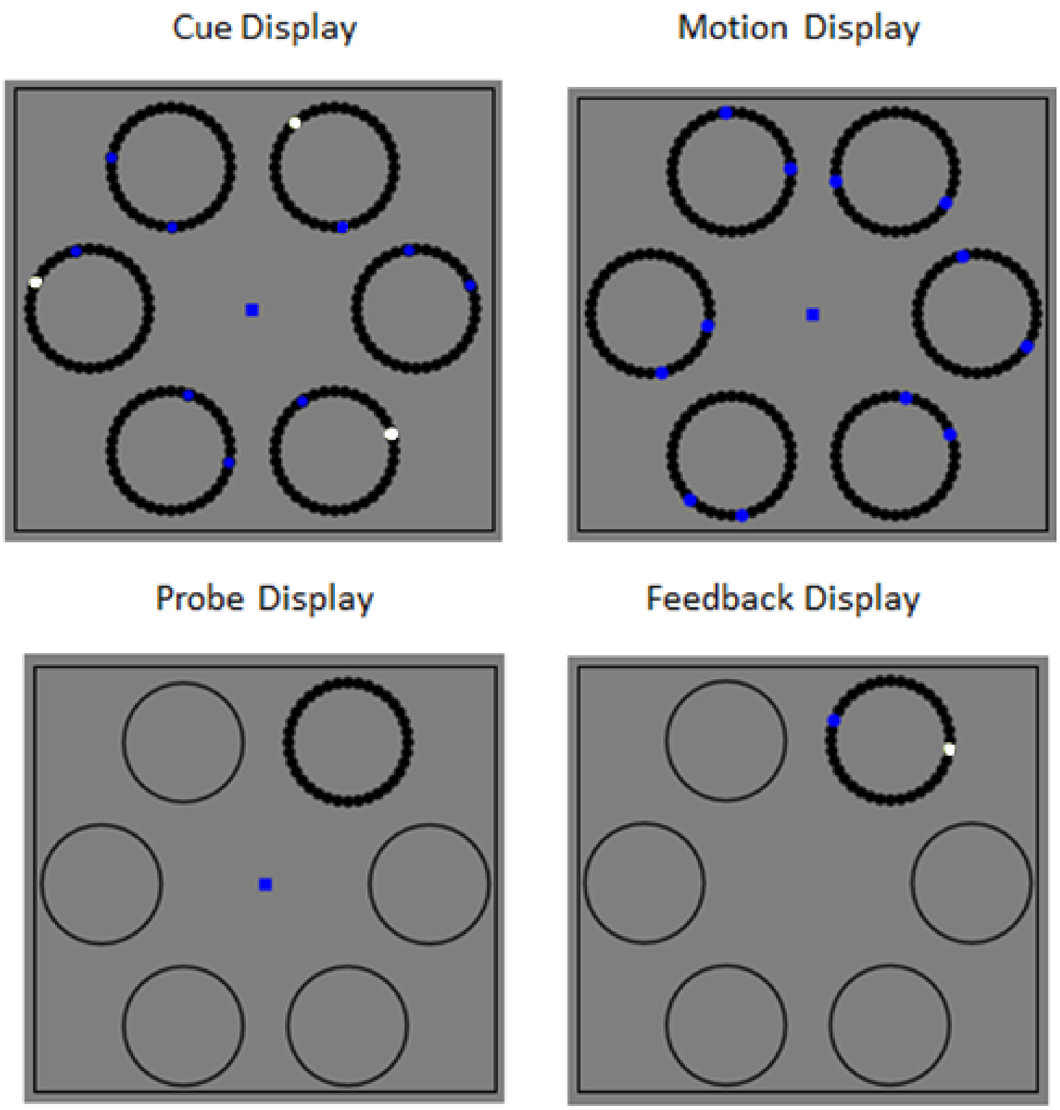


Figure 2.1: A typical trial in Experiment 1. Participants were instructed to keep track of the targets (shown in white) at the beginning of each trial. Objects moved independently around the track during the motion phase. At the end of the motion sequence each moving object faded into a background object. For the tracking response, participants clicked on the last known location of the target on the probed track (indicated by the ring of circles). Immediate feedback was given by presenting the target (shown in white) at its correct location.

six stationary black circles of the same size as the moving objects were placed along the circular tracks. These stationary circles were spaced 10 degrees apart along each track. Each of the moving objects gradually faded for 250 ms into one of these circles at the end of the motion interval. This was done to prevent the disruption of focused attention on targets which may occur if objects disappeared abruptly from the screen as studies have shown that sudden visual disruptions such as saccades may disrupt tracking leading to a remapping of attention to tracked objects (Piers, Trafton, Pinto, & Horowitz, 2011; Pylyshyn, 2007). The display always contained six tracks, any of which could contain a target and a distractor. All objects were blue except for a subset that appeared in green for 1.5 s at the start of each trial to designate them as targets. At the initiation of motion, the objects changed color to blue and all objects moved (velocity = 6 dva/s) randomly clockwise and counterclockwise around the track for 2.5 s. The movement direction of each object reversed on 5% of the motion frames. Motion direction of objects also reversed on contact (i.e., objects bounced off of each other).

At the end of the motion phase, objects faded for 250 ms into the background circles along the track. Following this, all background circles disappeared from the tracks except for the track relevant for response. Participants were instructed to click on the last known location of the target on the cued track and the computer recorded the difference in angle between the reported and actual locations. Following this, participants were asked to rate their confidence in their tracking response by indicating whether they were “very sure,” “somewhat sure,” or “guessing.” This measure allowed us to empirically estimate the guessing probability to provide a check on the corresponding parameter delivered by the model. In addition, participants could choose a category labelled “not sure if it’s the target” to reflect the possibility that that a swap error had occurred because a distractor was mistaken for a target. There were 100 trials allotted to each of the four set size conditions which were randomly intermixed across trials.

2.3 Mixture Model Analysis

Response errors consisted of the angular differences between the correct and reported target locations. These data were analyzed with the mixture model described in Bays et al. (2009), which is a modification of the original Zhang and Luck (2008) method with an additional component that accounts for the probability of target-distractor swap errors. According to the mixture model, participants track objects with a spatial error corresponding to a circular normal or von Mises distribution centered on the correct target position. For trials in which the cued object was not tracked, participants either guess its location randomly, resulting in a uniform distribution across the entire circular track, or they track a distractor rather than the target resulting in a von Mises distribution centered on the distractor position. The entire set of response errors is modelled as a mixture of these three underlying distributions. We used the MemToolbox program (Suchow, Brady, Fougnie, & Alvarez, 2013; memtoolbox.org) to obtain, for each participant and experimental condition, maximum likelihood estimates of three parameters: the standard deviation of the von Mises distribution (sd), the probability of guessing (g), and the probability of a swap error (s). We used these parameter values to compute *tracking precision* (1/sd) and *number of objects tracked* (nt: (1-g)*set size). Note that the total number of objects tracked includes both targets being correctly tracked as well as distractors that are being mistakenly tracked.

2.4 Results and Discussion

The discrete model (without averaging of slots) predicts that tracking precision should be the same across set size up to some limit corresponding to the maximum number of indexes or pointers (approximately two-four). The rationale is that each object is tracked with the same "resource" (a pointer or index) regardless of how many other objects are being tracked. In contrast, the continuous resource model predicts that precision should decrease with increasing set size because a fixed capacity is being divided across more objects resulting in a smaller portion of the resource being allocated to each object. This effect of set size on resolution should hold for the entire range of set sizes (1-6) because this model doesn't assume any fixed limit to the number of objects that can be tracked.

The results revealed large differences across participants in the set size 6 condition. Approximately half of our participants (the "low capacity group", n = 9) tracked an average of 2.26 objects with high precision. The remaining participants (the "high capacity group", n = 12) tracked an average of 4.69 objects with lower precision. Group membership was established using an SPSS two-step cluster analysis using the number of objects tracked, number of swap errors, and sd in the set size 6 condition as factors in the cluster analysis (see Fig. 2.2). This clustering method determines the

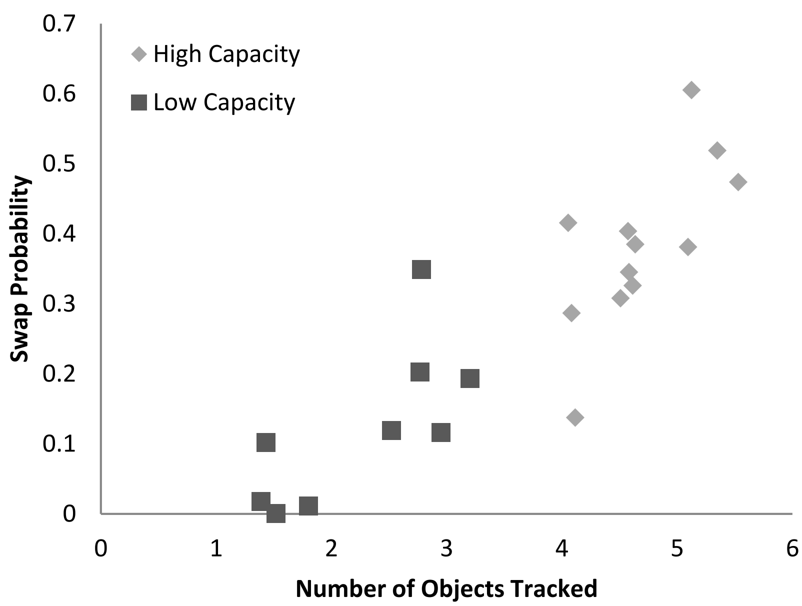


Figure 2.2: Group membership based on a cluster analysis of set size 6 data with number of objects tracked, sd, and swap probability as factors.

number of groups based on Schwarz's Bayesian Criterion (BIC) which penalizes solutions with larger degrees of freedom. This is expressed in terms of a qualitative measure of goodness-of-fit ranging from poor to fair to good. The current two cluster solution was judged as good.

Figure 2.3 shows the mixture model parameters representing the number of objects tracked and 1/sd (tracking precision) as a function of set size for each group. The number of objects tracked was analyzed using a mixed ANOVA with group (Low vs. High Capacity) as a between-subjects factor, and set size (1, 2, 3, and 6) as a within subjects factor. Note, that it wouldn't be surprising to find statistically significant main effects or interactions involving group because these groups were formed on the basis of differences in the number of objects tracked and swap probability as a function of set size. However, it is still important to determine which main effects and interactions are statistically reliable. For the number of objects tracked, there were main effects of group (High vs Low capacity; $F(1,19) = 74.76$, $p < .001$, $\eta^2_p = .79$) and set size ($F(3,57) = 164.88$, $p < .001$, $\eta^2_p = .89$ as well as their interaction ($F(3,57) = 50.29$, $p < .001$, $\eta^2_p =$

a

b

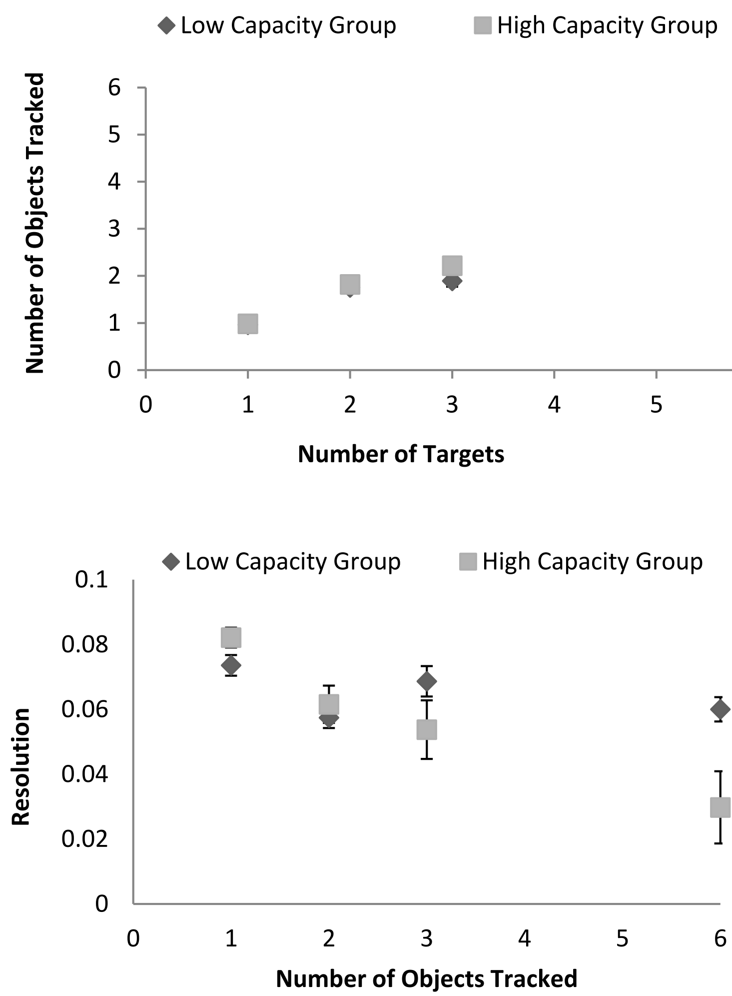


Figure 2.3: Estimated number of objects tracked and tracking resolution for Low and High Capacity observers. Observers tracking 3 targets or less in the set size 6 condition were placed in the Low Capacity group while those tracking more than 3 targets were placed in the High Capacity group. (a) Estimates of the number of targets tracked as a function of set size. (b) Tracking resolution (1/sd) of responses as a function of set size.

.73). Pairwise comparisons with a Bonferroni correction showed that significantly more targets were tracked by High Capacity participants (M = 4.69) compared to Low (M =

2.26) for set size six ($p < .001$), but there was no group difference in the other set size conditions (all p values > .08). It appears that the number of objects tracked was comparable across both groups for small set sizes but differed when tracking load increased to six objects.

A second ANOVA was conducted on the sd parameter of the mixture model. There was a main effect of set size ($F(3,57) = 13.71$, $p = .001$, $\eta^2_p = .42$) reflecting an increase in sd (loss of precision) with increasing set size as well as a group by set size interaction ($F(3,57) = 6.44$, $p = .01$, $\eta^2_p = .25$) reflecting a higher sd for the High vs. Low capacity group for set size six. Bonferroni-corrected contrasts showed that the sd in the set size six condition was larger for the High capacity group (*M* = 41.96 degrees) compared to the Low (*M* = 20.96 degrees; p = .02). No group differences were found in any other set size condition (all p values > .08). These results show a clear tradeoff between the number of targets tracked and tracking precision: some participants were

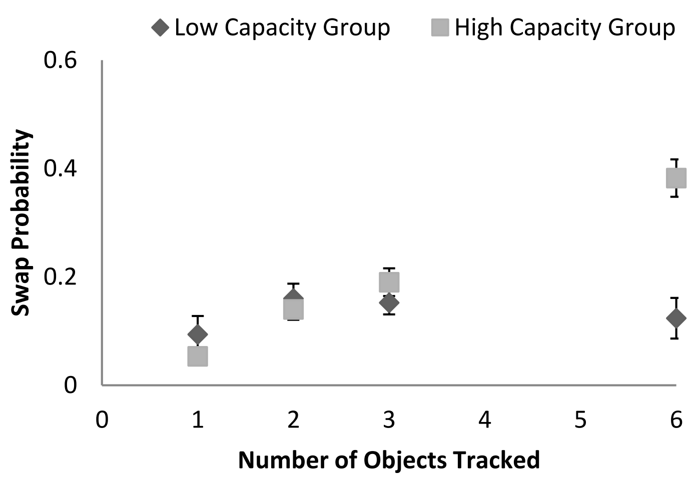


Figure 2.4: Swap probability as a function of set size. The error bars indicate the SE of the mean.

able to track more than three objects but only at the cost of a large decrease in spatial precision. This flexibility in resource allocation is consistent with the continuous resource account.

Figure 4 shows the average estimated swap probability as a function of set size for both the high and low capacity groups. An ANOVA on swap errors revealed a main effect of set size ($F(3,57) = 24.84$, $p < .001$, $\eta^2_p = .57$) reflecting an increase in swap errors with increasing set size. There was also a significant interaction between group and set size ($F(3,57) = 21.46$, $p < .001$, $\eta^2_p = .53$) reflecting greater swap errors in the High capacity group compared to the Low as a function of set size. The group difference appears to be restricted to the set size six condition where the High Capacity group had a larger number of swap errors (M = 38%) than the Low capacity group (M = 12%; $p < .001$) as there were no group differences at other set sizes (all p values > .23). The High Capacity group tracked more objects than the Low Capacity group in the set size six condition but they did so at the expense of decreasing precision (Fig. 3). This decrease in precision, in turn, may have increased the likelihood of mistakenly tracking the distractor object rather than the target.

These results show dramatic individual differences in performance when people attempted to track more than three objects. Approximately half of the participants continued to track roughly two objects with relatively high precision in the set size 6 condition. The remaining participants more than doubled the average number of objects they were tracking (4.69 vs. 2.26 for set size 6) but did so at the cost of a large decrease in precision and a tripling in the number of swap errors. The number of targets tracked and the spatial precision of tracking were comparable across the two groups of participants when tracking load was low (1, 2, or 3 objects).

However, there is one caveat to the conclusion that individuals in the high capacity group are capable of tracking a large number of objects by dividing their resources between all these objects. An examination of the confidence ratings reported by observers reveal surprising performance similarities between high and low capacity individuals. Table 2.1 shows observers' confidence rating and average absolute error in set size 6 for the high and low capacity groups ("Very sure" and "Somewhat sure" responses were combined into the "Sure" category due to low number of responses in the separate categories). Assuming that high capacity individuals were tracking most of the targets (with low spatial precision), they should show higher subjective levels of confidence. Yet, they were "sure" on each tracking trial just as often as low capacity trackers (17.37% for high and 24.87% for low; $t(19) = 1.39$, $p = .18$) in the set size 6 condition, and this was the case for their self-reports of guessing as well (44.48% and 51.85%, respectively, $t(19) = .85$, $p = .41$). Importantly, the two capacity groups' sure category responses show comparable average absolute errors (50 vs. 61 degrees for

Table 2.1: Confidence rating and average absolute tracking response error for high and low capacity trackers

High Capacity Trackers:

Confidence Rating	Frequency (%)	Absolute Error in degrees
Sure	17.37	60.99
Swap	38.14	64.18
Guess	44.48	84.50

Low Capacity Trackers:

Confidence Rating	Frequency (%)	Absolute Error in degrees
Sure	24.87	50.45
Swap	23.26	77.09
Guess	51.85	80.62

low and high capacity groups, respectively) in the set size 6 condition. This suggests that high and low capacity individuals may be tracking targets in similar ways.

Interestingly, it is in their self-report of swap errors that the two capacity groups show truly distinct performance patterns. The high capacity trackers reported significantly higher frequency of swaps (M = 38.14%) compared to low capacity trackers (M = 23.26%; $t(19) = -2.53$, $p = .02$). Figure 2.5 shows how closely responses to distractors overlap with target responses for the high capacity trackers, while the low capacity trackers show much fewer responses corresponding to the distractor location. This suggests that high capacity trackers may be tracking just a few targets with high spatial precision, similar to low

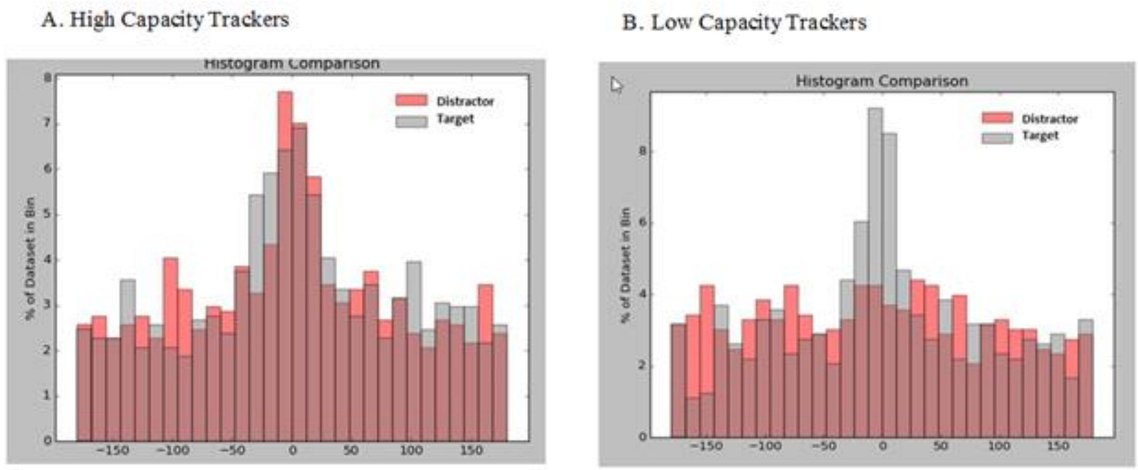


Figure 2.5: Tracking response distribution corresponding to target and distractor locations for high (A) and low (B) capacity trackers for Experiment 1.

capacity trackers, but they are using an additional component that provides them with information about many object locations without knowing whether they are targets or distractors, resulting in a high number of swaps. One possibility is that this component is fragile visual short term memory (Pinto, Vandenbroucke, Otten, Sligte, Seth, & Lamme, 2017; Pinto, Sligte, Shapiro, & Lamme, 2013; Sligte, Scholte, & Lamme, 2008), a temporary memory store that exceeds the capacity of visual short term memory but has a longer “shelf life” than iconic memory (250 ms to 3 s for fragile memory and only up to 250 ms for iconic memory).

High capacity trackers may be storing brief snapshots of the tracking display using their fragile visual short term memory. This would allow them to have information about the locations of some of the objects that they were not tracking, but they wouldn’t have information about which object was a target and which was a distractor resulting in high numbers of swap errors. It would be worthwhile to test this possible account in the future by masking the location of objects at the end of the motion period, which is known to eliminate fragile working memory (Pinto et al., 2013; Sligte et al., 2008). With visual masking eliminating fragile memory, high and low capacity trackers should be comparable in the number of objects tracked at all set sizes.

Chapter 3

EXPERIMENT 2

3.1 Introduction

There were striking differences between two groups of participants in Experiment 1 when they were required to track more than three objects. Two potential explanations for these individual differences were considered. The first is that there may be relatively immutable differences in the underlying architecture of the tracking systems in the two groups. Some participants appear to have the ability to spread their attention across a large number of objects (high capacity group) whereas others are restricted to a few (low capacity group). This might make sense from the perspective of the continuous resource model if it is assumed that some minimum allocation of attention to an object is required for tracking. That is, there may be constraints on the "continuous allocation" of attention such that tracking isn't possible if allocation of attention falls below some minimum amount. In this case, people with low capacity might be unable to track more than three objects because all objects would then have less than the required minimum resulting in a failure to track any of them. This is consistent with spontaneous subjective reports from some low capacity participants who indicated that when they tried to track more than three objects they suddenly lost track of all of them.

Alternatively, these differences might simply reflect different strategies that can be arbitrarily adopted by any participant. In this case, both groups may have had the same capacity limits but the "high capacity" group may have been more willing to incur the cost in precision associated with dividing attention across many objects. Participants in the low capacity group may have decided that it was more important to be very precise in tracking a few objects rather than incurring larger errors when tracking many objects. It is interesting to note that both groups had comparable average absolute errors (72 vs. 75 degrees for low and high capacity groups, respectively) in the set size 6 condition suggesting they may have been simply using different strategies to achieve the same end result in terms of overall error.

Experiment 2 directly examines the strategy explanation by using instructions and monetary incentives in an attempt to induce low capacity participants to increase the number of objects they tracked in the set size six condition regardless of any losses in precision.

3.2 Method

3.2.1 Participants

Twenty-three students from the University of Delaware were recruited. The mixture model failed to converge on parameter estimates for two individuals and they were excluded from further analysis. The remaining 21 students (13 females) were between 18 and 30 years of age (mean age = 22.09 years old) and were compensated at a base rate of $10 per hour for their participation. They were given the opportunity to earn additional monetary rewards (up to $10) at the completion of the experiment based on their performance (detailed below). All participants reported normal or corrected-to-normal visual acuity and provided informed written consent.

3.2.2 Apparatus

The equipment and technology were the same as in Experiment 1.

3.2.3 Stimuli and Procedure

Stimuli and procedures were identical to those used in Experiment 1 except for the following changes. There were two parts to the experimental session. The first part was similar to experiment 1 with observers instructed to track two, four, or six targets on each trial. In the second part, tracking load was set to four or six targets on each trial and *observers were instructed to attempt to track all targets regardless of any loss in precision*. They were informed that they would receive a monetary reward on each trial of 5 cents for responses that were within +/- 40 degrees of the correct target location. After observers reported their confidence judgment on each trial, performance feedback was provided in the form of two orange colored dots placed along the circular track to indicate the interval (+/- 40 degree) in which they would be correct. The observers' actual response location was shown as a blue dot. This was designed to encourage observers to adopt a strategy of trying to track all targets, even at the expense of reduced precision. The correct response interval of 80 deg. was chosen on the basis of experiment 1 in which the responses (with guess trials removed) of most individuals who were tracking four or more targets were on average within 40 degrees of the correct location. Before initiating the second part of the experiment, observers were given 10 practice trials with the +/- 40 degree response criterion to familiarize them with the task. There were 300 trials in part one and 200 trials in part two of the experiment with 100 trials in each set size condition.

3.2.4 Results and Discussion

Results from part 1 of experiment 2 were submitted to the swap model which returned estimates of number of objects tracked, as well as guessing and swap probabilities. The SPSS two step clustering program used these parameters to determine the number of groups in the data (see Fig. 3.1). Once again, the best solution was two

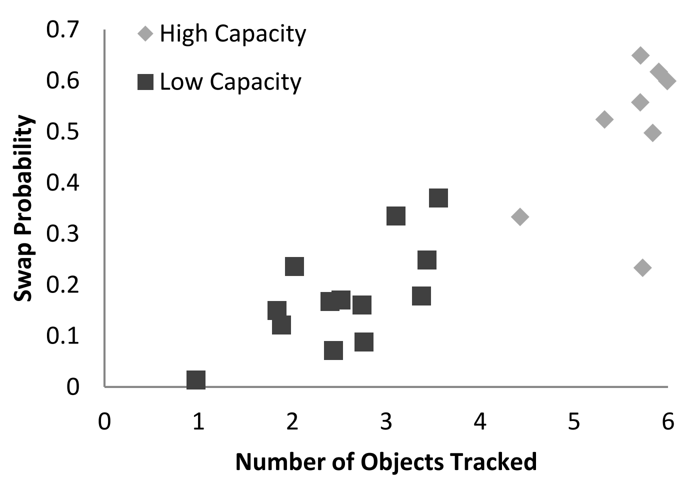
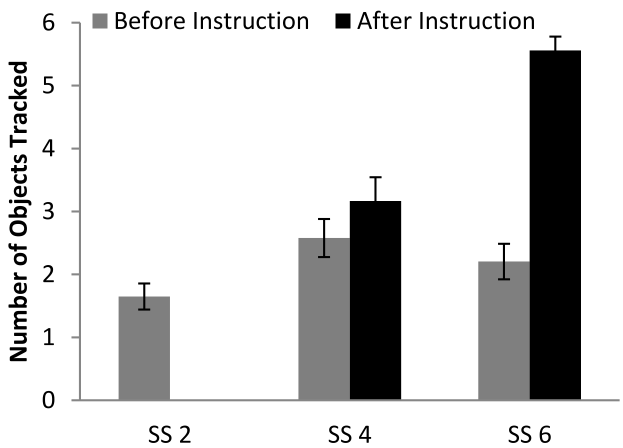


Figure 3.1: Group membership based on a cluster analysis with number of objects tracked, sd, and swap probability as factors in the set size 6 condition.

groups and the goodness of fit fell into the “good” category. Observers who tracked approximately three targets or less in part 1 were placed in the “low capacity” group (N = 13), while those who tracked four targets or more were labelled as “high capacity” (N = 8). However, one participant was classified as low capacity even though he was tracking a large number of objects (4.42) which favors placement in the high capacity group. However, this participant tracked with high resolution (.04 degrees) which would place him in the low capacity group. This participant is an outlier in terms of our classification scheme so we arbitrarily placed him in the high capacity group after determining that it did not significantly affect the results of the analyses reported below.

Interestingly, the mixture model results show two different patterns of performance (shown in Fig. 6) for the low capacity group in the second part of the experiment. Despite clear instructions and incentives to track more objects, approximately half of our “low capacity” participants (N = 7) continued to track a small number of targets with high precision. They were labelled as inflexible trackers because they did not change their tracking strategy despite incentives to do so. It’s not clear whether these individuals were simply unmotivated to adopt a different strategy or were unable to do so. The remaining observers (N = 6) in the low capacity group, called the flexible trackers, were able to increase the number of targets tracked (to an average of 5.56 tracked objects) following instructions, albeit at the cost of a 27 degree increase in sd.

a. Flexible Trackers



b. Inflexible Trackers

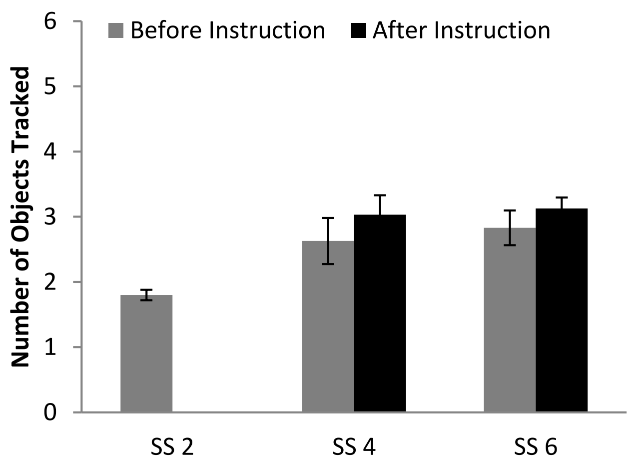


Figure 3.2: Estimated number of objects tracked for flexible (a) and inflexible trackers (b). Observers tracking at 3 targets or below in the set size 6 condition after instructions were placed in the inflexible group while those tracking more than 3 targets were placed in the flexible group.

Mixture model parameters for the flexible trackers in part 2 were analyzed with 2x2 repeated measures ANOVAs including factors of set size (4 vs. 6 targets) and instruction (before vs. after instruction). For the parameter of number of objects tracked, there were significant main effects of set size (F(1,5) = 6.84, p = .047, η^2_p = .58) and instruction (F(1,5) = 34.14, p = .002, η^2_p = .87). There was also a significant interaction (F(1,5) = 32.35, p = .002, η^2_p = .87). Subsequent pairwise comparisons revealed a significant increase in number of objects tracked after instruction for set size 6 (t(5) = -7.62, p = .001, d = -3.10), but not for set size 4 (p = .19).

Model estimates for the sd of tracking responses are shown in Fig. 3.3. Analysis of the sd parameter showed no main effects of set size or instruction. Crucially, there was a significant interaction (F(1,5) = 8.25, p = .035, η^2_p = .62) such that sd increased post instruction, but only in the set size six condition (t(5) = -4.0, p = .01, d = -1.63). Following our instructional manipulation, flexible trackers were able to adopt an alternate strategy of tracking a large number of targets, but with lower precision. This tradeoff is consistent with the continuous resource account of tracking.

Swap probabilities for both flexible and inflexible groups are shown in Fig. 3.4 and indicate that the probability of a swap error was higher in part 2 compared to part 1 (F(1,5) = 11.22, p = .02, η^2_p = .69). There was no main effect of set size (F(1,5) = .006, p = .94, η^2_p = .001). There was a significant interaction (F(1,5) = 12.46, p = .017, η^2_p = .71) reflecting an increase in swap errors in the set size six condition of part 2 (t(5) = -7.18, p = .001, d = -3.0), but not in the set size four condition (p = .39). It seems likely that the coarser tracking precision associated with set size 6 increased the likelihood of tracking the distractor instead of the target.

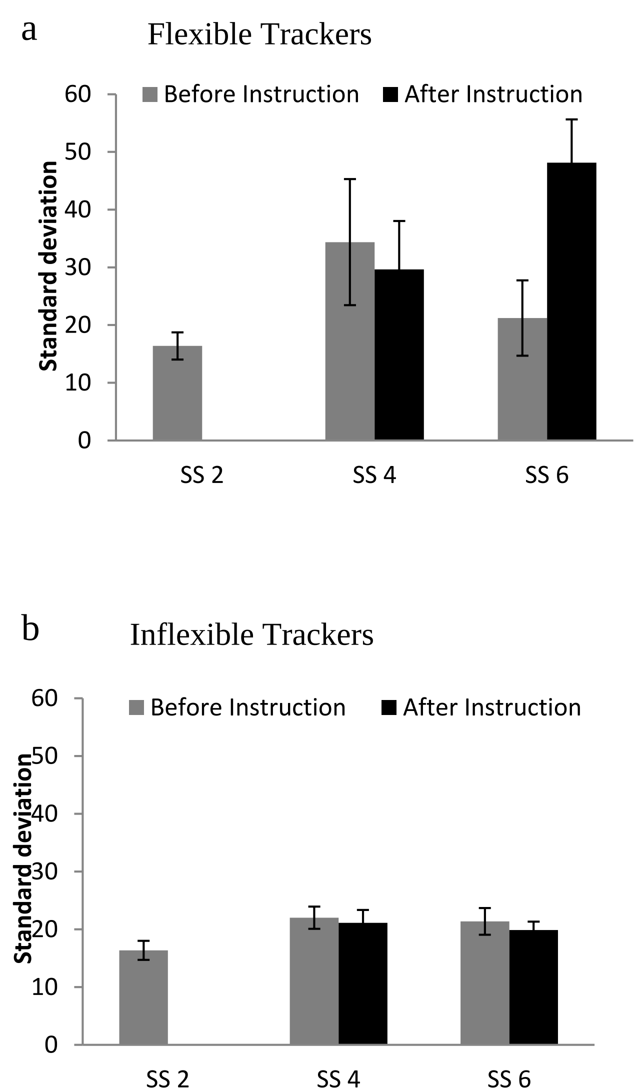


Figure 3.3: Estimated SD for flexible (a) and inflexible trackers (b). Observers tracking at 3 targets or below in the set size 6 condition after instructions were placed in the inflexible group while those tracking more than 3 targets were placed in the flexible group.

For the inflexible group, there were no significant main effects or interactions involving set size and instruction on the number of targets tracked (all p values > .11), tracking precision (all p values > .62), or the frequency of swap errors (all p values > .50). It appears that individuals in this group were either unable or unwilling to track more than two or three objects. Additional research will be required to determine if there may be stronger reward schemes that might lead these participants to change their strategy or whether this limitation is a fixed property of the observer (e.g., fixed limits on attentional capacity) which carries over into other attentional paradigms beyond MOT.

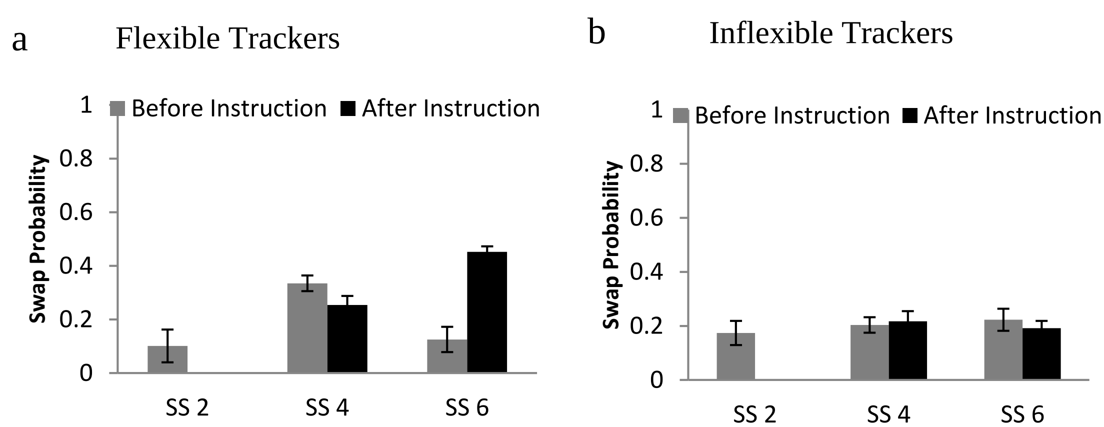


Figure 3.4: Estimated swap probability for flexible (a) and inflexible trackers (b). Observers tracking at 3 targets or below in the set size 6 condition after instructions were placed in the inflexible group while those tracking more than 3 targets were placed in the flexible group.

The group identified as high capacity trackers in part one isn't relevant for evaluating the strategy hypothesis because the instructions for part 2 are encouraging them to do something they are already doing (tracking a large number of objects). As expected, there were no significant differences in any of the model parameters for the "before" vs. "after" comparison: the number of objects tracked (M = 4.04 and 3.77, $F(1,7) = .52$, $p = .49$), tracking precision (sd = 43.15 and 38.19 degrees, $F(1,7) = .36$, $p = .57$), or frequency of swap errors (M = 38% and 34% ,$F(1,7) = .44$, $p = .53$). These results indicate that people in the "high capacity" group had adopted a strategy in part 1 that allowed them to track many targets and they simply maintained this strategy in the second half of the experiment.

Chapter 4

EXPERIMENT 3

4.1 Introduction

Another critical test for the discrete versus continuous resource models of MOT is whether or not observers have endogenous control over the amount of resources allocated to different targets. In a typical MOT paradigm, observers are told to track several moving targets, all of which are assumed to have equal value or importance. However, one could imagine that in a real-world scenario people are often tasked to monitor a particular target with greater priority while still keeping track of other lower priority targets. For example, a player on a soccer field may place greater priority on the whereabouts of the ball while monitoring the location of other field players. Whether our attentional resources can be divided unequally to favor one object over others is a fundamental question about the way our visual attention system operates.

The continuous resource model proposes that more attention can be willfully allocated to one target vs. another during tracking whereas the discrete model holds that all targets receive the same amount of "resource." In their MOT experiment, Chen, Howe, and Holcombe (2013) examined whether attentional resources could be allocated unevenly between targets by differentially varying the speed of two moving targets such that a second target moved at the same or slower speed than the first target. They found that tracking performance was higher for the faster target when the second target moved at a slower speed than when they moved at the same speed, which supports the flexible resource account as each target was allocated a different share of the attentional resource according to task demands. Similarly, Srivastava & Vul (2016) showed that the amount of attention allocated to each target could change dynamically to maintain individuation of a target in situations of crowding, even at the expense of other uncrowded targets (Srivastava & Vul, 2016).

A similar question regarding the allocation of resources has been raised in the VSTM domain. In characterizing the capacity of VSTM, researchers have examined the number of items stored and the precision with which they were stored while varying the complexity of the items (Alvarez & Cavanagh, 2004; Bays, Catalao, & Husain, 2009; Bays & Husain, 2008; Wilken & Ma, 2004). Memory capacity varied depending on the type of stimuli presented, as more objects were encoded for simple items like colored squares, but far fewer were encoded for more complex items like shaded cubes and Chinese characters (Alvarez & Cavanagh, 2004). Alvarez and Cavanagh reasoned that more complex items have greater information load resulting in fewer complex items being stored in VSTM. It appears that the amount of cognitive resources dedicated to each memory item is not fixed, but changes dynamically according to demands.

Moreover, Machizawa, Goh, and Driver (2012) showed that the precision of encoded items can be varied endogenously independent of the physical features of the items to be encoded. In their VSTM task, participants had to discriminate whether a test item matched the orientation of an encoded item. While the memory items did not vary across conditions, Machizawa et al. manipulated observers' expectancies about the level of precision required for the memory discrimination task. Their study revealed that items were encoded with greater precision on trials in which participants anticipated having to make a finer discrimination. Critically, this only occurred when the number of items to be remembered was two or fewer. These findings support the idea that encoding resources are allocated in a flexible manner that enables endogenous control over the contents of VSTM.

Oksama and Hyona (2008) proposed that during MOT, the spatial locations of targets are stored and updated online in VSTM, such that tracking limits may depend directly on the capacity of VSTM. If tracking and VSTM share a common resource, and allocation of this resource can be strategically adjusted in the case of VSTM (Machizawa et al., 2012), then tracking performance should also reflect the flexible distribution of resources to tracked objects.

The purpose of the proposed experiment is to determine whether people can vary the amount of attention allocated to particular targets during MOT, as predicted by the continuous resource models. Observers were asked to track two target objects and were instructed that accuracy on one target would provide a larger reward relative to the other. Importantly, participants were encouraged and incentivized to keep track of both targets to deter them from simply tracking just the prioritized target. If tracking reflects a flexible attentional process, we should observe greater tracking precision for the prioritized target at the expense of the non-prioritized target. Alternatively, attentional instructions will have no effect on performance because objects can only be tracked with a fixed precision, as claimed by the discrete resource account.

4.2 Method

4.2.1 Participants

Participants were University of Delaware students (13 females and 2 males with a mean age = 18.8 years) who received credit towards their introductory psychology research participation requirement. Additionally, participants were given a performance-based monetary compensation (up to $10) at the completion of the experiment. They all reported normal or corrected-to-normal visual acuity and provided informed written consent. One participant was excluded from analyses due to interference with the eye tracker from his prescription glasses. Experimental procedures were approved by the University of Delaware IRB.

4.2.2 Apparatus, Stimuli and Procedure

The apparatus remained the same as in Experiment 1. A typical single trial sequence is depicted in Figure 4.1. The display contained four objects with a pair of objects at midline positioned above and below the fixation point, and a second appearing in lateralized locations in each hemifield. The object pairs moved on circular tracks (radius = 2 dva) whose centers were positioned on an imaginary circle with a radius of

5.5 dva centered on the fixation point. On each trial, single objects from one of the pairs located on the midline and in one of the hemifields were cued

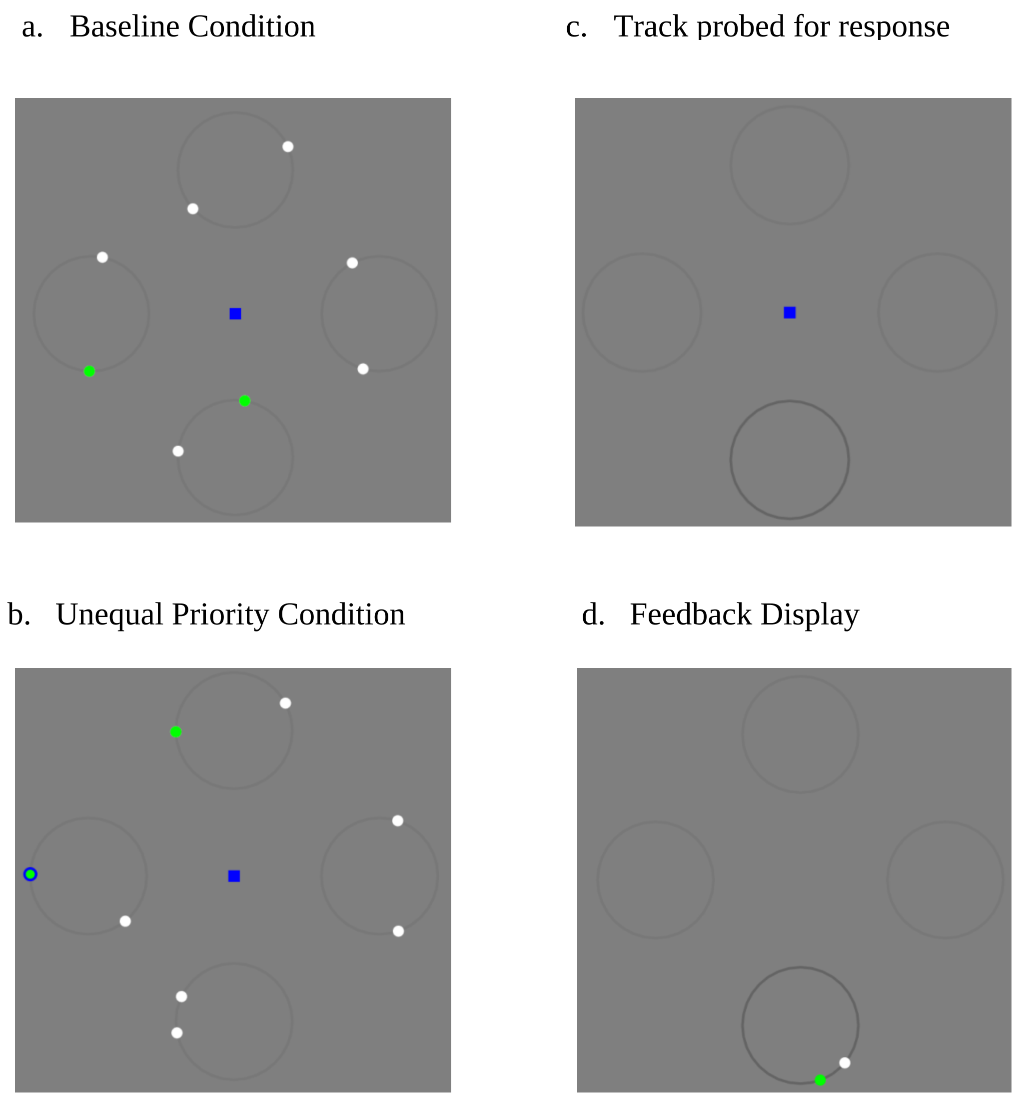


Figure 4.1: Sample displays of a trial sequence in Experiment 3. A) Cue display for baseline condition. Target cued in green. B) Cue display for unequal priority condition in which the high priority object was cued with a surrounding blue border. C) One of the circular tracks was cued for response at the end of the motion period. Observers were instructed to click on the final target position. D) Immediate feedback was provided. The correct target position was shown in green.

(shown in green) for 1.5 seconds to designate them as targets to be tracked. The upper and lower locations on the midline and the left vs. right locations of the lateralized targets were counterbalanced across trials.

After the cueing interval, all the objects appeared in the same color (black) and moved (velocity = 6 dva/s) randomly clockwise and counterclockwise along the circular track for 2.5 s. On each frame, each object had a 5% chance of reversing its direction of motion. At the end of the motion phase, objects stopped and then faded into the background for 250 ms until they disappeared from the display. Afterwards, one of the circular tracks that had contained a target would be cued (shown in black) for response. Participants were instructed to click on the final target location on the cued track. The angular difference between the reported and correct target positions was recorded by the computer. Immediate performance feedback was provided in the form of a green colored dot placed along the circular track to indicate the correct location of the target and a black colored dot indicating the location reported by the participant.

On unequal priority trials, observers were told to prioritize one target (cued with a surrounding blue border) over another. The prioritized target was positioned at the midline and lateralized locations equally often. Participants were told that they would receive a monetary reward on each trial for responses that were within +/- 20 degrees of the correct target location. The response criterion was chosen based on average response sd for tracking a single object in Experiment 1. On each trial, participants earned 1.5 cents for accurate tracking on the non-prioritized target and 2.5 cents for the prioritized target. This was designed to encourage participants to place more emphasis on the prioritized target while also rewarding them for tracking the non-prioritized target. On baseline (equal priority) trials, targets were not cued with a blue border and participants were instructed to consider both targets equally important and they earned 2 cents on each trial for precise tracking of a target. The experiment consisted of 5 blocks of approximately 100 trials each with trial conditions randomly intermixed in each block. There were 100 trials in the equal priority condition. There were 400 trials in the unequal priority condition with the prioritized target appearing equally often at the midline vs. lateralized locations.

4.2.3 Results

The mixture model provided parameter estimates of the guessing probability, sd, and swap probability in each of the priority conditions. These parameters were analyzed in separate one-way repeated measures ANOVAs with object priority as a factor (equal/baseline vs. high vs. low priority target performance). Figure 4.2 shows the model estimates for guessing probability as a function of object priority. Guessing probability was significantly different across object priority conditions ($F(2,28) = 11.82$, $p = .001$). Least significant difference (LSD) pairwise comparisons showed no significant difference in guessing ($p = .49$) for equal ($M = 8.10\%$) and high priority objects ($M = 8.99\%$). However, baseline and high priority objects had significantly lower guessing probabilities compared to the low priority object ($M = 15.72\%$; $p = .004$ and $p = .001$, respectively).

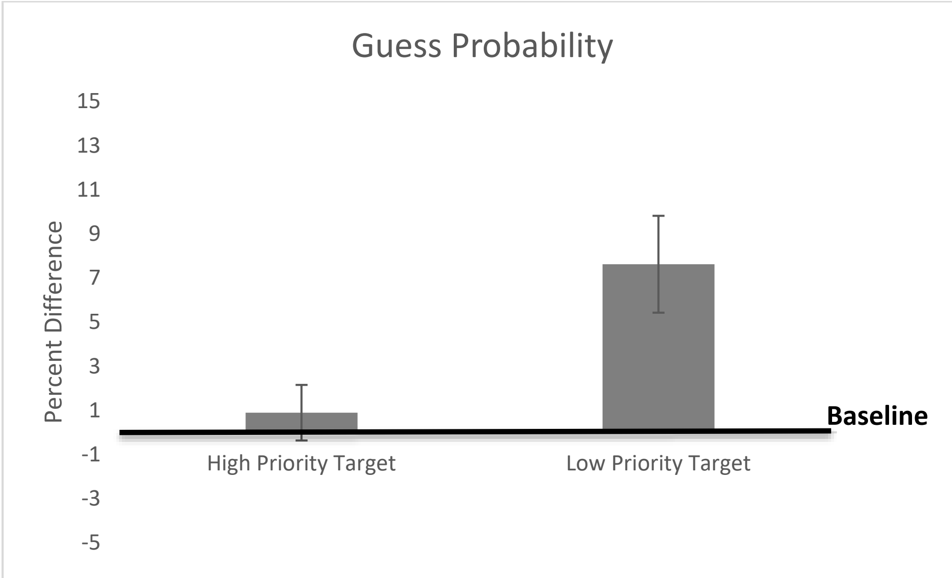


Figure 4.2: Estimated guessing probability as a function of priority compared to baseline. Error bars represent standard error.

Moreover, there was a similar effect of priority instructions on tracking precision ($F(2,28) = 12.24$, $p < .001$; see Fig. 4.3). There appeared to a be a slight improvement in tracking precision for the high priority target ($M = 15.15$ sd) compared to baseline targets ($M = 16.90$ sd), however the difference was not significant ($p = .05$). Relative to low priority targets ($M = 19.01$ sd), both high priority and baseline targets were tracked with significantly greater precision ($p < .001$ and $p = .02$, respectively). These results indicate a flexible endogenous shift in resources away from the low priority target, leading to decreased tracking precision and higher likelihood of guessing for this object.

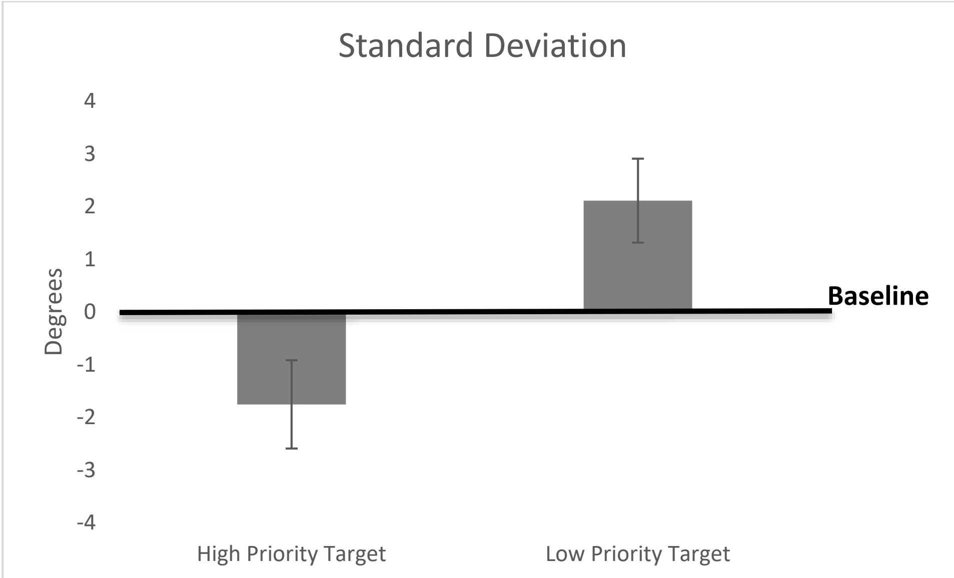


Figure 4.3: Estimated standard deviation as a function of priority compared to baseline. Error bars represent standard error.

Although one might have expected that the coarser tracking precision associated with the low priority target (see above) might have increased the likelihood of mistaking a distractor for a target there was no significant effect of priority conditions on the probability of making a swap error, ($F(2,28) = .74$, $p = .49$). It may be that the relatively small tracking set size in this experiment was well below capacity limit, which could have allowed each target to receive sufficient resources to be tracked with minimal error. It appears that while resources were withdrawn from the low priority target, this shift in resources may be small and conferred little advantage to the high priority target, as demonstrated by the comparable tracking performance for high and equal priority targets. It may be that some minimal amount of attention is necessary for accurate tracking (Tran & Hoffman, 2016) limiting the amount of resources that can be removed from the low priority target without losing track of it altogether.

4.2.4 Discussion

Targets in tracking tasks have traditionally had equal value. The focus of the present experiment investigated whether participants could maintain an uneven distribution of attention across tracked objects differing in their reward values. Observers were given instructions and incentives to place higher priority on one target vs. another. The results indicated that participants were more likely to guess the locations of low priority targets and when not guessing, they had lower resolution estimates of their location compared to targets with higher priority. Resource sharing between tracked objects appears to be amenable to instructions, which supports the flexible resource policy proposed by the continuous resource account.

Previous research has shown that attentional allocation can be driven by momentary increases in tracking difficulty. For example, increasing the number (Alvarez & Franconeri, 2007; Oksama & Hyona, 2004), or speed of target objects (Liu et al., 2005), as well as their proximity to distractors, increases the uncertainty of target locations (Alvarez & Franconeri, 2007). In Srivastava and Vul's (2016) computational model of tracking, resources are allocated to resolve localization uncertainties within the constraints of a limited capacity system. In these cases, the allocation of attention to various targets changes in response to external conditions in order to maintain accurate localization of targets.

Tran and Hoffman (2016) recently showed that the amount of attention devoted to targets could also be willfully adjusted by the observer. They required participants to simultaneously track a set of moving objects while also searching for a target that could appear on a tracked object or a distractor. Attentional allocation was manipulated by varying the probability that the search target would occur on tracked objects versus distractors. They found that both tracking accuracy and probe identification improved when observers knew that probes were more likely to occur on targets than distractors. Observers exhibited flexible control by endogenously shifting more attention to one group of objects vs. another according to task instructions.

Although Tran and Hoffman (2016) showed that the amount of attention allocated to targets vs. distractors could be willfully adjusted, they didn’t examine whether attention could also be unevenly divided between a pair of tracked objects. The current findings show that attention can also be strategically divided between tracked objects. This might be surprising given prior evidence that observers find it difficult to maintain separate identities for targets during MOT. For example, Pylyshyn (2004) had participants associate different names with physically identical targets prior to each tracking trial and found that they had difficulty recalling the labels at the end of the trial. Without any perceptual marker, one target could easily be mistaken for another, particularly when they are in close proximity. In the present experiment, this scenario was avoided by placing each target in separate quadrants.

Targets could then be spatially differentiated allowing observers to maintain more attention on the high priority object. These findings provide a challenge to the claim that attentional resources can only be allocated in fixed quantities.

Chapter 5

EXPERIMENT 4

5.1 Introduction

Receptive fields in the primary visual cortex respond to input from the contralateral visual field (Bullier, 2004). Recent evidence suggests that this early hemifield independence in visual processing may apply to visual attention as well, as there may be separate attentional systems for each hemifield (Alvarez & Cavanagh, 2005; Shim, Alvarez, & Jiang, 2008; Shim et al., 2010). Alvarez and Cavanagh (2005) showed that the number of objects that can be tracked was doubled if the tracked objects were divided across the two hemifields as opposed to appearing in a single hemifield, suggesting independent tracking capacities in each cerebral hemisphere.

This claim was supported by a study that examined the steady-state visual evoked potentials (SSVEPs) elicited by flashing stimuli located on tracked objects and distractors (Stormer, Alvarez, & Cavanagh, 2014). SSVEPs are neural potentials occurring over the visual cortex that change in amplitude at the same frequency as the flickering visual stimuli. Stimuli on targets and distractors flashed at different frequencies in order to allow for separation of the corresponding SSVEPs. The amplitude of the SSVEP was found to be modulated by attention with increased activity for attended relative to unattended stimuli (Morgan, Hansen, & Hillyard, 1996).

Critically, this effect only occurred when tracked objects were arranged bilaterally, but not when they were displayed unilaterally. The authors suggest that the increased cortical competition when targets occur within the same visual field interferes with early sustained attentional selection of targets during tracking. Object speed threshold for 80% accuracy was maintained for within and between visual field conditions. Consistent with the idea of increased interference when targets are located within the same hemifield, their behavioral results showed that two targets could be tracked at higher speeds when they were located in different hemifields compared to the same hemifield (Stormer et al., 2014).

Moreover, evidence from a neuroimaging study showed that brain areas (the superior parietal lobule and the transverse parieto-occipital area) that were sensitive to the number of targets being tracked also had greater activity when both targets were located in the same vs. different hemifields (Shim, Alvarez, Vickery, & Jiang, 2010). They also found greater tracking accuracy for bilateral vs. unilateral tracking unilaterally. These findings support the idea that there are bilateral advantages to tracking.

The discrete resource model could account for these findings by assuming that there are a separate set of indices in each hemisphere. In this case, all objects should be tracked with the same resolution regardless of their hemifield spatial arrangement. In contrast, if tracking capacity in each hemisphere is dependent on a separate continuous resource, there should be greater competition for this resource within compared to between visual fields. Thus, tracking precision should be worse for multiple targets located in same vs. different hemifield conditions.

The performance gain observed with bilateral displays could also be explained by a hybrid common resource account in which there are, for example, two indexes in each hemisphere, but a single continuous resource that is shared across the hemispheres. This flexible resource would be allocated to indexed objects according to tracking demands. Like the discrete resource model described above, the hybrid model predicts an increase in the number of objects that can be tracked when targets are divided between visual fields. However, the spatial precision for targets should show a gradual decline with each additional target, independent of hemisphere spatial arrangement, because a common pool of attention is divided between targets even when they occur in different visual fields. Previous unpublished research in our lab, shows an advantage for bilateral displays, but one that is significantly smaller than the doubling of performance predicted by hemispheric independence (McLean, 2013; Hoffman, Doran, Tran, & Nguyen, in preparation). These results provide support for the hybrid common resource view of tracking resources which predicts a limitation on the bilateral advantage to tracking due to the decline in spatial resolution for target positions with increases in target set size. To our knowledge, there are no previous investigations using the mixture model to analyze performance in bilateral tracking.

5.2 Method

5.2.1 Participants

Participants were University of Delaware students (9 females and 3 males with a mean age = 23.5 years) who received participation credit to fulfil a university course requirement. They all reported normal or corrected-to-normal visual acuity and provided informed written consent. Experimental procedures were approved by the University of Delaware IRB.

5.2.2 Apparatus, Stimuli and Procedure

The apparatus remained the same as in Experiment 1. A sample of the experimental displays is illustrated in Figure 5.1. The stimuli and procedures were similar to Experiment 1 with a few exceptions. Observers were told to track one or two objects on each trial. Two circular tracks were be placed on each side of fixation. In the case of one tracked object, it could appear on any of the four circular tracks. When two objects were cued, tracked objects occurred either unilaterally (above and below fixation), or bilaterally (left and right of fixation). Using the swap model (Bays, Catalao, & Husain, 2009) to analyze target location errors made it possible to assess

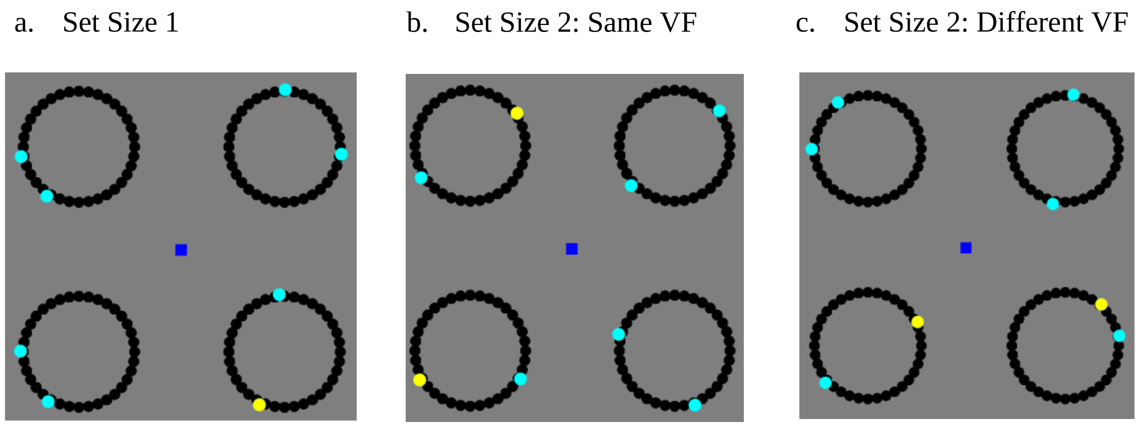


Figure 5.1: Sample cue display for Experiment 4. Targets were cued in yellow. A). Set size one condition. B). Set size two with targets arranged in the same visual field. C). Set size two with targets arranged in different visual fields.

the effects of hemifield arrangement on the number of targets tracked as well as tracking resolution.

5.3 Results and Discussion

Model estimates (number of objects tracked, sd, and swap error frequency) were analyzed in a one-way, within-subjects ANOVA examining three conditions: set size 1, size 2 same hemifield, and set size 2 different hemifield. The number of objects tracked significantly differed across conditions ($F(2,22) = 1245.98$, $p < .001$). Not surprisingly, observers tracked more objects in set size 2 than in set size 1 ($M = .99$ object; $p < .001$) for both unilateral ($M = 1.76$ objects; $p < .001$) and bilateral ($M = 1.91$ objects) conditions. Critically, there was a significant advantage to distributing targets between hemifields as more objects were tracked bilaterally compared to the unilateral arrangement for set size 2 ($p < .001$). Note that the number of objects tracked did not double with a bilateral compared to a unilateral display, as expected from independence (Alvarez & Cavanagh, 2005), but this result was likely because of ceiling effects (tracking was quite good in the unilateral condition preventing a doubling in number of objects tracked in the bilateral condition).

Figure 5.2 shows that tracking precision (sd) was significantly different across conditions ($F(2,22) = 14.24$, $p < .001$). Unilateral tracking of two targets ($M = 19.30$ sd) was less precise than bilateral tracking (M = 17.15 sd; p = .002) and was also worse than tracking a single target (M = 16.45; p = .001). In addition, bilateral tracking precision was comparable to tracking precision for a single object ($p = .20$).

These results suggest that resources are continuous as tracking precision decreases when more objects are tracked. Importantly, this effect only holds when targets were placed in the same hemifield but not when they were distributed across hemifields. Consistent with previous reports, our results showed a bilateral advantage to tracking, both in terms of the number of objects tracked as well as precision.

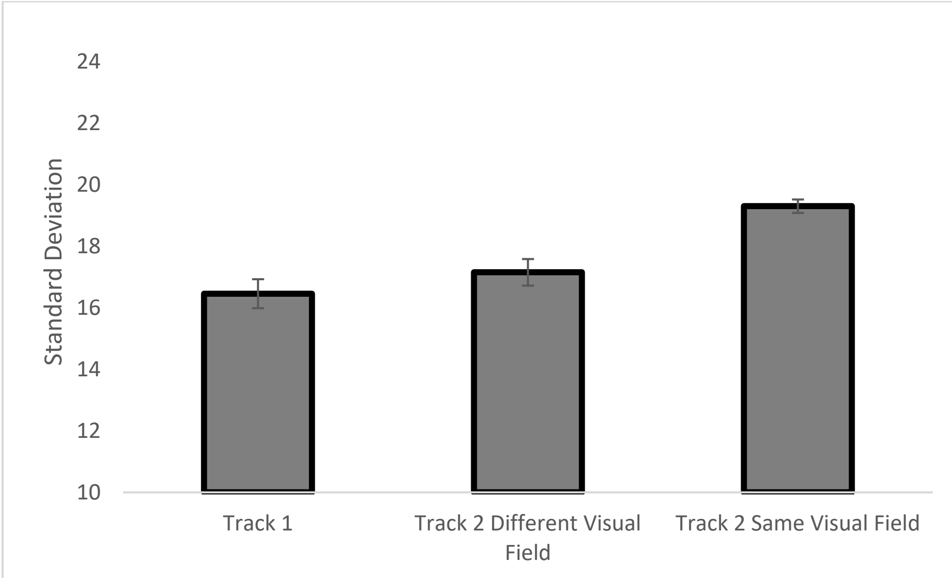


Figure 5.2: Estimated standard deviation of tracking responses according to spatial arrangement of targets. Error bars represent standard error.

Additionally, there was a significant difference in the probability of swaps across conditions ($F(2,22) = 247.69$, $p < .001$; see Fig. 5.3). Swap frequency for set size one ($M = 7.9\%$) was smaller than both set size two conditions, for unilateral ($M = 20.8\%$, $p < .001$) and bilateral trials ($M = 10.8\%$, $p < .001$). The likelihood of mistaking a distractor for a target would increase simply by chance when more objects are tracked, which appears to the case for the small increase in swap error for the bilateral condition compared to set size one. Critically, there was an effect of hemifield arrangement effect, showing significantly greater swap errors in the unilateral condition compared to the bilateral condition ($p < .001$).

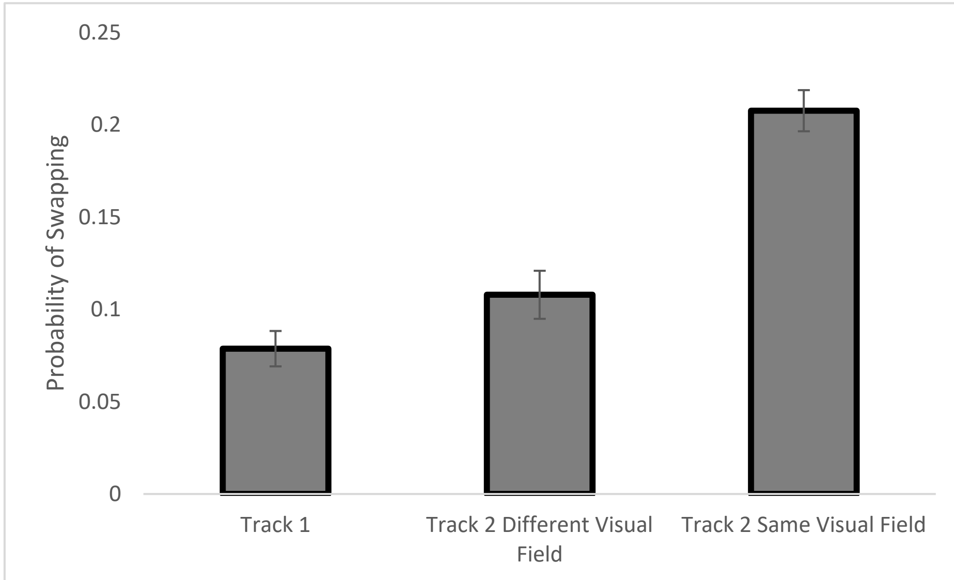


Figure 5.3: Estimated probability of swap errors according to spatial arrangement of targets. Error bars represent standard error.

The results show a robust bilateral advantage for tracking, with greater number of objects tracked, higher tracking precision, and fewer swap errors when targets appeared in *different* hemifields compared to the same hemifield. These results challenge the discrete resource prediction that objects are tracked with the same precision regardless of spatial arrangement. Tracking precision significantly decreased when tracking load increased from one to two objects appearing in the same visual field, suggesting that attentional resources are divided between targets within the same hemifield. Note that tracking precision for two bilateral targets was comparable to tracking a single target, which would be consistent with the idea of hemisphere-specific resources. Similarly, observers were more likely to mistake a distractor for a target when tracking load increased, and this was particularly true when targets were in the same visual field.

While the results of the present experiment may be in line with the hemifield independence claim, it is difficult to reconcile this finding with unpublished studies conducted in our lab which showed that tracking accuracy for two targets in different hemifields were not as good as tracking a single target. Moreover, other studies have also reported tracking results that fell short of hemispheric independence (Holcombe & Chen, 2012; Hudson, Howe, & Little, 2012; Shim et al., 2008). Holcombe and Chen (2012) found that two objects could be tracked at significantly higher speeds when they were in different hemifields compared to the same hemifield. However, tracking two objects bilaterally was not comparable to tracking a single object. Hudson and colleagues (2012) attempted a replication of Alvarez and Cavanagh's MOT study (experiment 4), yet they also failed to find a doubling in capacity when objects were distributed between hemifields as opposed to appearing in a single hemifield. Although some studies have found evidence of hemispheric independence in attentional tasks (Alvarez & Cavanagh, 2005; Alvarez, Gill, & Cavanagh, 2012; Delvenne & Holt, 2012), the current literature appears to be more in line with the idea of bilateral advantage rather than independence (Chen, Howe, & Holcombe, 2013; Holcombe & Chen, 2012; Holt & Delvenne, 2014; Hudson et al., 2012; Kraft, Kehrer, Hagendorf, & Brandt, 2011).

Chapter 6

EXPERIMENT 5

6.1 Introduction

Does MOT depend on a serial or parallel mechanism? A parallel account holds that attention is divided and allocated simultaneously to multiple targets, whereas in a serial operation, attention moves sequentially between tracked objects.

6.1.1 Serial vs. Parallel Processing in MOT

It was previously assumed that attention acts as a unitary “spotlight” that can operate across a visual field independently of eye saccades (Helmholtz, 1909; Hoffman & Nelson, 1981; Hoffman, Nelson, & Houck, 1983; Posner, 1980). Although the focus of attention can be altered like the zoom lens (Eriksen & St. James, 1986) of a camera to vary the size of the spatial region being attended (Kinchla, 1974; Shriffin & Gardner, 1972, Shriffin, McKay, & Shaffer, 1976), it was believed that only a single focus could be allocated to the visual field, which restricts the access of visual information to a serial process (for a review, see Pylyshyn, Burkell, Fisher, Sears, Schmidt, & Trick, 1994). If attention operates as a unitary spotlight, it would need to sequentially move from one object to another during object tracking. Pylyshyn and

Storm (1988) developed the MOT task to test this assumption. They showed that observers can continually track up to four independent targets (Pylyshyn & Storm, 1988). They compared this to predictions from a model simulation that assumed a single spotlight constrained to move at physiologically realistic speeds to keep track of multiple objects. They found that human tracking performance exceeded the predicted number of tracked objects from their model.

More recent efforts to address the debate between serial and parallel models of tracking have been mixed. For example, Howe, Cohen, Pinto, & Horowitz (2010) compared tracking performance across simultaneous versus sequential object movement. Display objects were confined to two separate regions. In the simultaneous movement condition, all objects moved and paused at the same time. In the sequential movement condition, when objects in one region were in motion, objects in the other region were stationary. If target locations are updated sequentially as attention moves from target to target, as proposed by serial models, then performance should be improved in the sequential movement condition relative to the simultaneous movement condition. Results showed that performance in the simultaneous motion condition was comparable to or even better than performance in the sequential motion condition as predicted by parallel models.

In contrast, Holcombe and colleagues (2008; 2013) found that the frequency with which people update target positions (which they called temporal resolution) to be more in line with the serial account. Tracking accuracy typically declines with increases in number of targets to be tracked. According to the serial account, this occurs because the positions of individual targets are updated less frequently when attention needs to cycle through an increasing number of targets. And because objects are continuously moving, there will be a larger disparity in location between successive visits to the same object with increasing set size.

It is also likely that a distractor may be mistaken for a target if it occupies the last known position of a target (Holcombe et al., 2008). Using a task like that of Experiment 1 in which observers clicked on the last known location of a target, Howard and Holcombe (2008) found a lag in the reported position of targets compared to their actual positions, and this lag increased with the number of targets tracked. This inverse relationship between tracking set size and temporal resolution was later corroborated by evidence showing that when the number of tracked object increased from one to three, the temporal resolution dropped from 7 Hz (updating 7 spatial positions per second) to less than 3 Hz (3 spatial positions per second; Holcombe & Chen, 2013). This suggests that the number of objects being tracked affects the speed with which each target position is updated.

6.1.2 Evidence from Electrophysiological Measures

Electrophysiological recordings utilizing the N2pc component of the event-related brain potential can be used to examine the time course of covert allocation of visual attention during MOT. In particular, the N2pc is a negative wave appearing over posterior sensors contralateral to the visual field of attended objects, and usually begins 180-200 msec after stimulus onset. This component is thought to reflect the attentional selection of targets among distractors (Eimer, 1996; Woodman & Luck, 1999, 2003), and is generated in extrastriate occipitotemporal and posterior parietal areas (Hopf et al., 2000, 2006). Hopf et al. (2000) found that retinotopic locations corresponding to attended object positions were selectively enhanced.

Recent evidence for parallel attentional selection of visual objects comes from N2pc studies conducted by Eimer and colleagues (Eimer & Grubert, 2014; Grubert & Eimer, 2016, Jenkins, Grubert, & Eimer, 2016). Grubert and Eimer (2016) investigated the efficiency of attentional selection of targets by testing whether the N2pc component to a target is affected by the presence of a second target. They presented observers with two displays, each containing a pair of letters, one of which was a target. The displays appeared sequentially (10 ms SOA) with one letter pair presented on the vertical meridian and the other on the horizontal meridian. The temporal order of these arrangements varied randomly. The horizontal and vertical arrangement of stimuli were used because the N2pc is a lateralized component exclusively reflecting selection of targets in contralateral visual field. Targets appearing on the vertical meridian do not elicit lateralized N2pc activity and therefore their contributions are subtracted away in a contralateral-ipsilateral subtraction.

Their results showed that the onset latency of the N2pc elicited by a target was not affected by the concurrent attentional selection of another target. It appears that there was no competition in attentional selection between the two targets despite their virtually simultaneous onsets, demonstrating independent and parallel selection of multiple targets (Grubert & Eimer, 2016).

The use of this component in the domain of MOT has provided insight on the attentional mechanisms involved in the visual selection and tracking of objects. Drew and Vogel's (2008) showed observers bilateral displays of identical objects with a subset of objects appearing in the left or right visual field designated as target objects to be tracked. The onset of this display generated an N2pc in the hemisphere that was contralateral to the cued side. The amplitude of this component increased with each additional target to be tracked. Furthermore, the amplitude plateaued at the same set size that behavioral measures identified as that individual's tracking capacity (Drew & Vogel, 2008; Drew, Horowitz, Wolfe, & Vogel, 2011). In summary, the properties of the N2pc component appear to be sensitive to the timing and capacity limits of attentional selection.

6.1.3 Goal of the current study

The current experiment addresses the question of whether tracking depends on serial or parallel processes by using ERPs to provide a precise temporal measure of the deployment of attention to tracked objects. A combined MOT and visual search procedure, is used to examine the N2pc component elicited by the search targets. The dual task required observers to track one or two circles while searching for a gap that could appear on the left or right side of a tracked circle or a distractor. The task was to make a speeded response indicating the side of the gap on target-present trials. Included was a subset of trials in which the gap target was absent in order to measure tracking performance without the interference of responses to the gap. Target present and absent trials were intermixed.

To determine whether attention can be concurrently divided between more than one target, the N2pc activity elicited by gap targets in the tracking set size 1 condition was compared to the N2pc elicited in the tracking set size 2 condition. If MOT is performed by serially switching attention between the two tracked objects, there would be more variability in the onset latency of the N2pc from trial to trial. In which case, the N2pc averaged across trials would be wider when observers are tracking two objects compared to one. In contrast, parallel processing predicts that attention can be simultaneously maintained on both tracked objects, and therefore predicts no differences in the onset latency the N2pc wave between set size conditions. Additionally, to assess whether the latency of the N2pc is sensitive to attention switching, the experiment included trials in which the gap targets were presented on a distractor rather than a tracked object. It is thought that spatial attention is focused on tracked objects during tracking (Alvarez & Cavanagh, 2005; Tran & Hoffman, 2016), therefore attention has to switch from the tracked object set to search the distractor set for the gap target. This should result in a wider N2pc waveform, when averaged across trials, for gaps occurring on distractors compared to tracked objects.

6.2 Method

6.2.1 Participants

Participants were University of Delaware students (6 females and 9 males with a mean age = 20.2 years) who received participation credit to fulfil a university course requirement. They all reported normal or corrected-to-normal visual acuity and provided informed written consent. Experimental procedures were approved by the University of Delaware IRB.

6.2.2 Apparatus, Stimuli and Procedure

The equipment and software used were the same as Experiment 1. On each trial, circles with a minimal inter-object spacing of 1.1^{o} were randomly positioned within rectangular gray areas (11.65^{o} X 7.94^{o}) on each side of the fixation cross (see Fig. 6.1). The center of each rectangular area was located 7.7^{o} from a fixation cross located in the center of the monitor screen.

At the start of each trial, observers fixated the screen-center cross and pressed a mouse button to initiate the display. Five open circles (1^{o} in diameter) appeared in each hemifield. A single object to be tracked in one of the hemifields was cued (shown in green, duration = 500 ms.) in the set size one condition, while one object from each hemifield was cued in set size two. The remainder of the disks were black. The number of targets to be tracked (one or two) and the assignment of the single target to left vs. right visual fields varied randomly across trials within the constraint that each combination of set size and attended visual field occurred equally often over trials. Following the cueing phase, all items moved in random directions with a velocity of 3.4 ^{o}/sec. Objects moved on a straight path and bounced off the sides of the rectangular region as well as each other when they were closer than the minimal inter-object spacing.

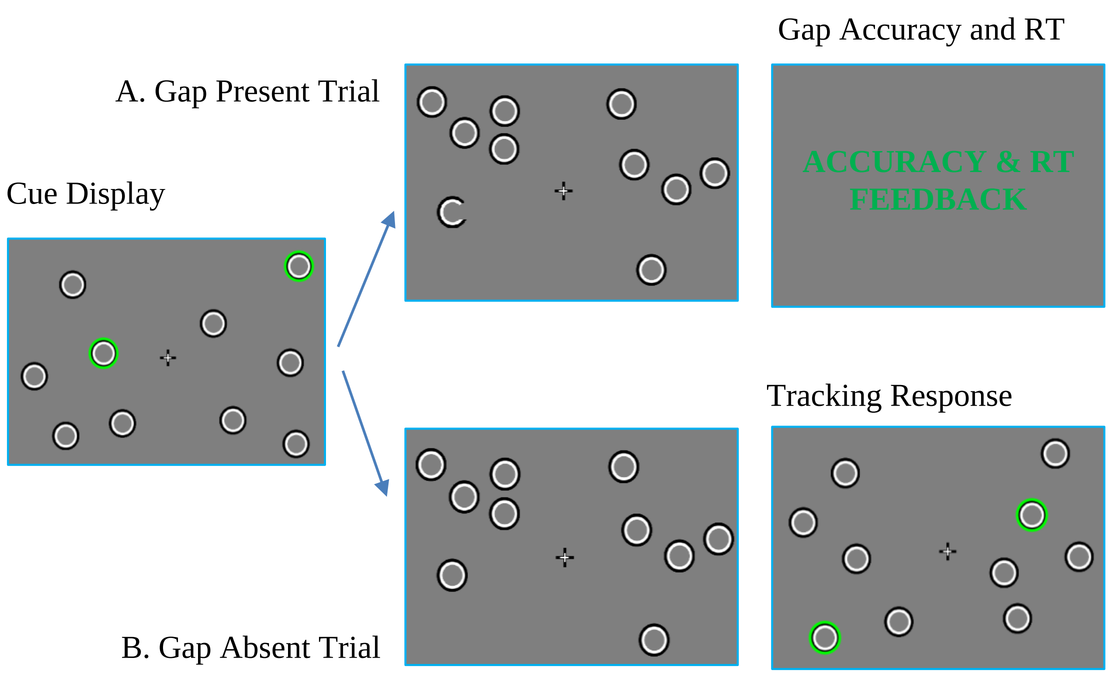


Figure 6.1: Trial displays for Experiment 5. Objects-to-be-tracked cued in green. Observers tracked one or two objects on each trial. A) Gap appears on tracked objects or distractors. Observer made a speeded response to indicate whether the gap was facing left or right. Feedback on gap accuracy and response time (RT) was provided at the end of the motion period. B) The gap was not present on a subset of the experimental trials. Tracking was tested at the end of gap-absent trials. Observers clicked on the objects that they were tracking. Immediate feedback was provided by turning the selected objects green (correct) or red (incorrect).

A small gap (see Fig. 6.1) appeared on the left or right side of a tracked object or a distractor between 300 to 1300 ms after the start of a trial. Observers were instructed to make a speeded discrimination response to the gap. They were instructed that the tracking task was primary and they should maintain high accuracy on it. The gap only appeared in the same visual field as the tracked object, and it was equally likely to appear on a tracked object or a distractor randomly over trials. Object motion ceased 500 ms after the observer made their target response at which time the trial terminated. No tracking response was required on trials with a gap.

The experiment consisted of 600 trials, and the gap appeared on a subset of 400 trials. There were 200 trials where a gap did not appear and the motion sequence lasted 2 s. The experimental conditions were presented in random order. When the objects stopped moving on no-gap trials, they remained stationary on the display and observers were instructed to click on the objects they were tracking. Tracking was not tested on trials containing the gap to allow observers to freely attend to its appearance without penalizing their tracking performance. Observers received immediate feedback regarding the accuracy of their response on either task. RT feedback was provided on accurate trials containing the gap. The experimental design was a 2 (set size 1 vs. set size 2) by 2 (gap on target vs. gap on distractor) by 2 (left vs. right visual field) within-subjects, repeated measures study. Participants were given a short break after every 100 trials. Before the start of the experiment, participants were provided with practice trials to ensure task comprehension and proficiency at maintaining eye fixation.

6.2.3 Electrophysiological Recording

The electroencephalogram (EEG) was recorded with an Electrical Geodesics Inc. (EGI; Eugene, OR) 128-channel Geodesic Sensor Net with individual electrode impedances kept below 50-75 kΩ, as recommended by the manufacturer. The data were referenced online to the vertex, bandpass filtered between .01-80 Hz, and were digitized at 200 Hz. Digitized waveform data were processed off-line using the EGI Net Station 4.1.2 with a lowpass 40 Hz filter and were segmented using a 1600 msec epoch that included a 100 msec prestimulus baseline. Net Station's artifact detection routines were then applied. Individual channels were marked as bad if there was zero variance, the fast average amplitude exceeded 200 µV, or the differential average amplitude exceeded 200 µV. Individual segments were rejected if they contained eye movements or blinks (threshold = 70 µV) or if more than 10 channels were marked as bad. For the remaining segments, bad channels were replaced using interpolation from surrounding channels. Finally the segments were averaged, rereferenced to the average reference, and baseline corrected using a 200 ms prestimulus interval.

All ERP analyses were based on correct gap identification trials. Each ERP waveform was defined and analyzed using a certain time window. N2pc difference waves were computed by subtracting the activity from ipsilateral from contralateral sensors. Left hemsphere activity was recorded from posterior electrode sites 58, 59, 64, 65, while the right hemiphere activity used corresponding electrode sites 90, 91, 95, 96. Others have similarly measured the N2pc from posterior scalp sites from corresponding PO7, PO8, P3, P4, O1, O2, T5, and T6 electrodes of the 10/20 system (Eimer, 1996; Grubert & Eimer, 2016; Luck & Hillyard, 1994). The measurement window used was 280-320 msec after gap target onset. P3b amplitude was calculated by averaging six contiguous sensors (54, 55, 61, 62, 78, 79) over the central parietal area where the P3b is maximal. The time window used to measure the P3b was 440-690 msec post gap onset.

Mean amplitude was computed in a time window defined by the half amplitude points on either side of the ERP peak (Luck, 2005). A fractional area latency analysis was conducted by capturing the time point that divides the area under the waveform in half (Luck, 1998; Luck & Hillyard, 1990) to assess the time course of the components in each condition. The ERP amplitudes and latencies were analyzed with repeated measures ANOVAs using Greenhouse-Geisser correction for violation of sphericity.

6.3 Behavioral Results

6.3.1 Tracking Accuracy

All analyses were based on trials in which no eye movements were detected. A tracking trial was considered correct if the observer accurately selected *all* targets Tracking accuracy as a function of set size is shown in Figure 6.2. A one-way repeated-measures ANOVA showed that tracking of a single target (M = 88.99%) was more accurate than tracking two targets (M = 72.46; $t(14) = 5.93$, $p < .001$).

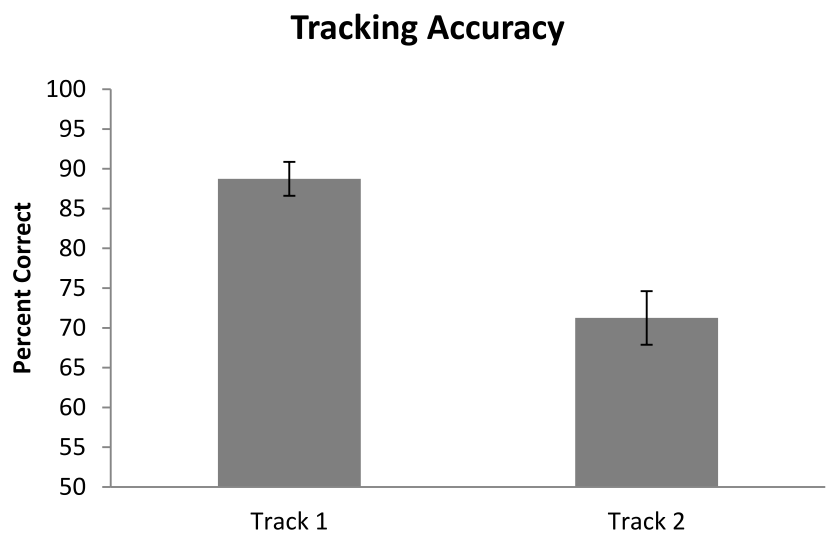


Figure 6.2: Tracking accuracy as a function of set size for Experiment 5. The error bars reflect the standard error of the mean.

6.3.2 Search Response Time

Figure 6.3 shows RT for the gap discrimination task as a function of tracking set size and gap location. The data were analyzed using a repeated-measures ANOVA with two factors: Set size (one vs. two tracked objects) and Gap location (tracked object vs. distractor). Observers were faster at identifying gap targets when they were tracking a single object (M = 602 ms) compared to two (M = 625 ms; $F(1,14) = 43.99$, $p < .001$). There may be less available resources for each tracked object when set size was increased, as reflected in the minor slowing of responses (M = 25 ms). Search was also faster for targets appearing on a tracked object (M = 565 ms) relative to distractors (M = 662 ms; $F(1,14) = 113.84$, $p < .001$). Similar RT results were found in previous tracking and search experiments in our lab, demonstrating the robustness of these effects. The slower responses to gaps on distractors, relative to tracked objects,

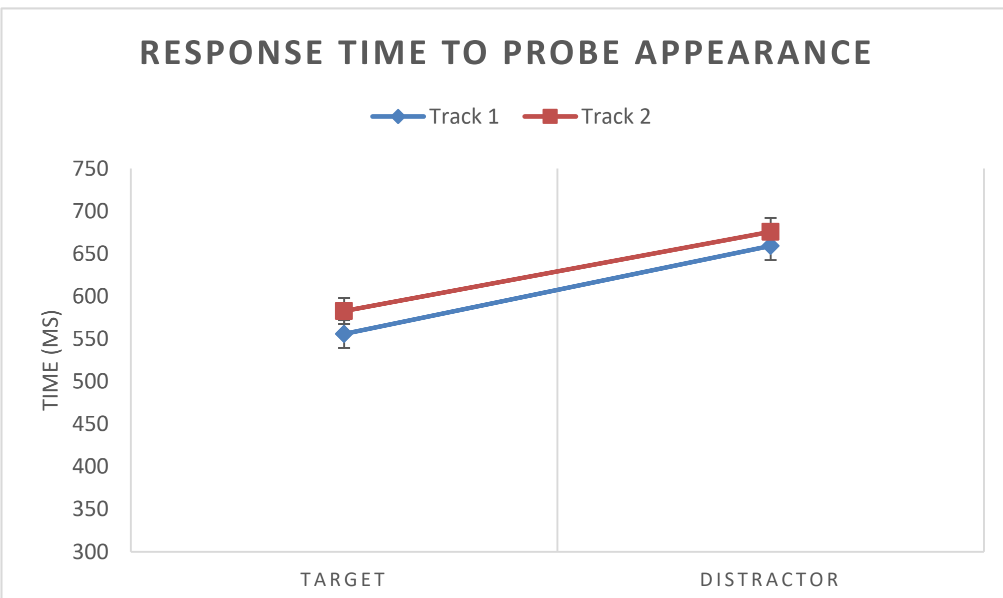


Figure 6.3: Search reaction time as a function of gap location and set size for Experiment 5. The gap was presented either on a tracked object or a distractor. Tracking set size varied from one to two objects. The error bars reflect the standard error of the mean.

suggest that attention had to be switched away from tracking to pick up the target on a distractor. There was no significant set size by gap location interaction ($F(1,14) = 1.25$, $p = .28$).

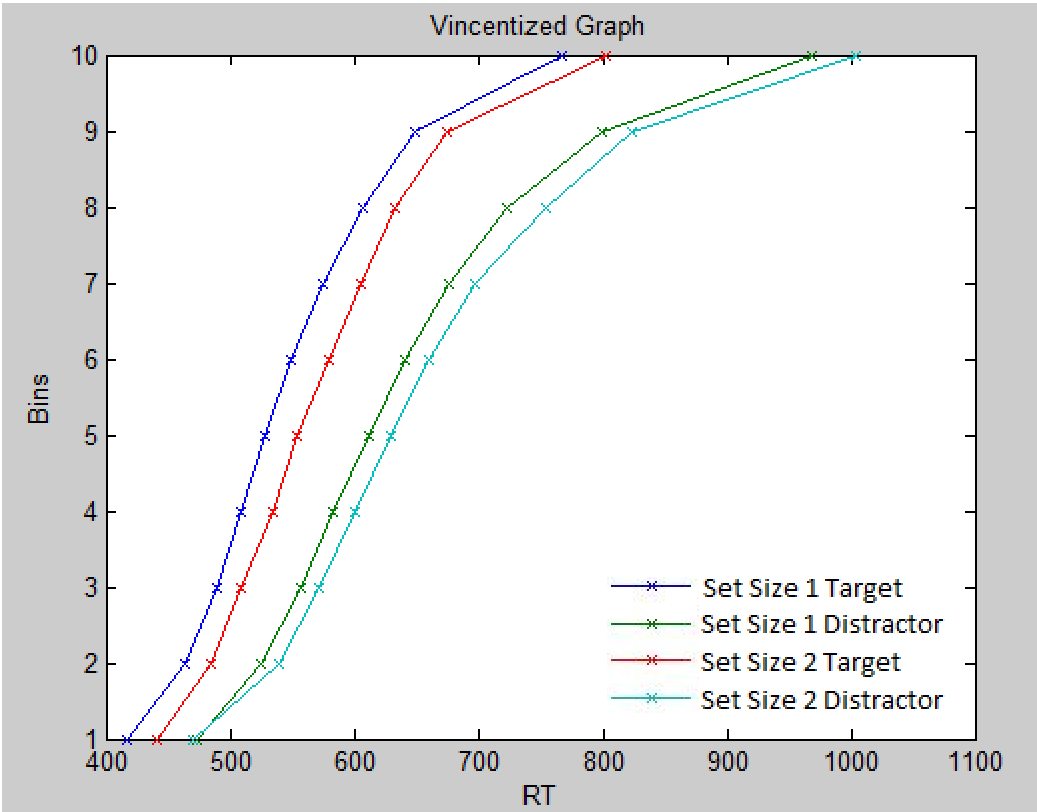


Figure 6.4: Vincentized RT distributions for responses to gap targets occurring on tracked objects and distractors for tracking set size one and two.

Figure 6.4 shows vincentized RT distributions for tracking set size one and two as a function of gap location. The vincentizing method was used to average individual RT distributions to produce a group distribution for each experimental condition.

Relative to gaps on tracked objects, the RT distributions for gap responses on distractors are centered on a clearly later time point and are more positively skewed.

6.3.3 Search Accuracy

A second ANOVA was conducted on gap accuracy (see Fig. 6.5). Observers were more accurate at identifying gap targets on tracked objects (M = 82.14) relative to distractors (M = 90.07; $F(1,14) = 28.20$, $p < .001$). There was no main effect of set size ($F(1,14) = 4.22$, $p = .059$), or its interaction with target location ($F(1,14) < 1$). Moreover, observers were also significantly more likely to miss gap targets appearing

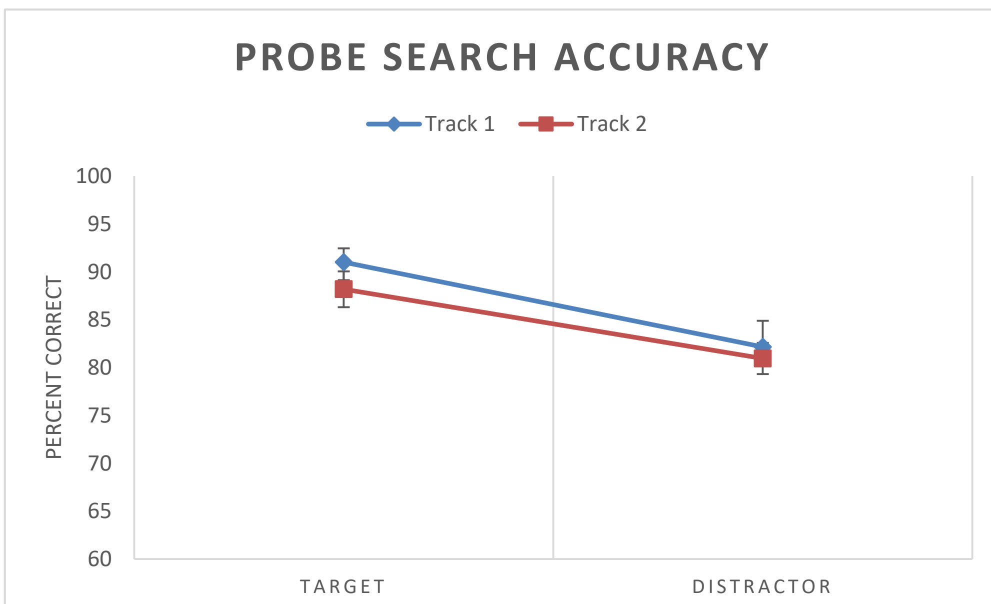


Figure 6.5: Search accuracy as a function of gap target location and set size for Experiment 5. The gap target was presented either on a tracked object or a distractor. Tracking set size was one or two objects. Error bars reflect the standard error of the mean.

on distractors (*M* = 11.53% miss errors) compared to tracked objects (*M* = 2.54% miss errors; $F(1,14) = 48.12$, $p < .001$). No main effect of set size ($F(1,14) = 4.08$, $p = .06$), or its interaction with target location ($F(1,14) < 1$) was found. The higher frequency of target misses and poorer search performance for gaps appearing on distractors vs. targets is consistent with previous research showing that visual attention is required for tracking and this preferential allocation of attention to tracked objects improves detection and discrimination of targets appearing on tracked objects relative to distractors (Tran and Hoffman, 2016).

6.4 ERP Results

6.4.1 N2pc

N2pc waves were averaged over left and right hemispheres and are shown in Figure 6.6 for tracking set size one and two. A 2 (set size: one vs. two) x 2 (gap location: tracked object vs. distractor) repeated measures ANOVA on N2pc amplitude showed a significant main effect of set size ($F(1,14) = 6.68$, $p = .02$), reflecting slightly higher amplitude for set size two (*M* = -2.41 µV) compared to set size one (*M*

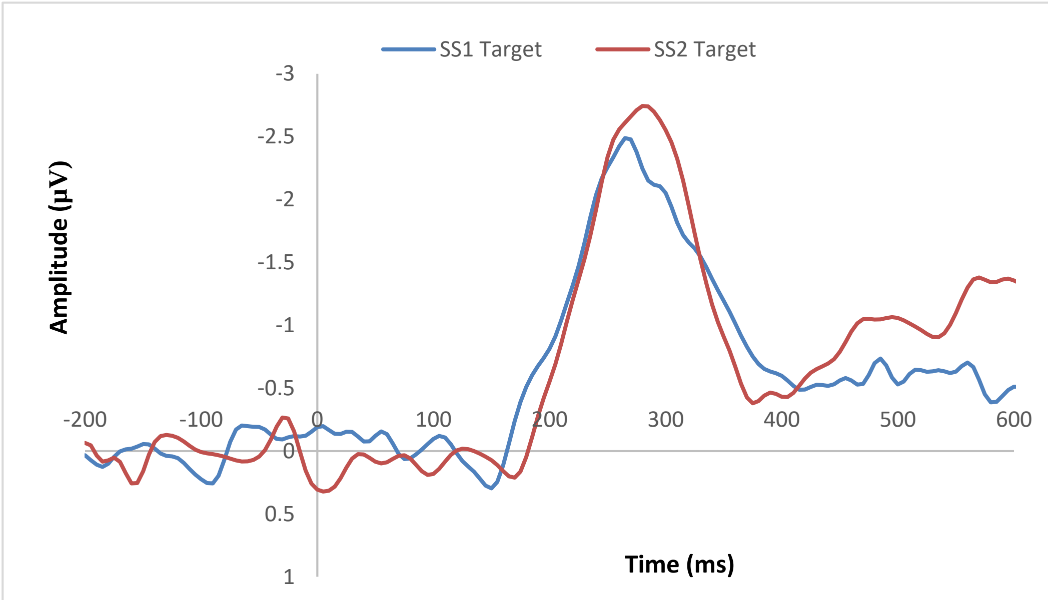


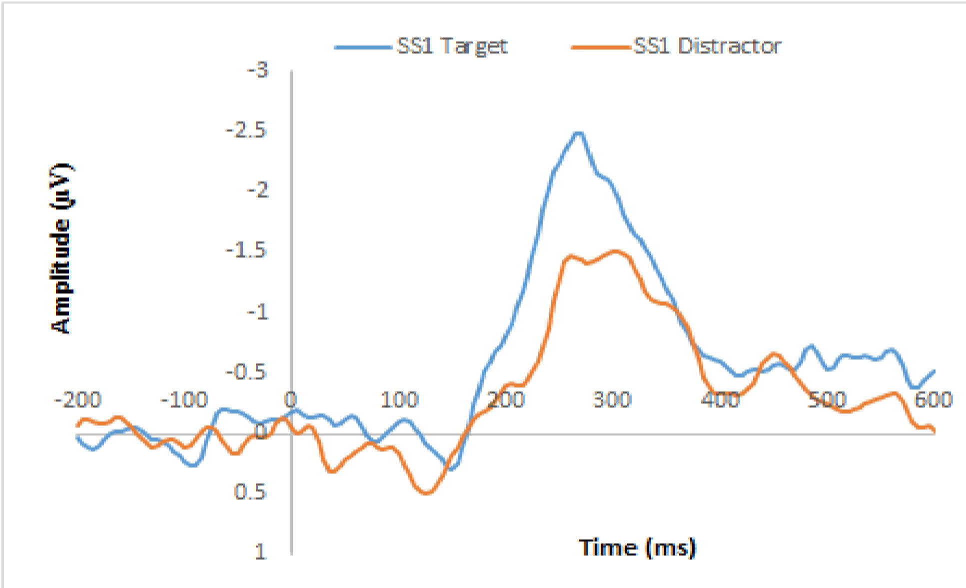
Figure 6.6: N2pc component elicited by gaps occurring on tracked objects plotted as a function of tracking set size for Experiment 5. This component is an averaged ERP difference wave (ipsilateral activity subtracted from contralateral activity) time-locked to the onset of the gap target. ERP activity was computed by averaging across posterior parietal electrode sites.

= -1.91 µV). The N2pc elicited by gaps was significantly reduced on distractors (M = -1.53 µV) compared to tracked objects (M = -2.16 µV; $F(1,4) = 14.43$, $p = .002$; see fig. 6.6). There was no significant interaction between tracking set size and gap location ($F < 1$).

To examine our primary question of whether attention is allocated to tracked objects in parallel or if attention is moved serially between targets, the latency of the

5, the

a.



b.

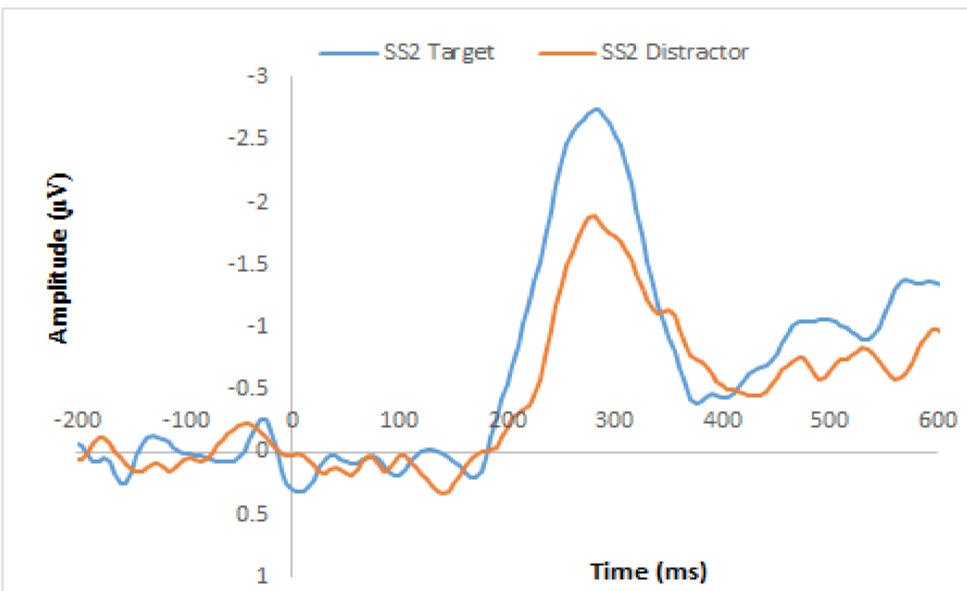


Figure 6.7: N2pc component plotted as a function of gap location for tracking set size one (a) and two (b) for Experiment 5.

N2pc was compared across tracking set size conditions. As shown in Figure 6.6, N2pc latency was not affected by set size ($F(1,14) = 1.65$, $p = .22$), indicating that allocation of attention to the gap was not delayed in the set size 2 condition as would be predicted by the switching hypothesis. It appears that attention is allocated and sustained simultaneously on multiple tracked objects.

However, one caveat to accepting this explanation is the possibility that the gap targets are attention capturing or may be detected automatically without attention. This was evaluated by comparing N2pc latency gaps on appearing on distractors vs. tracked objects. Presumably, attention is sustained on tracked objects and not distractors (Tran and Hoffman, 2016) so that N2pc latency might be delayed for gaps on distractors compared to targets. Figure 6.7 shows the N2pc as a function of gap location (tracked object vs. distractor) and set size (one vs. two). There was a small but significant increase in the N2pc latency to gaps on distractors ($M = 296.5$ ms) relative to tracked objects ($M = 276.5$ ms; $F(1,14) = 5.2$, $p = .03$). No interaction between gap location and set size was found ($F < 1$). The averaged N2pc component is a distribution of individual trial waveforms, and a broader component reflects more variability in their onset latency on a trial-by-trial basis.

6.4.2 P300

The P3 is thought to be a neural measure of the availability of cognitive resources and the amount of time required to categorize and evaluate a stimulus for response (Luck, 1998; Pitts et al., 2014). Figure 6.8 shows P3 waveforms as a function of gap target location for tracking set size one and two. A 2 (set size: one vs. two) x 2 (gap location: tracked object vs. distractor) repeated measures ANOVA was conducted on the P3 data. The amplitude of the P3 to gap targets occurring on distractors was significantly reduced compared to tracked objects ($F(1,14) = 51.07$, $p < .001$). P3 activity was comparable across tracking set size ($F < 1$), and there was no interaction effect ($F < 1$).

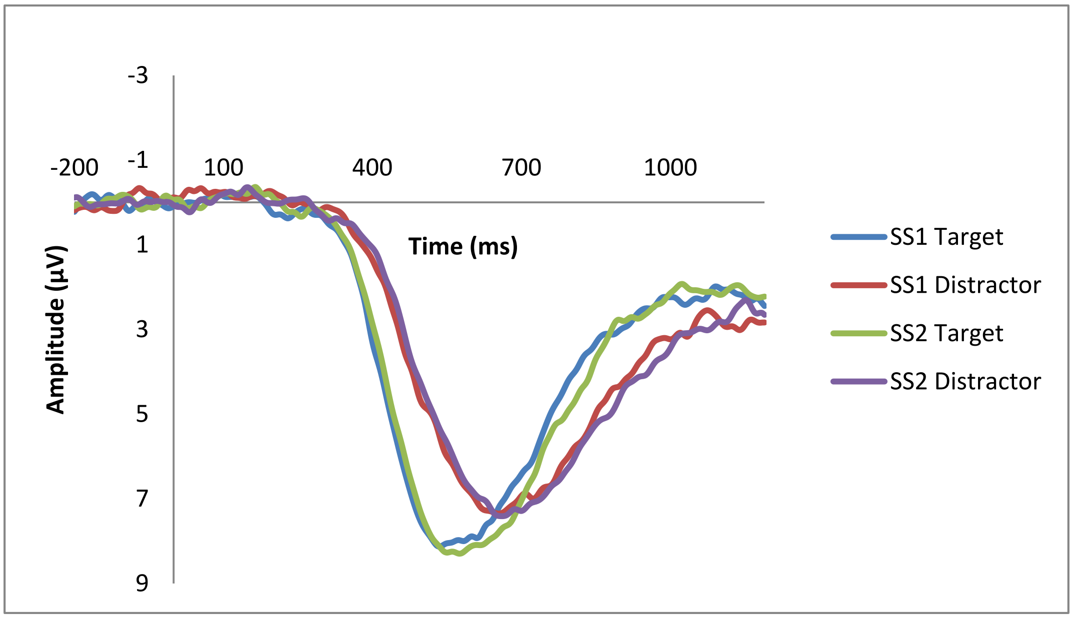


Figure 6.8: P3 component plotted as a function of gap target location for tracking set size one and two for Experiment 5. This component is an averaged ERP wave time-locked to the onset of the gap target. ERP activity was computed by averaging across posterior parietal and occipital electrode sites.

Furthermore, this pattern of results was reflected in the P3 latency data (see Fig. 6.8). There was a significant increase in the P3 latency to gaps on distractors (M = 697 ms) relative to tracked objects (M = 589 ms; $F(1,14) = 148.31$, $p < .001$). The 108 ms difference in P3 latency between gaps on distractor vs. tracked objects corresponds well with the 97 ms difference observed in the RT performance. This is consistent with previous studies showing comparable changes in RT and P3 latency (Kutas et al., 1977; Luck & Hillyard, 1990). Importantly, there was no main effect of set size ($F(1,14) = 1.78$, $p = .20$), or its interaction with gap location ($F < 1$) on the P3 latency. It is worth noting that although response time was faster for gaps on targets when only a single object was tracked compared to two, the effect is not present in the P3 latency. Granted that the RT difference between set sizes one and two was only 25 ms, it is likely that more power is required to reveal small effects in an ERP component as recorded EEG signals are susceptible to various sources of noise. Alternatively, the absence of set size effects on P3 latency might suggest that the RT difference is a result of processes occurring after stimulus evaluation, such as response selection.

6.5 Discussion

The present study used electrophysiological evidence evaluate whether objects are tracked simultaneously or serially during MOT. Observers were tasked to track one or two objects while making speeded responses to the appearance of a gap that could occur on a tracked object or a distractor. The occurrence of these target gaps provide a way to examine the time course of attentional processing on objects during tracking. Previous ERP studies have measured the N2pc waveform as a neural marker of attentional target selection of targets among distractors in visual search (Eimer, 1996; Luck & Hillyard, 1994; Woodman & Luck, 1999) and MOT (Drew & Vogel, 2008; Drew, Horowitz, Wolfe, & Vogel, 2011). The latency of the N2pc time-locked to the occurrence of a gap can provide a measure of when focal attention is allocated to a target event. If attention moves as a unitary spotlight between tracked objects, as claimed by a serial account of tracking, attention to the gap target would be modulated by tracking set size. However, the results showed that the latency of the N2pc waveform elicited by gaps on tracked objects did not differ between tracking of one vs. two objects. This suggests that attention can be simultaneously sustained on tracked objects.

In contrast, N2pc latency was significantly increased for gaps occurring on distractors compared to tracked objects. This observation was supported by behavioral performance showing delayed responses to distractor gaps (with a magnitude of around 100 ms). The presence of this difference is consistent with a biased search model (Sears & Pylyshyn, 2000) in which attention is preferentially sustained on tracked objects resulting in faster responses to targets appearing on them. However, the N2pc latency difference between tracked objects and distractors is small (around 20 ms) and substantially reduced compared to the RT difference observed in the behavioral data. If attention is indeed being switched from the tracked object set to serially search each distractor object until the target gap is identified, such a model should produce much larger effects on the latency of the N2pc. One possibility is that substantively slow trial responses were not represented in the averaged N2pc waveform, and such responses were more likely in the distractor gap condition as demonstrated by the skewed RT distribution in figure 6.4.

A similar pattern of results was reflected in the P3 waveform. The latency of this component to gaps on tracked objects was statistically the same for set sizes one and two while an increased latency was observed for gaps on distractors compared to tracked objects. Moreover, the magnitude of the difference in latency across gap locations has close correspondence with the effect observed in RT performance. This demonstrates that the time required to attend and evaluate a target for response is relatively quick when it appears on objects that are already attended, whereas a slower serial operation is needed when attention needs to be switched to an unattended object. Together, these effects are consistent with a parallel attention account of tracking wherein attention is simultaneously maintained on tracked objects, and appear to contradict a serial processing account of tracking multiple objects.

Chapter 7

GENERAL DISCUSSION

Visual information from our environment often competes for access to visual perception, and contrary to our rich conscious experience, there is in fact restrictions to how much our visual system can process at any given moment. In what appears to be a simple task of monitoring several moving objects, there is a capacity limit restricting the number of objects the human visual system can accurately track. The limitation was assumed to be set to the “magical number” 4, a term coined by Cowan (2001) to describe a ubiquitous discrete limit across visuospatial domains, such as enumeration and tracking (Pylyshyn, 1998), and visual short term memory (Zhang & Luck, 2008).

Pylyshyn and Storm (1988) examined the capacity of our tacking mechanism through a laboratory task known as multiple object tracking (MOT) and found typical capacity estimates in the range of three or four objects. They suggested that tracking limits reflect a small number of discrete indexes or pointers that can be assigned to tracked objects. Alvarez and Franconeri (2007) disputed the claim of a fixed item limit in tracking. They showed that observers could track up to eight objects when the tracking task was made easier (by decreasing the velocity). On the other hand, even tracking a single moving object can apparently exhaust tracking resources if it is moving fast enough (Holcombe & Chen, 2012). These results are consistent with an alternative conception of MOT known as the flexible resource theory (Alvarez & Franconeri, 2007; Cavanagh & Alvarez, 2005). In this model, tracking capacity depends on the availability of a finite visual attention resource that can be flexibly divided among targets.

In the current experiments, I applied a mixture model analysis to performance in a novel version of the MOT task to evaluate whether MOT depends on a discrete vs. continuous limited capacity resource. The model was used to derive estimates of the number of objects tracked, tracking precision, and the frequency of swap errors (interchanging a distractor and target object) for different set sizes. This fine grain analysis of MOT performance allowed us to evaluate two major theories of MOT which differ in their predictions of how set size should affect these measures.

7.1 Discrete vs. Continuous Resource Models

According to the discrete model, capacity is allocated in fixed amounts corresponding to a limited number of "pointers or indexes" (Pylyshyn & Storm, 1988). The number of indexes, in turn, corresponds to the maximum number of objects that can be tracked. This theory predicts that the number of objects tracked should increase with set size only up to the maximum number of slots/indexes (assumed to be 3-4) and the precision of tracking should remain constant over set size. For set sizes that exceed the index limit of 3-4 objects, the percentage of guessing trials should show a sudden increase. In contrast, the continuous resource model holds that a fixed capacity is continuously divided among the tracked objects predicting a continuous decrease in tracking resolution. In addition, this model predicts that participants should be able to track even six objects, well beyond the three or four that is typically cited as the number of available indexes. This should only occur however at the cost of reduced tracking resolution.

The tracking set size was varied in Experiments 1 and 2 to test the limits of observers' tracking capacity as defined by the number of objects tracked and the precision with which they were tracked. The results showed that all participants were able to accurately track 1-3 objects with high precision although there were small but significant reductions in tracking precision with increasing set size over this range. These results are similar to those reported by Zhang and Luck (2008) for visual working memory capacity. They found that the precision of working memory representations decreased with increasing set size even in the range of 1-3 but further increases in set size from 3 to 6 had no additional effects on resolution or the number of objects tracked. They accounted for these results in terms of a "slots + averaging model." They interpreted the similarity between set sizes 3 and 6 as evidence that the number of slots is fixed at approximately three so that participants were tracking three objects even in the set size 6 condition. The decreasing resolution over the set size 1-3 range was explained by allowing memory items to be redundantly stored in multiple slots and then averaged to increase resolution.

7.2 Individual Differences in MOT

Surprisingly, the tracking data in experiment 1 revealed striking differences in tracking 3 vs. 6 objects in a subset of our participants. One group that we dubbed the low capacity group behaved like participants in the Zhang and Luck study. In the set size 6 condition, they continued to track approximately two objects with high precision (sd = 20.96 degrees). A second group that we labeled "high capacity," increased the number of objects tracked to an average of 4.69 objects but did so at the expense of a large increase in the variability of their location responses (sd = 41.96 degrees). The low capacity group appears to act in accordance with the predictions of the discrete model while the high capacity group behaves as predicted by the continuous resource model.

Experiment 2 tested the possibility that the differences between these two groups simply represented two different strategies that could be freely adopted by any participant. If this were the case, it should be possible to convert low capacity participants to high by instructing and incentivizing them to spread their attention across all six objects. The results showed that half of the participants in the low capacity group did indeed adopt an alternative strategy that allowed them to track a larger number of objects (mean number of objects tracked = 5.56) at decreased resolution (sd = 48.14 degrees); however, the remaining participants stubbornly continued to track a few objects with high precision raising the possibility that there may be a subgroup of participants who are unable to track a large number of objects even when they are instructed and rewarded for doing so. This might occur, for example, if tracking an object required some minimum allocation of resources. If capacity was severely limited, it might not be possible to track more than a few objects without causing a complete failure in tracking any of the objects. In this case, our label of “low capacity” trackers would be apt as their inflexible tracking of just a few objects would reflect immutable capacity limitations in visual attention. Alternatively, they may simply be resistant to using a strategy that they are actually capable of adopting. Additional research is needed to examine the generality of these individual differences over different attentional paradigms and reward manipulations.

Large individual differences in tracking performance have also been noted by previous investigators (Drew & Vogel, 2008; Ferrara, Hoffman, O’Hearn, & Landau, 2016; Howard & Holcombe, 2008; Huang, Mo, & Li, 2012; Oksama & Hyona, 2004; Pylyshyn & Storm, 1988). Oksama & Hyona (2004) found that these individual differences generalized to other attention paradigms supporting the claim that MOT relies on the same visual attention mechanism that mediates selective processing in a variety of sustained attention paradigms (Alvarez & Cavanagh, 2005; Tran and Hoffman, 2016). Importantly, selective attention capacity doesn’t appear to have a fixed item limit but instead varies with precision requirements (i.e., dense vs. sparse display) for all individuals (Franconeri, Alvarez, & Enns, 2007).

7.3 Flexible allocation of resources between targets

Critical to the continuous resource theory is the assumption that observers have flexible control over the distribution of resources between targets. Recent tracking studies have shown that accuracy for one target improves when another is moving at a slower speed instead of the same speed (Chen, Howe, & Holcombe, 2013), and that performance gains for a particular target is achieved at the expense of others (Srivastava & Vul, 2016). It appears that attention can be differentially allocated to each target on the basis of external task demands. The present work extends current findings on the flexible nature of visual attention by examining whether unequal distribution of resources between targets could be driven endogenously. In order to test whether people could vary the amount of resources allocated to each target, in experiment 3. Observers were instructed to prioritize one target at the expense of another while the physical properties of the tracking task were held constant. Although observers were incentivized to track all targets, they were given a larger reward for accuracy on the high priority target. We found that tracking performance varied with priority instructions, such that observers were less likely to lose track of the object assigned with higher priority and also tracked it with greater precision compared to the low priority object. This tradeoff in performance between the high vs. low priority targets suggests that observers could strategically allocate differential amount of attention between targets, as predicted by a flexible resource model.

7.4 Hemisphere-specific resources in MOT

Previous studies have found that observers could track twice as many objects when they were presented across both visual fields vs. a single visual field (Alvarez & Cavanagh, 2005; Battelli, Alvarez, Carlson, & Pascual-Leone, 2009). Based on these findings, Alvarez and Cavanagh (2005) proposed that there are hemisphere independent resources for attentive tracking. If so, we should observe no additional performance cost in tracking two vs. one object if targets are divided across hemifields. The current results did show a robust bilateral advantage for tracking, with more objects tracked and higher precision when targets were presented in different hemifields relative to the same hemifield. While tracking two bilateral objects was just as precise (M = 17.15 degrees) as tracking a single object (M = 16.45 degrees). However, distractors were more likely to be mistaken for a target when more objects were tracked, independent of hemifield arrangement. Tracking an additional target in different hemifields should not incur any performance costs if tracking in each hemifield is independent.

Other researchers have also found reductions in tracking performance for targets in one visual field when targets were added to the other visual field (Chen, Howe, & Holcombe, 2013; Holcombe & Chen, 2012; Hudson, Howe, & Little, 2012; Shim et al., 2008). Note that in most of these cases, and in the current experiment, the cost of adding a target in the opposite visual field is smaller relative to adding targets in the same visual field. These results suggest that although resources may be shared across hemispheres to some extent, tracking may be largely independent in each hemifield. Studies reviewed below have shown that there are separable processes involved in tracking, such that the attentional selection of targets operates independently in each hemisphere, while other attentional components are sensitive to task demands across visual fields.

In an fMRI study, Shim et al. (2009) found that activity in the superior parietal lobule (SPL) was modulated by whether targets were in the same or different visual field, whereas the frontal eye fields (FEF) were sensitive to the degree of spatiotemporal precision required for accurate tracking using a speed manipulation. This would be in line with a *hybrid common resource model* which holds that there are independent indexes in each hemisphere, but a common pool of attentional resources that is shared across hemispheres. This predicts a decline in tracking precision with increasing set size, regardless of visual field arrangement. Future work to test the hemisphere-specificity of tracking resources may consider parametrically manipulating hemifield arrangement of targets and the spacing required for the task. By testing whether difficult tracking conditions, such as crowding, in one hemifield would affect tracking precision for objects in the other hemifield, we would have a better understanding of the degree of resource separation between hemispheres.

7.5 Parallel vs. Serial Processing

Since the conception of the MOT paradigm developed by Pylyshyn and Storm in 1988, tracking research has consistently showed that the human capacity to track multiple objects is finite. People can typically track a maximum three to four objects

(Pylyshyn & Storm, 1988; Scholl, Pylyshyn, & Feldman, 2001; Yantis, 1992). There is an on-going debate on the underlying mechanism that gives rise to this capacity limit. A serial processing interpretation holds that a single attentional spotlight is allocated to one target at any given moment and then switched serially between targets (Oksama & Hyona, 2008; Tripathy & Howard, 2012; Tripathy et al., 2011). When the spotlight returns to a given target, the object nearest to its last updated position is assumed to be the target (Tripathy et al., 2011). Serial updating of target positions presumably becomes more difficult and less frequent when object velocity and/or tracking load are increased (Howe, Cohen, Pinto, & Horowitz, 2010; Tripathy et al., 2011). Moving objects at greater speeds increases the likelihood of a target object being dropped (Drew, Horowitz, & Vogel, 2013), while adding to the tracking load increases both the likelihood of dropping a target and confusing a distractor for a target as demonstrated in the present experiments (1 & 2). Tracking capacity is constrained by our ability to successfully recover and update each target position as all the targets continue to travel away from their previously registered positions.

Alternatively, tracking errors can be explained by an attentional resource that is finite in quantity but can be simultaneously allocated to multiple tracked objects (Alvarez & Cavanagh, 2005; Alvarez & Franconeri, 2007). According to this parallel model of tracking, capacity constraints depend on task demands on a limited resource. Because this resource is simultaneously shared between targets, the spatial resolution for each target is reduced when more objects are tracked, resulting in more tracking errors under difficult tracking circumstances such as when objects are crowded together or move at high speeds (Alvarez & Franconeri, 2007; Holcombe & Chen, 2012).

Assuming that multiple objects are tracked using a single spotlight, as proposed by the serial tracking model, this attentional spotlight would have to rapidly switch between tracked objects (Oksama & Hyona, 2008; Tripathy & Howard, 2012; Tripathy et al., 2011). However, Pylyshyn and Storm (1988) argued that the spotlight would have to move at implausible speeds to minimize mistaking distractors for targets. Their computational modeling results, which analyzed how a single spotlight of attention constrained to realistic human speeds would perform in an MOT task, showed that it fell well short of actual human performance in MOT (Pylyshyn & Storm, 1988).

Howe and colleagues (2010) provided empirical evidence supporting the parallel processing model using a novel MOT paradigm. In their task, objects either moved in simultaneous or sequential fashion. In the simultaneous condition, all objects moved and paused synchronously. In the sequential condition, objects moved in turns such that only half of the objects would move at any given time while the other half would be temporarily paused. They reasoned that if tracking proceeded in parallel, performance should be comparable across the simultaneous and sequential motion conditions. Whereas, the serial model predicts that tracking should be easier in the sequential motion condition as only half of the targets have to be tracked at a time. Howe et al. consistently found performance to be equal across conditions or even better in the simultaneous motion condition. These results are consistent with the parallel processing model prediction.

Holcombe and colleagues (2008; 2013) proposed that the amount of resources allocated to an object has direct correspondence to the temporal resolution for tracking that object. They quantified temporal resolution as the rate with which observers could update tracked object locations. When objects move at faster speeds, there is a need for greater temporal resolution as their positions have to be sampled more frequently to maintain accurate performance. However, as tracking load increases, the amount of resources available to each target is reduced resulting in lower temporal resolution. Using a task requiring observers to report the final position of a target, Howard and Holcombe (2008) found a lag between the reported positions of targets and their correct positions, and the magnitude of the lag increased with tracking load. The results were interpreted as a challenge to the parallel tracking model. According to the serial account, the lag occurs because the positions of individual targets are updated less frequently when attention needs to cycle through an increasing number of targets.

In contrast to these results, Iordanescu, Grabowecky, and Suzuki (2009) showed that observers used object velocity and motion direction to predict target positions. Using a similar task requiring observers to click on the final position of tracked objects, they found that motion direction information contributed to a forward shift in the reported target positions. Overall, it is clear that tracking precision declines when more objects have to be tracked as there appears to be a correspondence between the amount of attention allocated to an object and spatial resolution. However, the behavioral data thus far do not provide a definitive account for how attention operates during tracking.

In Experiment 5 of this thesis, the question of whether tracking is achieved by a serial or parallel process is addressed using ERP techniques to reveal the dynamics of visual attention during tracking. Observers were instructed to track one or two objects while searching for a target probe that appears on a tracked object or distractor on each trial. Response time to the target probes provide a measure of the speed with which attention could be allocated to the object containing the target. The result was that participants were on average 97 ms faster at identifying targets on tracked objects compared to distractors. This observation is consistent with previous experimental results in our lab and with those cited in Sears and Pylyshyn (2000). Moreover, there was also a small difference in the latency of the N2pc component elicited by changes to tracked objects relative to distractors. It is known that that the latency of the N2pc component reflects attentional allocation to objects (Eimer, 1996; Luck & Hillyard, 1994; Woodman & Luck, 1999), suggesting that our results indicate that attention was preferentially allocated to tracked objects. This results in rapid identification of probes occurring on attended objects relative to unattended objects.

To examine whether attention acts as a unitary spotlight that is switched between objects in order to track them, the latencies of the N2pc elicited by probes on tracked objects were compared across set size one vs. two. Relative to set size one, a wider waveform, indicating greater variability and increased latency in attending to the probe, is expected for set size two if the spotlight has to switch between tracked objects. In contrast to this prediction, the latency of the N2pc waveform elicited by probes on tracked objects was in fact comparable across set size. Similar results were reflected in the latency of a later component, the P3. Studies have shown that the latency of this component is sensitive to the time required to categorize a target (Luck, 1998; Pitts et al., 2014). It follows then that any manipulation that postpones attention to an object should increase P3 latency. In fact, there was a P3 latency increase to distractor probes compared to target probes. Crucially, the latency of the P3 waveform elicited by target probes was the same for one vs. two tracked objects. This suggests discrimination of probes on tracked objects was unaffected by tracking load. In summary, the current ERP results demonstrated that probes are processed without delay whether people are tracking one or more objects, supporting the claim that attention can be simultaneously divided between multiple tracked objects.

7.6 Future Directions

Simultaneous attention to multiple tracked objects may be the default strategy that people use in MOT. However, a serial strategy might be adopted under different tracking conditions. Attention can be differentially allocated between targets when one of them is more important than the other, and this differential resource strategy could be driven by exogenous task demands or through endogenous control. For example, when a tracked object is in danger of being lost, more attention is devoted to that object at the cost of others (Iordanescu et al., 2009; Srivastava & Vul, 2015). And the current study has shown that people could flexibly divide attention between objects based on instructions (see Experiment 3). It isn't clear though how this uneven distribution of attention between objects is performed. It is possible that people are simultaneously tracking all targets while placing greater emphasis on one vs. another. Alternatively, attention may be allocated serially to each tracked object in turn and the spotlight remains on the prioritized object for longer periods. These alternatives could be examined using the N2pc component of the ERP. Using the same logic as our last experiment (Experiment 5), serial switching of attention between high and low priority objects would lead to more variable N2pc onset latencies, whereas parallel processing would not. Instead, parallel model predicts that uneven allocation of attention should modulate the *amplitude* of the N2pc with larger waveforms being associated with high priority objects. This study would provide further insight into how a limited tracking system operates in situations requiring uneven attentional allocation.

7.7 Evidence for the Continuous Resource Model of MOT

These results make a strong case for the continuous resource account of MOT. Participants were able to track more objects than the typical maximum of 3-4 that is assumed to reflect a small number of pointers or indexes and this was accompanied by a large decrease in tracking resolution as predicted by the continuous resource model. These results are consistent with those of Alvarez and Franconeri (2007) who reported that observers could track as many as 8 objects but only if movement velocity was reduced for larger set sizes. Notice that reducing velocity would also presumably reduce the capacity required to track each object thus allowing the same fixed capacity to be spread over larger set sizes.

The current results are consistent with other recent findings and models that point to a limited resource whose allocation is flexibly determined by tracking demands (Alvarez & Franconeri, 2007; Srivastava & Vul, 2015). For example, Srivastava and Vul (2015) proposed a computational model in which increased visual attention should be allocated to a tracked object when it is close to a distractor or moving with high velocity. Their model predicted that this increased allocation of attention to one target would be accompanied by coarser tracking precision for other targets which is what they observed.

7.8 Summary

Our findings are largely consistent with the claim that people can allocate different amounts of attention to different targets during MOT. Preferential allocation to a high priority object results in higher precision tracking of that object, but at the cost of lower precision tracking of other objects. Tracking performance is characterized by a tradeoff in the number of objects tracked and the resolution with which they are tracked. Critically, it was found that not every individual exhibits this tradeoff. A subset of participants continued to track a small number of objects with high precision despite instructions and rewards to track more. There may indeed be immutable architectural differences between individuals, lending credence to models assuming structural limitations in tracking capacity. A closer examination of these individual differences may provide further insight into the nature of limited-resource mechanisms of attention.

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Appendix

CERTIFICATE OF INFORMED CONSENT

INFORMED CONSENT TO PARTICIPATE IN RESEARCH

Title of Project: Is tracking capacity limited by a discrete or continuous resource?

Principal Investigator(s): Annie Tran & James Hoffman

You are being invited to participate in a research study. This consent form tells you about the study including its purpose, what you will be asked to do if you decide to take part, and the risks and benefits of being in the study. Please read the information below and ask us any questions you may have before you decide whether or not you agree to participate.

WHAT IS THE PURPOSE OF THIS STUDY?

The purpose of this study is to investigate your ability to track multiple objects that move around on circular tracks on the screen. Your performance will allow us to better understand the human visual tracking mechanism. In addition, we may be collecting EEG recordings during object tracking to investigate the brain mechanisms responsible for this skill. This research will be used in a student dissertation. You will be one of approximately 20 participants in this study.

WHAT WILL YOU BE ASKED TO DO?

As part of this study you will be asked to track a number of objects moving around on circular tracks on the screen. Before the objects begin moving, a subset of the objects will be highlighted in green to designate them as target objects. There is a fixation point at the screen center, it is important that you maintain your eyes on the fixation point while tracking the target objects. Once the motion has ended the objects will be removed and one of the tracks that had contained a target will be highlighted, at which point you will be instructed to click on the last known location of the target on that track. This experiment should take approximately 2 hours to complete.

The electrical activity of the brain will be measured using a sensor cap which fits snugly on your head and contains small sponges that record the electroencephalogram or EEG. These signals are stored in the computer and analyzed after you are finished. Each sensor is soaked in a saltwater solution consisting of potassium chloride, baby shampoo, and warm water. This solution helps conduct the tiny electrical currents coming from your brain to our computer. Application of the sensor cap does not involve any cuts or scrapes on your scalp and should not be painful in any way although you may notice a slight reddening on your forehead in the areas where the sensors are held against your skin. A towel will be placed around your shoulders to ensure that you remain dry. After you are finished, the cap is washed and sterilized as is normal after each use.

While you are viewing the display, we will monitor your eye movements using an eye tracker. This system works by illuminating the eye with an infrared light source and tracking the pupil with a camera located about two feet in front of you. Infrared light is similar to visible light but has a longer "wavelength" and cannot be seen by the human eye. The eye tracker poses no greater hazard from infrared radiation than is encountered during normal reading. Many labs all over the world have used this technology for over 30 years without any reports of adverse effects.

WHAT ARE THE POSSIBLE RISKS AND DISCOMFORTS?

The research team does not expect your participation in this study will expose you to any risks different from those you would encounter in daily life. Your hair will get wet because our sensors are soaked in a salt water solution. We will provide towels to keep your clothes dry and you will be provided with towels at the end of the study so you can dry your hair.

WHAT ARE THE POTENTIAL BENEFITS?

You will not benefit directly from taking part in this research. However, the knowledge gained from this study will increase our understanding of the brain mechanisms that allow us to track moving objects.

HOW WILL CONFIDENTIALITY BE MAINTAINED? WHO MAY KNOW THAT YOU PARTICIPATED IN THIS RESEARCH?

Your data are confidential and will be stored in the computer according to an arbitrary number and will not be identified with your name. All data will be retained indefinitely. However, any results will be presented in statistically aggregated form so that specific individuals will not be identified. No identifying information will be used in any publication or presentation resulting from this study.
The confidentiality of your records will be protected to the extent permitted by law. Your research records may be viewed by the University of Delaware Institutional

Review Board, which is a committee formally designated to approve, monitor, and review biomedical and behavioral research involving humans. Records relating to this research will be kept for at least three years after the research study has been completed.

WILL THERE BE ANY COSTS TO YOU FOR PARTICIPATING IN THIS RESEARCH?

There are no costs associated with participating in the study.

WILL YOU RECEIVE ANY COMPENSATION FOR PARTICIPATION?
If you are participating to fulfil a class research requirement, you will receive up to 2.5 subject pool credits for your participation. You may receive additional monetary compensation (up to $10) at the completion of the study based on your performance. If you are participating for monetary compensation, you will receive $10 per hour for your participation. You may receive additional monetary rewards (up to $10) at the completion of the study based on your performance.

DO YOU HAVE TO TAKE PART IN THIS STUDY?

Your participation is completely voluntary. You may choose not to participate at any time and may refuse to answer any question. If you decide not to participate or if you decide to stop taking part in the research at a later time, there will be no penalty or loss of benefits to which you are otherwise entitled.

If you choose not to participate or to terminate your participation before the study is over, you are free to go, but in place of the experiment your obligation will be to write 2 papers identical in format to the papers written by students who've chosen the Readings Option. As stated in the Research Participation Document the number of papers you will write will depend on the length of the study. Information regarding the papers can be found at the following internet address: http://fleen.psych.udel.edu/readings.php

If you elect not to participate or terminate your participation before the completion of the study, you will be paid a prorated amount depending on how much time you spent in the experiment.

If, at any time, you decide to end your participation in this research study, please inform our research team by telling the investigator.

WHO SHOULD YOU CALL IF YOU HAVE QUESTIONS OR CONCERNS?

If you have any questions about the procedures used in this experiment, please contact James Hoffman, Professor, University of Delaware (302-831-2453).

If you have any questions or concerns about your rights as a research participant, you may contact the University of Delaware Institutional Review Board at hsrb-research@udel.edu or (302) 831-2137.

Your signature on this form means that: 1) you are at least 18 years old; 2) you have read and understand the information given in this form; 3) you have asked any questions you have about the research and the questions have been answered to your satisfaction; and 4) you accept the terms in the form and volunteer to participate in the study. You will be given a copy of this form to keep.

Printed Name of Participant	Signature of Participant	Date
Person Obtaining Consent	Person Obtaining Consent	Date
(PRINTED NAME)	(SIGNATURE)	