Towards an Information-Theoretic Framework for Quantifying Wayfinding Information in Virtual Environments

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Abstract

Signage systems are critical for communicating environmental information. Signage that is visible and properly located can assist individuals in making efficient navigation decisions during wayfinding. Drawing upon concepts from information theory, we propose a framework to quantify the wayfinding information available in a virtual environment. Towards this end, we calculate and visualize the uncertainty in the information available to agents for individual signs. In addition, we expand on the influence of new signs on overall information (e.g., joint entropy, conditional entropy, mutual Information). The proposed framework can serve as the backbone for an evaluation tool to help architects during different stages of the design process by analyzing the efficiency of the signage system.

1 Introduction

Information theory is the branch of mathematics used to describe how uncertainty can be quantified, manipulated, and represented [Ghahramani, 2007]. According to Shannon and Weaver [Shannon and Weaver, 1949], a communication system can be characterized with respect to this uncertainty and the information being transmitted. Modeling the exchange of information within a system essentially involves representations of uncertainty and can facilitate an understanding of the behavior and properties of its individual elements. This approach has been applied to several different types of systems, including those from computer science, philosophy, physics, and cognitive science [Smyth and Goodman, 1992; Floridi, 2002; Still, 2009; Resnik, 1996]. For example, information may be transferred within and between internal and external representations of space [Craik and Masani, 1967] [Montello *et al.*, 2004]. In the present work, we propose an information-theoretic approach to quantify the spatial information provided by individual or sets of signs for wayfinding in a virtual environment.

Navigation is a process by which internal spatial representations are obtained. In turn, these representations act as the basis of future navigation decisions. In unfamiliar environments (i.e., before any initial representation), individuals often have to rely on knowledge that is immediately available in the environment [Golledge, 1999]. However, this relevant information must be separated from irrelevant information and noise. There are a variety of visual cues in the environment that can help individuals find their way (e.g., signage, maps, landmarks, and building structure) [Montello, 2005; Arthur and Passini, 1992]. Signs may be particularly easy to interpret (i.e., require less abstraction than a map), adapt (i.e., can accommodate changes to the environment), and quantify (i.e., allow for the measurement of relevant information). An efficient signage system can drastically reduce the complexity of the built environment and improve the wayfinding. In contrast, an inefficient signage system or lack of signage can render a simple built space complex and stressful for patrons. Indeed, signs are typically used to guide unfamiliar patrons to specific locations within shopping centers and airports [Becker-Asano *et al.*, 2014]. An efficient signage system can drastically reduce the navigational complexity of such environments, but this reduction in complexity or uncertainty (i.e., information) is not always evident to the architect using existing measures (e.g., space syntax; [Hillier and Hanson, 1984]). This is critical for both leisurely shopping trips and emergency evacuations in which the consequences of inefficient signage can range from getting lost to becoming injured. Individual signs must be placed at an optimal height and be sufficiently salient in different lighting conditions [Jouellette, 1988]. In addition, different signs within a wayfinding system must continuously provide complementary information rather than information that conflicts with other elements and confuses the users. Hence, the foundation of such a signage design tool should be grounded in research that investigates human perception and cognition.

In this paper, we first review previous research on information theory, human wayfinding, and signage systems. Next, we introduce our framework for quantifying information and uncertainty for systems of signs in complex virtual environments and apply these measures to signs within a virtual airport. The results are discussed with respect to the development of a novel application to aid architects in the (re)design of real environments.

2 Background and Prior Work

This section briefly describes both Shannon's basic measures of information and summarizes research on navigation and signage.

2.1 Information theory

Information theory was developed in the 1940s and 1950s as a framework for studying the fundamental questions of the communication process, the efficiency of information representation, and the limits of reliable communication [Atick, 1992] [Shannon and Weaver, 1949]. In information theory, entropy represents the amount of uncertainty in a random variable as a probability distribution. The Shannon entropy of a discrete random variable X with alphabet χ and probability mass function $p(x), x\epsilon\chi$ is defined as

$$H(X) = -\sum_{x\epsilon\chi} p(x)log_2 p(x) \quad (1)$$

The probability of x, $p(x)\epsilon[0.0, 1.0]$ and $-log_2 p(x)$ represents the information associated with a single occurrence of x. Entropy is always positive and represents the average number of bits required to describe the random variable. Entropy is a measure of information such that higher entropy represents more information.

There are several measures that combine information from two random variables [Cover and Thomas, 1991]. Joint entropy represents the information provided by either one random variable or a second random variable in a system. The joint entropy of a pair of random variables (X, Y) with a joint probability distribution $p(x, y)$ can be represented as

$$H\left(X, Y\right) = \sum_{x\epsilon\chi}\sum_{y\epsilon\gamma} p(x, y)logp(x, y) \quad (2)$$

In addition, conditional entropy $H(X|Y)$ is the entropy of one random variable given knowledge of a second random variable. The average amount of decrease in the randomness of X given by Y is the average information that Y provides regarding X. The conditional entropy of a pair of random variables (X, Y) with a joint probability distribution $p(x, y)$ can be represented as

$$H\left(X|Y\right) = \sum_{x\epsilon\chi}\sum_{y\epsilon\gamma} p(x, y)log\frac{p(x)}{p(x, y)} \quad (3)$$

Mutual information quantifies the amount of information provided by both random variables. The mutual information $I(X; Y)$ between the random variables X and Y is given as

$$I(X; Y) = \sum_{y\varepsilon Y}\sum_{x\varepsilon X} p(x, y)log(\frac{p(x, y)}{p(x)p(y)}) \quad (4)$$

In Section 3, we will describe how the aforementioned measures can be used to quantify the information provided by two (or more) signs in an environment.

2.2 Navigation and signage

In an unfamiliar environment, navigation largely depends on picking up ecologically relevant information (i.e., affordances; [Gibson, 1977]). In such cases, optic flow can be used to guide locomotion by distinguishing between self movement (relevant for navigation) and object movement [Fajen, 2013]. Signs are also capable of providing ecologically relevant information but need to be visible and interpretable [Becker-Asano *et al.*, 2014]. Indeed, Norman [1988] differentiates between knowledge in the world (e.g., information presented on signs) and knowledge in the head (e.g., the interpretation of signs).

The communication of wayfinding information from the world to the individual observer can be facilitated by an appropriate signage system or map [Arthur and Passini, 1990] [Allen, 1999]. Previous research has demonstrated that signage has distinct advantages over maps for navigating the built environment [Holscher *et al.*, 2007; O'Neill, 1991] also found that textual signage led to a reduction in incorrect turns and an overall increase in wayfinding efficiency compared to graphic signage (i.e., an arrow; see also [Wener and Kaminoff, 1983]). Both simulations and user experiments have suggested that the focus of visual attention can be improved with signage redesigns ([Becker-Asano *et al.*, 2014] [Buechner *et al.*, 2012]). In addition, signage can improve simulated evacuation times [Xie *et al.*, 2012] and the perception of crowding and its negative effects [Wener and Kaminoff, 1983].

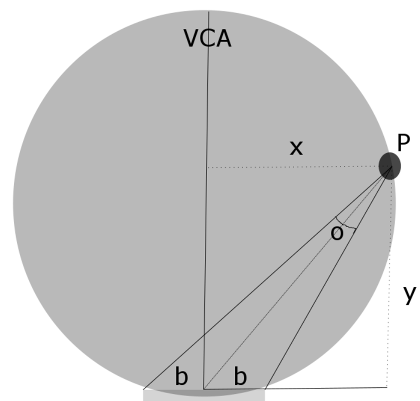

Figure 1: The circular visual catchment area (VCA) of a sign A. The sign is considered visible if an occupant is standing inside the circular area located at the tangent to the surface of a sign.

Visual Catchment Area. One existing way of quantifying the visibility of a sign is its visual catchment area (VCA; [Galea *et al.*, 2001]). VCA represents the area from which a sign is visible when the observer faces the sign. Xie and colleagues [Xie *et al.*, 2007] consider the visibility of a sign as a binary value. In other words, the sign is visible within the VCA and not visible outside of the VCA. The VCA of a sign is calculated using the location of the sign, the height of the occupant and the sign above the floor, viewing angle, and the maximum distance from which the sign can be seen based on the size of its lettering. According to the National Fire Protection Association (NFPA) Life Safety Code Handbook, signs with a lettering height of 152 mm are legible for up to 30 m [NFPA *et al.*, 1997]. The calculation of a sign's VCA are described below:

$$\left(\frac{b}{sin(o)}\right)^2 = x^2 + \left(y - \frac{b}{tan(o)}\right)^2 \quad (5)$$

Here, o is the angular separation of the sign and viewer, b is half of the size of the sign's surface, and *P(x,y)* represent the viewer's location shown in Figure 1. The center at location $(0, \frac{b}{tan(o)})$ with a radius of $\frac{b}{sin(o)}$.

3 Proposed Framework

In this section, we apply the principles of information theory to quantify the information provided by signage in a virtual environment. While there are a number of physical and psychological factors that influence the effectiveness of signage systems (e.g., color and contrast, interpretability and and attentiveness), we will focus exclusively on signage visibility. Rather than considering sign visibility as a binary value [Xie *et al.*, 2007], we model sign visibility as a continuous function, which depends on distance and direction from the observer. We model the entropy of a sign's visible information $P(l, s)$ as a measure of the navigation-relevant information that is available to an agent at location l from sign s. Let $X(l, s_a)$ be a random variable that represents a particular piece of information at a location l and sign s_a. The probability of a particular value for the random variable $X(l, s_a)$ will depend on the distance of sign s_a from the location l and the relative angle between location l and sign s_a. The probability distribution is generated by sampling information X from sign s_a at l 1000 times. Based on our experiments, we found 1000 samples to provide a reasonable trade-off between granularity of calculations, and compute time. Further investigation is needed to determine the sensitivity of our calculations based on this parameter.

The uncertainty function $U(l, s_a)$ represents the likelihood of viewing information from a sign s_a at location l as

$$U(l, s_a) = N(\mu, \sigma) \quad (6)$$

N is a normal distribution with mean μ and standard deviation σ. In addition, μ is directly proportional to the distance and relative angle between sign s_a and location l. Larger distances and relative angles between sign s_a and location l result in higher values for μ (i.e., closer to 1), and σ represents the range of uncertainty values (which are held constant). Here, μ is dependent on the mean of the normalized distance d_n (over 30 m) and normalized relative direction ra_n (over 180 degrees; see Equation 7). Δ is the weight of the sum between distance and the relative direction:

$$\mu = (d_n + \Delta ra_n)/2 \quad (7)$$

The work done in [Filippidis *et al.*, 2006], makes an assumption between the relationship of the relative direction between the observant and the sign with the probability of visibility (see Figure 2). We use this relationship in the calculation of μ (see Equation 7) and add our own assumption of probability of visibility with the distance between the observant and the sign (see Figure 3).

These two relationships form the basis of $I(s_a)$ (i.e., the actual information contained in sign s_a) and can be combined with Equation 6 to calculate $Noise$:

$$P(l, s_a) = Noise(I(s_a), U(l, s_a)) \quad (8)$$

We can then substitute $P(l, s_a)$ for $p(x)$ using Shannon's entropy equation (Equation 1) and Equation 8 to obtain a measure of entropy for a sign from the observer's location.

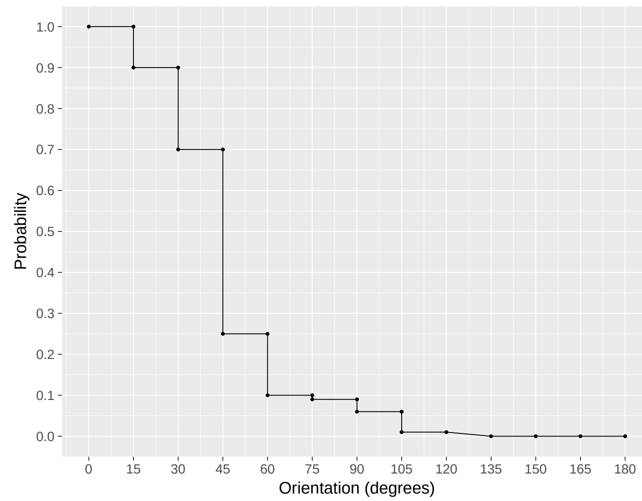

Figure 2: Proposed hypothetical detection probability according to the orientation between occupant travel direction and sign's directional vector

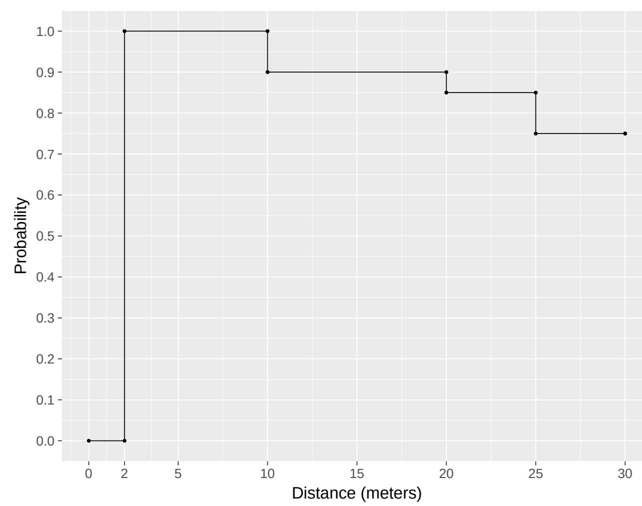

Figure 3: Proposed hypothetical detection probability according to the distance between occupant and the sign

Information measures that describe signage systems can also be extended for the combination of two or more signs. Another random variable $Y(l, s_b)$ can be used to represent the amount of navigation-relevant information available to an agent at location l from a second sign s_b. An uncertainty function $U(l, s_{a,b})$ can represent the likelihood of viewing information from two signs (s_a and s_b) at location l:

$$U(l, s_{a,b}) = N((\mu_a + \mu_b)/2, \sigma) \quad (9)$$

Finally, the joint probability distribution can be computed by sampling information X from sign s_a and sign s_b at l several times:

$$P_{a,b}(l, s_{a,b}) = Noise(I(s_a), U(l_i, s_{a,b})) \quad (10)$$

For all locations from which both signs are visible, we can calculate joint entropy, conditional entropy, and mutual information. The joint entropy of visible information from both signs s_a and s_b refers to the amount of information contained in either of the two random variables X and Y. For two mutually independent variables X and Y (i.e., when the two signs can be viewed from each other), joint entropy is the sum of the individual entropies $H(X)$ and $H(Y)$ for each sign. When the two variables are not mutually independent, joint entropy $H(X, Y)$ can be calculated by using equation 2 in which the joint probability distribution $P_{a,b}$ is defined by equation 10. In the case of signage, joint entropy indicates the extent to which an observer may navigate from one sign to another towards a goal location.

Conditional entropy is the reduction in uncertainty (i.e., information from the sign s_a) due to the presence of another sign s_b and vice versa. For example, an observer is located between signs s_a and s_b but closer to s_b. Both signs are indicating the same destination along the same route. The probability of viewing the information from sign s_a is low because the individual entropy of s_a is high. At the same time, the probability of viewing information from s_b is high because the individual entropy of s_b is low. Because the two random variables are not mutually independent, conditional entropy for s_a given s_b is lower than the individual entropy of s_a, and conditional entropy for s_b given s_a is lower than the individual entropy of s_b. In other words, both signs become more visible in the presence of the other sign. In addition, the conditional entropy of s_b given s_a is lower than the conditional entropy of s_a given s_b. Because entropy is inversely related to the probability of viewing each sign, s_b is more visible than s_a from this location.

Mutual Information measures the correlation of the two random variables X (information from sign s_a) and Y (information from sign s_b). It quantifies the amount of information known about sign A by knowing sign B and vice versa. Mutual information can be calculated as the difference between conditional entropy for any sign and its corresponding individual entropy. Higher mutual information represents higher redundancy, which may result in improvements in navigation performance. However, increases in redundancy may not be linearly related to improvements in navigation performance. The information measures presented here provide one method for estimating the expected increase in performance for each additional sign.

In Figure 9 MI can be computed by subtracting the entropy of sign A(in black) with the conditional entropy of sign A with sign B(shown in yellow).

4 Experiments and Results

In this section, we use a simplified building information model (BIM) of a virtual airport (Figure 4) in order to illustrate the information theoretic approach to signage systems. The model was created using Autodesk Revit [Revit, 2012] and then imported into Unity 3D [Unity3D, 2016] to perform simulations. In this example, the 3D model of the building includes two signs placed at different locations and pointing towards a common destination (represented by A and B in the Figure 4). The walkable region of the floor of the 3D built environment was divided into n square grid cells of 0.5 m x 0.5 m. This grid cell size approximates the space occupied by an average human.

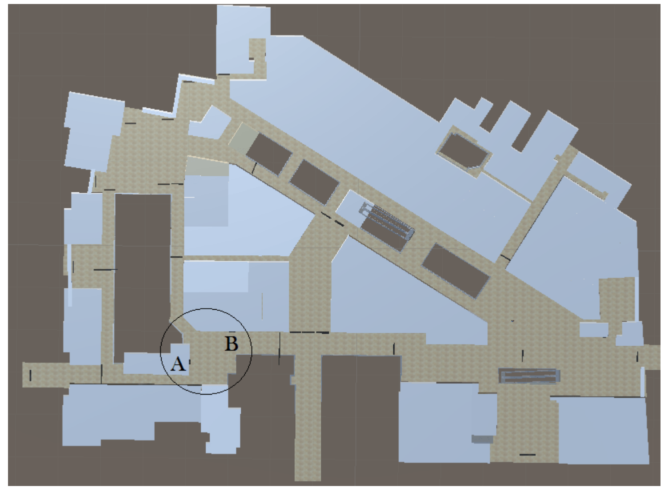

Figure 4: Top-down view of a virtual airport. Letters A and B indicate the location of two signs in a section of the airport.

Figures 5 (a) illustrate the probabilities of viewing wayfinding information provided by signs A from several locations (represented as density maps). These uncertainties are based on the distance and relative direction of the grid cell from each sign according to the functions in Figures 2 and 3 as well as Equations 6, 7 and 8. Agents at grid cells in a lighter shade of gray have a higher probability of viewing the information provided by the sign than agents at grid cells in darker shades of gray. Agents at grid cells at greater distances or larger relative directions from each sign have smaller probabilities of viewing the information compared to agents at grid cells at smaller distances or relative directions from that sign. Black grid cells do not provide any information to an agent. Figures 5 (b) and (c) represents the first person view of an agent from a location which has high information (shown in yellow star in 5 (a)) and an agent from a location which has low information ((shown in yellow circle in 5 (a)). The text on the signage is visible from a high information location since the distance between the agent and the signage along with the relative angle between them is acute. Which results in lower value of entropy and a higher probability of perceiving the information. Which is not the case from the location which is outside the VCA ((shown in yellow circle in 5 (a)). The relative angle between the agent and the sign is high which creates more noise and increases the entropy of visibility. We showcase the similar effect for the sign B in 6 (a), (b) and (c).

Figure 7 (a) illustrates the individual and joint probabilities of viewing the information provided by both signs A and B

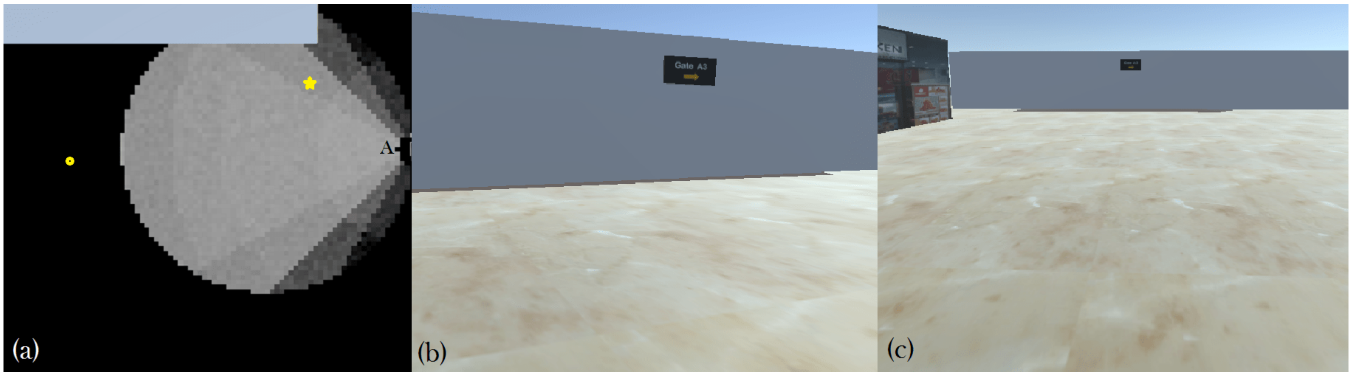

Figure 5: (a) Visualization of the probability of perceiving the information from Sign A. The yellow star and circle represent two locations where information is high and low with respect to sign A (b) First person view from yellow star where information is high with respect to sign A (c) First person view from the yellow circle where information is low with respect to sign A.

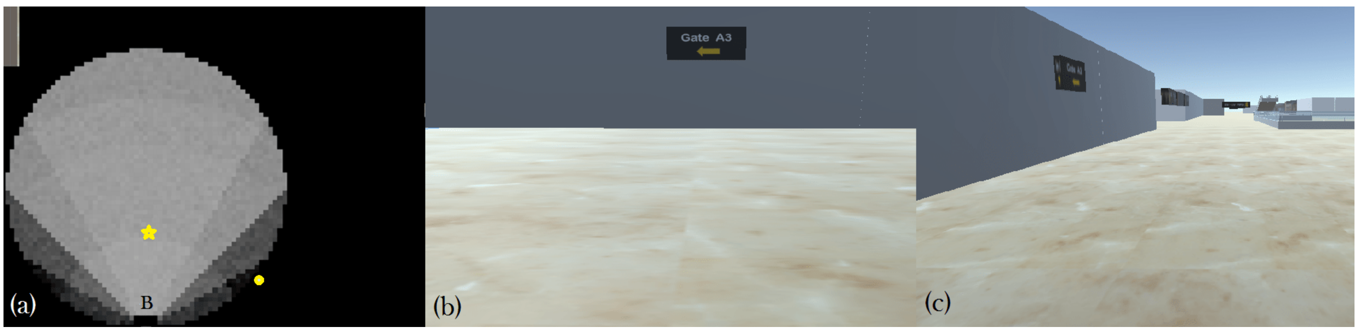

Figure 6: (a) Visualization of the probability of perceiving the information from Sign B. The yellow star and circle represent two locations where information is high and low with respect to sign B (b) First person view from the yellow star where information is high with respect to sign B (c) First person view from the yellow circle where information is low with respect to sign B.

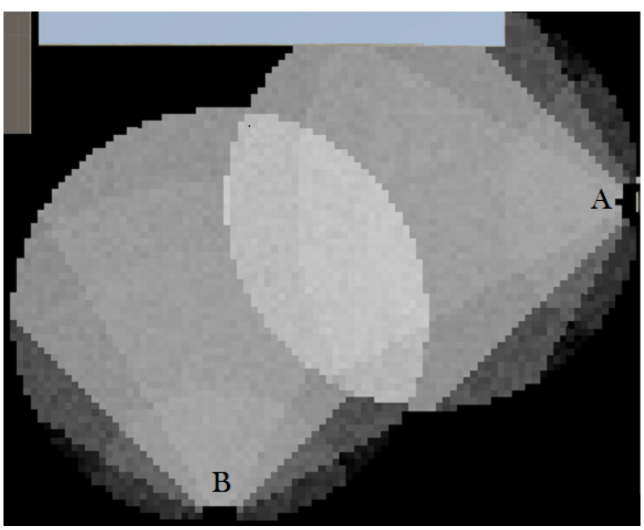

Figure 7: Visualization of the probability of perceiving the information from Sign A, B and the mutual information (lighter grids) between them

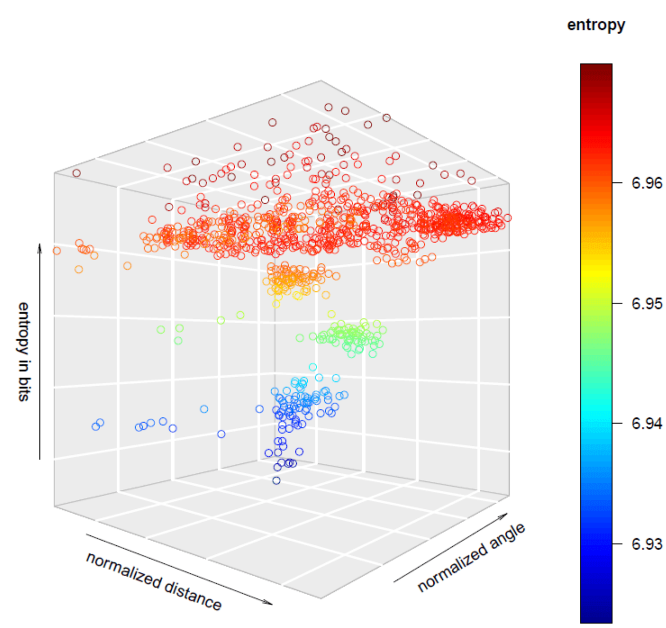

Figure 8: Entropy of the information perceived from varying distance and relative angle with sign A

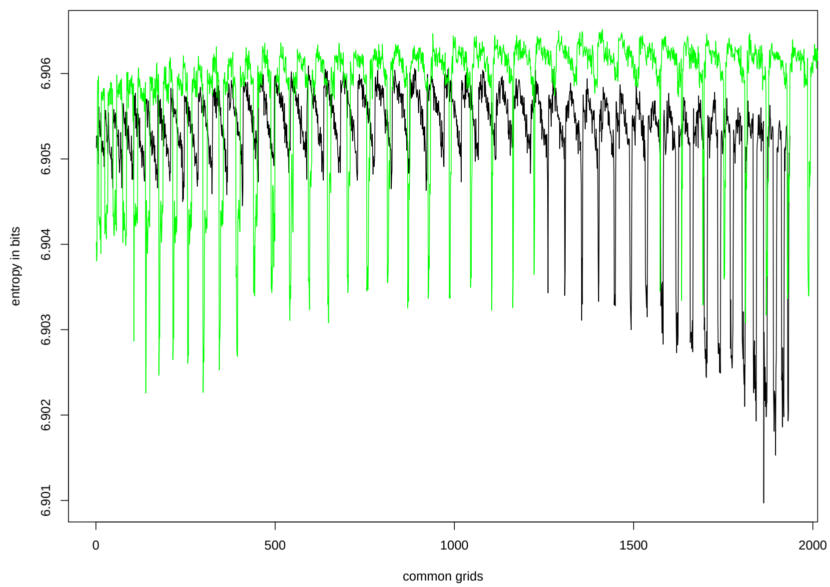

Figure 9: Entropy of perceived information from sign A (in green) and conditional entropy of sign A with sign B (in black).The difference in the entropy value captures the mutual information between the information from Sign A and Sign B.

from each grid cell. The probability of viewing information from both signs (i.e., mutual information) is higher than the probability of viewing the information provided by either sign in isolation for the common grid cells.

Figure 8 demonstrates the relationship between the information viewed from sign A, the distance of the observer from sign A, and the relative direction of the observer from sign A. An increase in entropy indicates higher uncertainty in viewing the information provided by sign A. Finally, Mutual information can also visualized in Figure 9 as the difference between individual and conditional entropies. Here, the green line represents the individual entropy of sign A, and the black line represents the conditional entropy of sign A given sign B.

5 Conclusions and Future Works

The quantification of information provided by a system of signs can be beneficial to architects attempting to improve the navigation of building patrons. This approach may be particularly useful for buildings that are especially complex and require redesigns of signage. For this paper, we adapted Shannon's entropy measures in order to study the information provided by two signs in a 3D virtual environment. We then visualized these entropy measures in an understandable way for practitioners, including architects and engineers. The benefit of using a gaming engine (Unity 3D) is that these visualization can be dynamically updated during navigation.

For simplicity, we have focused on the distance and relative direction between the observer and one or two signs. Future work will extend this framework to include additional physical and psychological factors (e.g., color and contrast, interpretability and attentiveness) and additional signs (i.e., more than two). The former addition will provide the groundwork for a cognitively inspired, agent-based model of navigation behavior. Additional signs will allow us to address some of the difficulties associated with decomposing complex systems in terms of information theory (see [Griffith and Koch, 2014] [Griffith and Ho, 2015]).

We also plan to further inform this framework with at least two empirical studies with human participants in virtual reality. The first study will investigate the relationship between the visibility of a sign at different distances and relative directions at a finer granularity than previous work. The second study will test different signage systems with respect to their effect on the wayfinding behavior in complex virtual buildings. Together, these studies will provide the necessary groundwork for incorporating research on human perception and cognition into evidence-based design.

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