Ontology-driven Methods and a Framework for Enabling Hybrid Adaptive Team Training using Task and Sensor-based Performance Evaluation

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INTRODUCTION

Adaptive Training is intelligently tailored, computer-guided experiences for individuals and units focused on optimizing training performance, training efficiency, deep learning, and transfer of skills to the operational environment. Training adaptation is multi-faceted. For example, training must adapt to the needs of the individual trainee as well as organizational groupings of trainees (e.g., an Army unit). Training must be tailored based on trainee and team state (cognitive, affective, social, etc.) and to trainee and team task performance. Adaptations might be determined and delivered in real time during training events or determined through assessment of learner data over extended time and delivered periodically (non-real time). Adaptations may seek to inform and optimize instructional strategies both during training and off-line (between training sessions). From a "training systems" life cycle perspective, the adaptation approaches must seek to optimize training over learner and team lifecycles through optimal blending of training types and modalities (e.g., computer-based, game-based, simulation-based, Live, Virtual, Constructive, and Game (LVC&G), etc.). A central barrier that impedes increased use of adaptive team training is the time and cost required to build and maintain these complex training applications. This paper describes an ontology-driven framework method that targets this challenge. The paper describes: (i) an ontology-driven method for hybrid (multi-domain, multi-task, multi-objective) adaptive team training; (ii) an enhanced Generalized Intelligent Framework for Tutoring (GIFT) architecture to support the hybrid adaptive team training method; (iii) sensor and task based individual and team performance evaluation approach; and (iv) hybrid adaptive training application examples that show the practical benefits of the method.

Current simulation-based training systems are incapable of dynamically generating and maintaining scenarios in an instructionally sound manner. Instead, scenarios are hand-crafted, static representations of training and mission contexts [1]. The research described in this paper targets the multi-domain team adaptive training challenge – the ability to affordably build training applications in different domains that dynamically adapt training to rapidly changing learner needs. The long term goal of our research is to establish a multi-domain team, adaptive training capability suitable for application to a variety of warfighter contexts.

MOTIVATIONS

Current simulation-based training systems are incapable of dynamically generating and maintaining scenarios in an instructionally sound manner. Instead, scenarios are hand-crafted, static representations of training and mission contexts [1]. The research described in this paper targets the multi-domain hybrid team adaptive training challenge – the ability to affordably execute team trainings in different domains that dynamically adapt to rapidly changing learner needs. The long term goal of our research is to establish a multi-domain adaptive team training capability suitable for application to a variety of warfighter contexts.

Federated military simulation-based training exercises typically require the exchange of information between multiple warfighter functional areas and echelons. The complexity of mediating these information exchanges is intensified because of the multiplicity of simulation-based training tools and systems that are required in such training exercises.

Simulation-based training models require the representation of complex information structures. The information contained in these models depends on a systematic connection between the components of the representation and the real world. It is this connection that determines the semantic content of the data being represented. Generally, the semantic rules of a representation system for a given application of a simulation-based training tool and the semantic intentions of the tool designers are not advertised or in any way accessible to other agents in the warfighter organization. This makes it difficult for such agents to determine the semantic content of the simulation-based training models. We refer to this as the problem of *semantic inaccessibility* [2]. This problem often manifests itself in different ways, including *unresolved ambiguity* (as when the same term is used in different contexts with different meanings) and *unidentified redundancy* (as when different terms are used in different contexts with the same meanings).

An important practical problem is – how to *determine* the presence of ambiguity and redundancy in the first place? In other words, how can we assess the semantics of simulation-based training data across different contexts? How can we define the semantics objectively in a way that permits accurate interpretation by agents outside the immediate context of this data? Our focus in this paper is to provide a solution approach to address this problem for simulation-based adaptive training applications that use GIFT.

GIFT

The Army Research Laboratory (ARL) is developing GIFT as part of its adaptive training research program. *Adaptive Training* is "intelligently tailored, computer-guided experiences for individuals and units focused on optimizing training performance, training efficiency, deep learning, and transfer of skills to the operational environment" [4]. Training 'adaptation' can be multi-faceted. For the trainee, the delivery of training must adapt to individual trainee needs, as well as to the organizational groupings of trainees (e.g., an Army unit). Training must be tailored to trainee state (cognitive, affective, psychomotor, social, etc.) and to trainee task performance [5]. Adaptations might be determined and delivered in real time during training events or determined through assessment of learner data over extended time and delivered periodically (non-real time). Adaptations may seek to inform and optimize instructional strategies both during training and off-line (between training sessions). Training content adaptations might be automated, semi-automated, or human (instructor)-driven. From a 'training systems' lifecycle perspective, the adaptation approaches must seek to optimize training through optimal blending of training types and modalities (e.g., computer-based, tutor-based, game-based, simulation-based, live training-based, etc.). In support of ARL's adaptive training research, GIFT is being developed as open-source software, with a modular architecture whose goals are to reduce the cost and skill required for authoring adaptive training and educational systems, to automate instructional delivery and management, and to develop and standardize tools for the evaluation of adaptive training and educational technologies.

ONTOLOGY-DRIVEN METHOD FOR HYBRID TEAM ADAPTIVE TRAINING

The ontology-driven method for hybrid team adaptive training is summarized using the IDEF0 function modeling method (Figure 1).

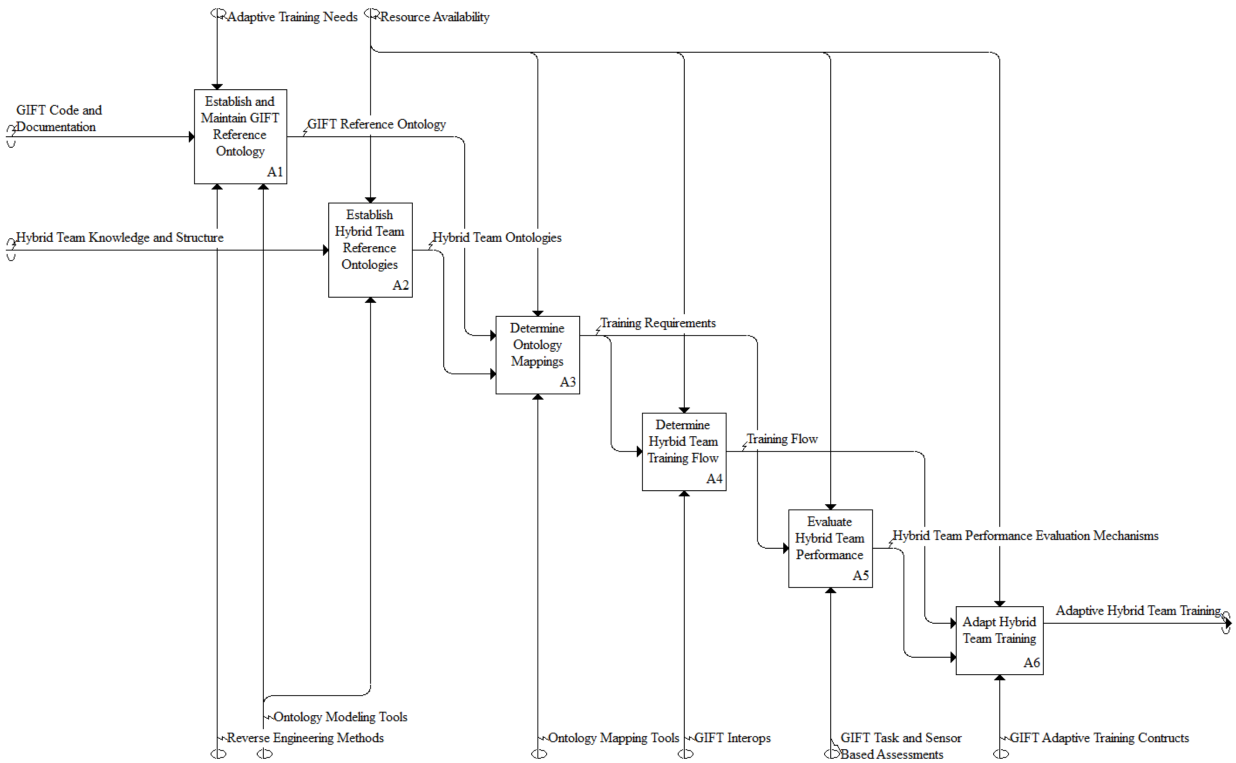

Figure 1. Ontology-Driven Training Application Integration Method

The steps of the ontology-driven training application integration approach are: 1) Establish and Maintain GIFT Ontology; 2) Establish Hybrid Team Reference Ontologies; 3) Determine Ontology Mappings; 4) Determine Hyrbid Team Training Flow; 5) Evaluate Hybrid Team Performance; and 6) Adapt Hybrid Team Training. These activities are described in greater detail in the following paragraphs.

Establish and Maintain GIFT Ontology

The creation and maintenance of a GIFT ontology is an important first step towards building GIFT-enabled integrated simulation-based training applications. The multifaceted GIFT ontology includes concepts such as course, scenario, task, assessment, and conditions, in addition to classes, vocabulary, and attributes (Figure 2). An important aspect of the ontology are the relationships between the concepts and the cardinality restrictions of GIFT attributes. An initial GIFT ontology has been developed [Benjamin et al 2016]. Once the GIFT ontology has been developed, it needs to be maintained over extended time.

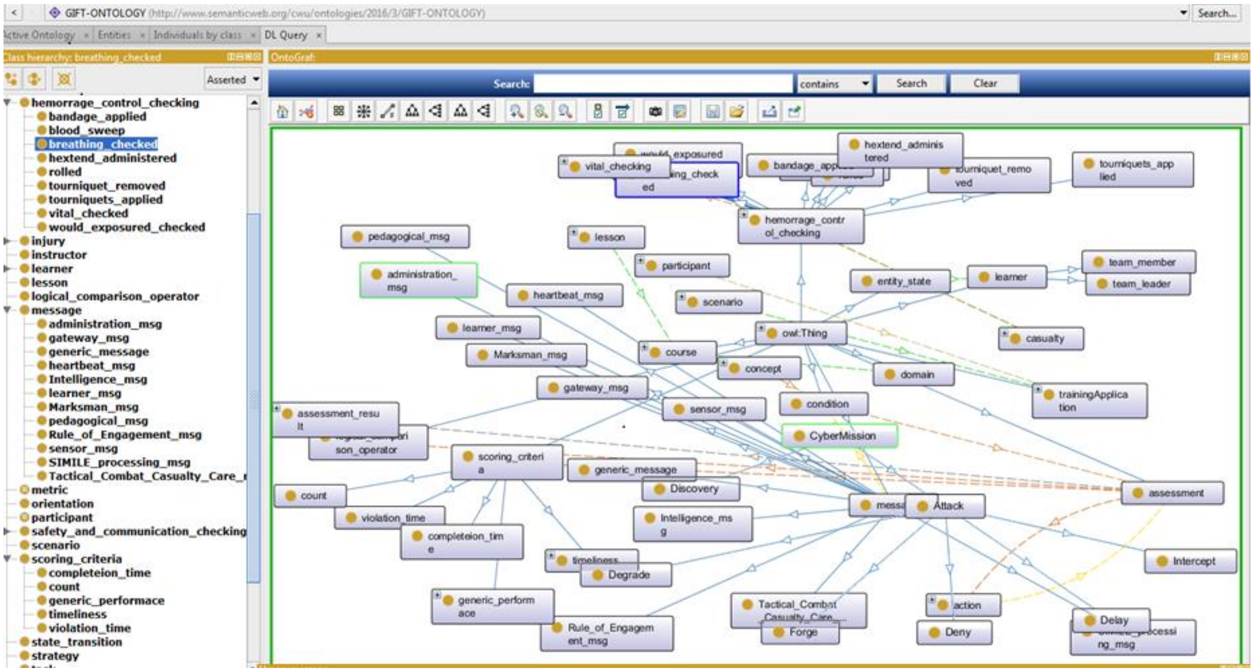

Figure 2. GIFT Ontology Fragment

Hybrid Team Ontologies

This important activity formulates mappings between the GIFT Ontology and the ontologies of the team or teams involved in the training (Figure 3). Note that for a given military training event, a federation of several simulation tools and models often need to be integrated and made to work together in an effective manner that addresses the warfighter training objectives.

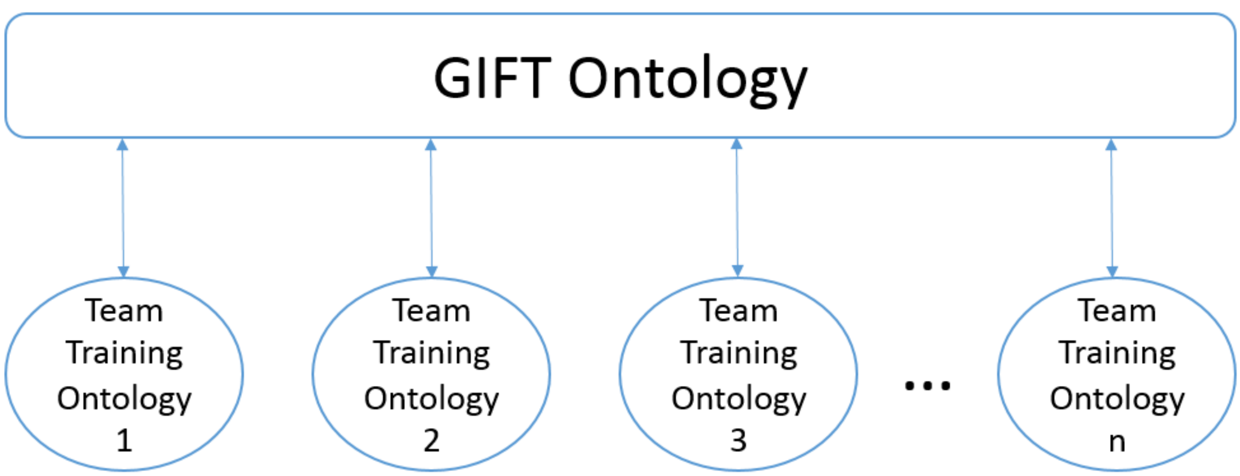

Figure 3. Mapping Team Ontologies to the GIFT Ontology

Such a method results in a framework that is configurable to different target domains through the insertion of an ontology of that target domain. We refer to this reconfiguration strategy using the term '***ontology-based***'. The basic idea is to create and maintain an adaptive-training reference ontology that is utilized to semantically determine and mediate the needed data and information exchanges between the adaptation framework elements and the core training system elements. Additionally, the ontology provides the adaptation framework with the domain knowledge required to evaluate team performance (using both task and sensor based methods).

Example Hybrid Team Ontology

An example application ontology for hybrid adaptive team training is shown in Figure 4. This ontology includes various components of an intelligence domain team interacting with a medical team to execute attending to wounded during attacks. The ontology is not meant to be comprehensive but is intended to provide basic constructs of an ontology that is useful for hybrid mult-doman adaptive team training. The ontology includes team member roles, training applications, tasks, dependencies (e.g. member 1 task 1 triggers member 2 task 2), and evaluation methods. If this type of ontology model was to be utilized by GIFT, it would need to be mapped to various components of the GIFT domain knowledge files (DKFs) for each member of team.

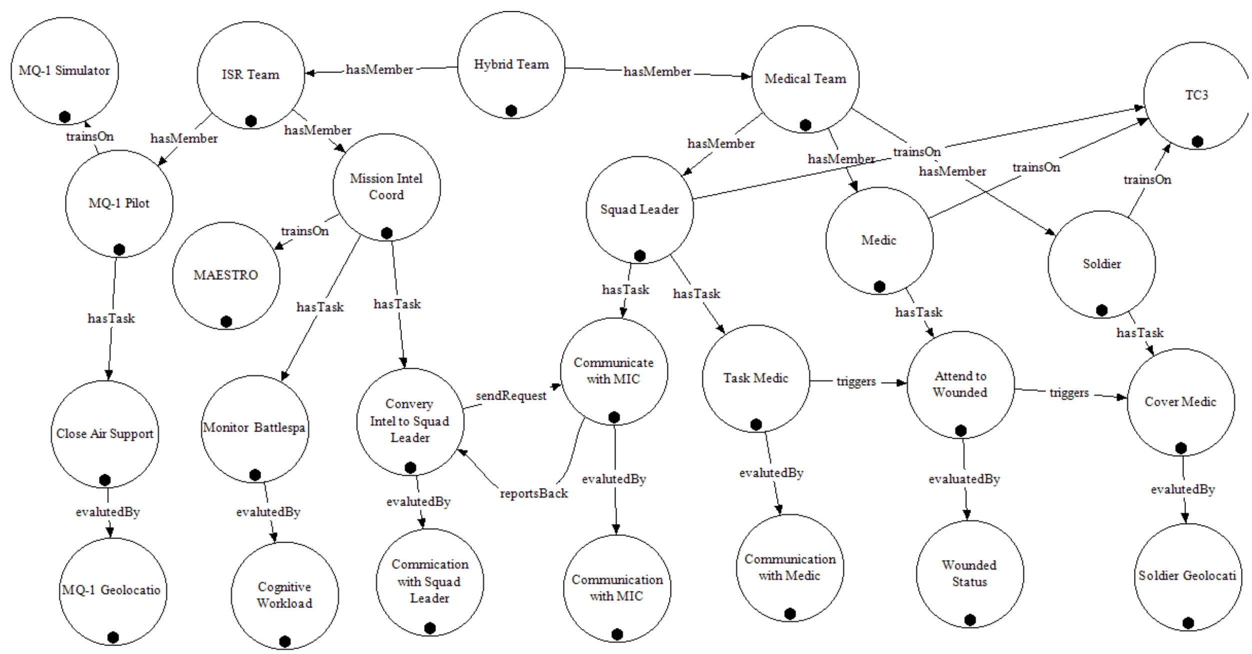

Figure 4. Notional Application Ontology Example for Hybrid Adaptive Team Training

Team Performance Evaluation Approach

The method incorporates the fusion of both sensor and task based team performance evaluation. Using an ontology (or set of ontologies), a system such as GIFT would help with the extraction of the necessary domain knowledge for robust hybrid team performance assessment. The method utilizes Bayesian data fusion techniques to integrate team sensor and task data in order to determine overall team performance scores.

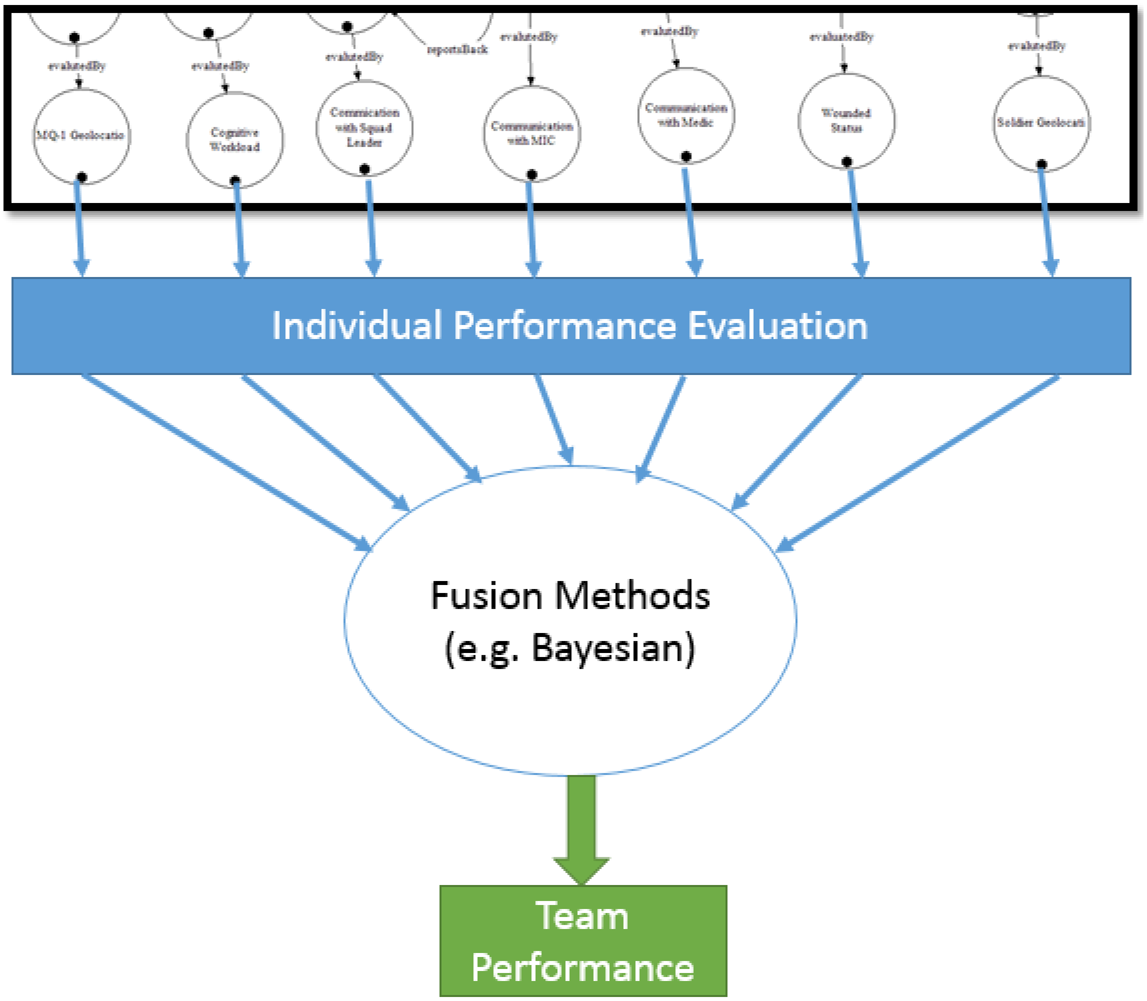

Figure 5. Evaluation Criteria Extracted from Ontology and Fused for Team Performance Evaluation

Sensor-Based Team Training Performance Evaluation

The sensor-based performance evaluation activity involves: (i) measuring cognitive indices from multiple sensors; and (ii) inferring cognitive states and trainee learning conditions using multi-senor data fusion. The reference ontology is used to: (i) select a set of cognitive indices and cognitive states relative to the training application objectives; (ii) adapt a multi-sensor data analyses suite to determine values of the selected indices and states; and (iii) map the cognitive states to trainee and team learning conditions. Figure 6 shows a high level concept of sensor data information fusion. It is assumed that artificial nueral networks (or other analytical methods) are being utilized within the sensor module to evaluate learner state based on data coming from sensors.

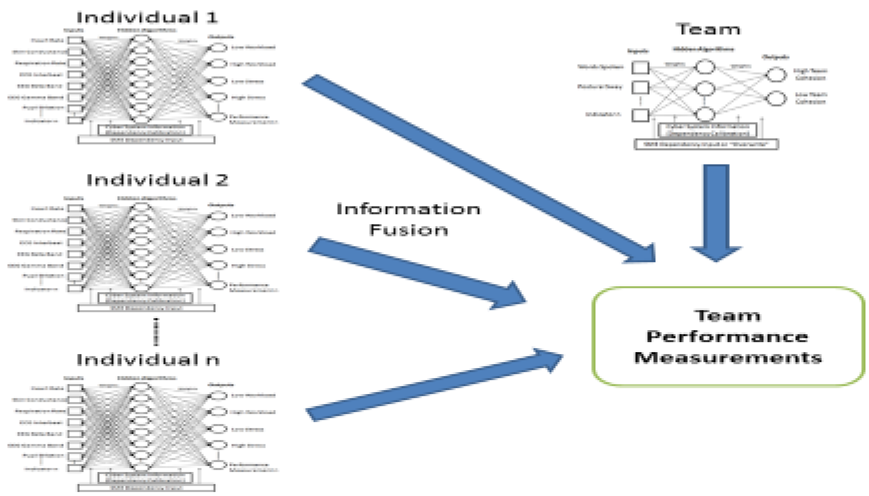

Figure 6. Sensor Data Fusion for Performancce Evaluation

Task-Based Team Training Performance

The task-based measurements are tied to: (i) the overall mission outcomes; (ii) individual trainee skills; and (iii) team skills. The reference ontology is then utilized to determine how specific task data applies to the outcomes and skills (both individual and team). A rule-based approach is then utilized to encode the logic to compute the values of objective metrics from training system output data.

Team Training Performance Evaluation Example

for a proof of concept demonstration implementation of multi-domain adaptive team training using Tactical Combat Casualty Care Simulation (TC3 Sim) tool, the Generalized Intelligent Framework for Tutoring (GIFT) software, and KBSI's MAESTRO™ (ISR training tool) is described here. TC3 Sim is used to run a battlefield medical evacuation training scenario where the trainee is a medic who is embedded with a unit patrolling hostile streets. The squad leader is tasked with locating the village elder to discuss opportuties for local support and humanitarian aid. Intelligence reports indicate possible insurgent activity in the surrounding buildings. The unit is to secure the area while discusions are held to improve safety. When the unit is engaging insurgents, the medic should apply proper techniques of care under fire and tactical field care where appropriate. In parallel, MAESTRO™ is training intelligence personnel to gather real-time hostile data, process them, and feed situational awareness information to the squad leader in the TC3 Sim. The functions supported for training in the MAESTRO™ scenario are ISR supported by the Mission Intelligence Commander (MIC), CAS supported by MQ-1 and A-10 platforms, JTAC who also interacts with the squad leader in TC3 Sim scenario, and the Ground Force Commander (GFC).

In this notional multi-domain team training, two sets of tasked-based performance evaluation metrics have been designed, one set of metrics for the ISR Team training in MAESTRO™ and the second set of metrics for the Patrol Team training in TC3 Sim. The metrics for the ISR Team include: (1) did the MIC review the COP and send out follow up information on time? (2) did the MIC send the message to the right person? (3) did the MIC follow up with the person to whom he send the information? and (4) did the MIC use communication standards (with brevity and using the right terminology) while relaying information? Example metrics for the Patrol Team include: (1) was the criteria "stay close" violated? (2) by what margin (distance and time) did the team violate safe distance from building? (3) did the medic stop bleeding and stabilize victim? (4) did MEDEVAC process get initiated at the right time? and (5) did the Tatrol Team leader send acknowledge message to the MIC after receiving recommendations? Each team is evaluated in their own environment and corrective (adaptation) strategies are used in each environment to rectify deficiencies. The advantage of using a multi-domain team in this example application situation is that there is real synergy with different team members complementing each other's effort while cooperatively working to achieve overarching and shared mission goals.

In addition to the task-based performance evaluation criteria, sensor-based measurements are also captured to determine the cognitive state of the MIC and the Medic. Example metrics for the ISR Team include (1) maintaining acceptable stress levels, (2) fatigue management, and (3) attentiveness. Metics for the Patrol Team include (1) limiting nervousnous (for example, manifested 'shaking') by the Medic, (2) alertness, and (3) maintaining acceptable stress levels.

Once the team performance evaluations are completed using the metrics described earlier, the individual trainees and the teams are 'graded'. The results of the performance evaluation areused to recommend adaptation strategies for (1) the two teams in MAESTRO and TC3Sim; (2) the ISR Team in MAESTRO; and (3) the Patrol Team in TC3 Sim. To illustrate, suppose that the MIC does not use communication standards to relay information and that the unit leader does not acknowledge the message after receiving information from the MIC, then recommending that both the teams (ISR and patrol) must review "communication standards" learning module is an example of an appropriate adaptation strategy. An example adaptation strategy for the ISR Team is as follows: when the MIC is overwhelmed because of 'information overload', he/she may not relay timely information to his/her squad leader. To rectify this deficiency, the ISR Team is introduced to several 'drills' (simple scenarios) to help them achieve higher levels of the "situational awareness" skill. If it is observed that a Patrol Team, in TC3 Sim, is violating the "stay close" criteria then the instructor would relax the 'distance margin'in order to help the team get more familiar with the team coordination effort and to better recognize uncertainties.

A GIFT-BASED ARCHITECTURE FOR MULTI-DOMAIN TEAM ADAPTIVE TRAINING

This section describes the two conceptual design options of a GIFT-based architecture for multi-domain hybrid team adaptive training using task and sensor based performance evaluation.

Overview

Currently, GIFT supports training in various domains with performance evaluations and adaptations specific to the training applications in those domains. Our goal is to enhance and extend GIFT so that it will be able to support multi-domain hybrid team adaptive training without the need for team-specific extensions to GIFT. In order to reach this goal, we have designed a method (outlined in the previous section) and two different architecture options for extending GIFT to support multi-domain hybrid team training. As noted in the previous section, the ontologies provide the basis for allowing GIFT to 'understand' team structures and appropriately adapt the training content. In GIFT terms, this would mostly involve an extension/plug-in utilized by the Domain Module. At the point of writing this paper, it is assumed that GIFT is being / has been extended to support team training (e.g. Team DKF, Team Model, and Team Pedagogy).

GIFT Architecture Extension Option 1

The first potential architecture extension (see Figure 7) is the less complex of the two options identified in this paper. It would include only extensions to the existing GIFT code base, with very little modification of the current code. This architecture would contain three new components/plugins/services: 1) an Ontology Mapper; 2) a DKF Builder; and 3) a Bayesian Fusion Engine. The Ontology Mapper would be utilized to map a team ontology to the GIFT ontology and the DFK Builder would build appropriate DKF files (both team and individual) based on the mappings. There would then be picked up and utilized by GIFT's current team and individual training execution and evalauation components. The third new component, the Bayesian Fusion Engine, would be utilized by the Learner/Team Module to fuse individual and team states into overall team performance states. In order for the Bayesian Fusion Engine to "know" how to fuse the states, the team DKF file would need to include state weighting information.

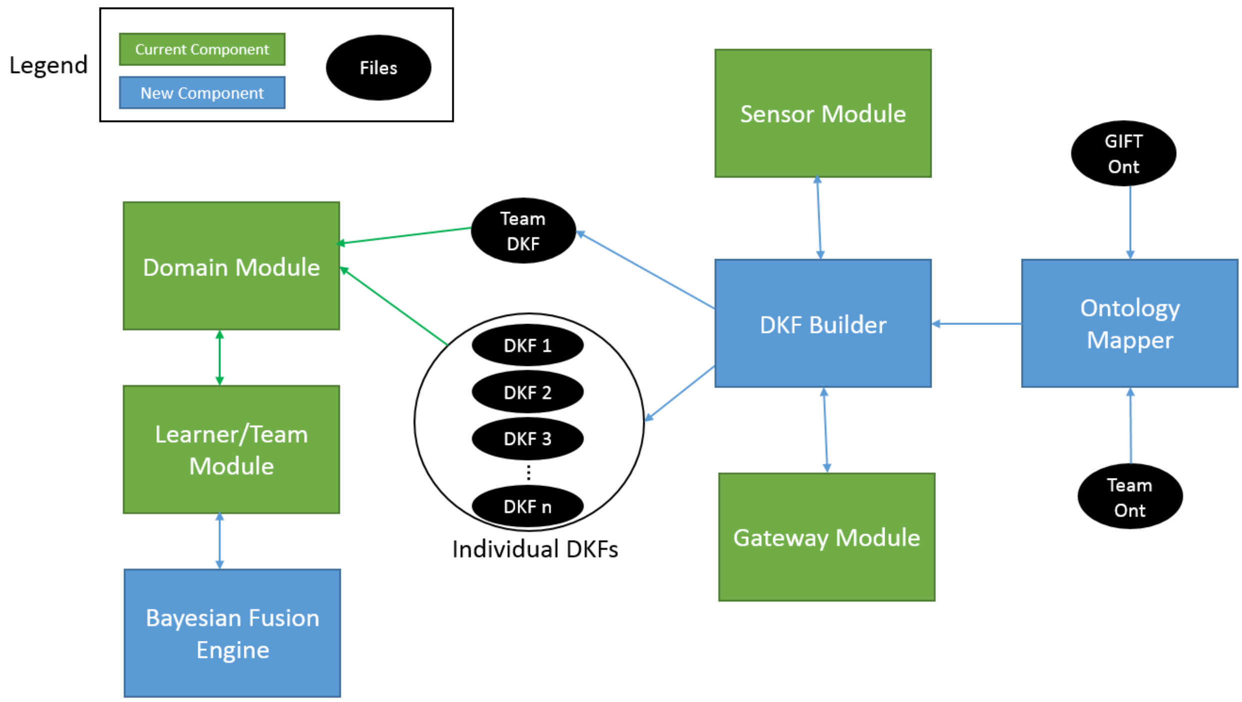

Figure 7. Option 1 GIFT Architecture Extensions

GIFT Architecture Extension Option 2

The second potential architecture enhancement (see Figure 8) would require more extensive modification to the existing GIFT code base. This architecture would contain two new components/plugins/services: 1) an Ontology Mapper; and 2) a Bayesian Fusion Engine. Additionally, the Domain Module would have to be modified so that it could not only interpret/read DKF files, but also various ontology files and format. The Ontology Mapper would be utilized by the Domain Module to map a team ontology to the GIFT ontology. The mapped ontology would then be utilized directly by the Domain Module to configure domain specifics of GIFT training sessions. Furthermore, similar to Option 1, the Bayesian Fusion Engine would be utilized by the Learner/Team Module to fuse individual and team states into overall team performance states.

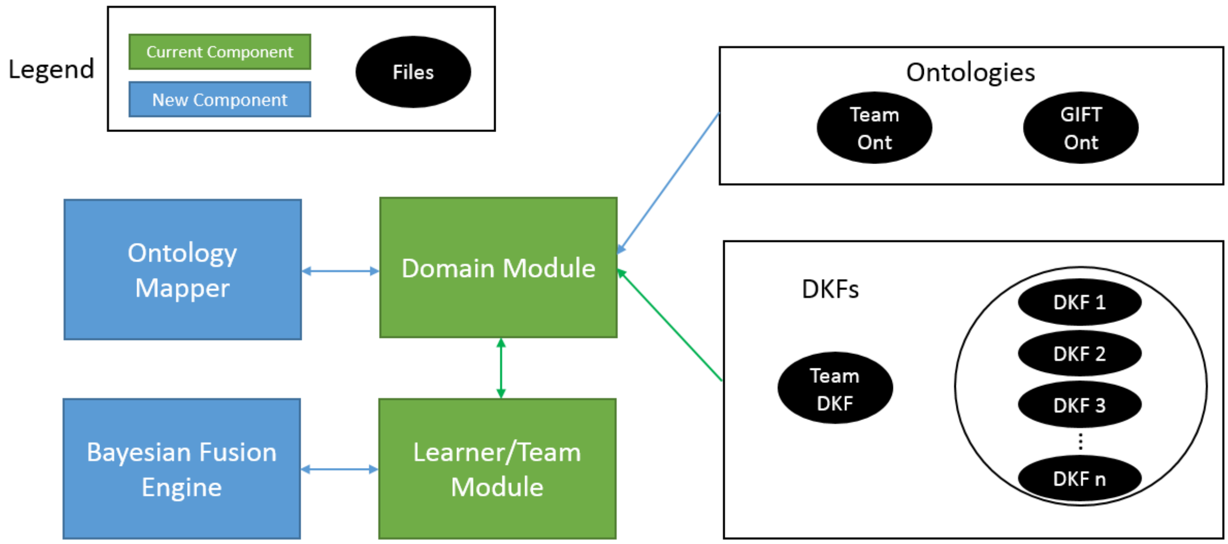

Figure 8. Option 2 GIFT Architecture Extensions

Example: Maestro™ with GIFT and TC3 Sim for Multi-domain Team Training

The notional scenario outlined in the "Task-Based Team Training Performance" section is described in detail here. The previously descried architecture options would support this training example in GIFT. For the example, we will refer to the overall team, which incluses the ISR Team and the Patrol Team, as the Hybrid Team. In Figure 9, the image of ground assault teams engaged in mission is presented as (Common Operational Picture) COP inject to the MIC in MAESTRO™. Looking at the image, the MIC should relay this information and follow up action (recommendation) to the unit on the ground within reasonable amount of time so that the relevance of the information remains current and timely. The recommendation can be relayed either via chat messages or audio messages and a notional message for this situation can take the form of "You are too exposed, stay closer to the buildings, and stay out of sight." This message is sent to GIFT software which is routed to the TC3 Sim scenario and evaluated by the learn module as a correct response (<u>at expectation</u>). As the unit is patrolling, suppose that an IED goes off at a distance and shrapnel hits a member of the unit. The medic embedded with the unit now initiates a 'victim stabilization' process and then GIFT evaluates the medic's performance as being '<u>at expectation</u>'.

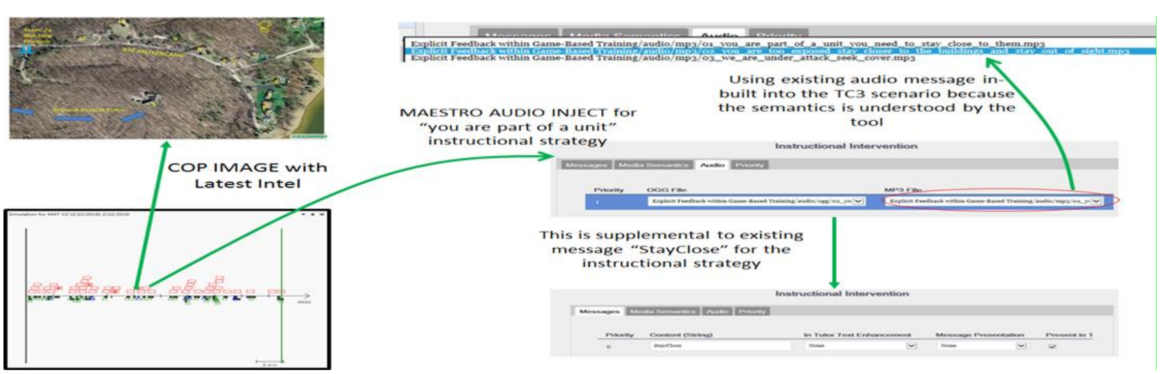

Figure 9: Information Flow between MAESTRO and TC3 Sim

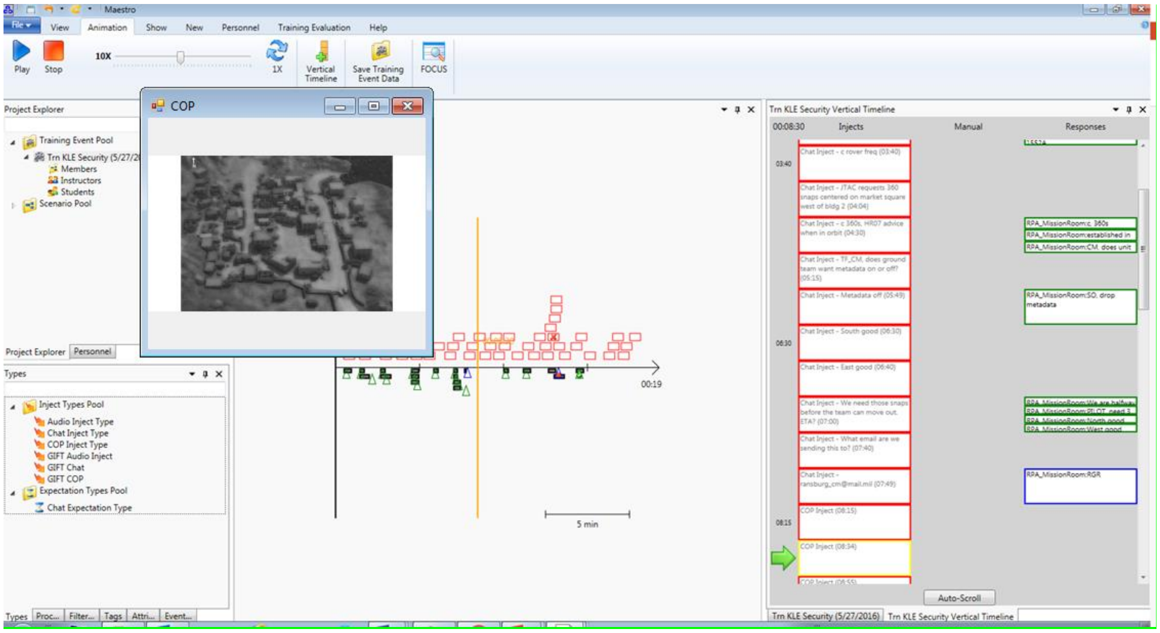

Figure 10: ISR Team Simulation Data Captured in MAESTRO™

When a scenario is executed in MAESTRO™, incorrect responses, correct responses, and instructor recorded comments are logged and persistently stored in the database. The categories of performance metrics are late response, echo in wrong chat room, incorrect response, response in wrong chat room, positive tag (best practices of trainees), and negative tag (egregious mistakes observed by instructor). Responses to injects, in the form of chat messages, are evaluated in MAESTRO™ as shown in the timeline view of Figure 10. MAESTRO™ has the ability to persistently store trainees responses and this give the ability to collect vital statistics on their performance like how many times a trainee responded incorrectly, how many times trainee missed to response, average late response time of a trainee, etc. The performance metrics derived from MAESTRO™ evaluation are sent to SIMILE workbench, performance evaluation engine in GIFT, to determine trainee's grade. For example, trainee's grade is set as below expectation if all the following conditions are met: (a) Echo in Wrong Chat Room > 3; (b) Incorrect Response >= 2; (c) Late Response > 3; (d) Negative Tag > 2; and (e) Positive Tag = 0. Likewise, other rules are scripted for at expectation and above expectation grades. These rules can be edited and tailored made for scenarios being trained. Adaptation rules can be developed to address observed deficiencies and recommend training scenarios for ISR Team in MAESTRO™ tool.

Audio Injects	TC3 Concepts	GIFT Evaluations	TC3 Metrics
Insurgents in the vicinity @ 00:12:15	"stay with unit"	Below Expectation	• away_from_unit (count > 3) • avg_time_outside_unit (violation time > 00:01:15)
Insurgents preparing for attack @ 00:15:30	"move under cover"	At Expectation	
Watch out BLDG 1, 5, 6, 7. Six hostiles identified @ 00:18:50	"return fire"	Below Expectation	• task_completed (completion time > 00:19:40)
Air support denied @ 00:19:40	"move to safe zone"	Below Expectation	• outside_safe_zone (violation time > 00:01:00)
All clear. No threats @ 00:21:15	"request CASEVAC"	At Expectation	

```
Rule "stay_with_unit_below_expectation"
{
    Concept( KeyName = "stay_with_unit" Transition = "below_expectation" Default = "unknown" )

    if( awayfromunit.count > 3 and avgtimeoutsideunit.violationtime > 00:01:15 )
    {
        Output( "stay_with_unit_below_expectation" )
    }
}
```

Scripted Rules used by SIMILE Engine

Figure 11: Notional Evaluation Rules Scripted in the SIMILE Engine Using TC3 Sim Data

There are a total of 60 injects defined in MAESTRO™ and five of those injects (audio format) are routed to TC3 Sim through GIFT software. The routed injects, initiated at certain times, are mapped to specific TC3 concepts. Three of the concepts – "stay with unit," "return fire," and "move to safe zone" – are found to be at '<u>below expectation'</u> grade. The trainee responses in TC3 environment is logged, which are evaluated to derive several metrics such as the one listed under the TC3 Metrics column in Figure 11. Derived metrics are used to evaluate the TC3 concepts by SIMILE workbench engine, which uses scripted rules as shown in the figure. Adaptation rules can be developed to address observed deficiencies and recommend training scenarios for Patrol Team in TC3 Sim environment.

Now that performance states have been capture for both the TC3 trainees and MAESTRO™ trainees, results are sent to the Bayesian Fusion Engine. The Bayesian Fusion Engine combines the performance states into a final team state, resulting in an <u>at expection</u> grade for the team as a whole.

Adaptation rules are scripted for various performance grades to help trainees learn skills better by gradually presenting complex training concepts in a methodical way. Examples of adaptation rules for the ISR Team in MAESTRO™ environment include: (1) for '<u>below expectation'</u> performance grade -- remove any TWO role types, remove injects that have more than ONE expectation, and remove injects that have expectation duration of less than 40 seconds; (2) for '<u>at expectation'</u> performance grade -- remove any ONE role type and remove injects that have expectation duration of less than 20 seconds; and (3) for '<u>above expectation'</u> performance grade -- reduce ALL expectations duration by 30% and eliminate FEW (three to five) COP images to impact situational awareness. The first two adaptation rules are meant to reduce the complexity of the scenario so that the trainees can assimilate concepts better. Third adaptation rule will increase the complexity of the scenario and help trainees enhance skills.

Adaptation rules are scripted for various performance grades to help trainees learn skills better by gradually presenting complex training concepts in a methodical way. Examples of adaptation rules for the Patrol Team in TC3 Sim environment include: (1) if less than 15% of the concepts are graded to be '<u>below expectation'</u> then have the trainees review PowerPoint presentation on TTPs of key concept areas and repeat the scenario; (2) if 20% to 30% of the concepts are graded to be ‘below expectation’ then relax grading criteria on concepts, for example, the distance range for being away from the unit can be increased from 10 meters to 20 meters and with these adjustments the scenario can be repeated; and (3) if more than 30% of the concepts are graded to be ‘below expectation’ then the interface with the external team (ISR Team in MAESTRO™) can be removed and have the Patrol Team train exclusively within TC3 Sim environment. These adaptation rules are gradually reducing complexity based on logical reasoning with the purpose of helping trainees learn better.

Finally, adaption rules are built for various performance grades of the Hybrid Team as a whole. These can become very complex if individual performance grades were taken into consideration. For simplicity, we will consider only the overall team grade for these adaptation rules. Examples of Hybrid Team adaption rules include: (1) if ‘below expectation’, remove MAESTRO™ injects containing more that one response expection and send a PowerPoint presentation to the TC3 team to review TTPS; (2) if ‘at expectation’, increate simulation speed for MAESTRO™ and TC3 by 10%; (3) if ‘above expectation’, reduce response time criteria for the ISR Team and the Patrol Team by 30%. In a more complex adaption configuration, team member weighting values could be utilized to determine more robust team adaptations.

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

The paper describes: (i) an ontology-driven method for hybrid adaptive team training; (ii) an enhanced Generalized Intelligent Framework for Tutoring (GIFT) architecture to support the hybrid adaptive team training method; and (iii) a hybrid adaptive team training application example that shows the practical benefits of the method. Innovative aspects of the research described in this paper include: (i) a new ontology-based approach for hybrid adaptive team training; (ii) a standards-compliant and component-based architecting strategy that allows for rapid and affordable deployment of the adaptive training framework; and (iii) the ability to automate the generation of adaptive training scenarios. Benefits include: (i) reduced training costs; (ii) improved team training effectiveness; (iii) reduced cognitive workload for instructors; (iv) significantly reduced time and effort for *semantic* knowledge sharing, communication, and *semantic integration* for distributed training applications; and (v) improvements in learner and team performance.

Areas that would benefit from R&D include: (i) methods for extending and generalizing the GIFT adaptive team training reference ontologies; (ii) design of automated support for ontology analysis and harmonization to support training application integration; (iii) design and implementation of inter-application information exchanges with GIFT for a broader range of training application areas; and (iv) design of mechanisms to mediate and exchange adaptive training content across multiple training modalities and types.

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