Using Ultra Wideband Technology to Improve Field and Experimental Tracking Methods

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Abstract

Though experimental research is at the heart of finding causal relationships, observational research plays an important role in scientific study. Unfortunately, due to the nature of observation, it is difficult to make precise measurements, especially because estimations can vary between observers. I attempt to use Ultra Wideband sensors as a method of measuring spatial relationships in both field and experimental scenarios. These sensors are extremely precise in smaller spaces, and can effectively map trajectory of human subjects. In order to test the sensors' usefulness for research, I used the Invisible Wall paradigm in an experimental SONA setup. I collected data from 20 participants between three conditions, finding the different strategies that subjects use to avoid breaking the Invisible Wall, and the ways that these strategies change their trajectories over time.

Introduction

While laboratory research plays an important role in advancing the disciplines of psychology and cognitive science, it can be difficult to generalize results to the natural world because these methods often lack external validity. Observational research is another option, but it is often overlooked because it is extremely time-consuming and it is more difficult to control for possible confounding variables, which causes these methods to have lower internal validity. Observational research, such as ethnography and other forms of naturalistic observation, involve data collection and note-taking in non-laboratory settings. This type of research is integral to understanding subjects' behavior in their day-to-day lives. In fact, experiments involving human or animal subjects generally stem from a desire to better understand behavior observed in natural settings.

Unfortunately, the methods that we use to conduct these naturalistic experiments are often tedious and can be imprecise. In the German lab in which my primary advisor, Dr. Rossano, worked for several years, he witnessed the development of a study of ingroup-outgroup dynamics in toddlers by relying on their positioning in space. After creating a visible grid on the floor, relying on fish-eye cameras from the top and assigning participants to different groups using the minimal group paradigm technique (e.g. Tajefel et al., 1971), the experimenter then filmed where children would position themselves in space, how much time they would spend in close proximity based on the groups they belonged to, the activities they engaged in, etc. After collecting several dozen participants, it became apparent that the mere manual behavioral coding of all the data collected and the subsequent analysis would have taken the entire remaining time of the PhD students who were working on the project.

Experimenters are often keeping track of multiple variables at once, and may have to conduct various scans while they record their participants. Proximity scans, for example, may occur once every 2 minutes and require the experimenter to manually record all individuals within a certain distance of their focal subject. Proximity and time spent together are considered to be a measurement of relationship (Hinde, 1979). Furthermore, individuals (children or adults) are social beings, and should be evaluated in relation to their surroundings, including their companions and their environment (Hinde and Stevenson-Hinde, 1987). This raises the question: how can the experimenter correctly judge the distance between the focal subject and those surrounding them? There is no way to measure, as the individuals are moving in real time. These scans can often therefore include a large amount of human error. Even if the scans are conducted after the fact, on recorded video data, it is very difficult to measure the distance between the individuals, since videos are rarely taken from a bird's-eye view, and exact distances are unknown. The method is therefore at least partially guesswork. There are studies that focus on *general* movement of individuals, using GPS as well as other data. In one such study, the focus was mostly physical activity and how communities can facilitate positive habits in children (Almanza et al., 2012). Many other studies rely primarily on gaze tracking to understand how children (especially children with autism or cognitive impairment) understand social interactions (Hosozawa et al., 2012). However, these studies are generally laboratory studies that cannot be performed in a naturalistic setting.

Overview – Ultra Wideband

In order to rectify this issue, I have proposed using technology, specifically ultra wideband (UWB) sensor technology, to measure the distances between participants in both naturalistic settings and experimental settings (for example, ingroup-outgroup studies). UWB sensors are specifically equipped to handle these kinds of setting because they are extremely precise. While GPS or Bluetooth tracking provide measurements with an error of feet or meters, UWB tracking is accurate within centimeters (Alarifi et. al, 2016, Pozyx Accurate Positioning). In my personal usage of UWB, the trackers were accurate to about 7-10 centimeters in either direction, with the potential for more accuracy with the addition of more anchors. The sensors also give 5 position samples per second. This is far more accurate than any other tracking technology currently in use, and allows precise tracking of individuals within a small space.

Several companies distribute UWB technology. For my experiment, I purchased technology from Pozyx, a small company based out of Belgium that distributes UWB for consumer use. Most companies advertise UWB for corporate use, so the usage of UWB in experiments with human subjects is relatively uncommon.

The basic setup of the UWB system is as follows: the system is comprised of both anchors and tags. The anchors are stationary, and are positioned around a room, while the tags are mobile (Figure 1). One tag (the local tag) remains stationary as well, and helps calibrate the other tags. My lab has purchased 9 tags and 9 anchors, and for the purposes of my research in this paper I use 8 anchors and 2 tags. Each tag also has a separate battery pack, purchased from Amazon, so that it may function wirelessly. The interface provided by the Pozyx developers also allows the positions of the tags in the room to be monitored online in real time.

Figure 1. Visualization of the Comparative Cognition Lab's testing room with anchors circled in red and tags circled in blue.

In this paper, I will use an experimental paradigm known as the "Invisible Wall" to create an experimental method from an observational study. This paradigm will allow us to study spatial relationships using the UWB technology. The "Invisible Wall" is the phenomenon, studied by the Comparative Cognition Lab, in which two individuals standing five feet apart (for our purposes, but they can be standing further or closer) and talking to one another create a "wall" which people will tend to avoid "breaking". That is, 94.5% of people in previous studies will not pass between two people standing five feet apart, talking to one another (depicted in Figure 6). The Invisible Wall demonstrates the importance of spatial relationships between individuals, and is therefore an ideal way to test the capabilities of the UWB sensors.

Methods

Before beginning my honors research setup, I piloted the UWB sensors to test their effectiveness and precision for indoor positioning. This involved extensive setup of the sensors and corresponding software. Even though Pozyx is a consumer-facing company, their target market seems to be more of an engineering demographic, therefore as a non-engineer setup was incredibly time-consuming. Debugging the software and its connection to the sensors, as well as setting up methods through which to record the positions of the tags, took multiple weeks. After setting up the sensors in the Comparative Cognition Lab's testing room, I ran a pilot study to test their functionality. The study consisted of placing pictures around the testing room and asking 2 participants to look at each photo , then asking questions about their interest in the photos. In total, 18 participants were collected (9 sets of 2). Participants were also video recorded in order to validate the positioning data. Though this was just for the purpose of testing the sensors, it became clear that there were multiple interesting ways of visualizing this data, including heatmaps of individual participants (Figure 2) and graphs of the distance between participants . This pilot study helped me decide what to test in my main experiment and ultimately led me to the Invisible Wall setup. It also allowed me to see the necessity of carrying cases for the tags, which need to be connected to a separate battery pack in order to connect. Before beginning the next experiment, with help from UCSD's Digital Media Lab, I created a 3D-printed case for the tags and their battery packs, which was attached to string so that it could be worn as a necklace by participants.

Figure 2. Heatmap of one pilot participant in the testing room. Darker areas correspond to the pictures, or points of interest, in the room.

Since it was clear from the pilot study that the UWB setup worked quite well in a small, confined space, we decided to study UWB in a larger outdoor space which included a hallway. We wanted to know how well UWB would adapt to this kind of space. In total, eight anchors were placed throughout the space at varying locations, four of which can be seen in Figure 3. It was within this space that we captured positioning data from participants.

Figure 3. Photo of the space in which we conducted the experiment. Locations of four of the eight anchors that were placed are circled in red.

Our experiment was a between-subjects design with 3 conditions. In total, 39 SONA participants were run through the study. However, only 20 usable data points were collected because there were significant technical difficulties throughout the study as well as issues with participants not correctly completing the study. Technical issues included failure to record data at the correct time and kernel timeouts in Jupyter Notebooks, a Python Integrated Development Environment (IDE). Video was recorded for all participants as well, but there was video dropout on 4 of the data points that were kept. In most cases, the study was performed by two individuals, and therefore the high number of moving parts caused a lot of the difficulty. In future data collection attempts, it would be best if more experimenters were present during data collection.

During the experiment, participants were given an arbitrary task to complete that would necessitate their movement through the UWB-equipped space. Participants met at the Comparative Cognition Lab, where an experimenter explained that they would be taken to a secondary location for the study. The experiment then walked the subject down to the hallway pictured in Figure 3, where they were given an UWB tag in the 3D-printed case to wear, and a map which showed their path to the secondary location. They were given a simple map with their current location and the secondary location marked, and were told that at the secondary location (the other side of Solis Hall), they would find a mural. Participants were instructed to view the mural carefully, then proceed back to the lab in the same exact path from which they came. By doing this, we were able to collect data both of the participant leaving the space to the secondary location, and of the participant returning back through the space to the lab. Once in the lab, the participants were tasked with drawing the mural that they viewed.

The three conditions were as follows: first, a baseline test of unimpeded movement through the space was taken. We collected 9 successful data points for this condition. The purpose of this condition was to observe the natural movement of individuals through the space so that we could have a point of reference for experimental conditions. In this way, we are able to see any differences from the baseline condition that are created by the other two conditions of the experiment.

The second condition was a “control” wall: two stacks of boxes, placed 5 feet apart, approximately 5 feet away from the end of the hallway (Figure 4). These boxes mimicked a “wall” created by humans, but we hypothesized that participants *would* break this wall. Only three participants were collected for this portion of the study, due to participant dropout, but more will be collected in the future, as the study is still in progress.

Figure 4. The experimental setup for the box condition, with boxes circled in red.

The third and final condition was the actual invisible wall condition. Two confederates standing 5 feet apart and talking to one another, in identical locations to the boxes in the box condition (Figure 5). We hypothesized that in this condition, the participants would not break the wall and instead opt to diverge around one of the two confederates. Eight data points were collected for this condition. Four of these were participants who encountered a wall with two female confederates, while the other four were participants who encountered a wall with two male confederates. There are two strategies to avoid breaking the wall: diverging around confederate 1 (circled in green in Figure 5), or diverging around confederate 2 (circled in blue in Figure 5). These will be discussed in further detail in the results section.

Figure 5. Setup for the confederate condition. Confederate 1 is circled in green, confederate 2 is circled in blue.

Overall, the purpose of this experiment is not to draw conclusions about the Invisible Wall paradigm as much as it is about testing the functionality of the UWB sensors in this setting.

We hope to make some conclusions about Invisible Wall in this setting as well; however, the primary goal of the experiment is to create a methodology by which we can verify use of the sensors this scenario and create methods for their use in other scenarios, especially naturalistic scenarios.

In order to analyze the data, we prepared a Jupyter Notebook to load and clean the data, and to split the data into separate dataframes for the participant's walk out of the space and their walk back into the space. Scatterplots of the data could then automatically be generated in order to visualize the participant's path. Animations of the participant's walk were also created so that their path over time could be understood. All of these methods were created in public notebooks uploaded to GitHub, so that other interested parties may, in the future, be able to use our methods to analyze their data.

Results

In discussing results, I will focus on specific subjects from each of the conditions in order to best communicate the trends we observed. Instead of conducting a large-scale statistical analysis, because the data are incomplete, specific subjects can provide insights into specific behaviors. Additionally, one issue we observed was that the data from when the participant left to Solis Hall had significant dropout and was not nearly as robust as the data from when the participant returned to the space. Because of this, we decided to limit analysis of data only to the participant's return.

In the baseline condition, participants tended to follow the most direct pathway back from Solis Hall to the hallway. Figure 6 shows the path of one such participant, whose movement towards the hallway is almost a straight line. Because the baseline condition shows the path of participants when unimpeded, we call this trajectory the “ideal path” of a participant returning to the space.

Figure 6. Trajectory of Subject 5 in the baseline condition. Movement is in a trajectory along the purple line, into the hallway.

The box condition, on the other hand, involved an environment with boxes laying on the floor. However, there does not seem to be much of a difference between the path of a participant in the box condition (yellow) and the path of a participant in the baseline condition (red) (Figure 7). It appears, from the data that we do have, that the presence of the boxes in this condition does not change the trajectory of the participant.

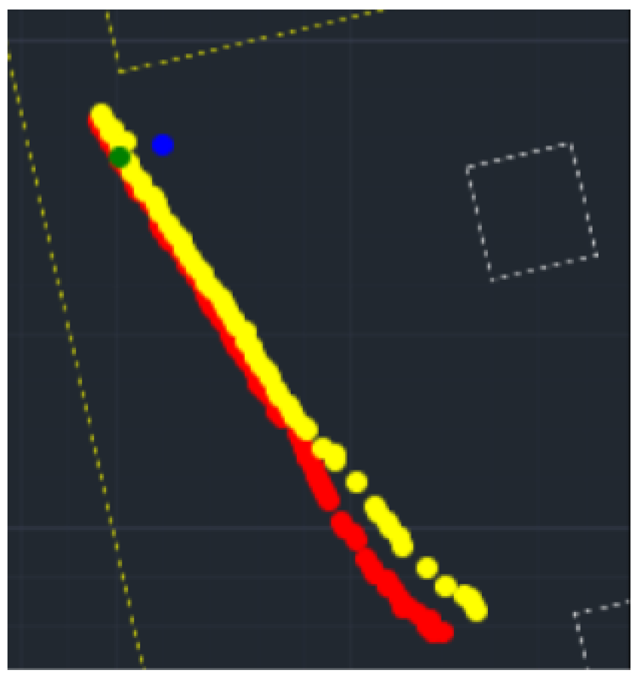

Figure 7. Subject 38’s trajectory (yellow) during the box condition overlayed with Subject 5’s trajectory (red) during the baseline condition. Location of boxes are in green and blue.

In our confederate condition, however, we do see a significant change of trajectory from the baseline condition. Unlike with the boxes, the presence of the confederates to form an invisible wall *does* visibly change the trajectory of the participant (Figures 8 and 9). The precise measurements from the UWB sensors allow us to see precisely when the participant deviates from the ideal path because of the wall. From this, two main strategies emerge: the participant may either avoid breaking the wall by diverging around confederate 1 (Figure 8) or around confederate 2 (Figure 9). Diverging around confederate 1 allowed the participant to slowly change their path from the ideal, creating a more curved path that then slipped behind the first confederate and into the hallway. In Figure 8, the participant began diverging from the ideal path at about 46 feet away. This path allows a smoother adjustment for the environment presented to the participant, and 6 of the 8 participants in this condition employed this strategy. By contrast, diverging around confederate 2 seemed to be a more abrupt movement that was not calculated from so far away. The participant followed the ideal path until they were less than 10 feet away, at which time they made a divergence around confederate 2 and into the hallway. It seems possible that instead of adapting to the environment that they were presented, participants who employed this strategy expected that the environment might adapt to them, then had to shift their expectations when it did not. Only 2 of our participants employed this strategy.

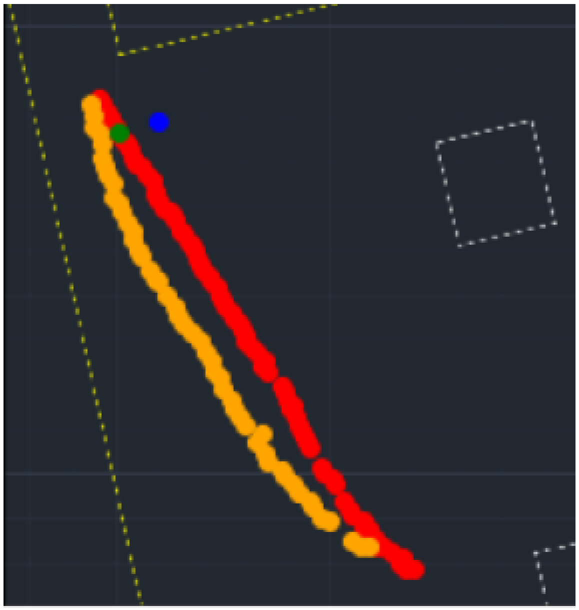

Figure 8. Subject 28's trajectory during the confederate condition (orange) overlayed with subject 5's trajectory during the baseline condition (red). Confederate 1's location (green) and confederate 2's location (blue) also depicted.

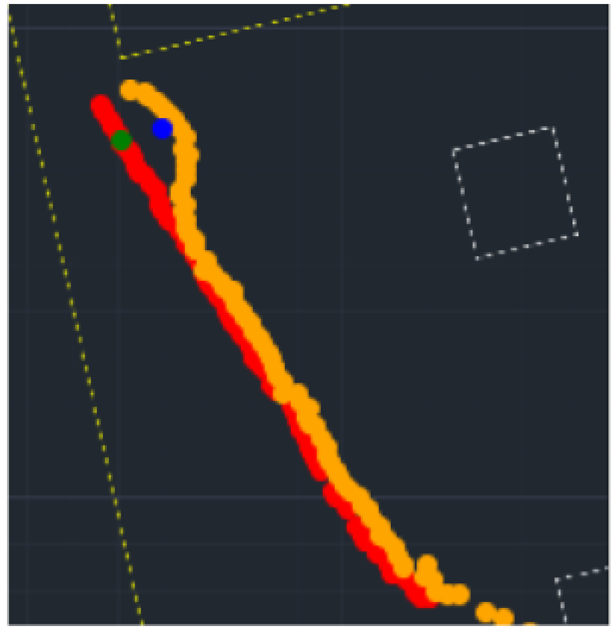

Figure 9. Subject 36's trajectory during the confederate condition (orange) overlayed with Subject 5's trajectory during the baseline condition(red). Confederate 1's location (green) and confederate 2's location (blue)are also depicted.

Discussion

UWB sensors are definitely useful in giving precise measurements of location within a space. Paths can be plotted and analyzed while maintaining the anonymity of the subject, which is helpful when considering the implications in naturalistic settings as well. By running the data through our Jupyter Notebook to automatically create visualizations, it was simple to classify whether or not a participant broke the wall and what technique they used within a matter of seconds. UWB therefore eliminates the need for video coding in this scenario as well.

Both of the two participants who diverged around confederate 2 were male and facing a two-female confederate wall. Because of the lack of data points, it is hard to know if this is significant; however we will investigate this phenomenon further as we continue the study. It seems possible that male participants could expect female confederates to move for them, while female participants may not expect male confederates to move for them. We will develop this finding further after collecting more data.

Limitations

Though we were able to successfully collect data recording precise positions from participants in this scenario, UWB has significant limitations. For one, the necessity of the presence of a local tag within the space can limit the scenarios in which the tags can be used. For example, if having a local tag connected to a computer is too out-of-place or conspicuous in a certain space, UWB recording may not be fitting for the space. Space configuration can also be unfriendly for UWB recordings because the technology has some issues with dropout around corners and walls. While recordings seem somewhat seamless in open space, the dropout when participants entered the hallway was extremely noticeable. Before using UWB, it is a good idea to consider if there are similar areas which would cause dropout in the recording space.

Another limitation is the lack of user-friendliness of this technology. It was only through the patience of one of the Pozyx support engineers that I was able to get the system running, even though I have significant experience with computer science. A user with no experience may not even be able to meaningfully communicate with the company to fix their problems. The unfriendliness of the system severely limits its user base to those familiar with engineering. For use in the social and behavioral sciences, teams working with UWB must be multidisciplinary and contain at least one engineer. This is the simplest way to ensure that teams will be able to effectively use the technology.

Conclusions and Future Work

Ultra Wideband sensors are very effective at location tracking of individuals in specific scenarios. In clearer spaces, like rooms without many corners or impeding walls, UWB can be very effective. However, these sensors will not accommodate all different types of scenarios. While we succeeded in testing the capabilities of these sensors and creating a methodology through which to parse the data gathered from them, further research is needed to truly test the capabilities of these sensors in naturalistic environments. That being said, our experimental setup uses the sensors well, and they provide robust, informative data. Even though they may not apply to every type of scenario, there are plenty of scenarios to which they may apply in the future.

Future work should further investigate signal dropout around corners and the ways that users can mitigate the effects of these dropouts. Additionally, there should be more investigation into whether or not the local tag can somehow be removed from the scenario, which would create a more versatile way to use the UWB sensors. Future work will also include further data collection with the Invisible Wall scenario, and a statistical analysis of the significance of that data.

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Works Cited

Alarifi, A., Al-Salman, A., Alsaleh, M., Alnafessah, A., Al-Hadhrami, S., Al-Ammar, M., & Al-Khalifa, H. (2016). Ultra wideband indoor positioning technologies: Analysis and recent advances. *Sensors*, *16*(5), 707.

Almanza, E., Jerrett, M., Dunton, G., Seto, E., & Pentz, M. A. (2012). A study of community design, greenness, and physical activity in children using satellite, GPS and accelerometer data. *Health & place*, *18*(1), 46-54.

Belapurkar, N., Harbour, J., Shelke, S., & Aksanli, B. (2018). Building Data-Aware and Energy-Efficient Smart Spaces. *IEEE Internet of Things Journal*.

Hinde, R. A. (1979). *Towards understanding relationships* (Vol. 18). Academic Press.

Hinde, R. A., & Stevenson-Hinde, J. (1987). Interpersonal relationships and child development. *Developmental review*, *7*(1), 1-21.

Hosozawa, M., Tanaka, K., Shimizu, T., Nakano, T., & Kitazawa, S. (2012). How children with specific language impairment view social situations: an eye tracking study. *Pediatrics*, *129*(6), e1453-e1460.

Pozyx Accurate Positioning. (n.d.). Retrieved October 12, 2018, from https://pozyx.io/

Tajfel, H., Billig, M. G., Bundy, R. P., & Flament, C. (1971). Social categorization and intergroup behaviour. *European journal of social psychology*, *1*(2), 149-178.

Appendix

Figure A. A Pozyx anchor.

Figure B. A Pozyx tag.