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Paper Title "Walk, Walk, Walk": Identifying Computational Thinking in Embodied Models Through Movement

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“Walk, walk, walk”: Identifying computational thinking in embodied models through movement

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Abstract

Computational thinking is becoming increasingly important as technology is becoming more integrated in everyday lives and most fields. We examine and expand upon three facets of computational thinking: 1) the practice of collaborative computational thinking within science, 2) the use of embodied computational models within science, and 3) methods for identifying collective engagement in embodied computational practice. Based on a study of 19 fifth grade students using a mixed reality scientific modeling system [blinded for review], we explore the emergence of collective computational thinking. We compare and contrast participation in embodied models. Through analysis, we identify a contribution to social computational thinking, *collective computational thinking*, and argue for its value in understanding abstract principles.

Introduction

Computing education, particularly computational thinking (CT), is becoming increasingly important as technology is becoming more integrated in everyday lives and most fields. Computational thinking (CT) is broadly understood as a “universal attitude and skill set” that “involves solving problems, designing systems, and understanding human behavior, by drawing on the concepts fundamental to computer science” (Wing, 2006, p. 33). Proponents of CT have argued for its integration in science and mathematics (Schanzer et al., 2015; Sengupta et al., 2012; Weintrop et al., 2016), showing success in deepening scientific and computational knowledge while increasing interest and engagement (Basu et al., 2013; Arastoopour et al., 2020; Dabholkar et al., 2018; Sengupta et al. 2012; Swanson et al., 2019).

This study contributes to the understanding of computational thinking situated in science. We explore social computational thinking that emerges during use of embodied computational models, suggesting new approaches for identifying computational thinking in this context. In the following section, we explore literature on collaborative and embodied computational thinking.

Literature Review

Collaborative CT

Collaborative problem solving can be understood as “a situation in which two or more people learn or attempt to learn something together” (Dillenbourg, 1999). Even though both CT and collaborative problem solving are well established research fields, their intersection is still understudied. Collaborative CT traditionally focuses on groups of learners with common goals accomplishing CT tasks or activities together (Dillenbourg, 1999). Scholars have found that working together in pairs or groups encourages reflection and sense making while grappling with new ideas and solving challenging problems (Berland & Lee, 2011; Fields et al., 2016). Negotiation of ideas with peers can create shared conceptual understandings (Farris & Sengupta, 2014; McDowell et al., 2002; Clark & Sengupta, 2020), develop critical thinking (DeLiema et al., 2020), and improve learners’ confidence (Fields et al., 2016).

Most literature on collaborative CT focuses on the benefits of learners working together or in tandem to solve problems. Little research has been done to explore the computational thinking that emerges when learners have an equal contribution to the success or failure of a group, which we explore in this paper.

Embodied CT

A growing body of computational thinking research highlights activities that involve the use of body movement or gestures to enhance the abstract concepts associated with computing and programming (Wang, Shen & Chao, 2021). Early agent-based modeling focused on the benefits of body synchronicity, or the connection learners can make when imagining themselves as agents in a programming environment (Papert, 1980;). Since then, other computational initiatives have leveraged embodied roles or movement, including work in participatory simulations (Danish & Enyedy, 2020; Abrahamson, & Chase, 2020; Brady et al., 2016b; Colella et al., 1998; Wilensky & Stroup, 1999). Other embodied activities have shown to help learners construct robust understanding of scientific inquiry (Wilensky & Reisman, 2006). More recently, social technology, like badges and tags, have been used to support embodied participatory simulations (Brady et al., 2016a; Brady et al., 2016b; Klopfer et al., 2005). Embodied research shows promising results both for CT and STEM in general in deepening the understanding (Sung et al., 2017), and shifting perspectives about the purpose of computing (Daily et al., 2014).

We contribute to the body of literature on embodied computational thinking through the [software] environment. [Software] leverages mixed reality to introduce learners to science and computing practices using embodied models and the integration of high-tech and low-tech computational thinking into the modeling cycle. The models offer learners a unique opportunity to play-act using gestures and movement according to their belief of how the scientific agents they embody would behave. It creates an embodied participatory model where individual behaviors in a shared model create a collective reflection upon nature ([blinded for review 1, 2, 3]). Research practices of CT and embodied CT usually analyze interactions and use assessment tests (Kopcha & Ocak, 2019; Daily et al., 2014; Sung et al., 2017) to better understand the development of CT. We suggest a new framework to help researchers make sense of CT in a multimodal analysis. We ask: How does physical movement during embodied computational modeling express growth in computational thinking?

Methods

This study focuses on the final three days of a nine day science unit implemented in a fifth grade classroom in a mid-sized southern middle school. A total of 19 learners (9 Male & 10 Female) participated in the study. The unit leveraged the anchoring phenomenon of peppered moths to explore camouflage, adaptation, and selective pressure through a series of embodied computational models in [software]. We analyzed 120 minutes of video data and learner artifacts. We focus on understanding and attending to growth in embodied CT based on movement and engagement in embodied computational models. To do so, we track the movement of learners on an 8x8 grid that maps onto an embodied model, described below. Movement for each learner was recorded over the course of the model round (30 seconds). We compare the rounds of play for two groups of learners (one group

occurring before a CT activity and one group after), comparing the success rate (total number of camouflaged moths), initial positioning (starting positions of learners in the model), strategy (a qualitative characteristic of group level problem solving), and movement (characterized patterns of individual learners). In addition to movement, learner vocalizations were captured and qualitatively described. Learners selected their own pseudonyms, which are used throughout the paper. We suggest a framework to analyze the movement of groups to help us attend physical movement when making sense of embodied CT.

Activity Design

The seventh day of the Moth Curriculum reinforced the notion that camouflaged moths survive better, inheritance, and the concept of migration as a survival tactic. The learners explored a computational model in which six learners embodied moths and camouflaged on one of two colors of trees in the environment within 30 seconds. After 30 seconds, predators were released and hunted moths that were not camouflaged. Moth color was obscured from the learners. To support the task, a match meter communicated the total number of camouflaged moths. The mechanism of the model encouraged learners to work together to determine the color of their moth and successfully camouflage on trees (see figure 1). After participating in the model, learners were given a small group CT activity to concretize their strategy through a new representational form - either a flowchart or a drawing - of their choice. The goal of this activity was to help learners shift from being an agent in the model to taking a global perspective. The learners created, shared, then played with the model based on another group's representation on the 8th and 9th days of the unit.

Findings

Below, we compare and contrast the rounds across two groups as characterized by their success rate, initial positioning, strategy, and movement.

Success rate

As was described above, the learners' goal in the model was to have six moths matching the correct color of tree, shown to them on a "match meter" of the total number of camouflaged moths. For the pre-CT group, we tracked the number of matches over time for their attempts before and after the low-tech CT representation activity (see figure 2). The learners were inconsistent in their matching before the CT activity. The total number of matches increased and decreased throughout the course of the round. Even though the trend line has a slightly positive slope, it has an alternating trend. However, the success rate of the group after the CT activity shows a step function slope with a positive trend. Based on triangulation with the video data of the second round, we found that outliers, or decreases in the total matched moths, were a result of subtle learner movement as they waited for peers to match their moths.

Initial Positioning

Learners acting as moths could pick their initial position in the embodied model. The two groups started the round with different success rates based on their initial positions (see figure 3). In the round pre-CT activity, the group initial positioning setup was in random starting positions, resulting in three unintentional matches from the beginning of the round. However, they did not know which three of the moths were actually matching so the success was both temporary and uninformative. On the other hand, after the CT activity, the learners deliberately started the round off of trees, vocalizing instructions “form a line over there” and “yeah, at the sky”. This second group intentionally started with zero matches so that when they moved, their first matches would be informative. As a result, the trend line’s slope of the round post-CT activity shows a higher improvement rate through time. This shift highlights computational growth in pre-planning the setup process of a model, which is essential to every algorithm.

Strategy

We identified shifts in strategies before and after the CT activity (see figure 4). The pre-CT group moved independently of each other, resulting in a shifting number of matches over time. While the meter would highlight new matches, it was unclear what learner was positioned in a safe space due to the overlapping movement across moths. The post-CT group understood that their actions impacted their peers in determining the colors of the trees and thus coordinated and communicated with one another. They implemented a strategy where only one learner at a time walks forward until the match meter identified a safe tree. They created an organized and coordinated pace, which was planned before the start of the model (see figure 5).

Movement

We suggest that by analyzing movement in space we can better understand if a movement was impacted by CT thinking. Looking at the 6 moths at the pre-CT group, we can notice scattered movement. Each moth moves in a unique shape than the others. However, looking at the group’s movement post-CT activity, we notice agents creating a similar movement to their friends (see figure 6). Each agent (learner) represents one loop in an algorithm. In a system, the movement will be similar as all of the agents are playing by the same rules.

Discussion

When combining these four elements (success rate, initial positioning, strategy, and movement), we identify a shift from individualistic to collective computational thinking (see figure 7). Collective computational thinking refers to the emergence of computational strategy and practice at the group level. Before learners were given the time to reflect on the global perspective as a group in the CT representation activity, each learner attempted to solve the model individually. The post-CT activity groups strategized and worked as a group, directing individual movement in order to accomplish a shared goal. Not only do the interactions between learners suggest similar findings, we claim that attendance to physical location adds important evidence.

The last group who tested their strategy (post-CT activity) further engaged in the collective debugging process by observing the previous groups, assessing and revising their strategy to improve the algorithm. The movement in space and the pace of their improvement is similar to the first round after the CT activity, however, they identified a more efficient initial positioning, which resulted in a major improvement in the efficiency of the algorithm (see figure 8 and 9). The success rate shows similar trends as well as the movement, the strategy and the shape which supports our argument of a collective understanding and development of CT.

Conclusion

We expand existing literature on collaboration and embodied computational thinking, suggesting a new approach for capturing computational thinking. We claim that the analysis of physical movement can denote computational thinking, particularly in embodied computational learning experiences. We argue that in learning experiences that require equal and active contributions from learners may result in the emergence of social CT, *collective computational thinking*. This form of computational thinking may result from the embodied context and may allow learners to more intuitively make sense of abstract computing principles, such as algorithms. Future work should examine the use of this framework in other contexts in addition to exploring the value that collective computational thinking brings to the individual as well as the group.

Figure 1. Group activity in the[software] mixed-reality system

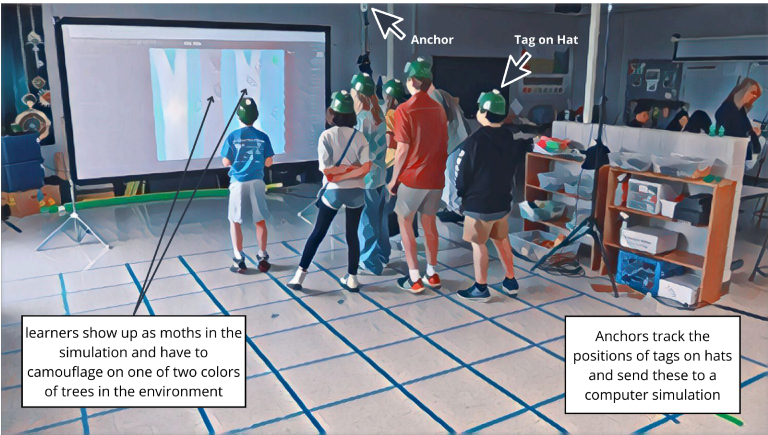


Figure 2. Number of moths matches out of 6 in a 30 seconds round

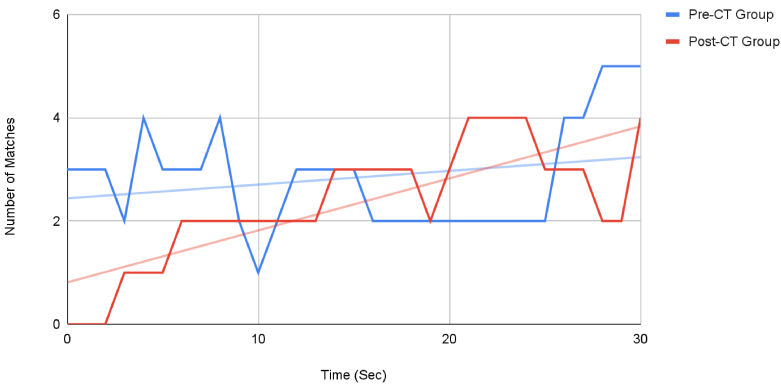


Figure 3. Initial positioning setup

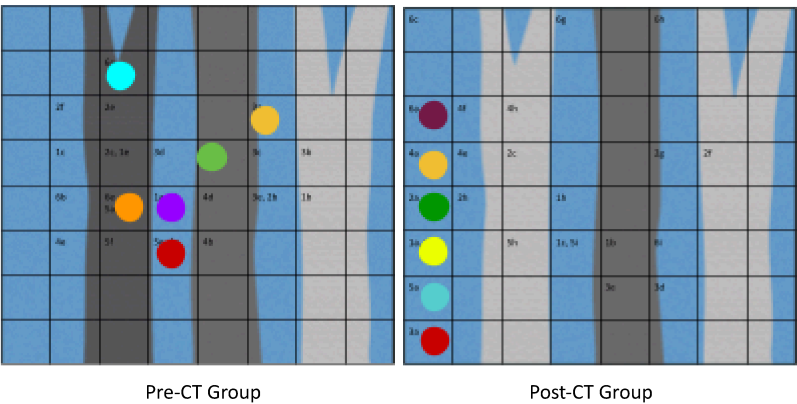
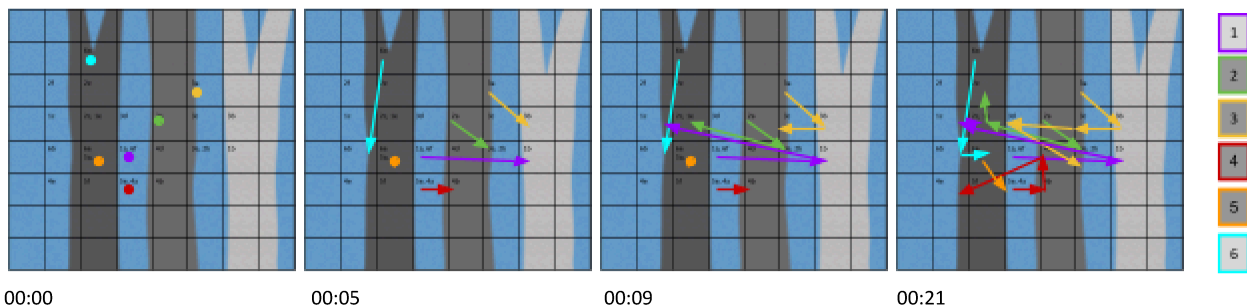


Figure 4. Pre and post groups strategy in frames. Pre-CT group moved independently while post-CT group understood that their actions impacted their peers

Pre-CT Activity Group



Post-CT Activity Group

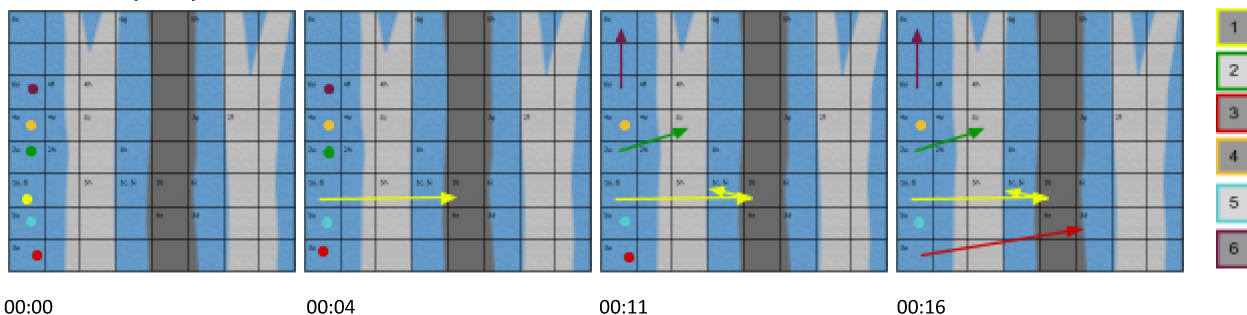


Figure 5. Strategy's conversations between learners during rounds. Pre-CT learners focus more on individualistic success where post-CT group focus on collective success

Pre-CT Activity with learner pseudonyms	Post-CT Activity with learner pseudonyms
Researcher 1: 27 second Crazy Wolf Love Pizza: Is this your tree? Katana: I might be over here Researcher 1: How do you know what to do? Researcher 2: wahhh. You got five out of six? you did pretty good	Swaggy Muffin: walk walk walk Researcher 1: You are going to have 30 seconds to do it once I [start] Swaggy Muffin: moth one do it. moth one Crazy Wolf Love Pizza: moth one go Crazy Wolf Love Pizza: Yes yes, no, no Crazy Wolf Love Pizza: oohh yess, professorX: no no wait. It's the first one, it's the first one

Figure 6. Summary of learners’ movements through 30 seconds. Learners in pre-CT group create unique shapes where post-CT agents move similarly to other learners

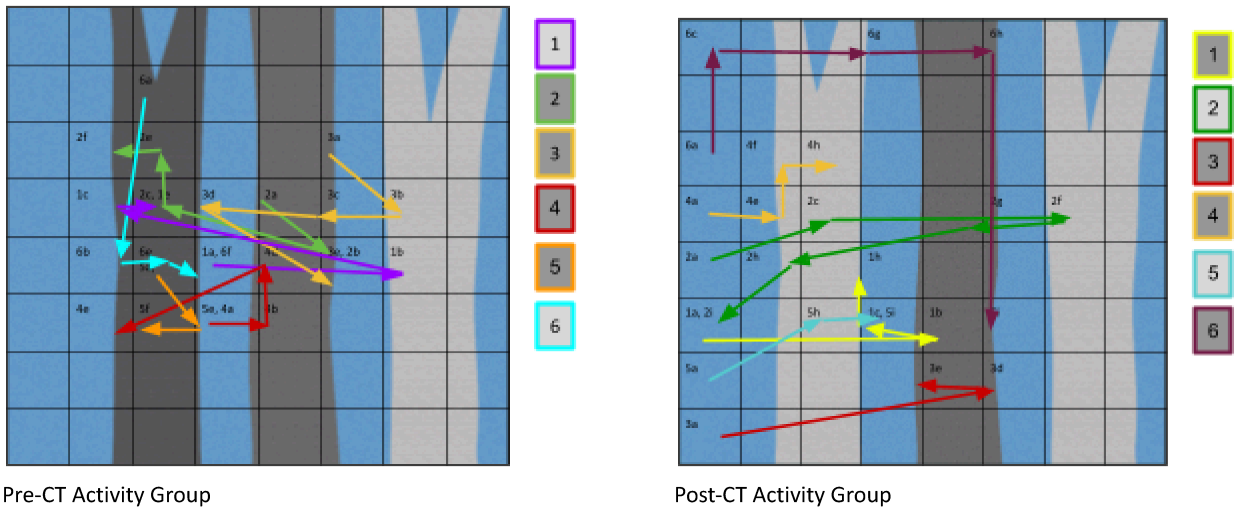


Figure 7. Summary of the findings

	Scattered individualistic	Collective CT
Success rate	Unsteady, sinuous change , a alternat trend	Gradually improving, one way trend
Initial Positioning	Random	Pre-planned location
Strategy	Uncoordinated	Coordinated
Movement	Unique	Similar

Figure 8. Summary of learners’ movements through 30 seconds round

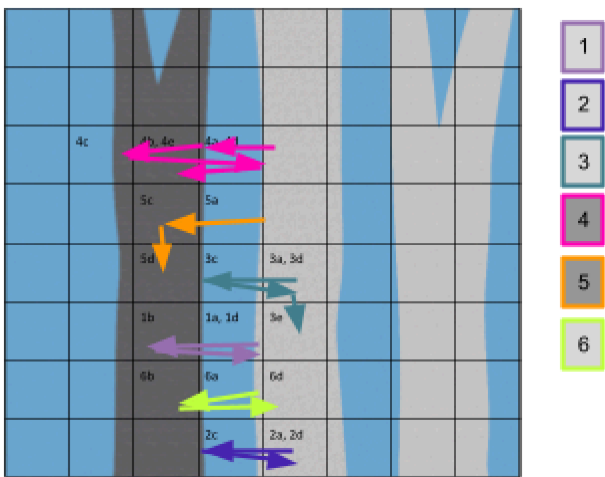
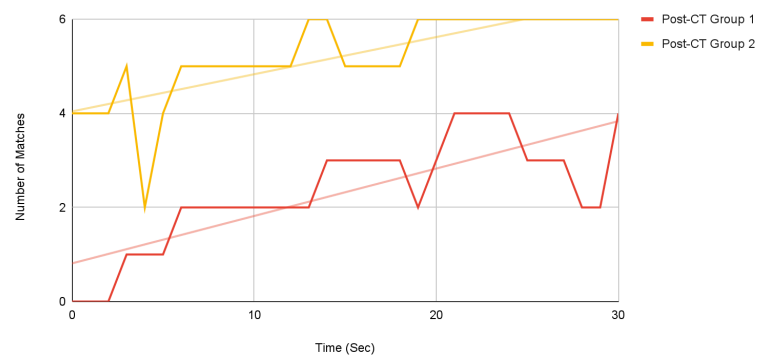


Figure 9. Post-CT Activity: Number of moths matches out of 6 in a 30 seconds round



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[blinded for review 1]

[blinded for review 2]

[blinded for review 3]

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