Targeting in Virtual Workspaces: motor learning consolidates spatial memory for performance clusters

Frank Biocca^{1,2}, Bradly Alicea^{1,2}, Charles Owen³, Fan Xiao³, Corey Bohil^{1,2}
Corresponding author (current address): Frank Biocca, Ying Wu College of Computing,
New Jersey Institute of Technology, Newark, NJ. frank.a.biocca@njit.edu

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ABSTRACT

Our objective was to focus on linkages between the process of learning and memory and the placement of objects within an array of targets in a virtual workspace. Participants were instructed to place virtual objects serially within a three-dimensional target array. One phase presented each target sequentially, and required participants to make timed ballistic arm movements. The other phase presented all nine targets simultaneously, which required ballistic arm movement towards the correct target location as recalled from the learning phase. Movement time and accuracy were assessed using repeated-measures ANOVA, a hierarchical cluster analysis, and a multiple linear regression. Collectively, this revealed numerous speed and accuracy advantages and disadvantages for various positional combinations. Upper positions universally yielded longer movement times and larger error measurements. Individual ability for mental rotation combined with task learning over a fixed training interval was found to predict accuracy for specific locations. The prediction that location influences movement speed and accuracy was supported, but with some caveats. These results may be particularly useful in the design of instructor stations and other hybrid physical-virtual workspaces.

Introduction

A hybrid mixed-reality system with dynamic inertial tracking system provides an opportunity to probe both the spatial structure of virtual workspaces and better understand human performance in a tracker-based environment. One example of such a system is the Mobile Infospace (MI). The MI is a virtual environment that allows for significant upper-body movement dynamics as a means for manipulating virtual objects distributed across the space. Specifically, this system provides a spatially-dynamic, computer-generated volume for presenting controlled tasks (Mou, 2004). The current experiment will explore how ballistic movement pathways to predefined target positions are learned and differentially executed in the context of a virtual workspace. To answer this, we investigated how spatial and behavioral asymmetries in a virtual workspace combine to optimize physical accessibility, learning, and memory. The targeting task required people to grasp virtual objects with an arrow and place them into a three-

¹ Department of Media and Information, Michigan State University.

² Cognitive Science Program, Michigan State University.

³ Department of Computer Science, Michigan State University.

dimensional target; there is a need for multimodal awareness of current end effector position relative to the computer-generated cues that requires a variable-feedback control system. Collectively, these virtual workspace features contribute to differences in user state, which ultimately lead to changes in performance.

Virtual Environments and Workspace Performance

This section is divided into three main parts. Use of the Mobile Infospace as a research tool will be discussed in part one, while part two will discuss how both internal states and spatial reaching behaviors in the Mobile Infospace contribute to task performance. Discussion of both the theoretical and applied aspects of this experiment will provide a basis for interpreting the results.

Mobile Infospaces: a spatial-and movement-oriented virtual environment

Virtual workspaces that combine heads-up displays with inertial tracking systems offer many ways of utilizing and manipulating virtual space. In the Mobile Infospace (Mou, 2004), interactive stimuli can be placed anywhere within peripersonal space (Holmes, 2004). The Mobile Infospace environment is centered on the human torso along the major axis of the spine, and resembles a toroidal space with a polar coordinate system representing the volume's interior curvature. Virtual objects can be moved from one three-dimensional position to another within the interior of this space by a participant. To measure performance at selected points within this volume, a targeting task was performed using a pair of pinch gloves, a virtual object, and a virtual target. To facilitate a tight coupling between object and participant movement, the MI system utilizes an inertial tracking system with a head-based reference frame. Virtual objects were continuously manipulated by an individual and tracked by the computer system as they made upper-body movements around a three-dimensional spherical volume. In an applied context, such tracker-based virtual workspaces could house spatially-sensitive applications that utilize movements to a target such as cursor control, automating aspects of laparoscopic surgery, or playing virtual chess (Azuma, 1997; Hettinger, 2003).

Targeting as a mechanism for learning

Targeting performance during learning leads to the differential consolidation of memory for specific workspace locations. While performance is ultimately determined by spatial memory, the nature of the experimental task requires a separate mechanism for acquisition (Hwang, 2005 #12). Shadmehr and Mussa-Ivaldi (1994) have demonstrated that controlled arm movements use a retinocentric spatial coordinate system, but later in the time-course of movement utilize head- and shoulder-centered frames of reference (Henriques, 2002). This interrelationship between spatial, visual, and physical parameters has been characterized by Krakauer and Shadmehr (2006) as a phenomenon called motor learning. Motor learning is considered a form of procedural memory that exhibits savings in performance across trials. During motor learning, visuospatial attention mechanisms enforce a form of supervised learning upon targeting movements; for retinotopic coordinate systems, the visual sensitivity of posterior parietal (PPC) neurons has been found to change systematically with the angle of gaze (Andersen, 1985). Fogassi (2001) have also shown that visuomotor transformation ability controlled by frontoparietal networks as being critical to making quick and accurate reaching movements to a target.

Training on Endpoints to Spatial Memory

From a computational standpoint, internal models are ultimately responsible for the encoding and consolidation of memory for a set of spatially-distributed targets. Internal models are sets of neuronal networks that use current arm position, visual information, and the spatial orientation of objects being moved to predict and constrain future performance dynamics (Tin, 2005). Mental modeling during learning provides a unified means to acquire, encode, and recall the complex dynamics of physically manipulating spatially-distributed information (Cheng, 2006). In a spatial context, this mechanism might also integrate multiple frames of reference into a single representational structure that facilitates speed and accuracy (Krigolson, 2004).

Wolpert (2000) conceive of internal models as a mechanism that establishes automatic movements. Automatic movements are characterized by their reflexive, stereotyped, and inherently curvilinear trajectory in relation to a target position (Morasso, 1983). Using multiple sources of afferent sensory information, the internal model estimates a difference vector representing the distance between the current state of a pinch glove and a given target position. Ultimately, an updated location map based on the difference vector is encoded in memory and represents a set of directional instructions for moving objects to specific points within a given spatial volume without direct conscious control (Shadmehr, 2005).

Asymmetrical Nature of Spatial Memory

According to (Klatzky, 2003), this allocentric spatial reference frame is also subject to a directional encoding bias. This encoding bias is established by differential spatial updating to various positions during the learning phase of a task (Loomis, 1992). Klatzky (2002) specifically point to differences in the quality of visual information during movement to a target as one mechanism affecting consolidation of the memory trace, which can in turn affect later performance. Heath (2004) found that full-vision reaches to targets whose position needed to be recalled later were more accurate and less variable than positional reaches trained under conditions of limited visual supervision.

Spatial relationships between a common starting point and specific target locations are constructed via encoding by neurons in the posterior parietal cortex (PPC), which serves as the major integrative mechanism for object-based spatial updating (Graziano, 1993; Graziano, 1998) using procedural learning information from the cerebellum-based internal model (Leggio, 1999). If a participant attempts recall when presented with a distributed set of spatial relationships, recall ability will be mediated by response execution (Loomis, 1992), which is in turn affected by the relative strength of the memory trace.

Shadmehr (1997) and Ishibashi (2002) provide evidence that procedural memory gradually consolidates over a period of several days, which affects the relative stability of the memory trace. For example, when the internal representation is less than an hour old, it is effective but relatively weak and vulnerable to interference (Condit, 1997). According to (Colby, 1998), the multiple frames of reference inherent in the targeting task must be successfully integrated into a single spatially-based representation during

encoding. Thus, it may be that differential spatial updating is partially determined by the relative success of integrating these frames of reference into a unified internal model, contributing to the relative strength of a memory trace for a given spatial position (Gnadt, 1998).

Experiment

We conducted an experiment to probe the movement abilities of participants given a spatially distributed array of objects. Two conditions were used to determine which, if any, positions in the space displayed an advantage for retrieval. Participants were first trained on a timed targeting task where objects were linked to spatial locations. The ability to adapt the internal model governing movements for this type of task to this novel environment constituted a learning phase, as the participant had to learn to correct timing and force fields along the trajectory to efficiently perform the task. The ability to retain a memory of these distinct movements requires two things: the ability to associate specific objects with certain movements, and the ability to perform one particular movement out of several possible trajectories.

The memory phase tested how well participants could integrate and associate specific visual cues with a specific location in the workspace. Their ability to reach this position as quickly and accurately as possible was directly related to how efficiently they could reach the target. This differential ability was due to a more consolidated internal model for that position, which resulted in a more effortless movement to the target. The participant received several forms of visual feedback during the targeting movement, but no explicit proprioceptive feedback when the object was placed at the target (i.e. the target was not represented by any inherent force as a tabletop might exhibit). This is different from what may be found in a purely physical setting, and was expected to play a role in the results.

Hypotheses

We expect that differential 'clusters' of performance abilities will emerge in the workspace. These "clusters" should hold together as coherent spatial regions, and may become apparent either in a manner imposed by the experimenters or revealed through multivariate analyses. We also expect that movement time and the amount of angular error for a given target will generally decrease with learning, but that the ability to move quickly and accurately to a specific target given an array of 9 positions will vary by location. We also expect the linear velocity of targeting movements to increase if the memory trace for a particular position is stronger. This is consistent with idea of different internal models being used to reach different positions.

Errors in the planning process during memory-guided reaching movements in peripersonal space are not corrected after the initiation of movement (Heath, 2004). Therefore, common constraints related to certain target positions may be made and will affect performance. Rosenbaum (1996) have found that when handle rotations are performed, the entire range of arm motion take longer than handle rotations that conclude at or near the middle of the arm's range of motion. Thus, targets that require extension and rotation in the same direction should also require fewer contrived motions to execute and thus be remembered more quickly (Hogan, 1984). These patterns were expected to consist of a strip of targets running across the workspace. Movement time advantages

grouped by pattern were also expected to be associated with lower absolute error, since “easier” movements should result in movement exhibiting less joint stiffness (Mussa-Ivaldi, 1985).

These hypotheses mean two things: sets of endpoints are encoded in memory as a result of arm movements being constrained by repetitive movements towards these endpoints (Ohta, 2004). In the context of this paper, “easy-to-reach” targets may be representative of more uniform spatial updating. This might be characterized by superior performance for certain targets across both the targeting and learning phases and differential rates of learning and memory across the workspace. Endpoints representative of harder to reach regions may involve novel learning dynamics, and so may exhibit higher degrees of error and longer movement times to target.

Methods

Subjects

Twenty-nine university students participated in this study for extra course credit. All were right-handed. All experimental protocols complied with standards approved by the home University’s human subject ethical review board (IRB).

Stimuli and Environment

The stimuli were shape combinations of geometric primitives (see Figure 1). While the component shapes may be easily recognizable in general, the objects used in this experiment are not. This was done to reduce any confounds based on differential semantic associations made both between objects and within individual participants. Novel objects were also used because they helped participants build associations between certain movements and certain positions with minimal interference from personal preferences. The results from the training experimental phase in particular should resolve any potential confounds by showing a generalized preference across participants for specific movements rather than for particular objects.

Stimulus materials were displayed in stereo using a Sony Glasstron LDI-100B HMD (Sony, Tokyo, Japan). Participant head and hand motions were tracked using an Intersense 900 magnetic tracker (Intersense, Bedford, MA). Intersense pinch gloves (Intersense, Bedford, MA) were worn on both hands, and were used to grasp virtual objects. Stereo graphics were rendered in real time based on data from the tracker. A black background was used with the see-through shutter on the HMD closed. This was done to provide a controlled environment with no masking or distractions from external visual stimuli. Reference frames (Mou, 2004) are emulated in a MI system by computing rotation matrices from two normalized vectors representing location and orientation to produce one derived movement vector representing directional movement. A single rotation matrix is used to both define three-dimensional position and transform a global coordinate system into a reference frame relative to the participant's viewpoint. The presentation of stimulus materials, audio instructions for participants, experimental procedure sequencing, and data collection were automated. All programming was done in ImageTclAR (Owen, 2003).

Figure 1. The nine virtual objects that were presented randomly at each location. LEFT: each object (unordered), RIGHT: each object associated with a specific location during a single trial. Full rotational views of each object are available in Supplemental Materials 1.

A polar coordinate system was used to represent spatial locations along the edge of the workspace where x denotes distance outward from the participant, y denoted lateral distance, and z denotes vertical distance. Each degree represents a unit, which is roughly equal to one inch. Each set of coordinates was based on angular measurements taken in reference to a center point located in front of the participant's collar bone and outward to the extent of a participant's reach (see Table 1).

Table 1. The 3-dimensional position of the nine target positions in polar coordinates. Each position is located in some direction relative to the array center (0,0). Negative values are down and to the left of the array center.

Target Position	Coordinates (x,y)	Relative position
1	0, 0	Center
2	0, -30	Far Down
3	-30, 0	Far Left
4	0, 30	Far Right
5	30, 0	Far Up
6	-15, -15	Left Down
7	15, 15	Right Up
8	-15, 15	Left Up
9	15, -15	Right Down

Sampling the workspace at these locations allowed for significant differences in arm movements to be utilized in reach for all positions, but at the same time restricted the amount of movement necessary for executing the task to the upper body. This resulted in nine target positions arranged in a symmetrical set of locations along the outer edge of an individual's workspace (see Figure 2).

Figure 2. The nine targets and their spatial positions looking towards the participant (array of target positions is only visible through HMD, size of targets relative to participant not to scale).

A target location was defined at this position in addition to targets 30 degrees up, down, left, and right of the central position. There were also four targets 15 degrees either left or right and 15 degrees either up or down from the center position. Collectively, these positions form “X” which converges upon the center position. Although all targets were the same distance from the participant’s shoulder, the array as a whole was parabolically curved along the far edge of the workspace with the central positions forming its outward extent. The numbering system was arbitrarily chosen by the experimenters, and was not presented to the participants.

Procedure

A pretest was administered to all subjects for purposes of measuring individual differences in mental rotation ability. This was done because previous studies (Pellizzer, 1993) have found a functional correlation between the onset of visuomotor rotation planning and the actual rotation of visuomotor objects during movement to a target. The test itself included both a card rotations test and a cube comparisons test. The card rotations test involved multiple comparisons of a given target shape and eight other

objects. These evaluations were made in relation to both all logical rotations of that object and fundamentally different objects. The cube comparisons test involves similar methods to the card rotations test, except that the surfaces of two cubes are the object of comparison. A percentage of correct answers were then calculated based on accuracy given time constraints.

Participants performed a targeting task for all experimental trials (see Figures 2 and 3). The targeting task can be defined as such: a three-dimensional object will appear in front of the participant's chest. Using a pinch glove, a participant grasps the object by pinching down with their forefinger and thumb. The hand position is represented by an arrow, which corresponds with the x , y , and z position of the hand tracker. Once the object is grasped, it will illuminate slightly, signifying that it is ready to move. When the participant reaches the target, they must intersect the target with the object in their grasp. Once the target is engaged, it illuminates slightly. At this point, the object can be released and the next trial can begin.

During a single trial, events were ordered in the following way: the participant was instructed to wait for a tone, which was followed by the appearance of a virtual object in front of the chest. The participants were instructed to look down towards their chest to search for and locate the object. Wearing pinch-sensitive gloves, the participant was then to pinch down on this object using their forefinger and thumb. The origin of the x , y , z coordinate system for the right hand tracker is congruent with the center of the object when the participant has it in their grasp. Thus, the right hand tracker reference frame was used by the mixed-reality system as a reference point. The plane formed by the pinching of these digits was represented in the virtual environment by an arrow (see Figure 3).

Figure 3. Participant performing a learning task (for right-hand manipulation, both hand and arrow are shown; only the arrow appears in the experiment). A: Participant grabs the object at origin location, B: participant releases object once the target location is reached.

When the arrow intersected the object and the participant pinched down properly, the trial timer was activated and the object could be moved towards the target. The object was illuminated slightly once the object was properly grasped, which served as a visual cue to commence moving the object. The object was then moved to a target and then released as soon as the target was illuminated. The target illumination also served as a

visual cue; both of these visual cues served as feedback mechanisms to calibrate the beginning and end of an arm movement.

Illumination of the target signified that the object was engaged with the crosshair, while illumination of the object and the target simultaneously was defined by the intersection of the x , y , and z coordinate planes concurrent with the glove tracker position. In order to intersect a crosshair, the absolute center of the object's volume had to be within the physical extent of the crosshair. Participants were instructed before this experimental phase both to perform the task as fast as possible and to memorize the target location associated with each object. The participants only needed to use one hand at a time to perform the task, but were free to use either hand on any trial. While this could be viewed as a potential confound, it was actually determined by surveying the tracker data that all participants used their right hand to perform the task about 90 percent of the time.

A pretest warm-up phase was administered before the main experimental conditions began. This involved nine trials in which each target location/object pairing was presented only once. The object of this exercise was to habituate participants to the environment and equipment. In the main experiment, participants completed two experimental phases. The learning phase consisted of 5 randomly presented repetitions of all 9 objects (45 trials). On each trial of the learning phase, the participant was presented with a single object which they had to grasp and move to a randomly-assigned target. This object-target assignment was retained for all subsequent trials in both the learning and memory phase for the same participant. While each object was tied to a specific target position for an individual participant, object-target associations were randomized with respect to each participant. Thus, each object was tested in multiple positions.

A brief five-minute break was given between the learning and memory phases, during which time the participant was taken out of the virtual environment. The memory phase consisted of 3 randomly presented repetitions of all 9 objects (27 trials). The experimental task in the memory phase involved a procedure nearly identical to the learning phase, except that instead of moving as fast as possible to a single target participants were presented with all nine virtual crosshairs simultaneously. Participants were instructed to move the object exactly as they did in the targeting task. The only difference was that participants were required to decide into which target the object should be placed. For every trial in the memory phase, the object could be placed at any of the crosshairs. This allowed relative recall error to be calculated.

Results and Discussion

Subjects

Due to technical problems with the apparatus, data from 26 participants was used in the analysis of the learning and memory tasks and data from 24 participants were used for analyzing errors made during the memory phase.

Measurements

Movement Time. Movement time was defined as the interval between when the three-dimensional object was first correctly grasped to the time it was deposited into the virtual

crosshair. This means that the participant could drop and grab the object again several times during the course of a trial and inadvertently extend the retinocentric phase of the movement by excessively searching for the object after activating the trial. However, this usually resulted in a much larger than normal movement time value. To remedy this, all movement times two standard deviations larger or smaller than the mean for a particular participant and experimental block were treated as outliers and normalized.

Imposed Partitioning. In both the learning and memory analyses, these data were partitioned in two ways (see Figure 4). This was done to determine the effects of movement performance by region, but also preserve the results of individual spatial positions. This partitioning was used as a top-down means of exploring the substructure of the workspace; this approach was expected to yield general linear trends in performance. For the vertical cluster, targets were divided into left, middle, and right regions (Figure 4A). The three crosshairs closest to the left side of the visual field constituted the left cluster, the three positions along the plane straight ahead of the participant constitute the middle cluster, while the three targets closest to the right side of the visual field constitute the right cluster. Spatial positions across the vertical clusters in the same section of the workspace were treated as independent but equally important horizontal clusters. For example, all positions closest to the top in each vertical cluster constituted the upper horizontal cluster. The three targets that formed a straight horizontal line through the center of the workspace represented the middle cluster, while the lowest three targets represent the lower horizontal cluster.

Figure 4. A: Data partitioning scheme. Sampled workspace positions were divided into strips from left to right (L,C,R), while positions were ordered from top to bottom (1,2,3). B: demonstration of the cone of mean error. The radius (diagonal vector running from L1 to C2) defines a circular area which defines the overall possible error for position C2.

Error Measurement

The absolute error measurement was derived from both vertical and horizontal error measurements. The absolute error measurement was derived from both vertical and horizontal error measurements. This can be defined as the number of degrees in the polar coordinate system by which a participant missed the target in the horizontal and vertical

direction, respectively. For example, if the participant was supposed to place the object in the far left target but instead placed it at the far right target, their error for that trial would be 60 degrees horizontal and 0 degrees vertical. Instead of measuring the number of degrees by which a participant missed the target in a cardinal direction, absolute error calculates a straight-line diagonal line in degrees from the correct target to the chosen target. The length of this vector, as the foundation for the radius of a three-dimensional conical space, forms a region of mean error around each target (see Figure 4B).

Movement Time Analysis

Movement time was analyzed separately for the learning and memory phases. The learning trials were analyzed using a 3 vertical cluster x 3 horizontal cluster x 5 repetitions repeated-measures ANOVA. For the memory phase, a separate 3 vertical cluster x 3 horizontal cluster x 3 repetitions repeated-measures ANOVA was conducted. An additional ANOVA was also conducted on error data for the memory phase. There were no analogous error data in the target phase. A hierarchical cluster analysis was also conducted. The cluster analysis was conducted on a transformation of the data that may reveal how speed as a function of end effector velocity differed when comparing performance in the learning phase as opposed to the memory phase.

Learning Experimental Phase

Among the learning trials, a significant difference was found for error among horizontal clusters, $F(2, 50) = 7.58, p < .02$ upper $\underline{M} = 9720$ ms, middle $\underline{M} = 9390$ ms, lower $\underline{M} = 8310$ ms (see Figure 5). Overall, participants tended to be faster when the target was lower in the workspace. However, significant differences for vertical cluster accuracy were not found, $F(2, 50) = .29, p > .05$ left $\underline{M} = 9140$ ms, center $\underline{M} = 9300$ ms, right $\underline{M} = 8970$ ms.

Figure 5. LEFT: Average movement time by horizontal cluster in the learning task (error bars were calculated using standard error). RIGHT: presentation of clusters and average response times in the context of the target array.

A significant difference was also found for repetitions, $F(4, 100) = 13.84, p < .01$ one $\underline{M} = 10920$ ms, two $\underline{M} = 9150$ ms, three $\underline{M} = 9000$ ms, four $\underline{M} = 8600$ ms, five $\underline{M} = 8020$ ms (see Figure 6A). Finally, there was an interaction between region and position, $F(4, 22) = 2.842, p < .05$. The repetitions finding was expected, since participants were

learning how to execute the task as they proceeded through each set of trials. This finding also indicates the learning rate throughout this part of the experiment.

Figure 6. A: Average movement time for repetitions in the learning task (error bars were calculated using standard error). B: Average movement time for repetition in the memory task (error bars were calculated using standard error). Graphs scaled to make a direct comparison along the y-axis.

Memory Experimental Phase

In the memory phase, no significant differences were found between horizontal clusters, $F(2, 50) = .50$, $p > .05$ (upper $\underline{M} = 8250$ ms, middle $\underline{M} = 7940$ ms, lower $\underline{M} = 7960$ ms) or vertical clusters, $F(2, 50) = .14$, $p > .05$ (left $\underline{M} = 7980$ ms, center $\underline{M} = 8130$ ms, right $\underline{M} = 8040$ ms). However, the mean movement times seem to reveal a slight preference for the lower right and left portions of the workspace. By contrast, movement time across repetitions were found to be significantly different, $F(2, 50) = 13.39$, $p < .01$ (one $\underline{M} = 8630$ ms, two $\underline{M} = 7970$ ms, three $\underline{M} = 7500$ ms) (see Figure 6B). Interestingly, the first memory repetition yields a slower movement time than the fifth learning repetition, but declines quickly in subsequent repetitions. It may be that adaptation to the environment is responsible for the results within each phase, while transfer-of- training may be the reason for this result across phases. This is why we conducted the cluster analysis; to see how “quickness” different between the learning and memory phases.

The performance for each position was calculated to determine if there were common errors made across subjects in moving objects to their correct position. A confusion matrix containing these data (see Table 2) revealed that adjacent positions were indeed often confused with each other. In addition, many of the most common errors corresponded with movements to positions 1 (center) and 2 (far down). This may mean that since these positions are easiest to reach, objects are placed in these positions when memory for the movement to the correct position fails. On the other hand, a sizable number of errors were also made in the opposite direction; however, the three most common errors that were not made to positions 1 and 2 were made to positions with the minimum cone of mean error (21.2 units) for this workspace. The positions were adjacent and movements to the most likely utilized similar movement dynamics.

Table 2. confusion matrix showing correct target positions (along left hand side) and positions where targets were actually placed during the memory phase (along top). This chart should show both exactly how many errors were made and common confusions between target positions. The target positions were located relative to the participant's point of view (for definitions, see Table 1).

		Targets Placed								
		1	2	3	4	5	6	7	8	9
Correct Position	1	18	7	8	7	5	4	8	5	11
	2	6	28	3	4	6	4	7	5	9
	3	7	8	23	5	4	10	5	4	6
	4	6	3	8	20	7	8	7	5	8
	5	15	8	5	3	21	5	3	5	7
	6	6	16	4	4	7	18	6	5	8
	7	16	6	5	2	7	9	15	7	5
	8	5	10	8	4	6	8	6	16	9
	9	9	8	4	6	5	6	4	7	23

Degree of Error Analysis

For this analysis, data from twenty-four participants were used due to instrumentation malfunction. The error measurement was found to be significant for horizontal cluster, $F(2, 46) = 9.67$, $p < .001$ (top $\underline{M} = 31.7$, middle $\underline{M} = 25.7$, bottom $\underline{M} = 24.2$). As in the case of the learning and memory trials, a vertical asymmetry exists from top to bottom. However, there were no significant differences between vertical cluster, $F(2, 46) = 1.63$, $p > .21$ (left $\underline{M} = 27.06$, middle $\underline{M} = 25.52$, right $\underline{M} = 28.41$) nor repetitions, $F(2, 46) = .30$, $p > .59$ (one $\underline{M} = 27.20$, two $\underline{M} = 27.01$, three $\underline{M} = 26.78$). In this case, participants performed better on targets located in the middle cluster. A survey of the absolute error data by position (Figure 7) suggests that participants made errors to adjacent positions rather than to the same few positions over and over. The distance between adjacent targets was 21.21 units, while the error distance was under 30 for all positions except the topmost one. This seems to suggest that participants only had excessive difficulty when reaching for the uppermost target in the array.

5.6 Multivariate Analysis: hierarchical cluster analysis

A complete linkage hierarchical cluster analyses were conducted to test how movement times vary across positions in relation to differences in learning and memory. This clustering technique was used as a bottom-up means to discover variability in the workspace substructure. A single linkage, or nearest-neighbor, algorithm was used to construct these trees. A Euclidian distance metric was used to normalize the means. Theoretically speaking, if the internal model representative of moving to a particular position is well consolidated, then the difference between velocities exhibited for the learning and memory phases will be short. In addition, the cluster analysis revealed like levels of performance for various regions of the workspace. Those positions that cluster together may utilize the same internal model.

Mean linear velocity was calculated for each participant based on the ratio between the workspace radius (measured from the shoulder to the fingertips) and movement time in seconds. The yielded a linear velocity to target (units per second)

which provided a scaling related to individual differences in workspace depth. The mean linear velocity was calculated across subjects for each position. This was done for all trials in both the learning and memory phases. Finally, the final movement velocity per position (V_{pos}) was calculated by taking the absolute value of the difference between mean velocity for the learning and memory phases (see Figure 8).

Figure 7. Standard error for spatial locations in learning task (standard error calculated on movement time).

The cluster analysis yielded two families and three subfamilies. When visualized from left to right relative to the target positions, it appears that there is a gradient of performance from the lower right to upper and leftward positions. The least difference between learning and memory trials in terms of velocity occurred in the lower right hand portion of the workspace. For some reason, position 8 was included in this cluster. Family A (Fam A) includes all other positions in the upper and leftward portions of the workspace. Upon eyeballing the data, it becomes apparent that linear velocity was greater during the memory phase for all positions except 3. Meanwhile, linear velocity was over 1 unit per second greater during the memory phase for the following positions: 4, 3, and 8. While the algorithm did not cluster these positions together, they sit in a diagonal line on the upper left side of the workspace.

Figure 8. Classification of biomechanical and spatial learning parameters. LEFT: hierarchical cluster analysis of all nine positions using the final movement velocity per position ($V_{pos} = |T_{ph} - M_{ph}|$). RIGHT: all nine workspace positions divided into families (Fam A, Fam B) and subfamilies (a,b,c) as determined from the cluster analysis.

Potential Predictors of Performance

Finally, a linear regression was run to test how well the pretest data predicted motor learning and memory in the virtual environment. A model that used both the pretest data predicting mental rotation ability and linear velocity in the learning phase as predictors of absolute error measurements derived from memory phase trials for all subjects was found to be statistically significant, $F(2,23) = 26.421$, $p < .002$, $R^2 = .845$. Individual differences in mental rotation ability contributed 78.6 percent of this variance, while the linear velocity achieved during the learning phase contributed 21.4 percent. It appears that the ability to internally model the trajectory and position to the correct target is variable across participants. This may mean that the consolidation of spatial memory requires a significant amount of internal modeling ability that exhibits large individual differences ($\{Wolpert, 2000 \#34\}$).

Collective Implications of Results

The prediction that location influences movement speed and accuracy was supported in three different ways. First, there are statistically-significant vertically-oriented clusters. However, these clusters have significant substructure, which are oftentimes consistent horizontally across the workspace. Initial surveys of these data revealed speed and accuracy advantages for the lower right quadrant, but the statistical analyses suggest that there is much more structure to these data than meets the eye. The hierarchical cluster and linear motor control analyses were especially informative, for they suggest that subtle vertical asymmetries can influence performance as much as horizontal asymmetries can. Generally, participants did better with central to lower targets than higher targets; this was a more pronounced difference than that found between targets near the dominant hand and those near the left hand. The advantage for positions in the lower portion of the workspace during the learning phase seems to be lost once participants either learn the task or have to choose between multiple targets.

It could be argued that a strategy of subsequently locating targets in upper regions of the workspace after reaching for objects of could result in a disadvantage for making quick moves to specific targets. Far from being a potential confound, the combination of remembering passive movements and natural asymmetries expected for certain positions in the workspace may contribute to the current finding.

Conclusions

This study makes its greatest contribution in terms of connecting spatial performance asymmetries with the dynamics of learning and memory. Over the course of task learning, visual inputs act to refine task performance, but within constraints imposed by arm movement. Again, this favors targets located downward and to the right. The finding of prior mental rotational ability and practice at the task leading to less error in the memory phase suggests that certain people may manage the sensorimotor transformation of spatial information faster and with less ambiguity than others. As Karniel and Mussa-Ivaldi ({Karniel, 2002 #15}) have found, once an internal model is well established for specific movement velocities and biases for different spatial positions, it is hard for participants to switch to another set of encodings. This makes the number of degrees by which a target is missed variable across a workspace, and may result in trajectories less consolidated in memory to be confused for other nearby target positions. Differences in the length of the planning and execution portions of the targeting movement might provide evidence for the existence of a biphasic short-term memory store, and might be inferred from performance differences.

Davidson and Wolpert ({Davidson, 2004 #36}) propose that two distinct types of internal model exist; one devoted to long-term memory and another devoted to short-term memory. It might be said that easy to reach and hard to reach positions utilize a common internal model updated in two distinct ways; easier targets by a long-term model and harder targets by a short-term model ({Sober, 2003 #32}). While it is tempting to think that simpler mechanisms provide an alternative explanation of these results, using several different analytical methods reveal that performance on a distributed targeting probe can be both subtle and complex. For example, the lowest absolute error rate exists for the central workspace position. This may suggest that for objects directly along the major axis of a participant's spine, the retinocentric portion of the movement is shorter, which makes easier to remember movements associated with targets not strictly influenced by gravity ({Bock, 1986 #5}).

The applications of these results are potentially wide-ranging. In particular, these results could inform initial design templates of a workspace. This has already been done with "instructor stations" ({Munz, 2004 #20}), which require the determination of a performance baseline for all tasks in a virtual environment. This baseline is then used as the criterion by which to automate certain tasks over others as the system is used and tasks are performed. There may also potentially interesting applications to wearable computing that could draw out larger differences in spatial performance asymmetries.

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