Engagement and Learning in Virtual Reality

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In a previous blog post, we described ways in which we measure VR learning and training effectiveness. But before any learning can occur, users must be sufficiently engaged. We know from a wealth of prior research that engagement influences learning, particularly classroom learning. Engagement also directly affects user performance in a variety of other 'real world' behaviors, particularly in the workplace (Rich, Lepine and Crawford, 2010). While self-report techniques are often used to measure engagement, they are subjected to a variety of shortcomings such as users reporting what they think companies want to hear or even having a hard time putting true feelings into words. While other techniques such as using physiological measurement (e.g., heart rate, pupillary response, brain activity) are objective and reliable markers of engagement (Berka, Levendowski, Lumicao, Yau, Davis, Zivkovic, & Craven, 2007) they are obtrusive and are difficult to capture at scale.

VR offers an unparalleled tool to give clues about user engagement. The tracking hardware that comes with all VR systems measures body language automatically, unobtrusively, and at a rate that gives more data about human gestures than have ever been possible before. These gestures and movements are the core behaviors associated with engagement (Reeve, Jang, Carrell, Jeon, & Barch, 2004). With STRIVR, we collect and calculate (a) what an individual is paying attention to at any given moment during their VR experience, (b) how long they have been paying attention to it, and (c) how many different places in space. This gives us unprecedented insight into user engagement.

Our Work

A first, logical place for us to start was to examine data from our STRIVR marketing experiences. In the past, we have created VR experiences targeted towards fans and attendees at sporting events, such as Boston Red Sox, New York Rangers, or New England Patriots games. Typically, the experiences are comprised of content specifically surrounding a given sports team or athlete and targeted to users that are fans of various these sports teams/athletes. Presumably, then, these experiences should be some of our more engaging experiences since users were fans of these teams. A screen capture from one of these VR experiences is provided below along with an image of the environment the users experienced STRIVR VR.

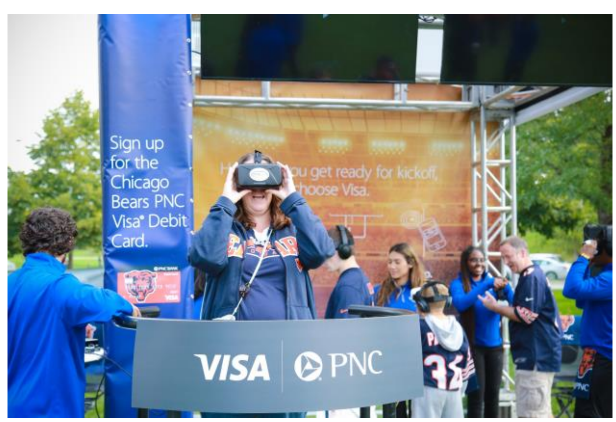

Figure 1

Each user going through a STRIVR experience generates a tremendous amount of data. We can analyze this data to come up with a variety of ways to examine engagement. The first feature we can look at is the *standard deviation* of the head movements. Simply put, this is a measure of the overall volume of head movements made during the experience. Standard deviation has been used in prior research as a measure of engagement in VR (e.g., Ooko, Ishii, & Nakano, 2011). Figure 2 shows the distribution of standard deviation for 352 users that finished a 90 second VR experience that took them behind the scenes with the Pittsburgh Steelers of the NFL. Notice that the values range widely, indicating a wide range of engagement levels. Getting a better understanding of who those high engagement and low engagement users are can help us better target STRIVR VR experiences in the future.

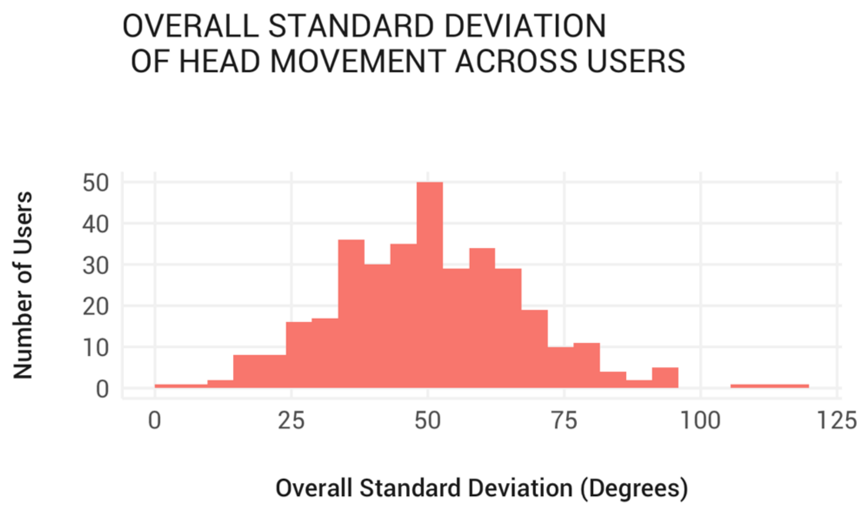

Figure 2

This presents STRIVR with a rare data collection opportunity. Since we captured this data "in the wild" with real users, we can truly start to validate standard deviation as a measure of engagement. As it happens, 49 users watched only part of the experience before voluntarily opting out. We assume these 49 'Non-Finishers' were less engaged by the content than the 352 'Finishers'. The data bears this out. The average standard deviation for Finishers was 50.61 degrees compared to Non-Finishers who had a mean value of 26.67 degrees.

While standard deviation of head movement is a good place to start to understand engagement, our current data gives us the ability to get deeper insights. A follow-up analysis performed on the data looked at whether greater standard deviations resulted in more meaningful head movements. It might be the case that those with lower or moderate standard deviations are simply looking at fewer things more meaningfully and those with higher standard deviations are not really paying attention to anything because they are trying to look everywhere. To better understand this, we first we looked at the relationship between standard deviation and number of distinct head movements. Visually the relationship looks like:

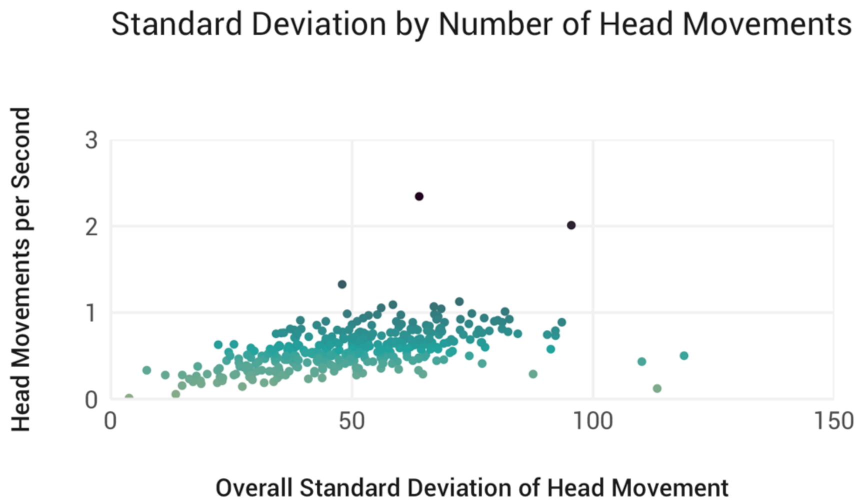

Figure 3

Statistically the relationship showed a significant correlation (r= 0.498, $p < 0.001$), meaning that greater standard deviations were associated with greater number of distinct head movements, indicating that more head movements were likely to represent greater engagement with the scene. This analysis only tells us that those users with greater standard deviations are looking at more places and not a mix of users that are making more, smaller movements or less but larger movements.

While this result is useful in understanding *how* high engagement users are moving, it still doesn't tell us anything about the *type* of movements high engagement users are making. Particularly, are user movements too rapid to make meaningful sense of the experience? In order to better understand this question we looked at another feature of the head movements that we call 'Staring Time'. As the name indicates, this is the proportion of head movements that the user stayed and inspected the scene in contrast to aimlessly looking around. Visually, the relationship between head movements and staring time looks like:

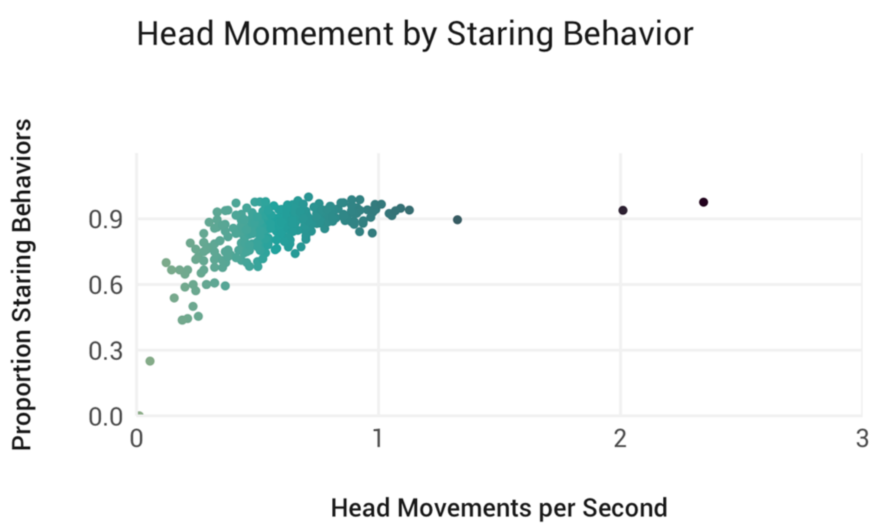

Figure 4

Statistically the relationship is strong (r=0.614, $p < 0.001$), meaning that greater head movements also resulted in greater staring time.

Takeaways and Future Direction

Taken in total, we can start to paint a better picture of what an engaged STRIVR user looks like. In the past, overall head movements were used to provide a coarse description of user engagement. But given STRIVR's unprecedented access to data from thousands of real world users using the latest VR technology, we're able to get better insight into what user engagement looks like. Given the important role engagement plays in training, it's critical STRIVR can assess users for their moment-to-moment engagement. Having this insight creates a multitude of opportunities for our training experiences going forward, such as creating VR content that maximizes engagement and adapting training content in real-time in order to sustain engagement.

References

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