Chen, W. et al. (Eds.) (2016). Proceedings of the 24th International Conference on Computers in Education. India: Asia-Pacific Society for Computers in Education

Detecting Metacognitive Strategies through Performance Analyses in Open---Ended Learning Environments

Michael TSCHOLL[a], Gautam BISWAS[a]*, Benjamin S. GOLDBERG[b], & Robert A. SOTTILARE[b]

[a]*Institute for Software Integrated Systems, Department of Electrical Engineering and Computer Science, Vanderbilt University, USA*
[b]*U.S. Army Research Laboratory – Human Research and Engineering Directorate, Simulation and Training Technology Center, USA*
*gautam.biswas@vanderbilt.edu

Abstract. The detection and analysis of students' domain-specific and metacognitive strategy use in Open-Ended Learning Environments (OELE) is a necessary step to support their learning and problem solving through contextualized scaffolding. We present an analysis of students' performance from information captured in log files in UrbanSim, a turn-based simulation environment for counterinsurgency training. We illustrate the benefits of this approach within a task-model framework. Our overall goals are to implement a generalizable detection and adaptive scaffolding framework in an extended version of the GIFT tutoring system developed at ARL.

Keywords: Open-Ended Learning Environments, Learning Analytics, Performance Analysis, Metacognitive Processes and Strategies

1. Introduction

Promoting students' learning of metacognitive and self-regulatory strategies is increasingly seen as an important component of Intelligent Tutoring Systems, especially those that support open-ended complex problem solving and decision-making. Such open-ended learning environments (OELEs) allow the learner to make choices in their approach to developing, monitoring, and managing their evolving solution paths (Land, 2000; Segedy, Kinnebrew, & Biswas, 2015). To be successful, learners have to become adept at employing metacognition and self-regulation processes and strategies (Butler & Winne, 1995; Kinnebrew, Segedy, & Biswas, 2016). Such processes and strategies encompass information acquisition, situation awareness, plan development and refinement taking into account resource limitations and trade-offs presented by the solution space, solution monitoring, evaluation, and, finally, reflection, to see how they may do better.

In a project supported by the Army Research Labs, we have been designing a metacognitive tutoring framework to the Generalized Intelligent Framework for Tutoring (GIFT), "a computer-based tutoring framework to evaluate adaptive tutoring concepts, models, authoring capabilities, and instructional strategies across various populations, training tasks and conditions." (Goldberg & Cannon-Bowers 2013; Sottilare, et al. 2012; Sottilare & Holden 2013). Among other services, GIFT provides tools that support authoring of tutoring system content, which includes domain concepts and remedial instruction modules (Sottilare, et al. 2012). Our goal is to extend the learner modeling in GIFT to capture a more continual and fine-grained assessments of learners' capabilities, and then use these assessments to provide adaptive scaffolding and feedback to learners as they work on their tasks. Our particular focus is on understanding the cognitive and metacognitive strategies students employ in their understanding and decision-making tasks, and provide adaptive scaffolding on these strategies to help students become better learners and decision makers.

In this paper, we present our work on leveraging and extending the capabilities of GIFT to provide contextualized conversational scaffolding to students' learning about counterinsurgency operations (COIN) with UrbanSim (McAlinden, et al., 2009), a turn-based game environment, where users take on the role of a battalion commander to deal with fictional counterinsurgency scenarios. UrbanSim simulates a complex social and political environment, where COIN operations can have multiple short-and long-term effects. This requires trainees to maintain awareness of the evolving simulation scenarios, and apply metacognitive processes, such as seeking and analyzing relevant information, using that information to select appropriate actions, and predicting, evaluating, and reflecting on the effects of operations. The turn-by-turn analysis of student performance is a first step toward inferring students' metacognitive and problem solving processes. We discuss our analyses methods, and how the results of our analyses will help us define learner models that capture students cognitive and metacognitive processes.

2. Background

In its general formulation, metacognition is the ability to reason about and manage one's own cognition (Flavell, 1976). When applied to learning, metacognition implies awareness of a learning or problem solving situation, and describes how learners are able to set goals, create plans for achieving those goals, monitor their progress, reflect on outcomes, and revise plans to improve progress (Zimmerman & Schunk, 2011). Typically, at the most general level, many models of learning and problem solving include processes for *information acquisition and interpretation*, *goal setting*, *planning*, and *operation execution*, and *assessment*. The Army's Common Operational Procedure (COP), for example, expresses complex problem solving as stages of *Visualization*, *Description*, *Direction* and *Assessment*, stages that map onto the more general processes above. Almost all current Army operations are mission-oriented, which gives sub-ordinates some flexibility in assigning operations in the field.

Our focus on metacognition is centered on students' understanding and use of strategies, defined as consciously controllable processes for completing tasks (Kinnebrew, Segedy, & Biswas, 2016). It is commonly assumed that learners possessing metacognitive skills are more able to learn in unfamiliar domains because common metacognitive strategies combining information acquisition, solution generation, and solution monitoring and evaluation, apply to many learning situations. Thus, our goal in UrbanSim is to support students' learning of metacognitive strategies and help them to apply them in complex tasks.

3. Counterinsurgency and UrbanSim

Understanding of the COIN doctrine and COIN strategies supported in UrbanSim is key to analyzing trainees' problem solving abilities and performance in UrbanSim. Counterinsurgency is the comprehensive civilian and military effort designed to simultaneously defeat and contain insurgencies and address their root causes. Legitimacy – fostering effective governance by a legitimate government – is its main objective. Counterinsurgency operations, therefore, aim to defeat insurgents while also working with local political and religious leaders to increase population support, separate (to protect) the population from insurgents, and ultimately install a Host Nation government that promotes self-sufficiency and economic growth.

As Host Nation security forces often have insufficient capabilities to defeat the insurgents, Coalition Forces may initially shoulder the burden of being the primary counterinsurgents. The overall goal is to apply a stated army doctrine called Clear-Hold-Build (CHB). Operations are conducted to engage and flush out insurgents in the *Clear* phase, to clamp down and prevent insurgent activity in the *Hold* phase, and to address the root causes of the insurgency and promote self-governance and economic viability in the *Build* phase.

UrbanSim (McAlinden et al., 2009) is a turn-based simulation environment in which users assume command of a COIN (Counter Insurgency) operation in a fictional Middle-Eastern country. Users can view information on the main interface or in pages that includes:

I. *Information* about economic, military, and political ties between local groups; the Army's current level of *population support*; and *PMESII* (Political, Military, Economic, Social, Information, Infrastructure) values to assess an operational environment;

II. *Progress* in achieving six primary lines of effort (LOEs): (1) Civil security; (2) Governance; (3) Economics; (4) Host Nation security forces; (5) Essential services; and (6) Information operations; and

III. *Intelligence reports* on events provided as Situation Reports (SITREPs) and Significant Activities (SIGACTs).

Mission goals are typically expressed in percentage values assigned to the LOEs. Students assign operations to 11 available units (e.g., E CO b). Once committed, the simulation executes the orders and models their effects on the regions of operation in the scenario. During this phase, additional events caused by other agents (e.g., the insurgents) can occur (e.g., an attack on a gas station) that are displayed at the beginning of a new turn. The combination of all activities may result in net changes to population support, PMESII values and LOE scores that provide the user aggregated feedback on how well they are performing.

4. Understanding student activities

Our approach to infer metacognitive processes that students may invoke as they perform their activities on the system is motivated by the rationale that, as their actions produce the context within which new actions are carried out, performance measures reflect how they engaged metacognitively with the context. We leverage context values (the Game state) to compute measures on whether the students: 1) execute the CHB (Clear-Hold-Build) strategy, 2) select operations in line with the LOEs, 3) conduct operations to increase population support and 4) monitor the situation for unexpected events and react appropriately

CHB Strategy execution. PMESII values, and especially the M value (representing the degree of military control over a region), play a particularly important role in executing the CHB strategy. Regions over which the Army has little military control (low M values) require Clear operations; regions where some control has been established (average M values) require Hold operations; and in regions with sufficient military control (high M values), Build operations can be conducted. We trace whether students' follow the CHB strategy through 3 measures: *CMatch*, *HMatch* and *BMatch*, calculated by counting the number of regions in the Clear, Hold and Build phase at the each turn, using a region's Political (P), Military (M) and Information (I) values. Executing CHB consistently and appropriate to a region phase will result in *CMatch* to decrease, and *HMatch* and *BMatch* to increase.

Lines of Effort. In UrbanSim, LOEs are represented as percentage values. A low percentage value of a high-priority Line of Effort indicates to the Battalion Commander that operations improving the conditions represented by a Line of Effort (e.g. Civil Security) are required. Tracing the trend of LOE scores allows inferences on whether students are able to translate the Battalion Commander's intent into effective operations.

Population Support. In line with the broad goal of COIN operations, student performance is measured in terms of the percentage values representing population support: support *for, against*, and *neutral*. The values add up to 100%. The causal model of UrbanSim reproduces to a large degree the COIN directive to avoid lethal force and instead undermine insurgents' popular support. Aggressive operations may have immediate security benefits, but are resented by the population, thus potentially increasing the tendency of local to join insurgents.

Situational awareness. The process consists in developing understanding of the situation as it undergoes change as a result of operations and unexpected events (which may result from operations). Primary sources of information are indicators of key operational values (e.g. population support), and SITREPs and SIGACTs. Students' situational awareness is measured by tracking their responses to events and changes in key values. We compute a measure of responsiveness – the number of events or changes a student responds to.

5. Task model

To represent student proficiency in domain-specific strategies and their more general metacognitive counterparts, we developed a task model consisting of a set of cognitive actions corresponding to relevant tasks that can be performed in the domain of operations organized in a hierarchal structure. This is shown in figure 1. The cognitive actions are themselves linked to strategic competencies (when should this action be executed and what are the expected consequences) that experts see as basic requirements in counter-insurgency operations. In UrbanSim, they include domain/task-specific actions, such as conducting operations, a user action that links up to the more domain-general task of Solution Construction (SC). Students' *View* actions involve clicking on an interface item to display a page with information on individuals or groups. These actions are linked to Information Acquisition and Interpretation Actions (IAI). The effects of operations can be assessed by viewing analysis pages (e.g. a causal graph); these are related to the domain-general action of Solution Assessment (SA).

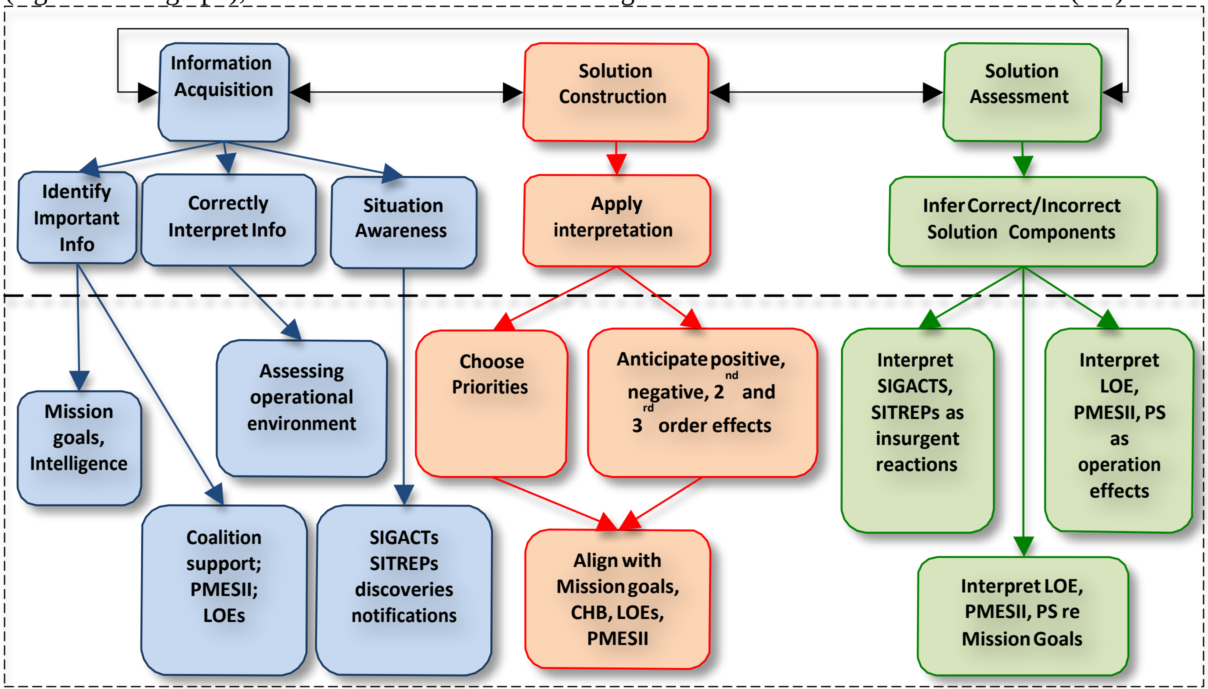

Figure 1: the UrbanSim task model. PS is 'Population Support'.

Building on the task model, the analysis involves making a set of inferences on students' actions while they are using the learning environment. Students' problem solving links directly to metacognitive processes through which students update their knowledge (information acquisition), assumptions and progress (solution assessment) that are the bases to select effective operations (solution construction).

6. Case Study

6.1 Aim and design

The aim of the analysis presented in the next section was to develop a qualitative account of students' cognitive and metacognitive activities and strategies, as the basis to subsequently develop links between log data and the task model. In the past 2 years we have conducted studies with ROTC students from which the data presented in this section are drawn. The students worked in pairs on a single computer terminal, with one student controlling the mouse; through this design we obtained verbal accounts on students' strategies, thinking and knowledge. The analysis leverages 1) log files and 2) audio-video data from web-cams synced to a screen capture video. In the analysis, we focused in particular on student behavior (e.g. viewing a display of LOE values), and behavior – operation selection relations. These relations are extracted from students' justification on operations selection.

6.2 Data analysis and interpretation

We begin with a turn-by-turn description of a dyad's (Group A) attention to and analysis of information, and which sources of information are the basis for selecting operations. We then offer a broad interpretation of the students' strategies and metacognitive processes.

Turn 1. The students activate the 'religious affiliation' overlay; notice that Shiite regions are more supportive than others; they decide to maintain control over Shiite regions while moving into hostile areas. Operations and regions are selected on the basis of location.

Turn 2. Students discontinue the strategy devised in turn 1 because they notice drops in LOE values; in effect, students stop clearing regions. They don't read PMESII values, and instead focus on LOE trend indicators. They decide to increase the LOE HN Security Forces by Recruiting Police in 3 regions; they read notifications, and follow Staff recommendations.

Turn 3. Students are concerned about drops in HN Security Forces, Governance and Civil Security; they attempt to identify the cause in HN Security Forces by consulting the Political Network page, and to counter it with further Recruitments; decide to increase Governance by hosting 3 meetings; and to increase Civil Security by attacking an insurgent group. No other efforts are made to clear regions.

Turn 4. Students read LOE trend indicators and are satisfied with the increase in HN Security Forces value; they focus their efforts on Civil Security and Government values. They consult the Political Network page and Intelligence entries on local political figures to find out how to increase Governance. They decide to host meetings with tribal leaders and to pay tribes.

Turn 5. Students are satisfied with LOE trends; they also notice that Population Support has increased. They discuss that following recommendations didn't prove to be useful, and decide to base operation selection more on their own analysis and understanding. They also decide to focus more in gathering intelligence and interaction with the population.

Turn 6. Continue with approach of previous turn.

Turn 7. All LOEs decrease as a result of a major insurgent attack. Students seem at loss on how to react; continue with approach of previous two turns. Operations are conducted with little analysis, and there is no clear focus.

Turn 8. Students notice increases of LOE trends, and continue with approach. As in the previous turn, there is no clear focus of the operations, but operations are selected because LOE trends are positive. Students discussions are infrequent now.

Turn 9. The approach of the previous turns is continued. There are no discussions in this turn.

A clearly evident aspect of the dyad's metacognitive behavior is the focus on a single source of information: the LOE trend indicators, and developing strategies based on the trend in these values. These indicators are displayed at the sides of the LOE value representations. The group uses the indicators as the primary source of information to assess progress. This single source is clearly insufficient to achieve high performance values and the mission goals. Students' very rarely read PMESII or Coalition Support values, indicating that they had no idea about differences in regions under the total area of operations.

In terms of strategic competence, students fail to execute Clear-Hold-Build. Starting at about turn 5 and 6, the students have, however, developed an approach: after noticing scant progress and some dissatisfaction with Staff recommendations, students decide to conduct operation in line with a Soft approach – to increase LOE values by interacting with the population.

A key problem we identified through this analysis is that students notice changes in some of the values and are aware of events, but may conduct ineffective operations for two or more turns before becoming aware that the operations don't advance a set goal. For example, to counter the drop in Governance, the students decide to meet with tribal leaders and give payments to tribes, both operations that have little effect on Governance. LOE trend indicators aggregate the effects of all operations and also NPC moves, making it difficult to pinpoint cause-effect relations. The students in this group never consult regional PMESII values to identify specific problems, or study the Causal Graphs to determine the longer term effects of actions, and thus continue with ineffective operations for several turns.

Overall we find that the students in this group frequently engage in limited amounts of information acquisition and analysis activities, but exhibit sub-optimal strategies in identifying all of the relevant information that would best serve their analytical and information-gathering aims.

Students' overall performance is would be classified as weak. By turn 7, only 5 out of 15 regions have been cleared, and population support is low throughout all turns. Failing to view PMESII values and execute Clear-Hold-Build operations in their proper sequence as required in the different regions, is the main reason of the low performance; also, the exclusive focus on LOE trend indicators prevents students from developing a more informative picture of progress, one which could have instigated them to adapt operations better to the changing environment.

7. Discussion and conclusions

This paper reports our work on the automated detection of students' strategies in complex OELE, the necessary step to provide contextualized feedback and scaffolding for students. We have advanced the work to a degree where students' problem solving is tracked as a function of how their choice of operations matches with the CHB strategy, advance the mission goals, align with the LOEs, and take into account regional PMESII values. The details are discussed in Tscholl, et al. (2016, in review), where we show how quantitative calculations are performed to establish students' cognitive and metacognitive proficiencies.

Our future work will consist in conducting further data analyses. We predict that by developing characterizations of a larger number of groups, we will be able to uncover patterns of behavior and relationships between behavior and problem solving. This will enable us to develop inferences from performance values to metacognitive processes and strategies, which will then allow us to evaluate further data or probe students.

By tracking in detail problem solving we are gradually identifying components of a learner model. It represents the learner at several levels: the learners' domain competence and assumptions about operations effects, the competence to chose appropriate and effective operations, a tendency to thoughtful planning or more spontaneous actions, and a tendency for reflective assessment on prior actions.

References

Basu, S. & Biswas, G. (2016). Providing adaptive scaffolds and measuring their effectiveness in open ended learning environments, in Proc. of ICLS 2016, Singapore, June 2016.

Butler, D. L. & Winne, P.H. (1995) Feedback and self-regulated learning: a theoretical synthesis, Review of Educational Research, 65, pp. 245-281

Flavell, J. (1976). Metacognitive aspects of problem solving. In L. Resnick (Ed.), The Nature of Intelligence (pp. 231-236). Hillsdale, NJ: Erlbaum.

Goldberg, B., & Cannon-Bowers, J. (2013). Experimentation with the generalized intelligent framework for tutoring (GIFT): a testbed use case. In AIED2013 Workshops Proceedings v. 7.

Land, S. M. (2000). Cognitive requirements for learning with open-ended learning environments, Educational Technology Research and Development, 48(3), 61-78.

Kinnebrew, J., Segedy, J.R. & Biswas, G. (2016). Integrating Model-Driven and Data-Driven Techniques for Analyzing Learning Behavior in Open-Ended Learning Environments. IEEE Transactions on Learning Technologies.

McAlinden, R., Durlach, P., Lane, H., Gordon, A., & Hart, J. (2008). UrbanSim: A game-based instructional package for conducting counterinsurgency operations. In: Proceedings of the 26th Army Science Conference, Orlando, FL.

Segedy, J. R., Kinnebrew, J. S., & Biswas, G. (2015). Using coherence analysis to characterize self-regulated learning behaviours in open-ended learning environments, The Journal of Learning Analytics, 2(1), 13-48.

Sottilare, R. A., Goldberg, B. S., Brawner, K. W., & Holden, H. K. (2012). A modular framework to support the authoring and assessment of adaptive computer-based tutoring systems (CBTS). In Proceedings of the Interservice/Industry Training, Simulation, and Education Conference.

Sottilare, R. A., & Holden, H. K. (2013). Motivations for a generalized intelligent framework for tutoring (GIFT) for authoring, instruction and analysis. In AIED2013 Workshops Proc., v. 7, pp. 1-9.

Tscholl, M., Ramkumar, R., Biswas, G, Goldberg, B. S. & Sottilare, R. A. (in review). Integrating UrbanSim and GIFT to Support Complex Problem Solving with Metacognitive Tutoring. *International Journal of Artificial Intelligence in Education* (Special Edition: GIFT).