Challenges and Emerging Concepts in the Development of Adaptive, Computer-based Tutoring Systems for Team Training

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ABSTRACT

A renaissance in the research and development of computer-based, tutoring systems over the last ten years is motivating scientists to ponder the application of intelligent tutors and coaches in more challenging team training problem spaces where human tutors are either unavailable or impractical. This paper reviews some of the challenges and emerging technologies (tools and methods) that might influence the development of adaptive, intelligent tutors for geographically-distributed team training. Team tutoring presents many challenges. Even human tutors struggle to develop team cohesion, coordinate roles and responsibilities of team members and assess their contributions (Sottilare, 2010). Computer-based tutors face additional challenges: sensing and assessing the cognitive state (including affect) of each team member (Sottilare and Proctor, *in press*; D'Mello and Graesser, 2007) in near real-time to understand each team member's readiness to learn (e.g., their engagement and motivation); measuring team performance; perceiving and weighing team member contributions to team performance; and selecting instructional strategies that will optimize team performance. Emerging sensing technologies are showing promise as enablers of computer-based perception of each team member's behavior and physiology with the goal of predicting unobserved variables (e.g., cognitive state). Along with performance measures, historical and self-reported data, behavioral and physiological measures can provide the tutor with the information needed to model the trainee's state and their relationship with other team members and the tutor. Accurate (and timely) trainee and team state information (e.g., performance, competency, trust) are considered to be determining factors for the team tutor to select appropriate instructional strategies (e.g., support, direction) for optimal team performance. Design goals, ongoing experimentation, and potential applications of computer-based team tutors are also discussed.

ABOUT THE AUTHORS

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INTRODUCTION

The military has exploited artificial intelligence within existing technologies (e.g., virtual worlds, games, virtual humans) to provide/supplement team training, but limited attention has been given to the need for computer-based tutoring during distributed team training exercises where human tutors are either unavailable or impractical (e.g., not cost-effective).

In the 1980's and early 1990's there were significant military research investments in computer-based tutoring technologies for individual training in well-defined domains (e.g., development of procedural knowledge). These investments cooled off as the promise of ubiquitous tutoring systems failed to materialize in the military training domain where the emphasis tends to be focused on collective training. Over the last ten year, computer-based tutoring systems have advanced along with learner and expert modeling, authoring tools and methods to select instructional strategies. The maturity of technologies for individual tutoring systems bodes well for some near-term solutions to team tutoring.

Significant technical challenges remain in providing geographically-distributed team training. This paper evaluates the challenges related to the management of training vice its development and distribution to trainees. Specifically, we address the functions of an intelligent tutoring system (ITS) for distributed team training; how these functions might differ from distributed training for individuals; current capabilities/methods to support distributed team training; and areas for future research.

Thoughts on Team Training

What is needed now is a means to understand: the state (e.g., bored, frustrated or engaged) of each distributed team member; their individual performance; the interactions (e.g., communication) of team members; and the contribution of individual state, individual performance, and team member interactions to the collective performance of the team. Challenges include some of those documented for individual ITS, but there are also some new ones to be overcome if a collaborative training environment is to be fostered. Individual ITS must be capable of supporting the training needs of each team member, but also be able to communicate with other individual ITS regarding progress toward team goals, individual contributions toward team goals and the formulation of instructional strategies (e.g., support, directions, questions, feedback or hints) and interventions for the collective team and/or individual members. A large part of the process to determine an optimal instructional strategy is the tutor's ability to sense behavioral and physiological cues and use those cues to classify/predict individual trainee state (e.g., emotions, beliefs, desires or intentions). The premise being that the better the ITS understands the trainee (or the more comprehensive the trainee model is), the better the ITS will be able to select appropriate instruction and feedback.

Team ITS also have the added workload of coordinating the states of individual team members so a more comprehensive picture of the team state can be developed. Inputs to the "team model" might include the state of trust between individual team members, progress toward team goals, reassessment of team goals based on priorities and the distribution of workload.

Considerations for Team Tutoring

When trainees effectively learn in groups, they can encourage each other to ask questions, explain/justify their opinions and reasoning, and actively reflect upon their knowledge. Research has shown such situations to increase group performance and individual learning outcomes (especially motivation and engagement - Tchounikine, Rummel, and McLaren, 2010). However, these benefits can only be achieved in well-functioning, actively learning teams (Jarboe, 1996; Soller, 2001). While some teams may have successful interaction and communication naturally, others may be incapable of developing a balance of participation, leadership, understanding, and encouragement (Soller, 2001). This dysfunction can rapidly degrade group and individual performance, motivation, and engagement.

In order for a computer-based team intelligent tutoring system to be successful, three primary factors should be understood and addressed in its design: (a) the accountability collaborative learning interactions and communications; (b) the complexity of training tasks; and (c) the physical distribution of the team.

Foremost of the three factors with respect to establishing effective collaborative learning is the uncertainty and dynamic nature of team interaction and communication. New team members may enter the team and old ones may leave. The social interaction among team members that is necessary for trust-building will not always foster learning (Brown and Palincsar, 1989). Traditionally, trainees view learning as an independent and mildly competitive activity. Trainees typically do not ask for help from their peers for fear of appearing incompetent or dependent. Furthermore, peers tend to work together with the aim of just accomplishing tasks (e.g., finding the right answers) instead of facilitating each other's learning. A team's learning potential is maximized when each individual actively participates in the learning task, thereby increasing the probability all trainees understand the learning material and no one is left behind. To promote active participation, a successful team ITS must be able to (a) encourage the individual trainee to exchange ideas, information, and perspectives for interaction, and (b) provide real-time monitoring of individual and team participation level (e.g., interaction analysis), and react to low participation levels.

The second concern of team tutoring relates to the interaction differences within different learning tasks. Peer interactions have been found to vary enormously in collaborative learning initiatives within the same domain (Brown and Palincsar, 1989), but the same team will certainly communicate differently and unpredictably between two different domains. One aspect attributing to the variation in communication is the roles trainees assign themselves within a team to accomplish a targeted objective and how they might productively switch roles between tasks (Burton, 1998). Role identification and switching is good for social grounding development and can create an environment for collaborative learning and more effective communication (Soller, Linton, Goodman and Gaimari, 1998). However, not all individuals will be able to identify their roles within the team context. This can often lead the team falling off-track or misguiding each other. Even when team members are not strangers, they still need support and guidance on how to work together. Furthermore, as the task/objective becomes more complex, effective communication within the team becomes more important and more complex. To address this second concern, a team ITS should diagnose and redirect incorrect solution paths, divide complex tasks into sub-tasks for which each person could be responsible for a sub-task or the entire group tackles each sub-task together, and instruct/guide the team in the beginning on how collaboration should occur (Wu, Farrell and Singley, 2002).

Team locality is the third primary concern of team tutoring. Face-to-face or local teams have been found to have more favorable learning results over distributed or virtual teams (Andres, 2002; Warkentin, Sayeed and Hightower, 1997). Virtual teams exchange information less effectively than face-to-face groups (Warkentin, Sayeed and Hightower, 1997); however given sufficient time to develop strong group relationship and become comfortable with the communication environment, virtual teams may communicate as effectively as a face-to-face team (Chidambaram, 1996). In military team training and simulations, it may be impractical for the team to be in a centralized location. A mediation for the concern of geographical distributed team tutoring could be for the team ITS to provide team-building and team-readiness activities prior to beginning instruction.

DESIGNING A DISTRIBUTED TEAM TUTOR

A goal of this research is to develop a team tutor that will ultimately eliminate the need for human tutors for distributed training where interaction and direct access to trainees is limited. A large part of developing a distributed team tutor is defining which functions are desirable within individual ITS. We began with a model of an individual tutor and then explored which interactions between individual tutors were needed and which new processes were needed to realize a distributed team tutor.

Building upon an Individual ITS Model

As a starting point for our team tutor model, we adopted an individual ITS model based in part on Beck, Stern and Haugsjaa's (1996) Intelligent Tutoring System Model and in part on procedural reasoning systems (Georgeff and Lansky, 1987; Parunak, Bisson, Brueckner, Matthews and Sauter, 2006) which were used to model affect (e.g., emotions) within virtual characters. Sottilare (2010) adapted Beck, Stern and Haugsjaa's (1996) ITS model resulting in the individual affective ITS Model. This model was a basic building block for our initial team tutoring model due to its inclusion of affect, its extensibility, and its emphasis on a more comprehensive trainee model. In 2011, additional emphasis on learning factors (e.g., remembering, understanding, analyzing) and integration with a more long-term trainee model resulted in the enhanced tutoring model shown in

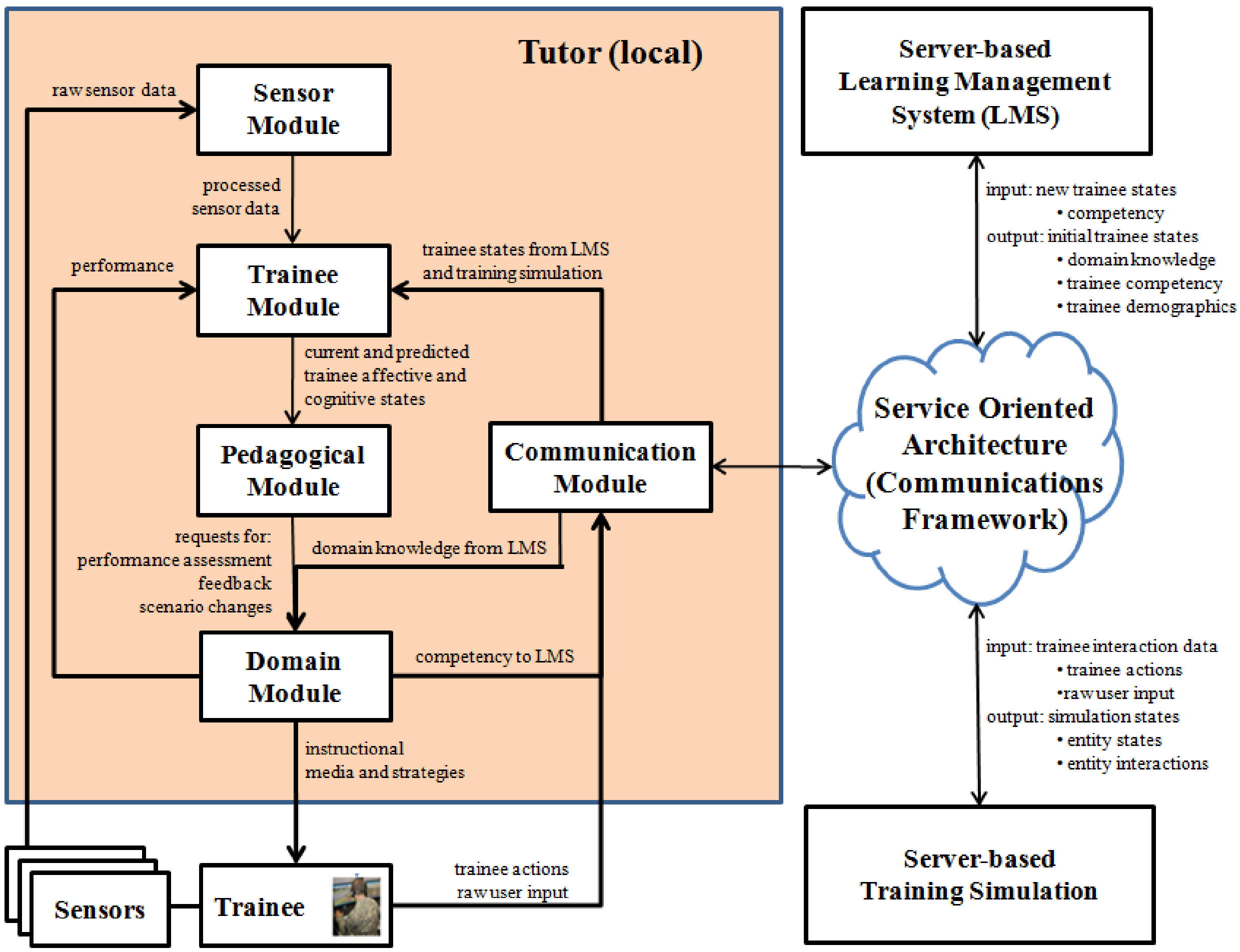

Figure 1: Enhanced Tutoring Model in the Generalized Intelligent Framework for Tutoring (GIFT)

Figure 1. This figure illustrates the Generalized Intelligent Framework for Tutors (GIFT) that is being developed by the Army Research Laboratory to test tutoring methodologies and their influence on learning.

The enhanced trainee model within GIFT accounts for competence, affect, physiological and behavioral data to assess new emotional states. Progress toward training objectives (e.g., knowledge or skill acquisition) is used to assess changes in competence level while competence level and new emotional states are used to make decisions about instructional strategies.

Team Tutoring Design Goals

Five goals were established for the design of our team tutor. The team tutor should be:

- *accurate*: methods used to assess affect, trust, etc. should correctly assess trainee state and produce a minimum of false negatives
- *low-cost*: the tutor should be software intensive and require minimum additional hardware beyond the training platform (e.g., laptop or other mobile computing device)
- *portable*: the tutor should be able to be hosted on a standard laptop and eventually other mobile computing devices (e.g. IPhone, Android) to provide a mobile team training capability
- *real-time*: interaction with the distributed tutor's architecture should be in near real-time

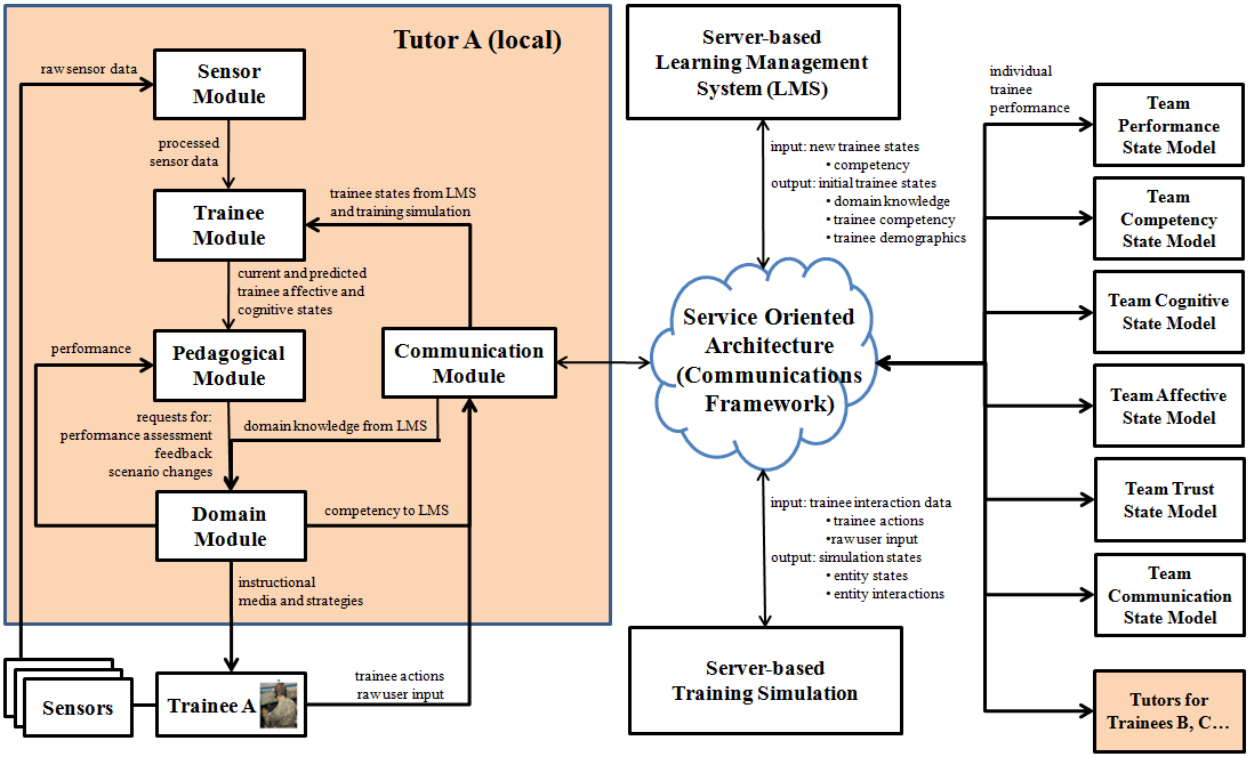

Figure 2. Enhanced Team Tutoring Model in the GIFT

- so as not to adversely influence individual or team learning or performance
- *unobtrusive*: methods should be passive in that they minimize disruption of the training process and be compatible with available technology (e.g., laptops or other mobile computing platforms)

Other considerations for designing and developing an effective team tutor are discussed below.

Interactions and State Models for Team Tutors

This section discusses which information should be shared between individual computer-based tutors and considers which state models should be maintained within the proposed team tutoring model. In a distributed simulation framework (e.g., High Level Architecture or Distributed Interactive Simulation) each local training simulation shares interaction data with other simulations to support a common view of the world or shared synthetic environment. We have adopted a similar framework to support our team tutor model. Consideration should be made to exchange any data that might be relevant to team performance including trainee communications, trainee behaviors (e.g., actions, performance), trainee affect, and any changes in state models. The type of information to be exchanged and frequency/triggers for exchanges (e.g., periodically or based on events/changes) are discussed below. The notional team tutoring model in Fig. 2 builds on Sottilare's (2010) team state model and illustrates interactions between geographically distributed autonomous tutoring systems to maintain a common picture of team performance and learning.

Team Performance State Models

Team Performance updates are event driven based on changes to the Team Performance State Model. As team members complete assigned tasks, progress toward team goals is registered within the individual ITS' Team Performance State Model and the ITS then generates an update message to the other ITS so all Team Performance State Models are synchronized.

Team Competency State Models

This model provides an index of team competency based on a composite of the competence levels of individual team members. Successful/unsuccessful performance influences individual competence and may influence team competence. Any significant changes in individual performance of team tasks are assessed by the individual competency state model to determine if the threshold has been met to change individual competency (e.g., beginner, journeyman or expert). Changes in individual competency may or may not be of sufficient significance to affect a change in the team competency state model, but if a change in the team competency state model occurs, a message is generated to update the team competency state models of the other team members.

Team Cognitive State Models
This state model is a compound model of the Cognitive State of all team members. Cognitive State models already exist as part of the individual ITS, but synchronization of this information with all the team member's ITS is critical in assessing the function of the team. Depending on the collaborative task and the roles of team members in accomplishing that task, the cognitive model may be key in determining instructional strategies. For example, for some tasks the weakest understanding of the task among team members may indicate the risk of completing the task successfully. For other tasks, only key team members may need to have higher understanding of the task to reach a successful outcome.

Team Affective State Models
This state model is a compound model of the Affective State of all team members. Affective State models already exist as part of the individual ITS, but distribution of this information to all the team member's ITS is critical in assessing the function of the team. For example, if team performance is below expectations and the affective state of one or more team members is negative, knowledge of their state by other individual ITS provides the opportunity to prompt their associated team members to take action (e.g., communicate – support or direct).

Team Trust State Models
This team state model is a compound model of the trust states existing between team members. The trust relationships are bi-direction in that Team Member 'A' may trust Team Member 'B' more, the same or less than Team Member 'B' trusts Team Member 'A'. Trust is influenced by several factors including perceived competency, perceived integrity, perceived benevolence, knowledge of the other team members (Hung, Dennis and Robert, 2004) and perceived benefits of the relationship (Gujral, DeAngelis, Fullam and Barber, 2006). Since teams work toward common goals where roles and responsibilities are distributed, perceived competency is an essential element of team performance. The perception that other team members may be unable to perform their tasks is detrimental to trust and team performance. Personality may also play a part in trust.

Individuals with low openness and/or high neuroticism scores in the Five Factor Model of Personality (McCrae and Costa, 1994) may have developed habits unfavorable to the development of trust. Low openness scores might indicate an unwillingness to disclose information while high neuroticism scores might result in more frequent perception of events/interactions as negative. Positive or negative emotions can also influence the assimilation of information (Linnenbrink and Pintrich, 2002) and thereby communications, understanding and trust.

Team Communication State Models
This model is composed of interaction data between team members for the purpose of observing team cohesion and task execution. Providing accurate information in accordance with operating procedures, providing communications when asked, repeating communications to ensure delivery, sharing information and acknowledging receipt of information are all vital actions observed in teams with effective communication skills (U.S. Coast Guard, 1998). In team settings communication among members builds holistic situational awareness and coordinates future actions to be carried out. Based on events and interactions in a scenario, team members are responsible for updating one another in real-time.

In computer-based team training, tracking communication between members can be valuable for identifying causes in performance deficiencies and providing feedback in after-action reviews (AAR). As well, modeling expert communication tactics for case-based scenarios can mark distinct environmental factors that warrant team-wide communication. Determining events that should trigger communication can allow for real-time interventions that emphasize the cause and need for conveying information on a team-wide level. Assessing communication effectiveness among teams can also inform the other team state models. Errors in statements and low communication rates can be used to inform both the trust and competency state models.

Challenges in the Development of a Team Tutor

In considering the design of computer-based team tutors, we identified five primary challenges in developing a computer-based team tutor.

Challenge 1: Low cost, passive sensing of behavioral and physiological data
Just as in individual tutors, the ability to accurately sense the behaviors and physiological responses of trainees is a key to building a comprehensive trainee model. This challenge is deepened when attempting to connect specific behaviors and physiological responses to a specific individual in another location to determine

the relationship of those team members and whether the tutor should intervene in some way.

Challenge 2: Classification of Affect and Trust
The ability to accurately classify the affective state of each trainee and their trust relationships will determine the ability of the tutor to select instruction and feedback that is tailored to each trainee and appropriate for the team.

Challenge 3: Selection of Instructional Strategies
A significant challenge is the selection of effective instructional strategies based on the individual trainee's state (e.g., competence level and affective state) that will support the trainee's individual needs and the team's needs. At times, individual and team needs may conflict. For example, if speed is a critical team performance measure and an individual tutor finds it necessary to provide remediation for a confused or frustrated trainee, what should take priority? Is the priority the needs of the trainee or the team? If the overall goal of the training is for team to improve, it may be important to address individual team member needs and then move on to team goals, but what if there are persistent issues with team members? Should they be addressed by the other team members, a team leader or the team tutor?

Challenge 4: Tracking Multi-Dimensional States
The size of the team can quickly affect the number of states the team tutor must synchronize. For example, the team trust state model is composed of the relationships between each pair of individual team members. Equation (1) shows the relationship between the number of team members, n, and the number of trust relationships, T.

$$\mathbf{T = n^2 - n} \qquad \mathbf{(1)}$$

The number of trust relationships which must be updated and synchronized for a squad of nine Soldiers is 72. Each of these relationships must be derived from the history the two individuals (e.g., just met or friends for life), the frequency of communications, their willingness to share information and their affective states (e.g., emotions and personality). The accuracy of these predictions should influence decisions by the tutor during training and inaccurate modeling of trust would likely be more detrimental than not modeling it at all.

Challenge 5: Real-time Interaction
The ability of training systems to provide relatively real-time interaction is an important part of the team being able to focus on team interaction and team goals rather than the shortcomings of the simulation. A more critical aspect might be the real-time interaction of the individual tutors especially the synchronization of team state models. Any significant delays could result in an individual tutor making instructional strategy decisions based on inaccurate information. Additional research is needed to determine what constitutes a "significant delay."

Any framework for a team tutor must account for optimal solutions to: where (locally or centrally via a server) states are determined; how frequently states need to be reassessed; and what information is to be distributed.

Passive Sensing Methods in Team Tutoring Environments

This section discusses available passive sensing methods found in the literature and how these methods might support or fall short in supporting the concept of a team tutor. Passive sensing methods were chosen so as to minimize interference with the learning process. Our goal was to find accurate, low-cost, portable, real-time, passive sensing methods that would be compatible with available technology (e.g., laptops or other mobile computing platforms).

Using Conversation to Assess Affect
Conversational patterns, content and flow have been used to assess affective state. Frequent conversation patterns (D'Mello, Craig, Sullins and Graesser, 2006; D'Mello, and Graesser, 2007) have been used to predict affect (i.e. confusion, eureka, frustration) and have been tied to ITS instructional strategies (e.g., pumps, hints and assertions) to influence the trainee's progress.

While these methods meet our goals for passive sensing, a major drawback to these approaches relative to our team tutor design goals are the labor intensive nature of the data collection and analysis which limits the tutors ability to provide a real-time assessment of the trainee's affective state. Another limitation to consider is that conversational data is not always present to support affective assessment. Psychophysiological sensing methods offer a distinct advantage over conversational sensing methods in that data is always available (Parsons, 2011).

Using Trainee Actions to Assess Affect
Trainee behaviors were used to unobtrusively detect mood and determine the relationship between mood, performance and the selection of successful coaching strategies (Zimmermann, Guttormsen, Danuser and Gomez, 2003). Passive sensing included capture of control selection rates (Sottilare and Proctor, *in press*)

and mouse movement rates (Sottilare and Proctor, *in press*); Zimmermann, et al, 2003). Significant relationships exist between pleasure and dominance mood variables (Mehrabian, 1996), trainee performance, a priori knowledge, state and action variables (e.g., control selection and mouse movement rates) (Sottilare and Proctor, *in press*; Wingrave, Hoffman, LaViola, and Sottilare, 2011). These approaches were affordable, accurate and passive. Limitations of this research were their discrete self-report measurements of mood which was only assessed during pre-training and post training and not continuously during training to provide real-time assessment of trainee affect. Expanded modeling of affect using other (non-survey) methods will improve the accuracy and real-time support of these techniques to detect individual differences.

Using Facial Changes to Assess Affect

Eye tracking has been used in an embedded training tutor (Zachary, et al, 1999) to assess what the trainee viewed, when, and for how long, but was not used to assess affect. The same or similar technology could be used to determine the trainee's level of engagement. Given the state of camera technology, a laptop camera could be used to measure changes in pupil dilation. Significant relationships were assessed between six universal emotions (sadness, joy, anger, fear, disgust and surprise) and six facial measurements (D1: the opening of the eye; D2: distance between the interior corner of the eye and the eyebrow; D3: opening of the mouth in width; D4: opening of the mouth in height; D5: the distance between the eye and eyebrow; and D6: the distance between the corner of the mouth and the external corner of the eye - Neji, and Ben Ammar, 2007).

Assessing Team Performance

One of the challenges of developing a team training system is the challenge of assessing team performance. Typical team simulation trainers accomplish this in two manners, through After Action Review (AAR), and through human-in-the-loop feedback. These traditional methods are simply not an option for a team-based ITS, which much performance assessment as part of the course. Research in the area of team performance measurement contains many helpful suggestions on how to automate this assessment.

A recent review of performance measurement in simulation recommended the following series of 'best practices' in order to automated team performance measurement (Salas, Rosen, Held, and Weissmuller, 2009). Performance measurement works best when performance from multiple sources can be captured, when the assessment is tightly coupled to the action to take, when validated expert models perform the assessment, when it directly supports learning, and when it is able to provide real-time corrective feedback. Additionally, Salas indicated that performance assessment should be divided into two phases: a process phase and an individual phase. They draw the line between meeting a team goal, and doing a good job individually. ITS systems, unlike their human counterparts, are able to provide real-time feedback to all of the individuals simultaneously and can collate multiple assessment sources.

In addition to the team performance assessment, each individual must be assessed based on contribution to the joint goals of the team. This is a problem that has been well studied in the domains of agent-based systems (Yen, Yin, Ioerger, Miller, Xu and Volz, 2001), human-computer interaction (Lewis and Wang, 2009), and human performance (Rothrock, Cohen, Yin, Thiruvengada and Nahum-Shani, 2009). The conclusions in these domains are similar to the conclusions found above. A solution to individual assessment is presented by determining when each user is able to take an action, the amount of time delay each user has introduced, and the value of the taken actions. Team assessment might be performed in similar manner.

APPLICATION SCENARIOS FOR DISTRIBUTED TEAM TUTORS

Two scenarios are put forth to illustrate how a distributed ITS architecture might be used to support team training. The first is a hypothetical military training scenario and the second is a hypothetical medical scenario.

Distributed Team Training for Military Search and Rescue Operations

Search and rescue missions are multi-dimensional involving many different military assets. For example, in the aftermath of Hurricane Katrina, National Guard assets (air and ground) conducted coordinated operations to rescue people stranded by the floods. Training for these kinds of operations would be nearly impossible on this kind of scale in a live (real) environment. The uses of simulations (e.g., games or virtual worlds) offer an opportunity to train complex missions without significant risks to the trainees who are in various geographic locations. The shortfall in these simulations is the lack of a team tutor so this task is often left to a cadre of facilitators who are often not co-located with the pilots, aircrews, ground vehicle crews and dismounted soldiers who are performing tasks during the training session.

The objective of many large-scale training scenarios is to exercise the decision-making skills of the trainees. It is desirable that the trainees experience some level of affect (e.g., stress) and are able to continue functioning as a reliable team member. A distributed tutor with the capability to assess affect and manipulate the simulation to support the individual and team training objectives would also be desirable.

Distributed Team Training for Medical Emergency Management

Municipalities throughout the United States conduct emergency management exercises based on medical crisis. A team tutor would be useful in providing a distributed capability to understanding the performance of team members.

Emergency management scenarios include the coordination of first responder assets (e.g., police and firemen), hospital space and ambulances. The ability to practice communications across the various disciplines required to deal with emergency medical incidents is critical. An understanding of the trainees and the training domain (e.g., medical emergency management) would enable a team tutor to provide valuable decision support to trainees at the junction of critical decisions. The distributed nature of the tutor would enable trainees that normally do not work in the same location to understand the limitations of voice and written communications methods.

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

Significant technologies (tools and methods) exist to support a distributed ITS architecture for team training, but additional research is required to fully realized the lofty design goals set forth in this article. Research to mature distributed team tutoring technologies should continue with significant emphasis on: passive behavioral and physiological sensing methods; accurate, real-time classifiers to assess the cognitive and affective states of trainees; and optimal instructional strategy selection techniques based on limited trainee modeling.

Future research should also include enhancements to conversational pattern recognition and other sensor methods to allow streamlined computing methods to be used on laptops and other mobile computing devices (e.g., Blackberry, Android, Treo or iPhone). Additional research is needed to make it easier to setup methods (e.g., emote aloud sensing) to evaluate affect through prosody (e.g., rhythm, stress and intonation of speech).

It will be critical to be able to measure team learning and understand the unobtrusive modeling of cognitive skills that include remembering, understanding, applying, analyzing, evaluating and creating (Anderson and Krathwohl, 2001) for collaborative team tasks.

Approaches that consider training across a soldier's career vice a single training event, will be enabled by additional research in portable career learning management systems. The development and maintenance of a trainee model specific to an individual over the course of his/her career will highlight learning trends and be useful to initialize whatever training system the trainee might use.

Based on successes in sensor technology, researchers can begin quantifying significant relationships between behaviors/physiological measures and trainee states, and then trainee states and successful instructional strategies. The key is to evolve a more comprehensive trainee model without the use of self-report methods that can interfere with the training process.

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