Examining Modalities of Embodied Interactions and the Effects on Learning From a Collaborative Science Simulation

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Abstract: Advances in motion tracking and gesture recognition technologies have opened the door to new lines of investigation around leveraging physical body movements to enhance the learning of critical STEM concepts. While significant progress has been made, there remain several challenges to supporting productive embodied learning with technology. This paper describes the design, implementation, and initial results from a study comparing two approaches to whole-body gestural input framing: personalized gestures or prescribed gestures based on their alignment with the target content. Two participants engage collaboratively with two science simulations linked by the "rates of change" NGSS crosscutting concept. Data collected shows significant individual and dyad gains in learning after engaging with the simulations, and video transcript samples show the effective facilitation of collaborative discourse.

Introduction

Technologies that allow learners to engage with STEM concepts through embodied interactions, such as gestures or whole-body movements, have received considerable attention in recent years (Johnson-Glenberg & Megowan-Romanowicz, 2017; Lindgren et al., 2016). Using the body to represent one's formative understanding of critical STEM ideas, and to be able to reflect upon and receive real-time feedback on those enacted ideas, has been shown to be an effective way to cultivate new learning (DeSutter & Stieff, 2017; Gallagher & Lindgren, 2015). These interventions are based in theories that view learning and cognition as fundamentally embodied, inseparable from our movements and systems for perceiving and acting within the physical world (Johnson-Glenberg et al., 2014; Shapiro, 2019).

Despite significant promise, however, there remains challenges to developing robust and impactful embodied STEM learning environments. First, not all forms of embodiment are equal in terms of their potential for generating new learning (Johnson-Glenberg et al., 2014). Second, few demonstrations of embodied learning show effects that go beyond the specific context of initial learning even though embodiment theorists frequently argue that embodied knowledge is intuitive and core (e.g., Lakoff & Núñez, 2000). Third, cueing specific actions can support metaphors that have been shown to be productive for learning (Lindgren, 2014), but inventing one's own representations can make learning more personal and potent (Schwartz & Martin, 2004). Finally, studies have emerged recently that have examined embodied learning in more collaborative contexts such as classrooms (e.g., Enyedy, Danish, Delacruz, & Kumar, 2012), but there is still much to be investigated about how embodied interactions can be synergistic in multi-learner environments. The following study describes a closer look at these issues in the context of a full-body simulation platform for two users that targets learning in multiple science domains related to the "rates of change" crosscutting concept identified in the Next Generation Science Standards (NGSS Lead States, 2013).

Methods

Simulation design

To allow for the exploration of the complex connections between the body, STEM learning, and collaborative interactions, a series of body-based simulations were developed. Unobtrusive, yet robust body tracking was achieved via the Microsoft Kinect depth sensor, coupled with custom gesture recognition software that allows for the use of pre-programmed or personalized gestures. Figure 1 (left) shows the use of shared interface conventions (participant position, graphs, rate limit icons, and dynamic model placement) across the two simulations utilized in this study (a population dynamics simulation and a climate change simulation).

Each subsequent task within one of the simulation domains increases in complexity, requiring communication between the participants in order to achieve the target input, output, or dynamic equilibrium needed to reach the task goal. Within the domain of climate change (top of Figure 1) the tasks have participants embody the rate of industrial activity releasing carbon dioxide into the atmosphere (left side of screen) or the amount of trees absorbing carbon dioxide via photosynthesis (right side of screen), with the resulting climate effects observed in the center of the simulation. For the domain of population dynamics (bottom of Figure 1) participants control either the amount of food presented as grass (left) or amount of predation presented as wolves (right) on a sheep population (center).

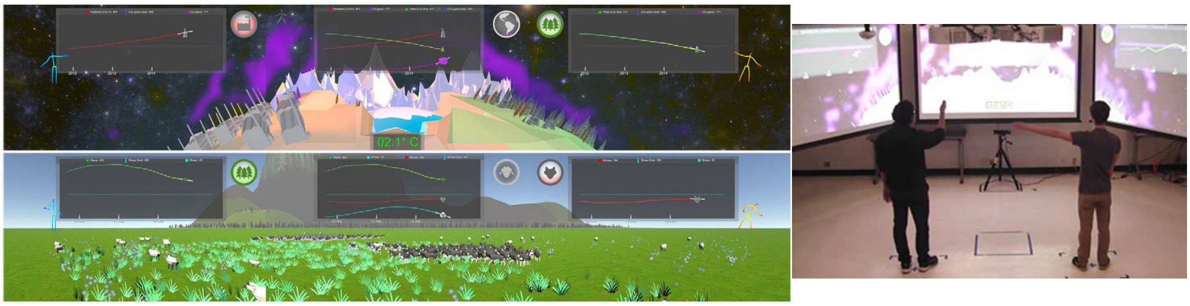

Figure 1. Sample screen layout of the climate change (left-top) and population dynamics (left-bottom) simulations with study setup (right).

Experimental design

Each data collection session consisted of an initial pre assessment focusing on rates of change and domain-specific (climate change or population dynamics) content. This was followed by a video and audio recorded dyad interview where both participants worked together on a multi-part short answer dynamic equilibrium word problem (modifying flow rates in a large aquarium and controlling rates of charge and discharge in a battery).

Participant pairs were then placed into one of four potential treatments based on the type of gestural framework (*Personal* or *Prescribed*) and the order of the simulations (*Population* or *Climate* first). Alternating the gestural input framework allows for the exploration of the costs and benefits of increased gestural agency afforded to the participants. Transfer of knowledge and experience across science domains, another area of evolving research, is the driver behind the simulation alternation. This allows for the exploration of potential effects of introducing one science content domain (and associated rate model) before the other while examining the potential transfer of crosscutting concept knowledge between domains. For the personal gesture group, participants were prompted to designate two gestures in the simulation: one representing a decrease and another representing an increase. For the prescribed gesture group, participants were instructed to spread their arms wide and alter the angle of their arm span to directly control the slope of the rate of their system component. Simulations sessions were audio and video recorded, and software log data were also collected. The sessions concluded with post-assessment iterations of both the dyad and individual assessments, as well as a 20 item Likert-scale engagement and perception survey.

Participants

70 undergraduate students were recruited from a non-STEM pre-service education course at a large midwestern university to participate in the study (16 male, 54 female). The demographic breakdown of all participants was 70% White, 21% Asian, 4.5 % Black, and 4.5 % Multiracial. 35 total sessions were completed (9 *Prescribed Gesture - Population First*, 9 *Personal Gesture - Population First*, 9 *Prescribed Gesture - Climate First*, and 8 *Personal Gesture - Climate First*). Of the 35 sessions, 15 signed up together, with the remaining 20 pairs assigned semi-randomly based on schedule compatibility. At the conclusion of the sessions, 63 of the 70 participants completed the post-session engagement and perception survey.

Results and discussion

Individual learning gains and engagement

Individual learning gain performance based on pre and post assessment scores analyzed via a paired sample t-test shows a significant gain in assessment scores when comparing pre-test (M = 0.505, SD = 0.17) and post-test (M = 0.626, SD = 0.16) scores after interacting with the simulation ($t(69) = -5.427$, $p < .001$). Additional means comparisons found no significant differences ($p < .05$) for gender, race, ethnicity, or year in school of the participants. As the simulations were the primary method of instruction (with the facilitator providing context and support), this significant difference highlights the value of engaging with the population and climate simulations while learning about general rates of change concepts such as dynamic equilibrium.

In order to analyze the potential effects on learning gains from the treatments, a normalized change score was calculated for each individual. Normalized change is a ratio measure of gain compared to maximum possible gain, as well as loss compared to maximum possible loss, ranging from -1 (maximum loss) to 1 (maximum gain).

Individual normalized change was calculated using pre and post assessment scores and a resulting whole group average normalized change score of 0.224 was calculated. Using the individual normalized change scores in a 2x2 factorial ANOVA, no significant treatment effects for gesture framework ($F(1,66) = 0.4358$, $p = 0.511$) or simulation order ($F(1,66) = 1.55$, $p=.217$) were found.

Collaborative interactions

To examine an initial dimension of collaborative interactions, a paired sample t-test found a significant difference in means in the pre ($M = 0.558$, $SD = 0.285$) and post ($M = 0.676$, $SD = 0.310$) dyad short answer assessments ($t(34) = -3.0862$, $p > .05$), with an average normalized change score of 0.385. While this difference is significant on a shared word problem, it highlights the possibility of changes in collaboration and conceptions resulting from engagement with the simulations.

As an exemplar for potential collaborative variations in dialog interactions, two participant pairs were selected for their individual assessment score similarity, one from the prescribed gesture treatment and one from the personalized treatment (both interacting with the population simulation first). Pairs were identified based on proximity of the group means for pre and post-tests. In pair 31 (personal gesture), participant 31A chose a rapid raising of their left arm over their head to represent an increase in rate, and a slow raising of their right arm to represent a decrease. Participant 31B chose to raise their right arm above their head for an increase gesture and performed a small circular motion at hip-level with their left hand for their decrease gesture. Audio and video data from the pair's simulation tasks were then reviewed with a focus on comparing dialog instances for two critical feedback points in the simulations: reflecting on model behavior and collaborative directives. Table 1 below shows sample dialog for both pairs from these instances.

Table 1: Comparison dialog between two pairs of participants at two points in the climate change simulation where they are prompted to reflect on their process by the session facilitator

<table>
<tr><td colspan="2">Predicting Model Behavior

Facilitator asks participants to compare the rate of change model exhibited in the climate change simulation to the population change model they just completed at two points during their tasks.</td></tr>
<tr><th>Pair 31 (personal gesture)</th><th>Pair 42 (prescribed gesture)</th></tr>
<tr><td>[Facilitator prompts for differences after initial experimentation with the system]
A: So, I think I'm the one that makes it increase? [performs increase gesture]. Hmmm…what are we noticing B?
B: I don't know…[gesturing increase]
A: So, make a factory [gestures increase]. Isn't it the same as the sheep one though? It's like an inverse relationship between the two?
B:[gestures decrease]</td><td>[Facilitator prompts for differences after initial experimentation with the system]
A: The last simulation was population, and the slope was population change over time [gestures change in CO2 simulation slope line].
B: [laughing while varying positive and negative slope gestures]
A: This time we are looking at a rate instead of the actual number…[begins to adjust slope gesture]</td></tr>
<tr><td colspan="2">Collaborative Directives

Facilitator asks participants to maintain a CO2 value of 700 ppm while simultaneously adjusting both their input and output to the system.</td></tr>
<tr><th>Pair 31 (personal gesture)</th><th>Pair 42 (prescribed gesture)</th></tr>
<tr><td>[CO2 level is below goal]
B: We need more factories.
A: [begins increase gesture] More factories? B, you are supposed to be moving!
B: [begins increase gestures]
[700 ppm goal reached]
A: I'm just gonna do a one [gestures increase once] and one [gestures decrease once]…look at that! Look at that wave B! [referring to the up and down slope of their rate line produced by the contrasting gestures]
B:[continues to gesture increase]</td><td>[CO2 level is at goal]
A: We need to keep the difference at 0…
[CO2 level drops below goal]
B: Wait, come back!
[Both participants begin using slope gestures]
A: Let's get it back in there… [the goal range]
[Both continuing to gesture]
A: What are you doing?!
B: Oscillating…[laughter]</td></tr>
</table>

Concluding remarks

The early findings of significant learning gains, coupled with no significant differences in learning gain or participant engagement across the treatment groups, establishes the necessity for a more focused analysis of the nuanced relationships contained in the pair simulation task video data. The significant individual and collaborative pre-post performance increase shows the overall value of the simulations, tasks, and facilitation as a productive engagement with critical crosscutting concepts knowledge and potential transfer effects between simulations. These findings suggest that, unlike previous embodied literature which places value on personalized over prescribed gesture, this distinction may be less of a concern when engaging with content designed around crosscutting concepts.

In addition, the sample dialog shows that the simulations and their corresponding gestural input frameworks can facilitate productive dialog around the target rates of change task. These dialogs vary widely in their content and context, and as exemplified in this paper even between groups scoring similarly on the written assessments. These dialogs are a rich source of further investigation, and more purposeful analysis of all participant dialog for emergent themes and interaction schemes using methods and visualizations such as those outlined in Shebab & Mercier (2019) and Csanadi (2018) have the potential to highlight changes in collaborative interaction between the treatment groups that are not visible in the pre and post task individual assessments.

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