UNDERSTANDING FULL-BODY EXPERIENCE WITH A SCIENCE LEARNING SIMULATION

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RESEARCH CONTEXT

Body-based interactions can play a critical role in the development of both concrete and abstract understandings in STEM. With the refinement of body detection and tracking technologies arising out of the entertainment and virtual reality industries, software designed to utilize dynamic and continuous body tracking and gesture recognition can now be leveraged to facilitate embodied learning with platforms such as whole-body interactive science learning simulations

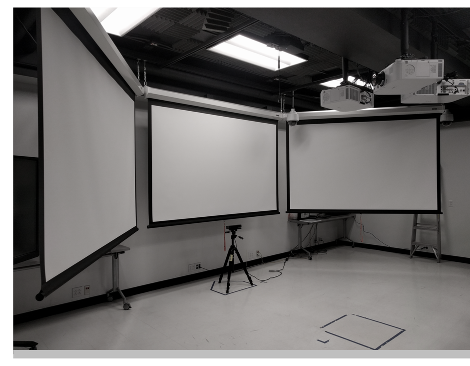
However, there is still a need to explore specific features that can inform the way that these environments support student learning, and in particular how to analyze and integrate the real-time multimodal data that is collected as students interact with the environment.

More clarity and innovation is needed to discover and articulate effective multimodal metrics within immersive and interactive learning environments. More effective metrics will allow for an increasingly sophisticated understanding of how multimodal environments facilitate student learning and provide valuable feedback on the design of specific features in these environments.

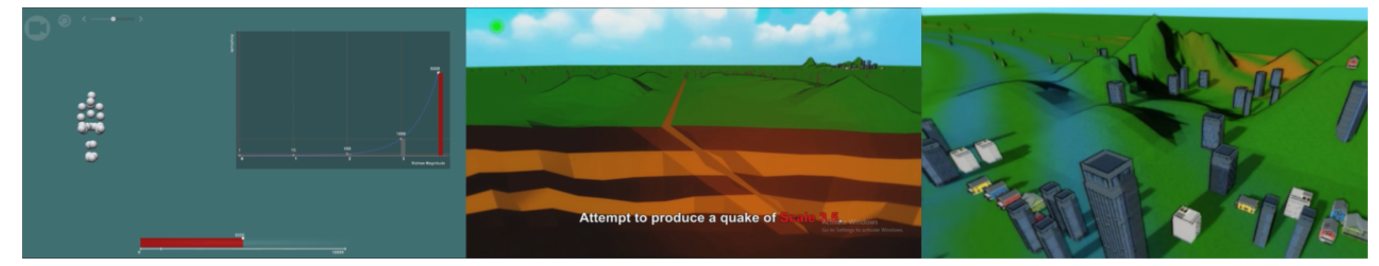
In this study, we examined what multimodal interaction metrics are available to capture student behavior as they engage with cross-cutting science concepts within an embodied learning simulation.

ELASTIC^{3}S

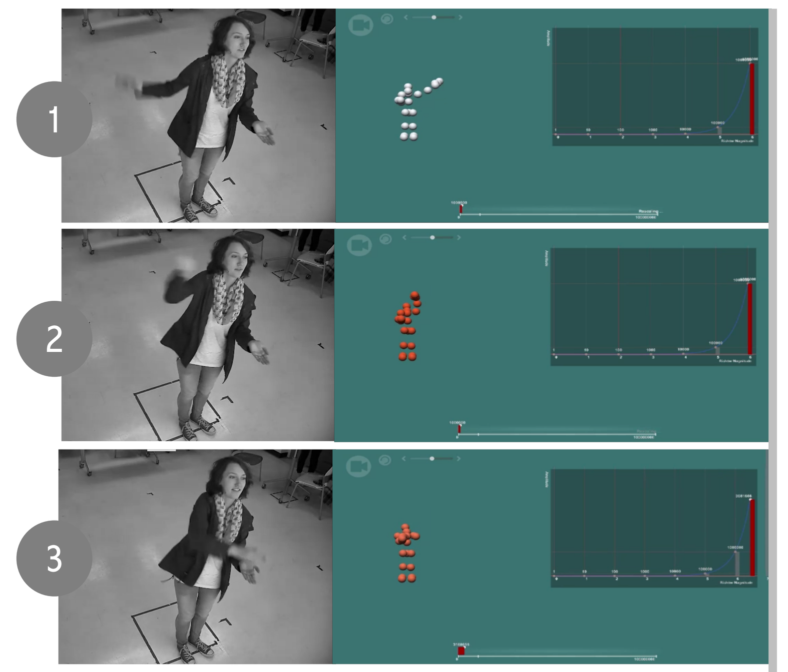
Embodied Learning Augmented through Simulation Theaters for Interacting with Cross-Cutting Concepts in Science



Simulation space configured for motion tracking of a three-screen simulation: ceiling mounted audio/video recording and Microsoft Kinect V2 body-tracking sensor



LEFT: Gesture tracking skeleton and graph visualizations; CENTER: Earthquake mechanisms and tasks; RIGHT: Earthquake effects



Student (left) and skeleton (right) showed the steps of making a multiplication gesture

Early pilot interviews with participants identified promising physical metaphors that resonated with students' intuitions about mathematical operations (e.g., stacking duplicates of a quantity on top of itself to represent multiplication).

Students are presented with a task that requires them to reach a certain numerical quantity using gestural inputs of **four mathematical functions (+1, −1, ×10, and ÷10)** while being given as much time as they need to perform the quantitative operations required to reach the goal.

Training phase where students are creating cubes, students are initially given straightforward objectives to gain familiarity with the system (i.e., create 234 and 431 cubes (C234, C431)).

Earthquake simulation students explore the cross-cutting concepts of scale, proportion, and quantity via the Richter scale. Students start with a straightforward task (i.e., create a magnitude 2 earthquake, which corresponds to 100 amplitude units, 10^2). Moving through subsequent tasks (obtain a Richter scale of 2.0, 3.0, 3.5, 7.0, and 8.0 (R2, R3, R3.5, R7, R8), the complexity of both their gestural inputs and conceptual understandings is progressed as they become more acclimated with the system.

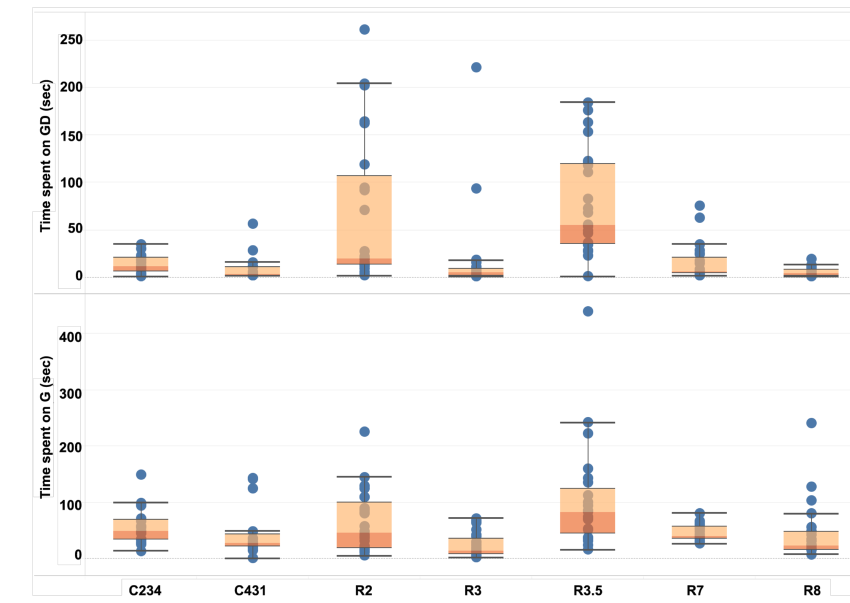
24 undergraduate students

PRE-TEST
Conceptual/Exponential knowledge

SIMULATIONS
Training (Cube) – Earthquake

POST-TEST
Conceptual/Exponential knowledge

PRELIMINARY RESULTS



Boxplot of students' time spent on gesture development and gesturing of each task

Students spent time quite differently during the tasks: R2 as the first task of the earthquake simulation, and R3.5 as the most challenging task.

Significant relationships were found between **gesture development time** of a task and **gesturing time** of the subsequent task.

- GD_C431 and G_R2: r = .567 (p < .05)
- GD_R3.5 and G_R7: r = .504 (p < .05)
- Students whose thinking process took longer before gesturing tended to spend more time on gesturing in the following task.

Accuracy of the students' submitted score on R3.5 showed a significant correlation with their exponential growth knowledge communicated during the simulation (r = 0.543, p < 0.01), indicating that **R3.5** was **a key indicator of students' conceptual understanding**.

Significant relationships were found between **speed of gesture** and **learning gain**.

- Speed_R8 and Conceptual knowledge gain: r = -.657 (p < .05)
- Speed_R8 and Exponential knowledge gain: r = -.584 (p < .05)
- Students who took longer on gesturing during the final task tended to gain more conceptual/exponential knowledge.

METRICS

Videos (Logs)

(1) Number of gestures
(2) Submitted quantity
(3) Time spent on gesture development
- Duration between when a task was given and when a student started gesturing (GD)

(4) Time spent on gesturing
- Duration between when a student started gesturing and when a target quantity (the number of cubes or the size of seismic activity) was submitted; G)

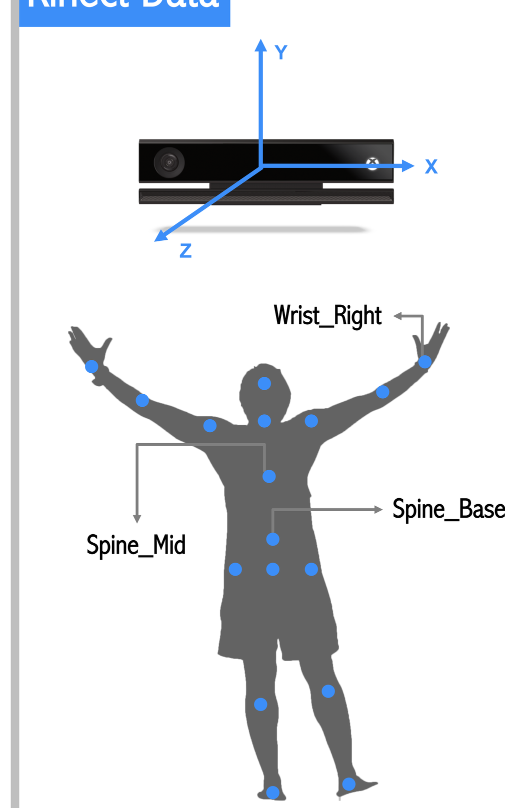
(5) Gestural time spent
- Time spent on gesture development and gesturing for each student can be compared with the average for the participants via a normalized sigmoid function:

$$\tau = \frac{1}{\left(1 + e^{-\left(\frac{\text{Average Timespent} - \text{Actual Timespent}}{\text{Average Timespent}}\right)}\right)}$$

(6) Accuracy score of each task
- e.g. While the correct answer for the amplitude of an earthquake that has a Richter scale magnitude of 3.5 is 3610 (i.e., target quantity), a student can submit what they think is the closest amplitude (i.e., actual quantity).

$$A = e^{-\left(\frac{\text{Target Quantity} - \text{Actual Quantity}}{\text{Target Quantity}}\right)}$$

Kinect Data



Kinect V2 joints (25 joints) and coordinate system

(1) Speed of gesture
- measured by finding the magnitude of the velocity of a given joint (i.e. Euclidean distance between p_0 and p_1, and time interval):

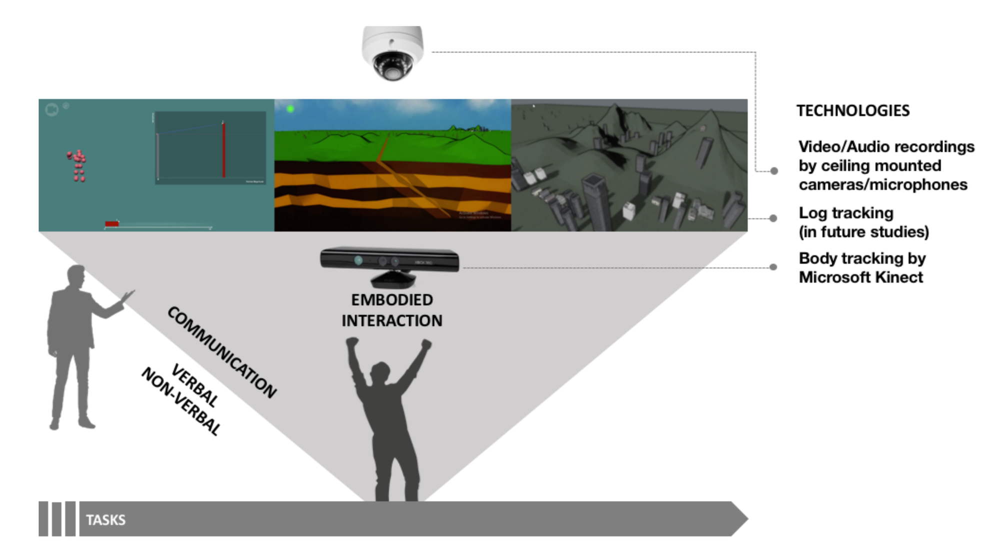
$$\Delta p = p_1 - p_0;\ \Delta t = t_1 - t_0;\ s = \left|\frac{\Delta p}{\Delta t}\right|$$

- calculating a total velocity of all joints of interest and repeating this for all frames; then calculating stats (e.g. mean, variance)

(2) Volume of gesture
- measured by finding the product of the Euclidean distance between the maximum and minimum points at each dimension.
- e.g. MULTIPLY gesture: Use Wrist_Right as a maximum point, Spine_Base as a minimum point, and repeat this for all frames. Use the distance between Spine_Base and Spine_Mid for normalization (rescaled by each body size)

$$d_x = \sqrt{(XWrist_{Right} - XSpineB_{ase})^2}$$
$$d_y = \sqrt{(YWrist_{Right} - YSpineB_{ase})^2}$$
$$d_z = \sqrt{(ZWrist_{Right} - ZSpineB_{ase})^2}$$
$$d_{ref} = \sqrt{(YSpineM_{id} - YSpineB_{ase})^2}$$
$$V = d_x \times d_y \times d_z$$

FUTURE WORK



Exploratory Data Analytics to Multimodal Learning Analytics

- Investigate causal relationship between interaction metrics and learning and affective engagement
- Visualize Kinect data to understand the role of gestures in learning
- Design powerful forms of feedback and automated prompts based on their tracked progress to further enhance student learning and engagement and reach more populations of learners in diverse environments

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