Kinesthetic Curiosity: Towards Personalized Embodied Learning with a Robot Tutor Teaching Programming in Mixed Reality

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Abstract. Personalizing interactions in socially assistive robot (SAR) tutoring has shown promise with a wide variety of learners, especially when using multiple interaction modalities. Many of those interactions, however, focus on seated learning contexts, creating a need for multimodal personalization measures in kinesthetic (i.e., embodied) learning contexts. This paper proposes a multimodal measure of **student kinesthetic curiosity** (KC^S) that combines a student's movement and curiosity measures into a single, personalized measure. This work evaluates the efficacy of KC^S in a SAR tutor interaction by conducting a within-subjects ($n = 9$) pilot study where participants completed kinesthetic mixed reality coding exercises alongside a curious robot tutor whose actions were determined by KC^S. The study results indicate that the stationarity assumptions needed for KC^S were met and that the robot tutor was able to successfully use KC^S to personalize its action policy, thereby positively affecting short term KC^S. However, no significant results were found for longer state changes for each student. The mixed reality visual programming language (MoveToCode) created for this work has been made open-source. This work aims to inform future online features and measures for mixed reality human-robot interactions.

Keywords: socially assistive robotics, augmented and mixed reality, embodied learning, visual programming languages

1 Motivation, Problem Statement, Related Work

A recent surveys of Socially Assistive Robot (SAR) tutors reports that SAR tutoring has shown great promise with various learners, especially when using multiple interaction modalities, but largely consists of one-on-one learning companions for children with an emphasis on personalizing the learning interaction [2]. This is often characterized by Bloom's two sigma problem [1] where students performed two standard deviations better when tutored one-on-one compared to traditional one-to-many lecture contexts. To personalize toward individual student needs, SAR tutor interactions have adopted interfaces (e.g., tablets) that increase the observability of student actions. The data from those interfaces are used to pursue multimodal reasoning about hidden student state such as a student's knowledge [11], affect [12], or engagement levels [6]. The emphasis on seated learning interactions creates a need to explore kinesthetic learning contexts (i.e., embodied learning [8]) that include the well-documented benefits of the physical embodiment of the SAR tutor [3].

Embodied learning can be effectively explored in virtual, augmented, and mixed reality human-robot interaction (VAM-HRI) settings. Consequently, this area of research has grown in recent years [15], focusing on design [14], teleoperation [7], and signalling challenges [13] [5]. Many of the studied interactions employ augmented reality head-mounted displays (ARHMD) that generate rich multimodal data minimizing or removing the need for external sensing.

This work explores using such rich, multimodal data for personalizing student interactions in an embodied learning context. We create synergies between SAR tutors, VAM-HRI, and embodied learning through the design and implementation of MoveToCode (Fig. 1), an open-source, mixed reality programming platform that interfaces with a robot tutor [4]. We introduce a real-time, multimodal measure of **student kinesthetic curiosity** **(KC^S)** and analyze how a curious robot tutor's actions impact KC^S during an interaction.

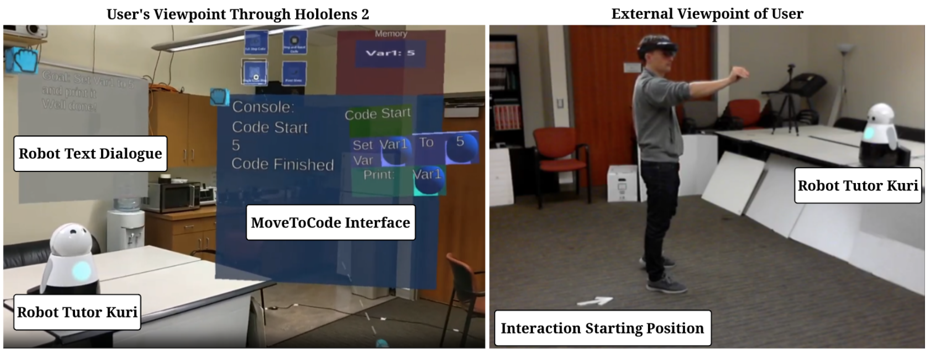

Fig. 1: MoveToCode Interaction; participants attempted to solve coding exercises involving 3D code blocks alongside the robot tutor, Kuri

2 Technical Approach

The key insight of this work is to combine the components of embodied learning (e.g., movement) and student curiosity (e.g., seeking new information) into a single measure of *kinesthetic curiosity* (KC^S) that is personalized for each student. To better understand how the design of KC^S can be leveraged for learning experiences with a robot, we designed a robot action policy that uses KC^S_t. With the hypotheses given in Sect. 2.3, participants completed mixed reality coding exercises with a curious SAR tutor described further in Sect. 4.

2.1 Measuring and Personalizing Kinesthetic Curiosity

To inform a robot's action policy, our real-time measures used a sliding-window approach to measure KC_t^S, a student's kinesthetic curiosity at a given time:

$$movement_t^S = \sum_{n=t-tw+1}^{t} dist(head\_pose_n, head\_pose_{n-1}) \tag{1}$$

$$curiosity_t^S = \sum_{n=t-tw}^{t} [ISA_n^S \neq NULL] \tag{2}$$

$$KC_t^S = w_0 * \frac{movement_t^S - \overline{movement^S}}{\sigma_{movement^S}} + w_1 * \frac{curiosity_t^S - \overline{curiosity^S}}{\sigma_{curiosity^S}} \tag{3}$$

where $movement_t^S$ (1) is measured with accumulated head pose change over a sliding time window tw, and $curiosity_t^S$ (2) is measured as the sum of information seeking actions (ISAs) over tw. ISAs are defined relative to the domain and action space of the learner. Specifically for this work, ISAs included snapping code blocks (Fig. 2), unsnapping code blocks, pressing interaction menu buttons (Fig. 1), and creating new code blocks. KC_t^S (3) assumes an underlying Gaussian distribution for $movement^S$ and $curiosity^S$ for all instances of time from 0 to t. This measure is a weighted combination of $movement_t^S$ deviation and $curiosity_t^S$ deviation from their respective mean (i.e., z-normalization [9]). The resulting normalized scores are therefore personalized to each student at time t.

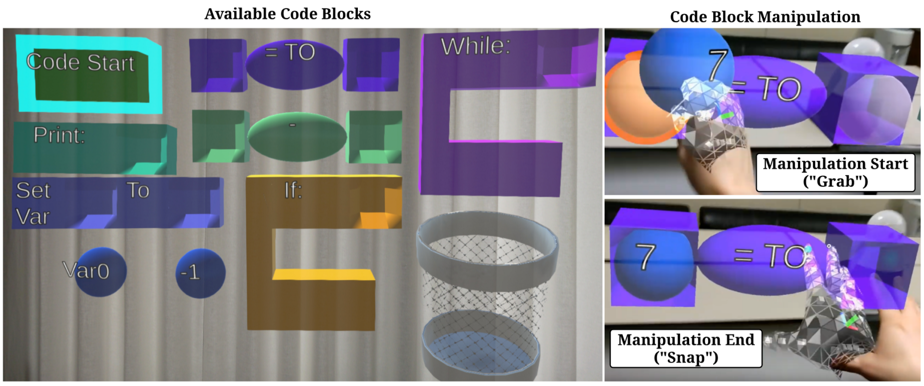

Fig. 2: Available MoveToCode code blocks (left) as seen by the participant through the Hololens 2. Code block manipulation (right) with a participant grabbing the block and letting it go to snap code blocks together.

For post-interaction analysis, a student's KC^S and a robot's KC^R values for an entire interaction consisted of the following:

$$KC^S = (movement^S, curiosity^S) \tag{4}$$

$$KC^R = (movement^R, curiosity^R) \tag{5}$$

where $movement^S$ is the student's total movement throughout the interaction, and $curiosity^S$ is the total number of ISAs throughout the interaction, allowing for normalization across interactions of varying lengths. Using the same set of actions to measure KC^S, a robot tutor's KC^R can be evaluated for both the real-time measure KC_t^R and the post-interaction analysis of KC^R.

2.2 *KC* Robot Tutor Action Policy

The robot's adjustable rule-based policy, shown in Table 1, was designed using a changeable threshold T^{KC} and time-window tw that triggered robot actions based on the time since last action $tsla^R$. For example, a lower T^{KC} causes the robot to take more information-seeking actions in order to motivate the user to do the same. The rule-based policy was designed to support a data collection for informing future data-driven policies.

Table 1: Robot Action Policy

Action	**Activation State**
Exercise Goal Dialogue	New exercise start
Virtual ISA	$KC_t^S < T^{KC}$ and $tsla^R \geq tw$
Positive Physical Affect	$KC_t^S \geq T^{KC}$ and $tsla^R \geq tw$ or Dialogue
Congratulatory Dialogue	Correct Answer
Scaffolding Dialogue	Incorrect Answer and Scaffolding Dialogue Left
Encouraging Dialogue	Incorrect Answer and ¬Scaffolding Dialogue Left

2.3 User Study Hypotheses

We performed a user study (described in Sect. 4) to evaluate the following hypotheses regarding KC^S with equal weights ($w_0 = w_1 = 0.5$):

H1: KC^S data fulfill the stationarity assumption needed for z-normalization.
H2: Robot virtual information seeking actions (i.e., curious actions) will positively affect student KC_t^S.
H3: A more curios robot (i.e., lower T^{KC}) will encourage a higher KC^S when compared to a less curious robot (i.e., higher T^{KC}).

For **H1**, KC_t^S assumes an underlying Gaussian distribution over the time series which implies that the time series data are stationary. For **H2**, we examined if robot virtual information seeking action (i.e., curious actions) could positively affect KC_t^S to better inform future robot action selection policies. For **H3**, we tested the differences in conditions to examine longer interaction effects of a more or less curious robot.

3 Results

KC_t^S depends on the time series for $movement_t^S$ and $curiosity_t^S$ to be stationary as they are modeled with the underlying assumption of a constant mean and variance needed for z-normalization. We performed an Augmented Dickey-Fuller test on each participants' $movement_t^S$ and $curiosity_t^S$ measures over the interaction to test for stationarity. With the exceptions of $movement_t^{P1}(p = .017, DF_\tau = -3.248)$ and $curiosity_t^{P2}(p = .012, DF_\tau = -3.378)$, all tests reported a significance of $p < .01$, supporting **H1**.

To analyze the effect of robot virtual information seeking actions (ISAs), we calculated the difference of measure (M) from time t to time $t + tw$ $(\Delta M_{t,t+tw})$ for all robot ISAs at time t. The robot totaled 170 ISAs with $\Delta M_{t,t+tw}$ distributions tested for normality (Fig. 3). A two-sided, single sample t-test was performed against a mean of 0. Significant results were found for all measures: $\Delta movement_{t,t+tw}^S(m)$ $(t = 4.51, p < .001, \bar{x} = 0.495, d = 0.35)$; $\Delta curiosity_{t,t+tw}^S(ISA)$ $(t = 4.637, p < .001, \bar{x} = 0.776, d = 0.36)$; $\Delta z\left(movement_{t,t+tw}^S\right)$ $(t = 4.623, p < .001, \bar{x} = 0.477, d = 0.36)$; $\Delta z\left(curiosity_{t,t+tw}^S\right)$ $(t = 5.087, p < .001, \bar{x} = 0.452, d = 0.39)$; $\Delta KC_{t,t+tw}^S$ $(t = 6.764, p < .001, \bar{x} = 0.464, d = 0.52)$. These findings demonstrate a positive short term effect of robot virtual ISAs on KC_t^S, supporting **H2**.

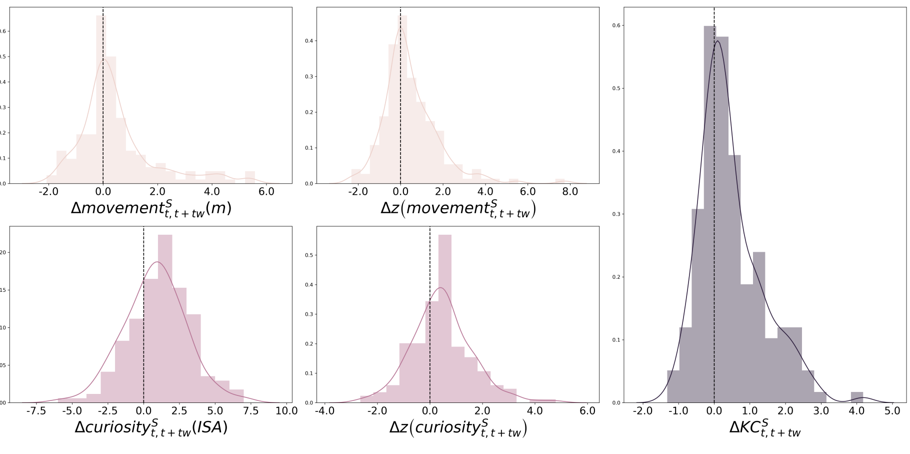

Fig. 3: Action distributions for all differences in measures where the robot took an ISA at time t to the score at time $t + tw$ $(\Delta M_{t,t+tw})$. Zero line is plotted to show distribution shifts.

We analyzed differences in total $movement^S$ and $curiosity^{S,R}$ measures between the robot action policy threshold conditions of $T^{KC}_{high} = 0.5$ and $T^{KC}_{low} = -0.5$ shown in Fig. 4. A Wilcoxon signed-rank test indicated a significant effect for $curiosity^R(ISA)$ ($\tilde{x}_{high} = 15, \tilde{x}_{low} = 3, W = 0, p = .008$). No significant effect was found for $movement^S(m)$ ($\tilde{x}_{high} = 52.2, \tilde{x}_{low} = 39.93, W = 21, p = .859$) or $curiosity^S(ISA)$ ($\tilde{x}_{high} = 90, \tilde{x}_{low} = 130, W = 11, p = .172$). These findings support the T^{KC} thresholds chosen but do not support a difference in KC^S between conditions posited by **H3**.

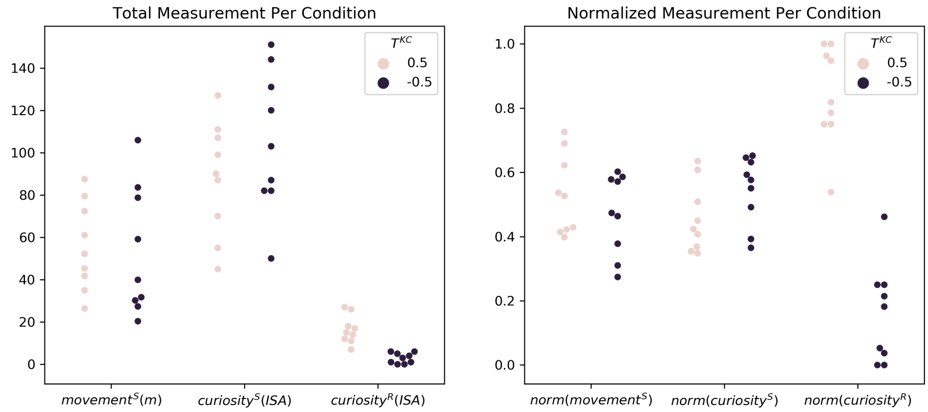

Fig. 4: Measures between the more curious ($T^{KC} = -0.5$) and less curious ($T^{KC} = 0.5$) robot conditions. The left depicts the total score for each measure for all participants. The right depicts normalized measures for each participant between conditions.

4 Completed Experiment

A single-session within-subjects experiment was conducted with approval by our university IRB (UP-17-00226) to evaluate a curious robot tutor policy (Table 1) with differing thresholds (T^{KC}). Ten participants (3F,7M) were recruited from the University of Southern California student population, with an age range of 19-27 ($\bar{x} = 22.8, \sigma = 2.9$). P8 experienced two separate operating system crashes (at 285.92 s and 341.44 s); having not experienced both experimental conditions, P8 was therefore removed from the behavioral data analysis.

Participants wore the ARHMD (Microsoft Hololens 2) and attempted to complete programming exercises with the help of a robot tutor, a Mayfield Robotics Kuri (Fig. 1). Kuri used the action policy described in Table 1 with tw empirically set to 20 seconds. The independent variable in the study was the robot KC threshold level using $T^{KC}_{high} = 0.5$ and $T^{KC}_{low} = -0.5$. The experiment lasted

20 minutes with T^{KC} substituted at 10 minutes. ISAs (see Eq. 2) in this experiment included snapping code blocks, unsnapping code blocks, pressing interaction menu buttons, and creating new code blocks.

5 Main Experiment Insights

This work developed a multimodal measure of kinesthetic curiosity (KC) and conducted and evaluated it in a pilot study. The study validated the efficacy of using multimodal data from an ARHMD to personalize student interactions via kinesthetic curiosity. MoveToCode, the programming language developed for this work, has been made fully open-source [4] and is extensible to any robot supporting the Robot Operating System (ROS) [10].

The study results demonstrate that z-normalization across modalities shows promise for providing a unitless comparison across measure modalities. Given time-synchronized data from the ARHMD, there is a significant benefit to further exploring additional interaction modalities the headsets contain, such as articulated hand tracking and eye gaze tracking. The logging system developed as part of MoveToCode has allowed multiple followup projects to use the collected behavioral data from this experiment with minimal processing, as each modality is logged at the same rate of 50Hz.

Our results indicate short-term effects of robot actions, but full interaction effects were not found across conditions. Based on the high post-interaction interview reports of novelty (7/10) within the interaction (e.g., users referring to the interaction as “cool”), future work will explore longer-term interactions with students. This work demonstrates that KC_t^S lends itself to reinforcement learning approaches for long-term personalization being explored in the rare long-term SAR tutoring interactions [2]. We plan to expand the virtual action space of the robot tutor and eventually study long-term personalization in school and home settings.

6 Acknowledgement

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