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Fuzzy Navigation Engine: Mitigating the Cognitive Demands of Semi-Natural Locomotion

Abstract

Many interfaces exist for locomotion in virtual reality, although they are rarely considered fully natural. Past research has found that using such interfaces places cognitive demands on the user, with unnatural actions and concurrent tasks competing for finite cognitive resources. Notably, using semi-natural interfaces leads to poor performance on concurrent tasks requiring spatial working memory. This paper presents an adaptive system designed to track a user's concurrent cognitive task load and adjust interface parameters accordingly, varying the extent to which movement is fully natural. A fuzzy inference system is described and the results of an initial validation study are presented. Users of this adaptive interface demonstrated better performance than users of a baseline interface on several movement metrics, indicating that the adaptive interface helped users manage the demands of concurrent spatial tasks in a virtual environment. However, participants experienced some unexpected difficulties when faced with a concurrent verbal task.

I Introduction

Virtual reality (VR) systems are used in many domains, often involving tasks with moderate to extreme cognitive demands. Unfortunately, the interfaces used to interact with virtual environments (VEs) often require movements unlike corresponding actions in the physical world. These unnatural control actions compete with a user's primary tasks for finite cognitive resources.

I.1 Virtual Locomotion

In this paper, the term *virtual locomotion* refers to the atomic actions performed by a user when attempting to navigate from point to point in a VE. For these actions, real walking has many benefits over other less-natural locomotion interfaces, including improved spatial orientation (Chance, Gaunet, Beall, & Loomis, 1998), reduced training time (Ruddle, Volkova, & Bülthoff, 2013), and higher subjective presence (Slater, Steed, McCarthy, & Maringelli, 1998). However, because VEs can be large in scale and VR systems are strictly confined by physical boundaries or tracking ranges, many systems cannot allow fully natural walking.

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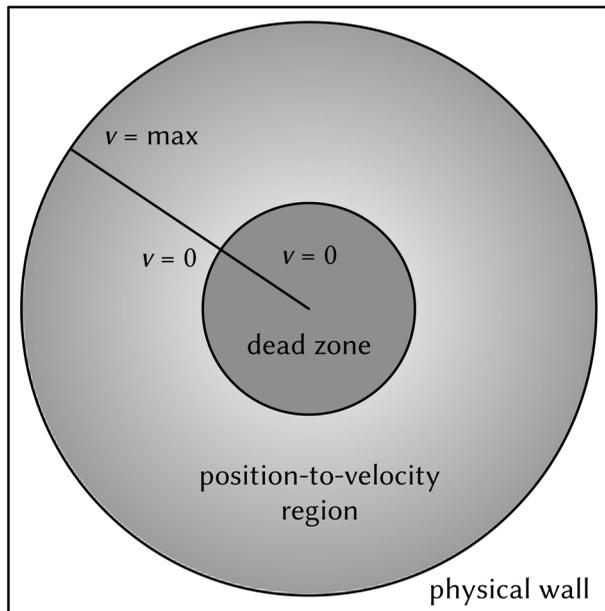


Figure 1. Top-down diagram of the P2V locomotion interface.

Many less-natural interfaces have been devised, allowing for infinite virtual locomotion from within a small physical area. Handheld gamepads are a common type of locomotion interface, requiring an extremely small physical space. They are considered very unnatural because completely different actions and muscle groups are required, as compared to real walking. Many interfaces have been created to mimic a real walking motion, but even these present problems for new users (Marsh, Hantel, Zetzsche, & Schill, 2013).

Hybrid interfaces have also been developed, in which movements are natural to an extent but less natural as users approach the systems' physical boundaries (e.g., Cirio, Marchal, Regia-Corte, & Lécuyer, 2009; Wells, Peterson, & Aten, 1996). Marsh, Kelly, Dark, and Oliver (2013) used such an interface, depicted in Figure 1, known as the position-to-velocity (P2V) interface. In this interface, the user's head position is used analogously to a typical joystick. The control scheme was designed for six-sided CAVEs, in which graphics appear on all sides, so rotation is completely natural. Translation is natural (walking) when the user is near the center of the CAVE (the *dead zone*). In this region, the virtual velocity magnitude (v) is zero. Once a user leaves

the dead zone, a vector is constantly updated reflecting the radial distance of the user's head from the outer boundary of the dead zone. The velocity magnitude varies linearly from 0, at the edge of the dead zone, to a maximum at the outer radius of the P2V region. The direction of virtual movement is the direction of the vector. If the user changes direction while outside the dead zone, the result is virtual steering. The user returns to the dead zone to stop.

Hybrid interfaces can often be altered to allow for a higher percentage of movements that are natural; however, this may lower the achievable virtual velocity. As an example of this trade-off, walking can be considered a very natural means of moving through the world. Flying can be much faster, though it would not be considered natural for most users.

1.2 Cognitive Resources

Many conceptual models of working memory have been proposed, many building on the work of Baddeley and Hitch (1974; see also Baddeley, 2002). This model draws a distinction between visuospatial and verbal working memory resources, with access to both resource pools mediated by general attention. More recent models also usually include this basic structure, with minor changes. For example, some research suggests that the visuospatial component actually comprises two separate components, for visual and spatial information (Darling, Della Sala, & Logie, 2009; Logie, 2003). Importantly, working memory is thought to be required for both storage and manipulation.

Working memory resources are considered finite, such that concurrent tasks must compete for them. If unnatural locomotion requires a given resource pool, those resources will be unavailable for a user's primary tasks in the VE. This competition will cause decreased performance on one or both concurrent tasks.

1.3 Cognitive Demands of Locomotion

Locomotion through VEs often employs interfaces that are less natural than physical walking, and therefore virtual locomotion may demand cognitive

resources. Suma, Finkelstein, Clark, Goolkasian, and Hodges (2010) investigated the impact of unnatural locomotion interfaces on users' ability to process stimuli encountered while navigating. They found that users performed better on these secondary tasks while walking than while using a less-natural pointing interface, indicating that walking caused less competition for cognitive resources.

Marsh, Kelly, et al. (2013) asked participants to remember either a spatial or verbal sequence (or no sequence) unrelated to navigation, while concurrently performing virtual locomotion tasks. The verbal sequences were lists of random numbers, to be recited after locomotion was complete. For the spatial sequences, virtual squares were displayed and the participant was asked to recall the positions of the squares, in order, after completing the locomotion tasks. The results showed that more unnatural locomotion interfaces were linked with lower performance on a concurrent spatial, but not verbal, task. Additionally, users of the P2V interface took longer to stop while performing a spatial task than while performing a verbal task.

In a followup study, Marsh, Kelly, et al. (2013) found that field of view (FOV) moderates the cognitive resource demands of locomotion. Participants who completed locomotion tasks with a reduced FOV exhibited lower performance on both spatial and verbal concurrent tasks. The results also pointed to individual differences moderated by scores on the Perspective Taking and Spatial Orientation Test (Hegarty & Waller, 2004), with the possibility that high-ability users spent more time planning their movements when they had no competition from a concurrent spatial memory task.

2 Adaptive Systems

When designing a system for a heterogeneous group of users with changing abilities, plans, and needs, it is often desirable for the system to adapt according to a user's current state. In this research, a fuzzy inference system has been designed to adjust an output variable according to the current values of two input variables and past performance.

2.1 Fuzzy Inference Systems

Often when categorizing a continuous variable, such as cognitive resource utilization, it is not useful to define absolute bounds on set membership. In fuzzy logic, continuous numerical values are segmented into overlapping fuzzy sets. In this way, instead of describing membership in the Boolean sense, where states change abruptly, one can speak of degrees of membership, in that an input variable gradually loses membership in one set while gaining membership in another. A variable is then a member of several sets to varying degrees. The degree of membership in a given set is defined by a membership function for that set, commonly in the shape of a triangle or trapezoid. Fuzzy logic is complementary to probability. Probability deals with the likelihood of an event, whereas fuzzy logic attempts to describe the degree to which it has happened (Kosko, 1994; Schwartz, 1992).

Implementing a fuzzy inference system involves the following steps (Cox, 1992), shown in Figure 2.

1. Start with one or more continuous numeric input values.
2. Using set membership functions, determine the membership of each input variable in each set (fuzzification).
3. Using if-then production rules, map membership in input set(s) to membership in output set(s) (inference).
4. Combine the output sets into a single set.
5. Produce a single numeric value (defuzzification).

An inference engine decides which rules to fire according to membership functions and current variable settings. In many cases, more than one rule may fire. These rules produce a firing set composed of multiple output sets according to the degree of membership of each premise. These output sets must be combined into a single set, often with a MAX composition. Finally, the inference engine must produce a defuzzified final result in the form of a number. Commonly, this defuzzified value is the x coordinate of the Center of Gravity (COG) of the combined output set.

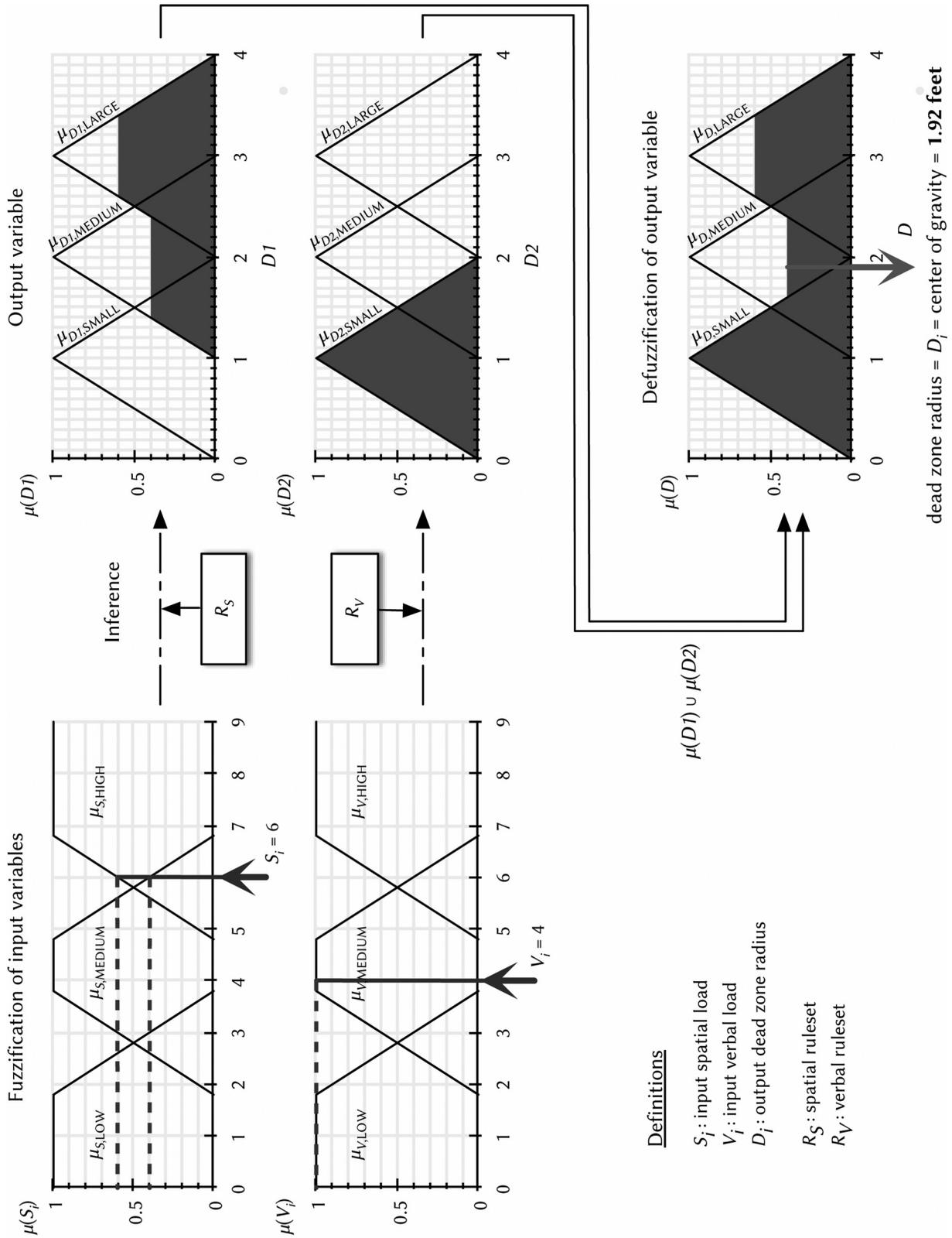


Figure 2. Example flow of the fuzzy inference system implemented in this paper.

2.2 Learning

Through learning, a system can use past results to increase future success as it interacts with the environment (e.g., Hayashi, 1992; Lin & Lee, 1992). A domain expert can specify initial fuzzy rules and set membership functions. A system can then attempt to minimize error over time by modifying rules, rule weights, or membership functions. Learning should be based on multiple error measures, as training data are often incomplete or noisy.

3 Approach

The objective of this research is to mitigate the dual-task performance problems arising from competition for resources during semi-natural virtual locomotion. The results described in Section 1.3 indicate that more natural locomotion should be preferred when a user is performing a concurrent spatial task. This amounts to a trade-off, with a more natural configuration often leading to a reduced potential velocity. It will thus be important to reduce the naturalness once the concurrent spatial task has been completed.

While preconfigured adaptation may provide general benefits, past findings also identified individual differences and often related to first-time users. As users learn to use an interface, it will become more natural, meaning that less adjustment should be needed as users improve. An effective system should, thus, learn to improve itself.

This paper details the design and validation of a system that uses information about a user's current working memory load to modify interface parameters. The adaptive system, Fuzzy P2V, is based on the P2V interface described in Section 1.1, but with the addition of the Fuzzy Navigation Engine, which uses the Fuzzy-lite (Rada-Vilela, 2011) open source library to implement a fuzzy inference system.

The basic input-output flow of the Fuzzy Navigation Engine is shown in Figure 3. Every time that the user's assigned memory task changes, the scene fires a memory load changed event. The Fuzzy Navigation Engine receives that event and uses two values, spatial load (S_i)

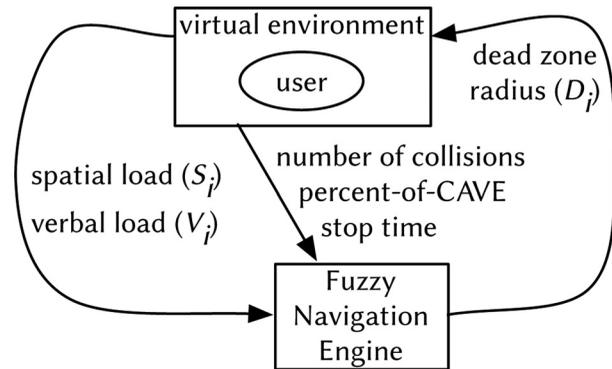


Figure 3. Basic input-output flow of the Fuzzy Navigation Engine.

and verbal load (V_i), to calculate a new dead zone radius (D_i). The new radius is then immediately updated and reflected in the Fuzzy P2V user interface. In the experimental scene, the dead zone is surrounded by a red circle drawn in the center of the CAVE floor, indicating the current size. Additionally, the figure shows the number of collisions, stop time, and percent of CAVE being passed to the Fuzzy Navigation Engine. These metrics, described in detail in Section 3.4, will be used to help the Fuzzy Navigation Engine learn to improve its performance.

This research was conducted in the C6 CAVE at Iowa State University, which surrounds the user with graphics on all sides and provides a 10-ft square movement area. The design decisions in this paper were made with these specifications in mind.

3.1 Fuzzy Inputs

Hardware specifications rarely change at runtime, so attributes such as FOV cannot provide a meaningful input to the adaptive system. Locomotion abilities will change as the user learns how to move more effectively, but it is not clear how to detect and quantify skill acquisition. However, the system has access to some information about concurrent tasks that the user is asked to complete. This is used as input to the Fuzzy Navigation Engine. It is difficult to effectively measure task load, so concurrent tasks were selected because they are well validated in the cognitive psychology domain.

In fact, they were the same working memory tasks described in Marsh, Kelly, et al. (2013) with the addition of a gamepad for spatial recall. The number of items in a given domain (spatial or verbal) that a user is currently required to maintain in memory provides a rough estimate of working memory load. Because both spatial and general resources have been shown to be used during locomotion, the Fuzzy Navigation Engine considers both spatial and verbal load. The following input variables were used to drive the fuzzy inference system.

- Number of spatial items currently held in working memory (S_i).
- Number of verbal items currently held in working memory (V_i).

To define fuzzy set membership functions (μ), the Fuzzy Navigation Engine implements overlapping trapezoid functions as shown by example in Figure 2, with each returning a value between 0 and 1. The functions will change to drive system learning, as described in Section 3.5. A general trapezoid function, μ_{trap} , is defined as follows, where x represents a specific verbal or spatial load (V_i or S_i), m is the slope, and b is the y intercept, with the subscripts L and R referring to the left and right sides of the trapezoid, respectively:

$$\mu_{\text{trap,L}} = \begin{cases} m_L \times x + b_L & \text{if } x_1 \leq x \leq x_2, \\ 1 & \text{if } x_2 < x, \end{cases} \quad (1)$$

$$\mu_{\text{trap,R}} = \begin{cases} 1 & \text{if } x < x_3, \\ m_R \times x + b_R & \text{if } x_3 \leq x \leq x_4. \end{cases} \quad (2)$$

$$\mu_{\text{trap}} := \mu_{\text{trap,L}} \cup \mu_{\text{trap,R}}. \quad (3)$$

This template is used to define the linguistic levels of load (low, medium, and high) for both spatial and verbal memory: $\mu_{S,\text{LOW}}$, $\mu_{S,\text{MEDIUM}}$, $\mu_{S,\text{HIGH}}$, $\mu_{V,\text{LOW}}$, $\mu_{V,\text{MEDIUM}}$, and $\mu_{V,\text{HIGH}}$.

Membership functions, μ_S and μ_V , map the numbers of items that are currently being maintained in spatial

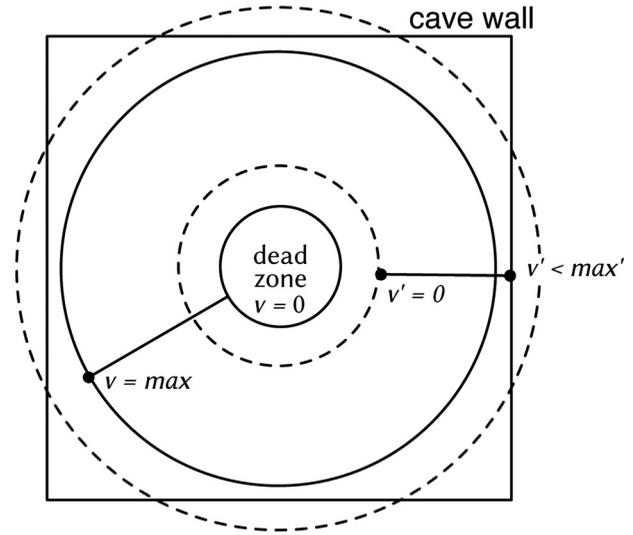


Figure 4. Top-down depiction of a CAVE, with circles illustrating how changing the dead zone radius affects maximum velocity. v : velocity; max : maximum possible velocity.

and verbal working memory, respectively, to fuzzy sets, as shown in the following equations:

$$\mu_S := \{\mu_{S,\text{LOW}}, \mu_{S,\text{MEDIUM}}, \mu_{S,\text{HIGH}}\}, \text{ and} \quad (4)$$

$$\mu_V := \{\mu_{V,\text{LOW}}, \mu_{V,\text{MEDIUM}}, \mu_{V,\text{HIGH}}\}. \quad (5)$$

3.2 Fuzzy Outputs

The Fuzzy Navigation Engine produces a single output value, the dead zone radius (D_i). As this increases, the outer radius of the P2V region increases at the same rate, as seen in Figure 4, capping the maximum possible speed only if it is larger than the CAVE. This has the following three benefits.

- It provides a greater area for natural movement. Because the C6 is a 10-ft square area, it is useful to describe the dead zone size in feet. In this way, it is easy to see that a dead zone with a radius of 1 ft allows natural movement for 1/5 of the distance from the center of the CAVE to the wall. Based on the findings in Marsh, Kelly, et al. (2013), an interface with a greater proportion of natural movement should require a smaller quantity of cognitive resources, leaving them available for concurrent tasks.

- It provides a larger target when stopping. Past research showed that users took longer to stop during concurrent spatial tasks. Providing a larger dead zone should make stopping easier and finding the dead zone should require a smaller quantity of spatial cognitive resources, leaving them for concurrent tasks. A disadvantage is that a user may not truly be in the center when stopped, potentially causing confusion when beginning the next movement.
- It limits the maximum velocity at the outer edge of the P2V region. This will act as training wheels of a sort when the user cannot expend the necessary cognitive resources but will allow for higher performance when the user is capable. Note that this could increase the risk of running into physical walls if the outer bounds provide a speed that is much slower than the user desires.

Three fuzzy output terms (small, medium, and large) are used to represent the dead zone radius in the fuzzy inference system, defined by the following triangle membership functions as shown in Figure 2: $\mu_{D,SMALL}$, $\mu_{D,MEDIUM}$, and $\mu_{D,LARGE}$. Triangle functions are a special case of the general trapezoid function described in Equations 1–3, so they can be specified using the same parameters. Example dead zone membership functions are shown in Figure 2 and μ_D is formalized in the following equation:

$$\mu_D := \{\mu_{D,LOW}, \mu_{D,MEDIUM}, \mu_{D,HIGH}\}. \quad (6)$$

3.3 Fuzzy Rules and Inference

The rules for the Fuzzy Navigation Engine are configurable before each run. Locomotion performance is thought to decrease as spatial load increases but performance is often not affected by verbal load (Marsh, Kelly, et al., 2013). General attention resources may be required and, thus, verbal load may affect locomotion performance. The rules have been defined accordingly, with spatial load (S) being given a greater influence on dead zone size (D) than verbal load (V). The following production rules (R_i) were used in the study.

- R_1 : IF number of spatial items is low ($S_i \in \mu_{S,LOW}$),
THEN dead zone size is small ($D_i \in \mu_{D,SMALL}$).
- R_2 : IF number of spatial items is medium
($S_i \in \mu_{S,MEDIUM}$),
THEN dead zone size is medium
($D_i \in \mu_{D,MEDIUM}$).
- R_3 : IF number of spatial items is high ($S_i \in \mu_{S,HIGH}$),
THEN dead zone size is large ($D_i \in \mu_{D,LARGE}$).
- R_4 : IF number of verbal items is low ($V_i \in \mu_{V,LOW}$),
THEN dead zone size is small ($D_i \in \mu_{D,SMALL}$).
- R_5 : IF number of verbal items is medium
($V_i \in \mu_{V,MEDIUM}$),
THEN dead zone size is small ($D_i \in \mu_{D,SMALL}$).
- R_6 : IF number of verbal items is high
($V_i \in \mu_{V,HIGH}$),
THEN dead zone size is large ($D_i \in \mu_{D,LARGE}$).
- $R_S := \{R_1, R_2, R_3\}$.
- $R_V := \{R_4, R_5, R_6\}$.

Because each of the rules has a single premise, no combination is necessary to determine the output of a given rule. However, it is still likely that multiple rules may fire at once. After a firing set has been constructed according to the production rules, a MAX composition is used to combine the outcomes of all fired rules. After a combined set has been constructed, defuzzification finds the COG. The x coordinate of the COG will be the new dead zone radius.

3.4 Error Metrics

A set of error metrics is introduced to drive learning. These are combined and used to adjust the membership functions for the fuzzy input variables, as described in Section 3.5. The Fuzzy Navigation Engine uses the following three error terms.

3.4.1 Collision Error Term (r_c). If a user collides with virtual objects frequently, virtual movement distance is likely to be limited. Also, collisions are unlikely to be intended and in some domains locomotion precision may be critical to successful task completion. For these reasons, the number of collisions within a 15 s window is used as a metric for system learning. The raw collision count is mapped to an error term (ϵ_c) in the range 0–1.

3.4.2 Stop Error Term (r_s). Past results show that users have problems stopping quickly using the P2V interface when completing a simultaneous spatial memory task. It is expected that increasing the radius of the dead zone will facilitate stopping. The number of seconds required to stop is mapped to an error term (e_s) in the range 0–1.

3.4.3 Percent-of-CAVE Error Term (r_p). The final metric used for learning is a windowed measure of the extent to which the horizontal movement area of the C6 is being utilized. This is equal to the windowed average percent of the 5-ft distance between the center of the C6 and each wall. It is possible for this value to be greater than 100% because a user could move toward the corner of the CAVE and have an average distance of greater than 5 ft from the center. This percent is mapped to an error term (e_p) in the range 0–1.

3.5 Learning

When a scenario begins, the dead zone radius and all fuzzy set membership functions are configured with initial values. To better accommodate the current user, the system learns at runtime. Whenever the current scene fires a learn event, the error terms are combined and a correction value is calculated that will be used to scale the fuzzy input sets.

3.5.1 Combining the Error Terms. After a learn event has been fired, the error terms must be combined in order to drive learning. The stop error (e_s) and collision error (e_c) terms indicate poor user performance, so these can be thought of as user error (e_u). The percent-of-CAVE (e_p) error term indicates that the user's velocity may be unnecessarily throttled by a large dead zone, so this term can be thought of as interface error (e_i) and should serve to counteract user error. The user error is subtracted from the interface error and that difference is multiplied by the correction magnitude (c_m), a configurable parameter to control the speed of learning. The result is added to the total (existing) verbal correction (c_v) if the current verbal load (V_i) is greater than zero, with the restriction that total verbal correc-

tion must never be less than c_{min} . If the current spatial load (S_i) is greater than zero, the result is added to the total (existing) spatial correction (c_s), with the restriction that total spatial correction must never be less than c_{min} . When the Fuzzy Navigation Engine starts, total verbal correction and total spatial correction are both initialized to 0.

$$e_u = e_c + e_s, \quad (7)$$

$$e_i = e_p, \quad (8)$$

$$c_{temp} = c_m \times (e_i - e_u), \quad (9)$$

$$c_v = \begin{cases} c_v + c_{temp} & \text{if } V_i > 0 \text{ and } c_v + c_{temp} > c_{min} \\ c_{min} & \text{if } V_i > 0 \text{ and } c_v + c_{temp} \leq c_{min} \\ c_v & \text{if } V_i = 0 \end{cases}, \quad (10)$$

$$c_s = \begin{cases} c_s + c_{temp} & \text{if } S_i > 0 \text{ and } c_s + c_{temp} > c_{min} \\ c_{min} & \text{if } S_i > 0 \text{ and } c_s + c_{temp} \leq c_{min} \\ c_s & \text{if } S_i = 0 \end{cases}. \quad (11)$$

3.5.2 Scaling the Fuzzy Input Sets. If a user has locomotion problems, then the dead zone may be too small. If the user has a concurrent task, the locomotion problems could be due to competition for resources. If so, this means that the system's current fuzzy sets may be inappropriately sized and that the user's load should be viewed as greater than the fuzzy terms currently indicate. A correction term was devised to adjust the fuzzy set membership functions for the input variables. Adjusting the sets using a negative correction term makes the system view a given numeric load as linguistically higher. If the input membership sets are corrected in this way, without changing the production rules, then the output variable (dead zone radius) will tend to be larger.

At other times, locomotion performance may be high and the user could benefit from a smaller dead zone in order to increase the maximum possible velocity. In this case, the user's load should be considered to be lower than the linguistic fuzzy terms currently indicate. Adjusting the sets using a positive correction term will make the system view a given numeric load as

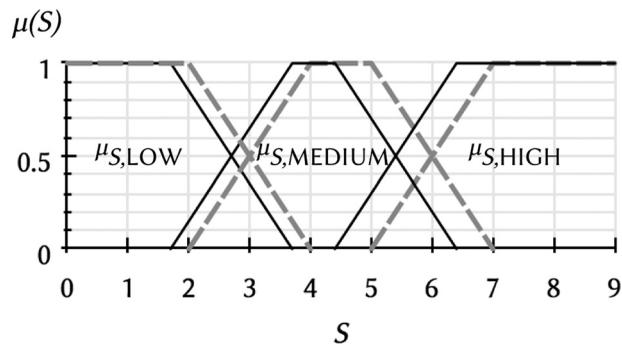


Figure 5. Example of membership set correction. Solid lines depict the new membership functions after a correction of -0.3 , whereas dashed lines depict the initial membership functions.

linguistically lower. When the input sets are corrected in this way, the dead zone radius will tend to be smaller.

During learning, the rules stay the same but the fuzzy input sets, μ_S and μ_V , are scaled based on the values of the error terms described in Section 3.4. This is accomplished by adding a correction term to input membership sets as shown by the example in Figure 5.

The correction term expands or shrinks each of the trapezoid membership functions. For example, in the case of spatial correction, the x intercept for the right side of the low term and the x intercept for the left side of the medium term will both shift by ϵ_s . The x intercept for the right side of the medium term and the x intercept for the left side of the high term will both shift by $\epsilon_s \times 2$. In Figure 5, the spatial sets have all been corrected by -0.3 . The solid lines are used to depict the new membership functions, whereas the dashed lines depict the initial membership functions (precorrection).

3.6 Experimental Scene

An experimental VE, *CogScene*, was created that allows users to traverse a brick corridor, shown in Figure 6, while periodically performing memory tasks, intended to simulate the existence of concurrent tasks. The corridor walls are taller than the participants, so only a small portion of the environment is seen at a given time. The corridors are wider at all points than the physical width of the C6, so maneuvering does not require great precision.

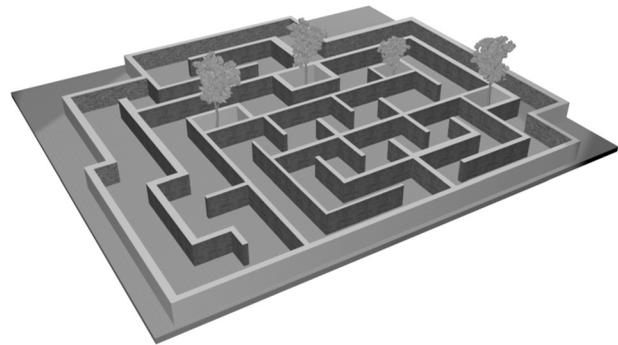


Figure 6. The virtual brick corridor.

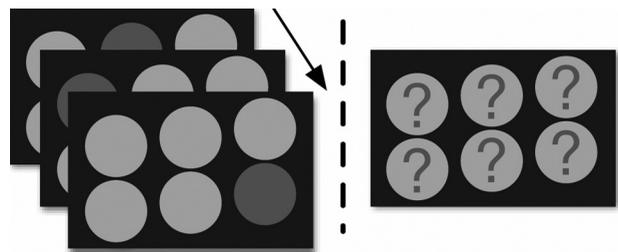


Figure 7. Spatial task presentation cards (left), with the highlighted circles corresponding to buttons on the gamepad, and spatial task recall card (right).

When a memory sequence is presented or recalled, *CogScene* fires an event indicating a change in the cognitive demands of the primary tasks. The levels of spatial and verbal resource usage are passed as parameters with the event, indicating the number of spatial and verbal items, respectively, that are currently being remembered by the user.

All spatial recall was done using a Logitech Wingman Cordless gamepad. The letters on the buttons were occluded with red tape. The task presentation was a sequence of virtual cards with circles, each corresponding to a button on the gamepad. When it was time to recall the spatial sequence, the recall card shown in Figure 7 was displayed and participants were tasked with pressing the same sequence of buttons. Verbal tasks were presented as a sequence of numbers on virtual cards. For recall, participants recited the sequence aloud when a card reading “Recite” was displayed.

Table 1. Initial Configuration of Trapezoid Membership Functions

Function	Trap,L			Trap,R		
	m	b	Range	m	b	Range
$\mu_{S,LOW}$	—	—	—	-0.5	2.0	2.0–4.0
$\mu_{S,MEDIUM}$	0.5	-1.0	2.0–4.0	-0.5	3.5	5.0–7.0
$\mu_{S,HIGH}$	0.5	-2.5	5.0–7.0	—	—	—
$\mu_{V,LOW}$	—	—	—	-0.5	2.0	2.0–4.0
$\mu_{V,MEDIUM}$	0.5	-1.0	2.0–4.0	-0.5	3.5	5.0–7.0
$\mu_{V,HIGH}$	0.5	-2.5	5.0–7.0	—	—	—
$\mu_{D,SMALL}$	1.0	0.0	0.0–1.0	-1.0	2.0	1.0–2.0
$\mu_{D,MEDIUM}$	1.0	-1.0	1.0–2.0	-1.0	3.0	2.0–3.0
$\mu_{D,LARGE}$	1.0	-2.0	2.0–3.0	-1.0	4.0	3.0–4.0

The Fuzzy P2V interface is currently designed to adjust the dead zone radius only when the load levels change. Coupled with the logic in CogScene, this means that learning takes place at the end of each trial, but the dead zone only changes size when a new memory task is presented or an old one is recalled. For the purposes of the study, this is ideal for two reasons. First, the participant should be standing still in the center of the CAVE during memory task presentation and recall, so there was no change in velocity during active movement or confusion about how far one must step in order to return to the dead zone. Second, changing the dead zone radius only when the cognitive task changed allows a more straightforward analysis because a given dead zone radius can be linked with a given task difficulty and performance measurements. If the system changes very conservatively, it may be possible to adjust parameters on the fly, but for many implementations, waiting until the user is known to be stopped may be the best solution.

4 Study

The Fuzzy P2V interface was tested with users to verify that it is beneficial. The adaptation is a success if users of the new interface are able to outperform users of the baseline P2V interface at basic locomotion tasks while completing concurrent cognitive tasks.

Participants were divided into two groups according to the interface in use: Fuzzy P2V (Fuzzy) and P2V. Interface was a between-participants variable due to the expected impact of participant learning. The initial configuration for each interface is described in Section 4.1.

4.1 System Configuration

Based on past experience, the dead zone radius for the P2V group was set to 1.5 ft and the outer radius of the P2V region was set to 5.5 ft. The maximum velocity was set to 30 ft/s. These settings remained consistent throughout the study.

The dead zone radius for the Fuzzy group was generated by the Fuzzy Navigation Engine. The size of the P2V region was fixed so that the outer radius of the P2V region was always 4.0 ft larger than the dead zone radius. The trapezoid membership functions were configured as shown in Table 1. The correction magnitude (c_m) was set to 0.1 based on prior experience. The minimum correction (c_{min}) was set to -1.0 to prevent the trapezoid sides from crossing.

Sections 4.1.1–4.1.3 describe the error term settings that were used to control system learning for participants in the Fuzzy group. Error was also calculated for the P2V group, for analysis purposes, but Fuzzy Navigation Engine was disabled so learning (and dead zone adjustment) did not occur.

To determine ranges for the error terms, learning was disabled and a semiformal pilot study was conducted. The details of the pilot study are beyond the scope of this paper, but the following sections describe how exploration of those data informed the choice of error values for this formal study.

4.1.1 Collision Error Term (e_c). Pilot results indicate that users who achieved the highest distances typically had a low number of collisions. The results also support the idea that a larger dead zone radius was associated with fewer collisions. Based on these results, a goal was set to make it possible for participants in the study to be able to travel a virtual distance of 150 ft in 15 s. This objective led to capping the upper bound of the error function at five collisions. The lower bound on the error function was set to 2 because that value represents the end of the third quartile performance of the pilot study data. This range should effectively capture the outliers, mapping the collision counts of 2–5 to error values of 0–1.

$$e_c = \begin{cases} 0 & \text{if } r_c \leq 2 \\ \frac{r_c - 2}{3} & \text{if } 2 < r_c < 5 \\ 1 & \text{if } 5 \leq r_c \end{cases} \quad (12)$$

4.1.2 Stop Error Term (e_s). Trends in pilot stop times indicate that when the dead zone was smaller, there were more outliers with large stop times. These outliers are what the system should prevent and this analysis indicates that adjusting the dead zone radius will help. The third quartile of pilot study stop times ends at 4,931 ms, so the error function is defined to start near that value. Only three data points are above 30,000 ms, so that is the upper bound for the error function in the formal study. The function for the stop error term in the learning system thus linearly maps stop times of 5,000–30,000 ms to error values of 0–1.

$$e_s = \begin{cases} 0 & \text{if } r_s \leq 5,000 \\ \frac{r_s - 5,000}{25,000} & \text{if } 5,000 < r_s < 30,000 \\ 1 & \text{if } 30,000 \leq r_s \end{cases} \quad (13)$$

4.1.3 Percent-of-CAVE Error Term (e_p). The pilot study provided insight on the relationship between dead zone radius and percent-of-CAVE measurements. The largest dead zone radius possible in Fuzzy P2V was 3 ft. When the dead zone is set to this largest size, a user must use 60% of the C6 in order to translate with the P2V locomotion interface. The pilot data reflect this expectation and larger dead zone sizes generally led to higher values for this metric. Because the objective is to capture outliers, the lower bound for the error function was set at 70%. It is important to prevent users from running into the physical walls and because the corridor scene is axis-aligned, movements to the corners of the CAVE are infrequent. Thus, the upper bound on the error function was set to 90%, or 0.5 ft from the CAVE wall, so the percent-of-CAVE error term (e_p) maps percentages of 70–90% to error values of 0–1.

$$e_p = \begin{cases} 0 & \text{if } r_p \leq 0.7 \\ \frac{r_p - 0.7}{0.2} & \text{if } 0.7 < r_p < 0.9 \\ 1 & \text{if } 0.9 \leq r_p \end{cases} \quad (14)$$

4.2 Methods

4.2.1 Participants. Twenty-six undergraduate students (19 men, 7 women) were recruited from the Iowa State University Department of Psychology research participant pool, by word of mouth, and by announcements in undergraduate courses. Participants came from multiple departments. All participants were required to have normal (corrected) binocular vision.

4.2.2 Procedures. First, participants completed a prequestionnaire covering demographic information and video game experience. Then they entered the C6 and were given instructions and a demonstration of how to complete working memory tasks in the VE. They were given an opportunity to practice so they would be comfortable and confident when remembering the items during the experimental phase.

Before the experimental phase, participants were given instructions and a detailed demonstration of the P2V interface. The demonstration took place in a corridor scene similar to the one used in the experimental phase.

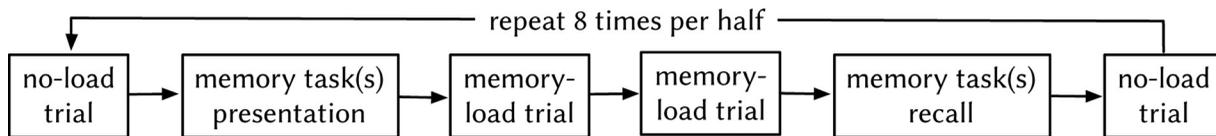


Figure 8. Task flow for one half of the study. This was repeated twice, separated by an intermission.

They were not allowed to practice locomotion. This was to ensure that movements were unnatural, thus increasing the demand for cognitive resources. Participants in the Fuzzy group were not informed about the adaptation of the navigation system.

In the experimental phase, participants were required to traverse a corridor with multiple turns while also completing memory tasks. The corridor was intended to simulate diverse types of basic navigation tasks that a user might encounter in a real-world VE. The memory tasks were the same as those used by Marsh, Kelly, et al. (2013), except that in this study, the cards appeared in the virtual corridor and a gamepad was used for spatial recall. Participants were instructed to move through the corridor whenever there was no memory card displayed, to stop whenever a card with a stop-sign shape appeared, and to stay stopped whenever a memory task was being presented or recalled. They were told that the memory tasks were the highest priority and that movement efficiency, stop times, and collisions with virtual walls would also be recorded.

The study was divided into two halves, separated by an intermission. The task flow of one half is pictured in Figure 8. Both halves were identical in structure, but all memory tasks were of random difficulty with random sequences, so each participant experienced different task loads, to test the system under unpredictable conditions. Each movement trial lasted 20 s. For memory task presentation, one of the following was displayed (randomly).

- a spatial task
- a verbal task
- a spatial task followed by a verbal task
- a verbal task followed by a spatial task

Two of each possibility were assigned during each half, for a total of 16 memory loads. Each memory

task was of random difficulty, containing between one and seven items, presented at a rate of 1.8 s per card. Each half took approximately 15 min to complete. At intermission, the scene was paused and participants completed a short questionnaire with questions about their experiences using the interface. They were allowed to rest as long as they needed before beginning the second half.

After both halves (64 trials) were complete, participants were asked to complete a postquestionnaire and answer questions in a semistructured interview. Topics covered included strategies employed as well as overall opinions and suggestions regarding the locomotion interface.

4.2.3 Response Variables. In this study there were two task types: locomotion and memory. Participants' head positions were tracked using an InterSense IS-900 and logged every frame. The following response variables were used for the locomotion tasks.

Stop Time Time from presentation of a stop card until completely stopped.

Number of Collisions Number of collisions with virtual walls in a 15-s window preceding presentation of a stop card.

Percent-of-CAVE Average percent of CAVE used in a 15-s window preceding presentation of a stop card.

Physical Distance Total physical distance traveled in a 15-s window preceding presentation of a stop card.

Virtual Distance Total virtual distance traveled in a 15-s window preceding presentation of a stop card.

Additionally, all responses on the spatial and verbal memory tasks were recorded and checked for correctness.

4.3 Results

Analysis focused on verifying that the Fuzzy Navigation Engine was functioning properly, checking for an improvement in user performance with the Fuzzy P2V interface over the P2V interface, and assessing the choice of error metrics and ranges.

There were several instances of the system losing track of a participant's head position. These problems were usually obvious to the experimenters watching the scenario on a monitor. Some tracker problems were due to wireless interference and others were caused by strategies employed by a participant. For example, some users employed a lunging technique, likely to simplify finding and returning to the CAVE center. These rapid movements sometimes evaded the tracker because the head position was near the physical wall and relatively low to the ground, far from the optimal tracking area in the center of the CAVE. The experiment log files were parsed with a Python script capable of identifying likely head-tracker malfunctions. The affected results were flagged and discarded if they corresponded with experimenter observations. However, some data points that were removed from the analysis were still used to drive system learning, because learning was computed at runtime.

Some participants experienced simulator sickness and were allowed to opt out early at their discretion. These participants still completed many trials, which were included in the analysis. Note, however, that this led to fewer trials in round two than in round one. This affected the Fuzzy group more than the P2V group, a result described statistically in Section 4.3.1. The total number of trials for the P2V group was 747 and the total number for the Fuzzy group was 654.

4.3.1 Simulator Sickness. Several participants discontinued the study early due to simulator sickness. In the P2V group, all 13 participants made it to the second round and 12 completed the study. In the Fuzzy group, eight participants (out of 13) made it to the second round and seven completed the study.

An additional variable, *incidence of sickness*, was created to indicate whether a given participant opted out

at any time due to sickness. Logistic regression was performed with interface as the independent variable and incidence of sickness as the response. An analysis of deviance was conducted on this model, showing a significant effect of interface on incidence of sickness, $\chi^2(1, N = 26) = 5.29, p = .02$.

In order to check for an impact of sickness on the remaining dependent measures, new models were created with incidence of sickness as an additional fixed effect (plus interactions). These models were compared to reduced models without this new variable, according to their Akaike information criteria (AIC). The only model that improved with the addition of this variable was that of physical distance traveled, discussed further in Section 4.3.3.

4.3.2 Dead Zone Radius. The P2V group's dead zone radius of 1.50 ft was significantly larger than the mean dead zone radius for trials in the Fuzzy group, $M = 1.29, SD = 0.43, t(653) = -12.4, p < .01$. This means that, if all other measures were equal, the Fuzzy P2V interface allowed higher velocity and required less physical movement than the P2V interface. The larger dead zone also meant that the P2V region was slightly smaller due to the fixed physical boundaries of the CAVE.

4.3.3 Efficiency. Locomotion efficiency is defined as:

$$efficiency = distance_{virtual} / distance_{physical}. \quad (15)$$

A two-factors mixed model was constructed with efficiency as a response, fixed effects for interface and round combinations, and a random effect for participant. An ANOVA using the Satterthwaite approximation for degrees of freedom showed a marginally significant main effect of interface, $F(123.89) = 4.18, p = .052$. The least-squares means are plotted in Figure 9. Although not significant, this suggests that users of the Fuzzy P2V interface may move more efficiently than users of the P2V interface.

To better understand efficiency, the physical and virtual distances traveled were also analyzed. First, a two-factors mixed model was constructed with phys-

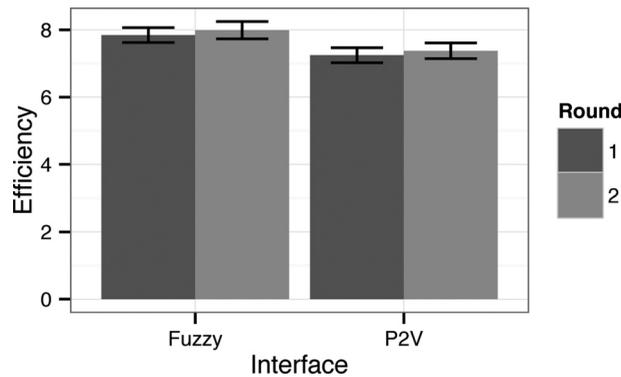


Figure 9. Least-squares mean (\pm standard error) efficiency as a function of interface and round.

ical distance as a response, fixed effects for interface and round combinations, and a random effect for participant. An ANOVA using the Satterthwaite approximation for degrees of freedom showed significant main effects of interface, $F(1, 23.99) = 4.50$, $p = .04$, and round, $F(1, 1349.28) = 9.46$, $p < .01$, as well as a significant interaction between interface and round, $F(1, 1349.28) = 8.24$, $p < .01$. The least-squares means are plotted in Figure 10(a).

Next, a two-factors mixed model was constructed with virtual distance as a response, fixed effects for interface and round combinations, and a random effect for participant. An ANOVA using the Satterthwaite approximation for degrees of freedom showed a significant interaction of interface and round, $F(1, 1349.10) = 8.19$, $p < .01$. The least-squares means are plotted in Figure 10(b).

These patterns of results indicate that the possible efficiency difference may have been driven primarily by reduced physical movement in the Fuzzy group, which was expected due to the smaller dead zone. The cause of the significant interactions in the physical and virtual distance results is unclear. It appears that users in the Fuzzy group may have tried not to (and thus did not) move as far in the second round.

As mentioned in Section 4.3.1, adding incidence of sickness as an additional fixed effect (plus interactions) led to a better fit in the physical distance model (AIC: 4,986.0; reduced model AIC: 4,986.9). A

new ANOVA was conducted using the Satterthwaite approximation for degrees of freedom. This showed a significant main effect of round, $F(1, 1329.20) = 7.56$, $p < .01$, a significant interaction of interface and round, $F(1, 1329.20) = 8.08$, $p < .01$, a marginally significant main effect of incidence of sickness, $F(1, 27.29) = 3.97$, $p = .056$, and a marginally significant interaction of incidence of sickness and round, $F(1, 1344.28) = 3.09$, $p = .08$. The interface main effect was not significant in the new model, meaning that efficiency results must be interpreted with caution.

4.3.4 Stop Time. If all other aspects were equal, the larger mean dead zone radius in the P2V group should have made stopping easier, leading to lower stop times. However, one objective of the Fuzzy P2V interface was to increase the dead zone radius when needed, due to the user's concurrent task load. This means that the interface is considered a success (with respect to stopping) if stop times are lower.

A two-factors mixed model was constructed with stop time as a response, fixed effects for interface and round combinations, and a random effect for participant. An ANOVA using the Satterthwaite approximation for degrees of freedom showed a significant main effect of round, $F(1, 1285.80) = 4.38$, $p = .04$, and a marginally significant main effect of interface, $F(1, 24.42) = 3.12$, $p = .09$. A corresponding plot is shown in Figure 11(a).

Recall that the system was not configured to directly lower the mean stop time, but to reduce the occurrence of outliers that were quantified using an error term that linearly mapped the range 5,000–30,000 ms to values from 0–1. A two-factors mixed model was constructed with the stop error term as a response, fixed effects for interface and round combinations, and a random effect for participant. An ANOVA using the Satterthwaite approximation for degrees of freedom showed significant main effects of interface, $F(1, 24.74) = 4.34$, $p = .048$, and round, $F(1, 1236.89) = 4.77$, $p = .03$. Figure 11(b) shows that the least-squares mean stop error term is lower for participants in the Fuzzy group than those in the P2V group.

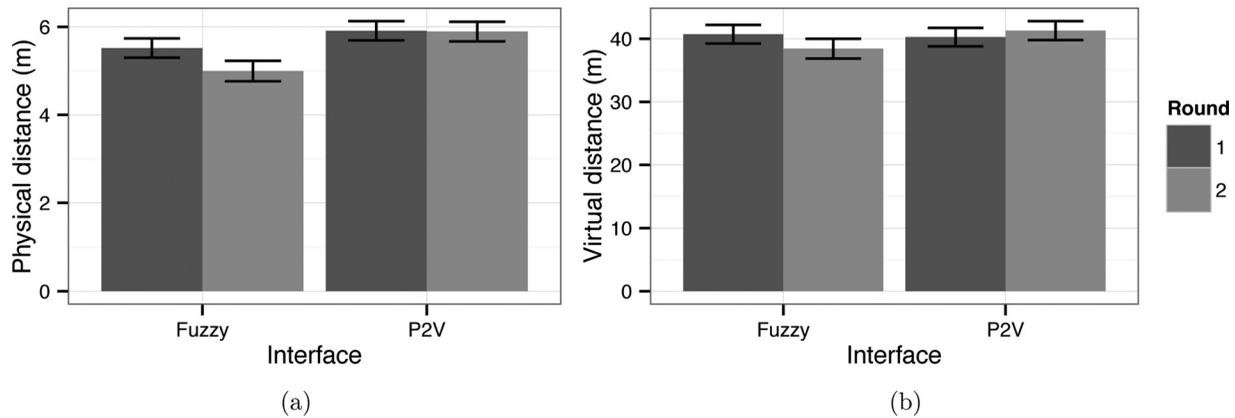


Figure 10. Least-squares mean (\pm standard error) distances that were (a) physical or (b) virtual as a function of interface and round.

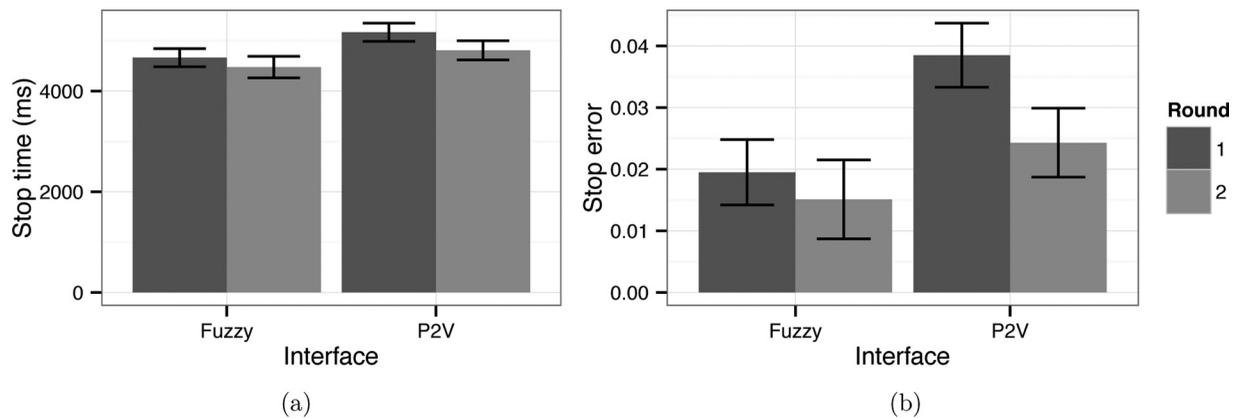


Figure 11. Least-squares mean (\pm standard error) stop time (a) and stop error (b) as a function of interface and round.

4.3.5 Number of Virtual Collisions. A two-factors mixed-model analysis was conducted with the number of virtual collisions as a Poisson response, fixed effects for interface and round combinations, and a random effect for participant. The analysis showed a significant main effect of round, $F(1, 1329) = 4.97$, $p = .03$, and a significant interaction between interface and round, $F(1, 1329) = 7.56$, $p < .01$. A plot of these results, shown in Figure 12(a), indicates that participants in the Fuzzy group reduced collisions in round two while those in the P2V group did not.

Recall that the system was configured to prevent collision counts greater than two, which were mapped to an error term. A two-factors mixed model was constructed with the collision error term as a response, fixed effects for interface and round combinations, and

a random effect for participant. An ANOVA using the Satterthwaite approximation for degrees of freedom showed a significant interaction between interface and round, $F(1, 1344.60) = 6.94$, $p < .01$. The plot in Figure 12(b) shows that the significant interaction seems to be due to a reduction in collisions from round one to round two in the Fuzzy group while the opposite pattern exists in the P2V group. It seems that participants in the Fuzzy group did better at learning to avoid collisions, perhaps because more cognitive resources were available to be allocated for this purpose. Alternately, the changing dead zone size may have made collision avoidance easier by restricting the users' maximum speed when resources were in demand by concurrent tasks. Collisions impede virtual travel, so this is a promising result.

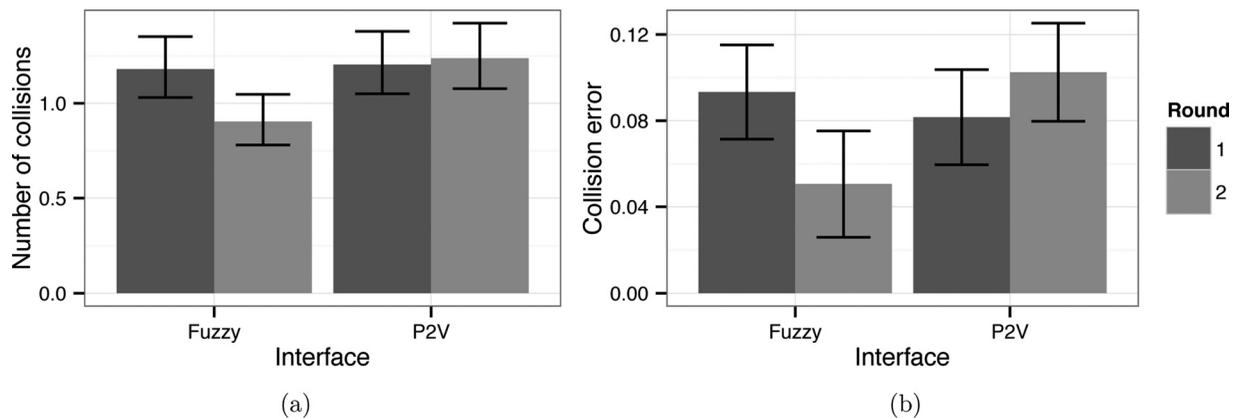


Figure 12. Least-squares mean (\pm standard error) for (a) collisions and (b) collision error as a function of interface and round.

4.3.6 Incorrect Memory Sequences.

A two-factors mixed-model analysis was conducted with spatial memory performance as a binomial response, reflecting correctness of the entire sequence, fixed effects for interface and round combinations, and a random effect for participant. The analysis showed no significant main effects or interactions. It seems that using the Fuzzy P2V interface had no impact on a participant's ability to remember a spatial sequence, although performance was low in both groups.

Another two-factors mixed-model analysis was conducted, this time with verbal memory performance as a binomial response. The analysis revealed a significant main effect of interface, $F(1, 24) = 12.34$, $p < .01$, a marginally significant effect of round, $F(1, 233) = 2.90$, $p = .09$, and a marginally significant interaction between round and interface, $F(1, 233) = 3.10$, $p = .08$. The plot in Figure 13 shows that these differences are driven primarily by extremely low performance in round two of using the Fuzzy P2V interface. Previous results fail to predict this pattern of means. In terms of multicomponent models of working memory, this may indicate that in the second round, participants either made a trade-off in which they sacrificed verbal performance in order to improve the movement performance described in Sections 4.3.3–4.3.5, or they utilized verbal or general attention resources in an attempt to understand the adaptation.

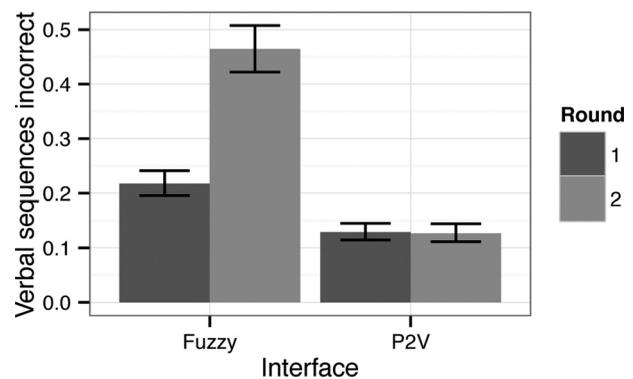


Figure 13. Least-squares mean (\pm standard error) verbal sequences incorrect as a function of interface and round.

4.3.7 Effectiveness of Learning. Participants in the formal study did not tend to use as much of the C6 as during the pilot study. The pilot study led to changes in the experimental procedures and also a different corridor model was used. Some combination of these factors may have led to users not needing or not wanting to use as large a physical area. This resulted in very few participants ever having percent-of-CAVE error terms greater than zero. For this reason, no analysis was performed on the percent-of-CAVE metric.

The results in Sections 4.3.3–4.3.5 provide evidence that adjusting the dead zone radius according to the defined fuzzy rules and sets was generally helpful in terms of locomotion performance, but these analyses did not directly assess the extent to which the system was

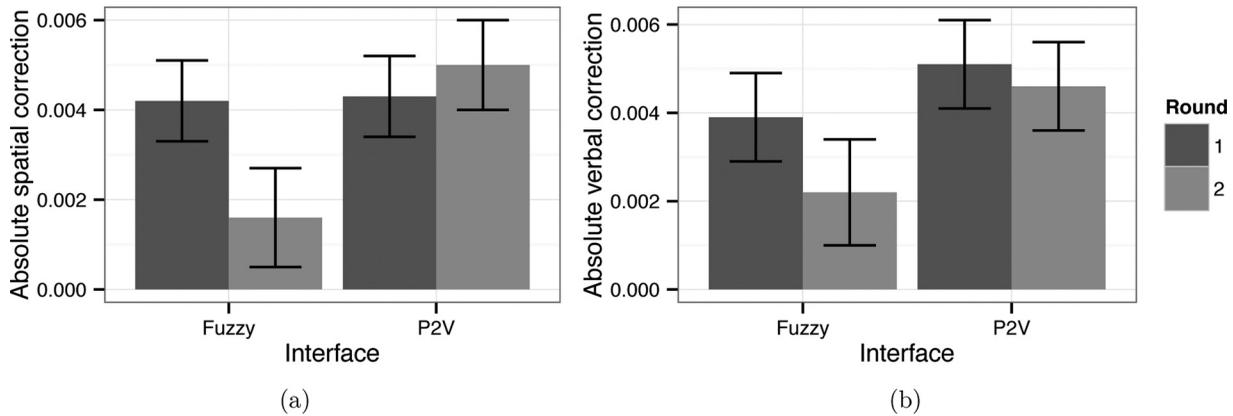


Figure 14. Least-squares mean (\pm standard error) absolute new (a) spatial and (b) verbal correction as a function of interface and round.

effective at improving itself. One way to measure how well the system learned is to look at the absolute value of the new verbal and spatial set corrections for each trial. As the system converges on optimal settings, the absolute value of new correction in each trial should tend to decrease, meaning that values should be lower in the second round if the system is learning effectively.

Recall that there were two broad types of error described in Section 3.5.1: participant error (collision error and stop error) and interface error (percent-of-CAVE error). User error means that the dead zone should be larger while interface error means that the dead zone should be smaller. Unfortunately, because interface error was rare, lower absolute new correction values may really mean that the user error is decreasing. In this way, participant learning may be confounded with system learning. However, a lower absolute correction value in round two than in round one would still reflect positively on the system.

Recall that error was calculated in each trial but correction was only calculated for a given memory type (spatial or verbal) if a task was assigned in that trial. Also note that correction was calculated for users of both interfaces, for comparison purposes, but it was not applied in the P2V group. A two-factors mixed model was constructed with absolute new spatial correction as a response, fixed effects for interface and round combinations, and a random effect for participant. An ANOVA using the Satterthwaite approximation for degrees of

freedom showed no significant main effects, but a significant interaction was found between interface and round, $F(1, 1192.87) = 3.98, p = .046$. As seen in Figure 14(a), there was a large drop in correction values from Round 1 to Round 2 in the Fuzzy group. Lower absolute new correction values indicate that the system may have been converging on more appropriate fuzzy input sets. This reduction is not seen in the P2V group.

Another model was fit with absolute new verbal correction as a response. The pattern of least-squares means, shown in Figure 14(b), looks similar to that for absolute new spatial correction; however, the analysis revealed no significant main effects or interaction.

5 Follow-up Trials

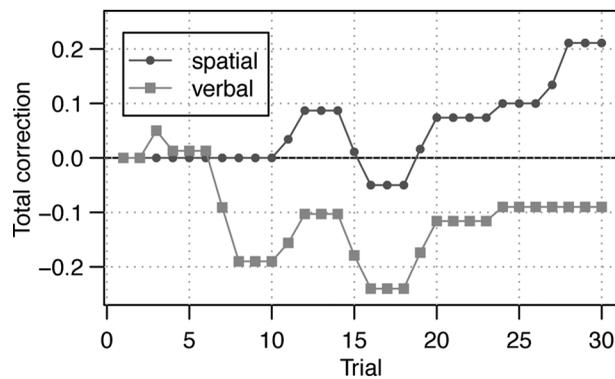
After analyzing the results from the study, the following parameters were modified and two more participants used the system:

- The dead zone membership functions were configured as shown in Table 2.
- The percent-of-CAVE error term (r_p) range was changed to 0.4–0.8, as shown in Equation 16.

$$e_p = \begin{cases} 0 & \text{if } r_p \leq 0.4 \\ \frac{r_p - 0.4}{0.4} & \text{if } 0.4 < r_p < 0.8 \\ 1 & \text{if } 0.8 \leq r_p \end{cases} \quad (16)$$

Table 2. Configuration of Dead Zone Membership Functions for the Follow-up Trials

Function	Trap,L			Trap,R		
	m	b	Range	m	b	Range
$\mu_{D,SMALL}$	2.0	-1.0	0.5-1.0	-2.0	3.0	1.0-1.5
$\mu_{D,MEDIUM}$	2.0	-2.0	1.0-1.5	-2.0	4.0	1.5-2.0
$\mu_{D,LARGE}$	2.0	-3.0	1.5-2.0	-2.0	5.0	2.0-2.5

**Figure 15.** One participant's total spatial and verbal correction with the new configuration.

The percent-of-CAVE error term was changed so that both positive and negative new correction values would occur, allowing the system to converge. The output set sizes were also adjusted because observations during the study indicated that the dead zone may have confused some users by changing too drastically. Both participants in these 32 trials used the Fuzzy P2V interface. They were familiar with VR and one had previously used the P2V interface.

Figure 15 is a plot of the total correction values for the first user, showing that the error function drove the total verbal and spatial correction in different directions. Recall that there is no change to a total correction value if the respective type of load (verbal or spatial) is currently 0. This is why there was no change to spatial for the first 10 trials and no change to verbal for the last six trials. The plot shows how the total correction of each variable behaves differently, in this case with total verbal correction being negative and total spatial correction being positive. The plot shows that the participant had

some locomotion troubles at first. He generated some user error that counteracted the interface error, meaning he would potentially benefit from a larger dead zone. After about 15–20 trials (about 8 min), he improved to the point where the interface error term was greater than the user error term. Using a large percent of the interface but not making many mistakes means that he may benefit from a smaller dead zone, at least during a concurrent spatial task.

6 Discussion

A fuzzy inference system was created based on past findings. The system adjusts the extent to which an interface is natural according to the user's current cognitive task load. The experimental results show that users of the new interface performed better on key performance metrics than users of a baseline P2V interface. On some metrics, it also appears that users of the Fuzzy P2V interface improved more from round one to round two.

The analysis of absolute new correction values provides evidence that the fuzzy inference system adjusted itself effectively, thus reducing the amount of needed correction to the input sets. The head-tracker problems during the experiment actually demonstrate robustness. Because these new correction values were affected by extraneous head positions, it is encouraging that the absolute correction values were still relatively low. This is an indication that the system adjusted itself conservatively enough that an occasional outlier did not impede learning. Unfortunately, learning typically only went in one direction for participants in

the study. Follow-up trials were conducted with an adjusted configuration of this error function. In these trials, the system adjusted itself in both directions, as expected. More testing is needed to further improve the settings.

In this study, users of the Fuzzy P2V interface were significantly more likely to opt out due to simulator sickness. Although the percentage of users experiencing sickness is not unprecedented (Kennedy, Lane, Berbaum, & Lilienthal, 1993), more research is needed.

Low verbal memory performance in the second round when using the Fuzzy P2V interface was unexpected and is difficult to explain in terms of past research. It will be important to do more research to determine whether this effect is real and, if so, to better understand the implications for future systems. It would be interesting to explore whether a trade-off exists in which users resorted to a verbally demanding strategy to improve upon stopping and collisions while using the Fuzzy P2V interface. Alternately, recall that the dead zone was depicted by a red circle on the floor, so participants probably noticed that the size changed from trial to trial. If participants had available resources during verbal tasks, they may have tried to understand how the interface was adapting. This may have required verbal attention resources.

In the future, the same basic fuzzy inference system can be extended by adding additional output variables or by changing the dead zone adaptation demonstrated here. For example, only the dead zone radius was manipulated in this research, and it was a symmetric adjustment. It is possible that other aspects of the P2V interface could be adjusted, such as the gain when outside the dead zone, although care must be taken not to hinder the user's learning process. It is also possible that the dead zone could be asymmetric. For example, perhaps natural walking is more important for movement in one direction than another, and the dead zone shape could reflect this. This presents some possible implementation problems, such as how to differentiate between the direction a user's head is facing, the direction the body is facing, and the direction of intended movement. It may also confuse the user, particularly when rotations are performed outside the dead zone.

For real-world use, more research should be conducted to learn how to more accurately assess current utilization of working memory resources. In some domains, such as piloting unmanned vehicles on search and rescue missions, keeping count of the entities that a user must track may be sufficient for a rough estimate of load. However, load would be very unpredictable in more complex scenarios. A future possibility would be to incorporate pupillometry or other physiological measures (Hirshfield et al., 2009; Grimes, Tan, Hudson, Shenoy, & Rao, 2008) for a true augmented cognition system. However, the power of the system described here lies partly in its use of basic, easily assessed metrics.

Acknowledgments

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