Towards a Virtual Reality Elicitation of Building Occupancy

R.N. Stewart*[1], M. Urban[1], D. Anderson[2], S. Duchscherer[1], E. Axley[2], and J. Piburn[1]
[1]Oak Ridge National Laboratory, 1 Bethel Valley Road, Oak Ridge, TN 37831
[2]Cadre 5, 804 Innovation Drive, Knoxville, TN 37932
*Email: stewartrn@ornl.gov

Abstract

Building occupancy estimation techniques vary widely and many require experiential knowledge to fill information gaps and harmonize disparate data sets to produce answers over large geographic extents. The tight connection between human experience and computational techniques means estimation is well suited for Bayesian approaches that encode prior occupancy knowledge in mathematical form. In 2013, Oak Ridge National Laboratory published a formal elicitation that transforms occupancy knowledge obtained through survey questions into a statistical prior distribution. While the transformation of answers into a prior was a key result, how those answers were collected require substantial improvements. Using only a personal knowledge/memory and limited graphical images of similar occupied facilities, users had to respond to questions about occupancy. This required them to recall past experiences and apply mental heuristics for estimating area and population count, a challenge for humans to perform accurately even under direct scene observation. We propose instead to immerse knowledge contributors in a virtual facility space where they can observe occupancy the same as in a real-life scene: namely a first person, navigable engagement with space and place. Users control and fine tune virtual occupancy until the scene looks like *what they know* and the computer easily calculates area and count. We assert this approach will alleviate much of the burden in responding to survey questions as well as improve occupancy estimation. We review prior work, propose a VR based elicitation approach, and indicate next steps.

Keywords: virtual reality, elicitation, occupancy, population, Bayesian.

1. Introduction

Elicitation is a formal process by which human knowledge is transformed into empirical, computer-friendly representations (e.g. prior) and has a long history of use where critical information is limited, expensive, or dangerous to collect (see Stewart et al. 2016 for a brief historical account). In the main, elicitation facilitators usher participants through an interview process with preparatory training, tools, questions, and feedback mechanisms designed to obtain a quality knowledge capture. Stewart et al. 2013 developed an ambient occupancy elicitation that transformed survey answers about area, typical occupancy ranges, unusually high occupancy and unusually low occupancy to moments of the Beta distribution (without saying so). For example, "What is a common range for the average (ambient) number of people?" related to a reasonable interval for the statistical mode of the Beta distribution (Question wording is slightly different over Stewart et al. 2013 due to operational feedback).

Mathematics developed for transforming survey answers into a prior is the key result of the paper. However, the process of obtaining answers with only the aid of memory and static facility images needs considerable improvement. Estimating area or crowd size in open or divided spaces requires mental and rule of thumb heuristics that are neither easy nor reliable even under direct observation (e.g. Watson and Yip, 2011). Estimating average occupancy is even more difficult. More difficult still are heuristics applied to a recollection of past experiences where one is a step further removed and limitations of human recall and biases enter the mix (Tversky and Kahneman, 1974).

We hypothesize that immersing contributors in a virtual reality (VR) space closely resembling the facility of interest will significantly outperform static images because it situates the contributor in a first person view of the scene, immersed in place, and among other occupant avatars. This is the perspective we all have of place, of divided rooms, people in motion, and our own ability to move through the scene. We anticipate pre-constructed navigable VR scenes with known area and user controlled occupancy will reanimate memory and remove mental heuristics for guessing empirical densities. Instead, users create scenes for themselves until it looks like they believe to be true at which point counting avatars and area is a trivial computer task. Furthermore, we demonstrate that by reintroducing time as a factor we can elicit actual occupancy scenarios rather than average occupancy scenarios by removing a second significant barrier to quality knowledge capture.

Herein we propose a VR adaptation of the elicitation process of Stewart et al. 2013 and report on implementation progress including a prototype VR, specific modifications, and next steps.

2. Virtual Occupancy (VO)

VO is a proof of concept immersive virtual reality experience developed for this study. VO was created in Unity and is deployable to desktop, web, or 3d device. 3D physical facility models developed for VO are enriched by avatar roles, spawn, path, and points of interest locations. For example, a restaurant facility model may include an employee role and a customer role. When users increase employees/customers they will spawn at predefined employee/customer points and move in approved employee/customer lanes to other points of interest such as the kitchen/table. During elicitation users control the temporal context (time, day, season) the spatial context (country, urban, rural), the number of avatars in each role, and how quickly they move between points of interest; this allows considerable control over scene creation.

Figure 1: First person view of village scene with multiple structures (unfortunately POC does not yet represent local ethnicity and clothing customs/fashion).

For multi-building scenes (Figure 1), users control whether avatars can move in and out of the separate structures. While PDT is focused on interior density allowing a full scene to unfold improves the realism of the experience.

3. Modified Elicitation

Contributors now report direct experience (rather than ambient) by creating an occupancy signature with VR elicitation at different points along a timeline. These signatures are later averaged into a single ambient occupancy. Four signatures for each elicitation are utilized: 1) High use 2) upper typical 3) lower typical, and 4) low use. Figure 2 illustrates a hypothetical “typical upper” signature. Temporal granularity will depend on the user and not everyone may have experience in each of these four scenarios. Multiple contributors can help complete signatures and we adopt the behavioral aggregation approach for collaborative elicitation (see Phillips, 1999).

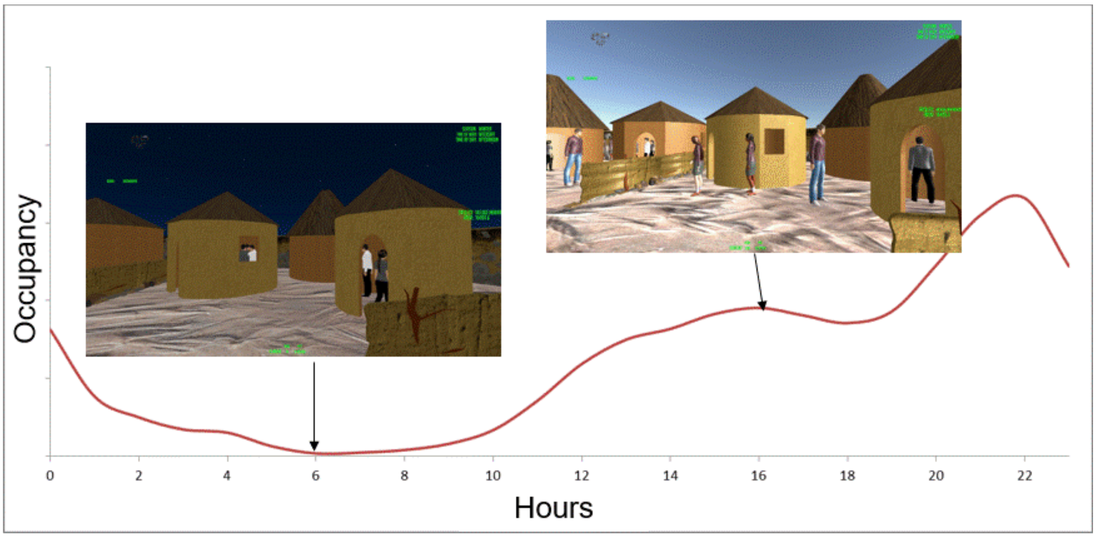

Figure 2: Hypothetical elicited occupancy signature using VR scenes (only 2 shown).

The signature could be developed entirely from scratch. The user selects timeline points, creates example scenes initiated with zero occupancy, and generates occupancy estimates which are then interpolated between for a complete signature. Alternatively, the user begins with a series of signature shapes obtained through social media check-in analytics (Stewart et al., 2017; Thakur et al. 2016) or existing signatures from similar geographic regions. Scenes at selected points are pre-populated with avatars expediting the process as users ostensibly make smaller up or down adjustments. This does introduce the possibility of anchor bias where initial suggestions tend to limit the variability of responses (Tversky and Kahneman, 1975) and will need to be investigated.

The average of the high use, typical upper, typical lower, and low use signatures are respectively the 90^{th}+ percentile, the lower and upper mode, and the 10^{th} percentile ready for input into the same transformation algorithms in Stewart et al. 2013. Facilitators can also report a confidence in the elicitation as in Stewart et al. 2013. Confidence in scenario lines depend on how deep the experience of the contributors goes. Contributors with a single restaurant visit will have a lower confidence than contributors with continued and wide experiences.

4. Discussion and Next Steps

The advance here is 1) contributors recount actual occupancy experiences rather than heuristically estimated average occupancy, 2) contributors are situated in a first-person view emulating a real-life perspective, and 3) removal of the requirement to count people or estimate area. In the next step, we propose an experiment in which subjects are exposed to an occupied space where the occupancy and square footage are accurately known (by the administrators). We then elicit these quantities from those subjects to address four specific questions about human estimation and recollection abilities. How well do humans estimate human count and square footage when present in the actual scene? How well do humans estimate these quantities when removed from the scene? Can humans outperform these estimates using VR scene construction? Finally, how does engaging a generic VR scene that represents the “essence” of the space they understand deteriorate the quality of the elicitation? The latter question emerges from a practical view that we cannot create exact replicas of each facility for each elicitation but rely instead on representative models. We anticipate these results to be critical in shedding light on how VR technologies can strengthen the accuracy of human estimation and recollection.

5. Copyright

6. References

Bolstad, W. 2007. *Introduction to Bayesian Statistics*. John Wiley & Sons, Hoboken: NJ.

Herrmann, C. and Metzler, J. 2013. Density estimation in aerial images of large crowds for automatic people counting In: *SPIE Proceedings: ISR Processing III: Image Exploitation*, Baltimore, MD.

Phillips, L. 1999. Group Elicitation of Probability Distributions: Are Many Heads Better than One? In: *Decision Science and Technology: Reflections on the Contributions of Ward Edwards*, MA: Kluwer Academic Publishers, pp. 313-330.

Stewart, R.N., Piburn, J., Weber, E., Urban, M., Morton, A., Thakur, G., and Bhaduri, B. 2017. Can Social Media Play a Role in the Development of Building Occupancy Curves? In: Griffith, D.A., Chun, Y. and D. J. Dean. eds. *Advances in Geocomputation: Geocomputation 2015--The 13th International Conference, Dallas TX.* Cham: Springer International Publishing: pp. 59-66.

Stewart, R.N., Urban, M., Duchscherer, S., Kaufman, J., Morton, A., Thakur, G., Piburn, J., and Moehl, J. 2016. *A Bayesian Machine Learning Model for Estimating Building Occupancy from Open Source Data*, Natural Hazards **81**(3), pp. 1929-1956.

Stewart, R.N., White, D., Urban, M., Morton, A., Webster, C., Stoyanov, M., Bright, E., and Bhaduri, B. 2013. Uncertainty quantification techniques for population density estimates derived from sparse open source data In: *Proceedings of the SPIE: Geospatial InfoFusion III (refereed)*: **8747** 874705-7. [Accessed 4/10/2017] Available from: proceedings.spiedigitallibrary.org/proceeding.aspx?articleid=1691370

Thakur, G. Sparks, K., Stewart, R.N., Urban, M., and Bhaduri, B. 2016. Curating Transient Population in Urban Dynamics System, In: GIScience 2016 Proceedings, Montreal, Canada.

Tversky, A. and Kahneman, D. 1974. *Judgment under Uncertainty: Heuristics and Biases.* Science **185(**4157), pp. 1124-1131.

Watson, R. and Yip, P. 2011. *How many were there when it mattered?* Significance **8**(3): pp. 104-107.