

## Visualizing Behavioral Data from a 3D Virtual Learning Environment: A Preliminary Study

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**Abstract:** This paper describes a preliminary study which attempted to apply learning analytics methods to usage data generated by students with autism spectrum disorders using iSocial, a collaborative, three-dimensional virtual learning environment. Drawing from similar methods in the area of learning and content management systems, the work presented in this paper considers two types of user behaviors that are not present in LMS/CMS and are unique to 3D VLEs: avatar movement and spoken dialogue. The method developed for capturing avatar movements and spoken dialogue and writing these data to a log file is explained, along with a description of the process the research team underwent in order to transform the log data into graphical depictions of user behavior over time. Examples of five different visualization types are examined. Conclusions and directions for future research are provided.

### Introduction

Generating and storing large amounts of data is a hallmark of the information age. With these large data sets come unique challenges and opportunities for understanding and making sense of massive amounts of information. Companies like Google and Facebook are mining these enormous data sets for information that is valuable and profitable for these service providers. Educational researchers have taken note and also are looking to large data sets to extract information that is pertinent to enhancing educational research and practice. Educational institutions are turning to advanced technologies to augment and enhance their courses and curricula. With increasing interest in and use of online learning technologies in the educational sector comes increased amounts of generated data. To illustrate, in 2007 nearly four million students in higher education were enrolled in online courses (Allen & Seaman, 2008). Blended and web-facilitated courses are also being implemented widely in higher education contexts (van Rooij, 2009). Rapid growth of online offerings is also apparent in K-12 education, with estimates of over one million

students having taken part in online education during the 2007-8 school year (Picciano & Seaman, 2008). It is predicted that 10% of all K-12 students will be learning online by 2013 and that by 2018 that number will grow to 50% (Christensen, Horn, & Johnson, 2008). With so many students and schools turning to online learning, the data being generated by online learning systems is also growing.

Data generated by online learning technologies such as learning management systems (LMS) and content management systems (CMS) are not limited to coursework and classroom materials. Information regarding patterns of usage, interaction and engagement are also generated *while* students and instructors use the systems. For example, course management systems can provide information on what students are doing when they are learning online, the length of time spent learning online, how active they are in their online courses, how they interact with others and how others' interactions affect their actions (Laffey, Amelung, & C, 2010; Laffey, Amelung, & Goggins, 2009). However, making sense of the data generated by online learning systems is challenging. In order to develop an understanding of what students are doing when they are learning online, the information must be processed and represented in a meaningful way.

One tool used by analysts to process massive data sets and discover meaningful patterns in the data are visual analytics (Keim, 2002). According to Card and colleagues, (Card, Mackinlay, & Shneiderman, 2009), such depictions of data are particularly useful because they "employ the sense with the most information capacity" (p. 510) and thus amplify the human capacity to make sense of the data. They maintain that visualizing data allows knowledge to crystallize through the process of acquiring the information, making sense of it, creating something new and acting on it. However, while visual analytics hold much promise for making sense of data generated by LMS/CMS, examples of researchers using this method to interpret these data are still rare (Aguilar, Guerrero, Sanchez, & Penalvo, 2010), although the field appears to be growing. Examples include visualizing activities to support formative assessment (Nulden & Hardless, 1999), the GISMO system for monitoring and tracking student data in a CMS (Mazza & Milani, 2004) and its predecessor CourseVis (Mazza & Dimitrova, 2004), Ariyasu and colleagues' system for visualizing textual dialogs in virtual classrooms as conversations in a 3D virtual environment (Ariyasu, Yamada, Sumiyoshi, Shibata, & Yagi, 2005), social network analysis in WebCT (de Laat, Lally, & Lipponen, 2007) and the ViMoodle visual analytical tool for creating social network graphics and word clouds using data from the Moodle CMS (Aguilar, Theron, & Pealvo, 2008).

Arguably, the predominant mode of online learning in higher education and K-12 is via LMS/CMS. However, a new technology that is beginning to gain traction is three-dimensional virtual learning environments (3D VLE). 3D VLE implementations like Quest Atlantis (S. A. Barab, Thomas, Dodge, Carteaux, & Tuzun, 2005; S. Barab, Sadler, Heiselt, Hickey, & Zuiker, 2007), Whyville (Neulight, Kafai, Kao, Foley, & Galas, 2007) and River City (Dede, Clarke, Ketelhut, Nelson, & Bowman, 2005) are being used in a variety of learning domains. However, unlike some of the efforts with LMS/CMS, very few attempts exist which attempt to apply visual analytics to investigate student 3D VLE usage behaviors.

The majority of visual analytics work applied to 3D virtual environments looks at using the 3D environment as a space within which data visualizations can be represented and collaboratively interpreted. The method used for visualizing data within 3D virtual environments is to import an external data set into a visualization tool and then to represent that data set visually within the 3D virtual environment. For example, the Glasshouse project by Green Phosphor (Lindquist, 2010) provides a visualization engine and API for presenting 3D representations of data in virtual worlds like Open Wonderland and Olive.

The utility of presenting data visually in 3D virtual worlds is clear, as the 3D representation of the data and the interactive nature of the environment provide for a powerful medium to represent and explore visualized data in novel ways (Bourke, 2008). But what of the data that are generated while users work, collaborate and learn within 3D virtual environments? 3D virtual environments generate massive amounts of data while users interact with the system and with each other. As with other data sets, data generated while using 3D virtual environments can be collected, made sense of, visualized and acted upon. For example, Börner and Lin (Börner, 2001) developed a method to visualize students' chat log data generated within Active Worlds to answer questions regarding the number of students involved in chats and who was most involved in chatting. Börner and Penumarthy developed visualization techniques for investigating social diffusion patterns in 3D virtual worlds (Börner, Penumarthy, & S, 2003). Chittaro and colleagues developed a VU-Flow for visually analyzing navigation patterns in virtual environments (Chittaro, Ranon, & Ieronutti, 2006). And VisTool for Wonderland allows researchers to play back user activities using a top-down display and provides other modes to investigate user behaviors (Hasler, 2010). Taking a cue from these prior works, this paper describes initial steps towards developing a robust process and method to collect and visualize data from a 3D VLE to depict user behaviors for rapid analysis.

### **Behavior visualization in a 3D VLE**

The authors have collaborated with an interdisciplinary team to create a collaborative 3D VLE-based intervention for social and behavioral outcomes for youth 11-14 years old with Autism Spectrum Disorders called iSocial (<http://isocial.missouri.edu>). Built using the Open Wonderland virtual worlds platform (<http://openwonderland.org>), the 3D VLE implementation is an adaptation of a clinic-based social competence curriculum based on a framework of cognitive behavioral intervention (Stichter et al., 2010). The virtual world and corresponding curriculum focus on social competence-related learning objectives, an area in which individuals with Autism Spectrum Disorders are particularly challenged. The virtual environment was designed for six participants to take part in 32 45-minute lessons with an instructor. More comprehensive descriptions of the 3D VLE, the curriculum used, the study participants, and ethical considerations such as institutional review board approval are beyond the scope of the current paper, but can be found in prior publications (Laffey et al., 2009; Laffey, Schmidt, Stichter, Schmidt, & Goggins, 2009; Laffey, Stichter, & Schmidt, 2010; Schmidt, Laffey, Stichter, Goggins, & Schmidt, 2008).

Given the unique nature of the targeted learners, the learning environment and the learning content, answering questions of how students use the learning environment and interact with one another and the instructor is important to the ongoing design and development of the 3D VLE. We apply usage and interaction data towards improving our curricular, activity and environment designs in an effort to provide the best conditions for learning in the 3D VLE. To this end, we have developed a method for recording students' screens and then later analyzing those screen recordings; however, this process is very time consuming, with each hour of instruction, yielding seven hours of video (six students and one instructor) and taking approximately 160 human hours for our team of researchers to analyze. While the outcomes of our research have been a primary driver of our design and development process, the amount of time between data generation to completed data analysis presents a challenge, as data is often still being analyzed when a new design and development cycle begins. Because of this, we began to look for ways to more rapidly move from data collection to analysis.

We began by investigating how to capture data beyond using screen recordings, with the plan that once data were captured we could then investigate ways to represent the data. This process was inspired by earlier experiments with eye tracking, in which we first developed a method to capture users' gaze data as time stamped X and Y coordinates and then later devised a process to represent those gaze data as heat maps superimposed over virtual scenes (Goggins, Schmidt, Guajardo, & Moore, 2011).

## **Method**

Given that our virtual learning environment is built using Open Wonderland, which is released under the open source GNU General Public License 2.0, the research team was able to analyze the underlying source code to determine how user interactions were generated and communicated in the system. From this, the team was able to devise mechanisms to write representations of user interactions to plain text log files and incorporate these methods into the system's source code.

Once able to capture target data, the task turned to deciding on a set of interactions and activities that were of interest (essentially a vocabulary of meaningful behavior in the VLE), and applying a standardized logging format to these activities. The team created a list of activities that would be logged, including avatar gestures, entering/exiting virtual spaces, speaking, etc. From these possible logging targets, we decided to use participants' speech and avatar movement as a starting point as these aligned with our design goals. Following this, the team developed programmatic methods for detecting and logging user interactions and automatically writing them to a log file. A preliminary data set was created by collecting log data over the course of eight usage sessions in which four students took part in eight lessons in the 3D VLE with an instructor. The full set of logged data comprised 11.2 MB of plain text with a total of 88,532 log entries.

Log files contained multiple entry types, including not only information on movement and speaking, but also avatar gestures, mouse clicks, login/logout information, text chat

entries and other data. A uniform structure for log entries was devised, in the form of: 1) activity type, 2) activity sub-type, 3) user name, 4) avatar location and rotation and 5) timestamp. Devising a uniform log entry structure was critical for later experimentation with visualization of the data, as different visualization tools required differently formatted input. The uniformity of the original log entries allowed for predictable parsing of the data and reformatting of the subsequent output, thus simplifying the process of importing into various visualization tools. Examples of log file entries are provided in Table 1.

**Table 1.** Example log file entries.

Behavior type	Log entry
Movement	Move;NA;CC;[tx=3.5, ty=0.08, tz=20.1] [rot= [X=0.0, Y=-1.0, Z=0.0]:31.9] [s=1.0];2010-04-28 17:04:14
Speaking	Speak;Start;sip:DS@192.168.1.1:5070;NA;2010-04-28 17:11:11 Speak;Stop;sip:DS@192.168.1.1:5070;NA;2010-04-28 17:11:12
Avatar gesture	Gestures;Male_Cheer;MD;2010-04-28 17:34:58

After generating the data set, we began working towards developing visual data representations. The research questions which drove this process were: 1) When are students conversing with one another, which students are speaking the most/least and how long are they speaking? and 2) When are students moving their avatars through the virtual environment, which students are moving the most/least and how far are they moving?

Research question 1 was motivated by the design goal that participants should be engaged in reciprocal interactions when working in the 3D VLE, that is, a series of reciprocal initiations and responses between participants. This is especially important for our user population, as individuals with ASD are challenged by initiating and sustaining conversation. Research question 2 was motivated by the design goal that participants should keep their avatars still when undertaking instruction and should not leave the group. Our initial investigations of individuals with ASD using iSocial indicated that there was often a tendency for participants to leave the group and to not keep their avatars still when the instructor was teaching.

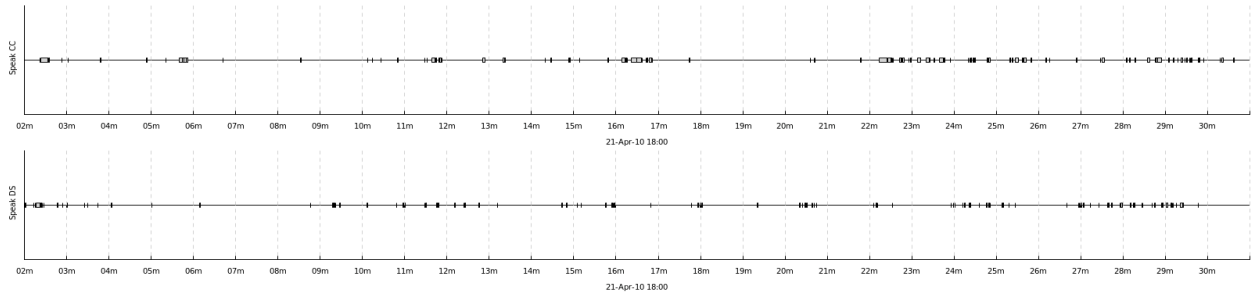
Our first attempt at answering these questions was performed using simple spreadsheet charts. We were able to create simple charts from the data set, but creating the charts was slow and labor intensive. We learned that the spreadsheet charts could provide a broad view of the data, but were limited in their ability to represent behavior in context. For example, we were able to see that a student had spoken a given number of times over the course of a lesson, but we were not able to determine at what point in the lesson that student had spoken, the duration of her speech, or the context for speech (who had spoken before and after). Creating more sophisticated charts using spreadsheet applications was time- and labor-intensive, which was not in line with our goal of being able to gain a rapid sense of the data.

Following this, we began to look into software that could be configured to rapidly depict user activities over time. Our focus was on tools that made possible the automation of our processes and could be used by users without advanced computer skills. We identified three tools for this: Google Gadgets' Time Series Chart (<http://docs.google.com/support/bin/answer.py?answer=91609>), MIT's Simille Timeplot (<http://www.simile-widgets.org/timeplot/docs/>) and Haskell Timeplot (<http://hackage.haskell.org/package/timeplot>) (Kirpichov, 2010).



**Figure 1.** All student activity from a single lesson plotted over time using three separate visualization tools.

The initial experiment with these three tools was to determine if they allowed for rapid visualization of our data. To this end, a simple visualization of all log entries as a single time plot was prepared using each of the tools. While the tools used different mechanisms for input and display of data, the results were fairly similar (Figure 1). The SIMILLE and Google Gadget output appear to be identical; however, the Haskell Timeplot output differs. For instance, it is missing the spike at 17:42, and the spikes at 17:55 and 17:56 are at different heights. This is due to the Haskell chart using a column chart representation and some of the data points being omitted due to the space limitations of the graph size. The Google and SIMILLE graphs are line charts and do not suffer this



**Figure 2.** Two students' turns at speaking and durations of turns represented as bars on a pulse chart.

limitation. Simille Timeplot (Tplot) and Google's Time Series chart required significant manual altering of the log files' in order to generate visualizations, whereas data could be prepared for Tplot using a simple shell command. The process of preparing data for tools other than Tplot was time consuming and increased the potential for human error. Given this and other limitations, we chose to use Tplot for our experiments. What made Tplot particularly compelling was its ability to visualize data from nearly any type of log file, its capability to represent data using multiple visualization types, the speed with which visualizations could be created and the ability to create scripts to automate processes.

## Results and analysis

### Research question 1: When are students conversing with one another, which students are speaking the most/least and how long are they speaking?

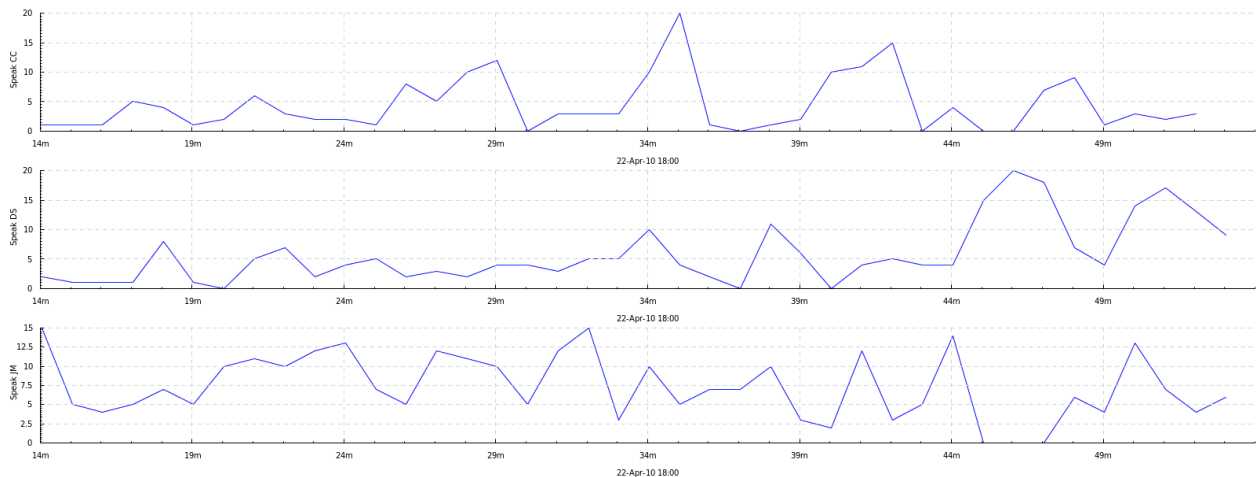
In order to answer the question of when students are conversing with one another and how long they are speaking, three separate visualization types were created: pulse charts, interval speaking duration line charts and cumulative duration line charts. The objective was both to provide input to answer the research question as well as to be able to create visualizations quickly.

Pulse charts allowed us to determine both when a student was speaking and for how long. Data are represented on a timeline as bars. Short bars indicate short speech durations whereas long bars indicate long speech durations. Figure 2 shows an excerpt from a lesson showing two of four students' speech. The gray bars indicate when and for how long each student spoke, and the flat areas indicate silence. A limitation of the way Tplot creates this visualization is that it is difficult to see high and low activity. Having a value on the y-axis or being able to adjust colors to represent intensity would improve readability.

Interval speaking duration line charts provided a visual depiction of the total duration of speech by a given student within an interval of time by depicting the duration in seconds (on the y-axis) over time (on the x-axis). We selected one-minute intervals since this time frame provided a view of conversation without getting lost in details as one would with one second intervals and while still retaining enough granularity to draw conclusions

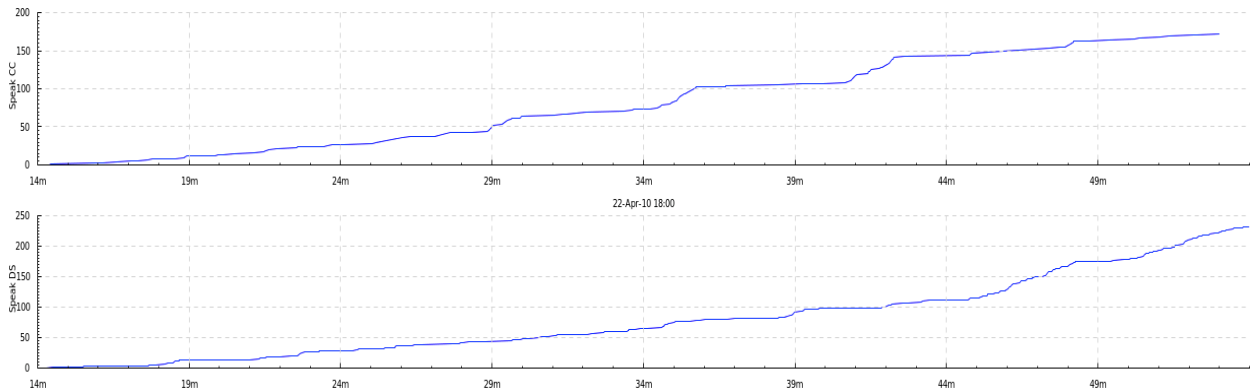
from the data, which proved to be challenging at longer intervals. When viewed over time, these depictions provide a representation of the flow of conversation, with peaks in the chart representing when a speaker is more active and valleys indicating when a speaker is less active. Figure 3 shows an interval speaking duration line chart. In this excerpt we see the fluctuations in durations of speech per minute for three participants. Limitations in how Tplot creates this chart type include axes labels and scale. The axes label is created from the log entry and cannot be easily changed. Hence, it is not obvious that the y-axis is in seconds. Further, the axis label size cannot be changed, making it difficult to read. In addition, it is not possible to force Tplot to use the same scale for each graph. Having different scales on each plot is confusing and could result in misconceptions.

Cumulative duration charts provide a visual depiction of the total duration of speech over the course of a lesson. Duration is depicted as seconds on the y-axis and time on the x-axis. The line starts at zero and as participants speak, the slope of the line changes its upward trend. When participants speak more, the slope becomes steep. When participants speak less, the slope plateaus. Figure 4 shows an excerpt from a cumulative duration chart of two participants. From this chart it is evident at which points in the timeline participants were speaking more and when they were speaking less. Using the last point on the chart, it can be determined the total amount of time spoken over the course of the lesson by comparing that point to the y-axis. Representing this chart type on a short x-axis is beneficial in that behavior patterns are more obvious. Using a shorter x-axis in Figure 4 makes it much more apparent that speaker DS contributes at a roughly constant rate, increasing at the end of the session (around 44m). This leads to the question of what might have caused this increase in speaking activity and provides a point for the researcher to examine the data around this time more closely. The shortened x-axis shows that CC's pattern of speaking is different, with contributions happening at a relatively constant rate, but in fits and starts. The same limitations of axis, label and scale apply to this chart type as with Figure 3.



**Figure 3.** Three students' speech durations represented as a line chart in one minute intervals.

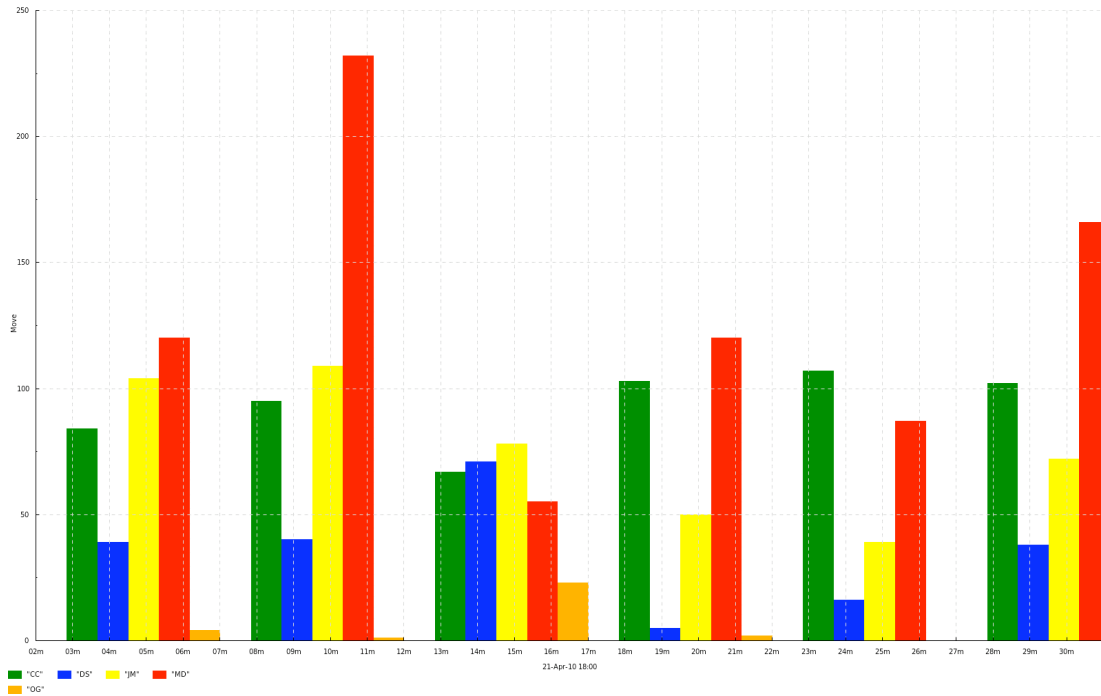




**Figure 4.** Two participants' speech durations (in seconds) represented as a cumulative duration chart over the course of a single lesson.

**Research question 2: When are students moving their avatars through the virtual environment, which students are moving the most/least and how far are they moving?**

To approach the question of when students are moving their avatars within the virtual environment and the total distance their avatars are moving, histograms and cumulative line charts depicting total distance moved over specified time intervals were created. These charts depicted avatar distance moved on the y-axis and time on the x-axis. Avatar distance in the virtual world can be interpreted as one unit equaling approximately one meter in the real world. Figure 5 shows a histogram of participants' avatar movement. At five-minute intervals we can determine which participant moved her avatar the most within a given five-minute interval, and in which interval the most avatar movement occurred. For example, it is clear that the participant "MD" moved her avatar the most in nearly all intervals and "OG" moved his avatar the least. It also appears that there is less variability in the graph from approximately 10 to 15 minutes into the lesson. This could be indicative of a point of interest that a researcher could further investigate in order to determine what, if anything, may have been involved in creating this effect. Limitations of Tplot in generating this chart type include colors and boundaries on the x-axis. The colors are not configurable, which is unfortunate, as the default colors are too saturated and unpleasant. In addition, it is not clear where the boundaries are for the five-minute intervals on the x-axis, and the labels are not aligned with the data.



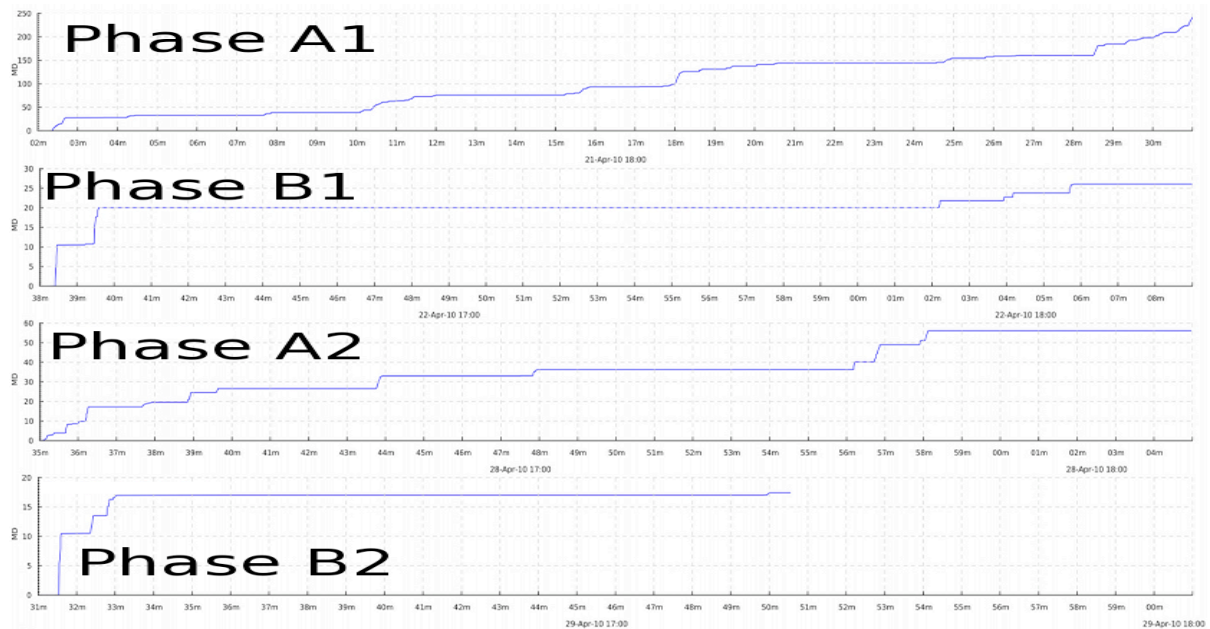
**Figure 5.** Histogram of all students' avatar movement in five-minute intervals.

Avatar movement data were also plotted as a cumulative line chart, depicting the total distance moved over the course of four lessons. These charts were then aggregated into a single chart for comparison purposes (Figure 6). In Figure 6, it is apparent that in the first lesson (phase A1), participant "MD" moves her avatar fairly regularly over the course of the entire lesson, whereas in the second lesson (phase B1), she moves her avatar for the first two minutes and then remains still until the final third of the lesson. The same pattern is seen in Phase A2 and Phase B2, with movement over the entire duration of the A lesson and movement primarily at the beginning of the B lesson. In addition, total distances moved change between lessons, with "MD" moving 250 meters in A1 but only 30 meters in B1, 60 in A2 and 20 in B2.

The visual comparison made possible by juxtaposing charts for an individual participant allow the researcher to make inferences about the participant's behavior. In this case, a software tool to constrain avatar movement was implemented in phases B1 and B2 that was not implemented in phases A1 and A2. The repeating pattern of behavior observed here is of interest and invites further investigation. Can this behavior pattern be attributed to the software tool that constrains avatar movement? Is this same pattern observed with other participants?

As with Figure 4, scaling the x-axis down with this type of chart makes behavior patterns obvious. However, the same limitations of Tplot are apparent here, in that the axis label and scale are not configurable. This is particularly problematic for creating publication-ready charts.

The example in Figure 6 is of particular interest because it illustrates the power of exploratory visualization by illustrating how visualization can lead to an interesting insight. It would appear that the software tool that constrains participants' avatar movement behavior may indeed impact participant behavior. This insight provides us a starting point at which to look at the data more closely. Our next step will be to look at avatar movement data more carefully, with more depth and using tools that lack many of the limitations of Tplot to further investigate this finding.



**Figure 6.** Cumulative line chart comparing one participant's avatar movement across lessons.

## Conclusions and Future Work

The exploratory methods and concepts discussed in this paper fit within a greater effort by educational researchers to use the affordances of advanced learning technologies to represent and investigate user behavior. The goals which drove this investigation were twofold: 1) to explore existing 3<sup>rd</sup> party software tools which might allow us to rapidly gain a sense of our data and 2) to determine if the outcomes of this exploration might help us answer questions about how participants are speaking and moving their avatars while undertaking instruction. The purpose of these questions was to inform and forward our design goals of supporting and enhancing participants' reciprocal interaction and limiting undesirable behaviors such as leaving the group.

While the results of our preliminary investigation are promising, they are also limited. We feel the main contribution of this work is in how we have used exploratory data visualization to understand student behaviors in a 3D VLE. Being able to know how much someone is speaking and at what time is valuable, but does not really help us to

understand the dynamics and ecology of conversation in the 3D VLE. Likewise, knowing the total distance an avatar has moved and when the movement happened allows us to see patterns of movement across lessons, but does not tell us much about the motivations for movement or lack thereof. Investigating more refined visualization techniques is a direction for future research and will allow us to go beyond simple questions of “how much” and “most and least” and begin investigating the relationships among social actors within the environment and begin developing a theory of social interaction within the 3D VLE. For instance, generating composite graphs or graphing composite metrics derived from the log data could yield interesting findings and would represent a level of sophistication in the data analysis which is not present in our current methodology.

Finally, the 3<sup>rd</sup> party tool that we selected, Tplot, was quite limited. Without the ability to manipulate graph labels and scale, the resulting data visualizations were not as readable or useful as we had hoped. While it could be argued that, aside from the pulse graph, all chart types illustrated here could have been easily created using a spreadsheet application, the purpose of this investigation was not to use known tools and methods; rather, it was to explore a variety of data visualizations and to do so rapidly. Tplot was able to generate hundreds of charts from over 88,000 log entries with only a few lines of shell commands and in less than one minute. While it is likely that the limitations of Tplot would not have manifested if we had used spreadsheet software, it is also likely that we would have had to spend a good deal more time creating the different charts. We do not argue that accuracy and quality of visualization should be sacrificed for speed. Instead we characterize the discovery of the shortcomings of Tplot as a lesson learned from our preliminary analysis and recognize that a direction for future research is to look for ways to achieve speed while maintaining accuracy.

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