Scoping report: AI-driven wargame replicator

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Abstract

The focus of this project was to assess potential improvements to the current wargame replication system used by the Land Force Operational Research Team (LFORT) in DRDC CORA through the integration of human interactors' intentions. The project, based on the analysis of problems in current wargame replication systems, reviews competing Artificial Intelligence (AI) and Human Behaviour Representation (HBR) approaches, tools and systems applicable to the wargame replication domain. For each identified approach, the main concepts, advantages, limitations and application areas are briefly described.

The typical problems in wargame replications are categorized widely as situation / pattern assessment and recognition, knowledge discovery, decision making and planning. There is no single AI or HBR tool that is appropriate for resolving all of these problems. This project proposes a framework-based solution by combining human science results, existing approaches and human behaviour moderators to solve various problems in wargame replications.

Résumé

L'objectif du présente projet était d'évaluer les améliorations possibles pouvant être apportées au système de réplication de jeu de guerre actuel qu'utilise l'Équipe de recherche opérationnelle de la Force terrestre (EROFT) de RDDC CARO à l'aide de l'intégration des intentions des interacteurs humains. Le projet, en se basant sur l'analyse de problèmes liés aux systèmes de réplication de jeu de guerre actuels, permet d'examiner des systèmes, des outils et des approches possibles d'intelligence artificielle (IA) et de représentation du comportement humain (RCH) applicables dans le domaine de la réplication de jeu de guerre. Pour chaque approche identifiée, les concepts, les avantages, les restrictions et les secteurs d'application généraux ont été brièvement décrits.

Les problèmes typiques de la réplication de jeu de guerre sont placés dans les catégories générales suivantes : reconnaissance et évaluation de la situation et de la tendances, découverte de connaissances, prise de décision et planification. Aucun outil d'IA ou de RCH ne résout entièrement tous les problèmes. Le présent projet propose une solution fondée sur un cadre en combinant les résultats des sciences humaines, les approches existantes et les modérateurs de comportements humains afin de résoudre les problèmes liés à la réplication de jeu de guerre.

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Executive summary

Scoping report: AI-Driven wargame replicator

Ruibiao Jaff Guo; David Unrau; Joe Armstrong, December, 2010; DRDC CORA CR 2010-269; CAE Professional Services.

Background:

The current wargame replication system used by The Land Force Operational Research Team (LFORT) in Defence Research and Development Canada (DRDC) – Centre for Operational Research and Analysis (CORA) cannot integrate human interactors' intentions for effective and efficient wargame simulation and analysis. To resolve this shortcoming, this project was intended to provide a review and definition of the utility in developing an Artificial Intelligence (AI) driven wargame replicator.

Objectives:

The overall objectives of the project consisted of:

- An analysis of methodologies to improve the current wargame replication system used by the LFORT;
- Identification of potential solutions to integrate human operator/interactor intent into wargame replications; and
- An assessment of competing AI approaches and the recommendation of solutions for AI-driven wargame replicator systems.

Methodology:

Based on the analysis of the project background and AI-driven wargame replication system definition, this project categorizes the AI approaches as logic-based, probabilistic, connectionism, evolutionary and memory-based approaches. Logic-based approaches consist of decision trees, rule-based methods, fuzzy logic, and non-monotonic logic. The typical probabilistic method is Bayesian Networks, while artificial neural networks are the popular method in connectionism, and genetic algorithms are the representative approach of evolutionary computing. Case-Based Reasoning is chosen as a characteristic method in memory-based approaches. For the recognized approach in related categories the main ideas, advantages, limitations and application areas are summarized briefly.

The following list includes a group of identified competing AI and Human Behaviour Representation (HBR) tools, systems and software for reasoning and problem solving in wargame replications:

- Adaptive Control of Thought – Rational (ACT-R);
- Belief-Desire-Intention (BDI);

- Connectionist Learning with Adaptive Rule Induction On-line (CLARION);
- Man Machine Integrated Design and Analysis System (MIDAS);
- Situation Awareness Model for Pilot-in-the-Loop Evaluation (SAMPLE);
- State, Operator And Result (Soar);
- Language of Agents for Modelling Performance (LAMP);
- Logic-based software;
- Statistical / Bayesian software; and
- Neural Networks software.

The problems in current wargame replications are analyzed and categorized as situation/pattern assessment and recognition, knowledge discovery, planning and decision making. There is no single tool, system or software that is perfectly appropriate for addressing the full-scope of problems in wargame replications. Therefore, this project proposes a generic solution that provides the following features:

- Combines results from human science to enhance reality including neural networks, human memory, analogy, dual-process thinking and human behaviour moderators;
- Integrates recognized tools to save development time;
- Offers multiple approaches to enlarge system flexibility;
- Models human behaviour moderators to characterize variability and individual differences; and
- Provides an approach adaptor to improve system adaptability.

Results:

Finally, the project recommends two alternative solutions: one is a set of short-term experimental solutions, in which competing approaches/tools are suggested based on problem categories in wargame replications, and another is a mid/long-term solution based on a unified, integrated and adaptable architecture.

The proposed mid/long-term architecture has the potential to be used for various Computer Generated Forces areas, for instance wargame replicators, virtual interactors/operators, virtual adversary, cognition functions such as situation awareness, decision making, planning and knowledge discovery, command and control, search and rescue, training, and also modelling and simulation.

Sommaire

Scoping report: AI-Driven wargame replicator

Ruibiao Jaff Guo; David Unrau; Joe Armstrong, décembre 2010; DRDC CORA CR 2010-269; CAE Professional Services.

Contexte :

À ce jour, avec le système de réplication de jeu de guerre qu'utilise l'Équipe de recherche opérationnelle de la Force terrestre (EROFT) à R & D pour la défense Canada – Centre d'analyse et de recherche opérationnelle (RDDC CARO), il est impossible d'intégrer les intentions des interacteurs humains aux fins de simulation de jeu de guerre et d'analyse efficaces et efficientes. Afin de résoudre ce problème, le présent projet avait pour objectif de permettre l'examen et la définition de l'utilité de développer un réplicateur de jeu de guerre axé sur l'intelligence artificielle (IA).

Objectif :

Les objectifs généraux du projet étaient les suivants :

- Analyser les méthodologies afin d'améliorer le système de réplication de jeu de guerre actuel utilisé par l'EROFT;
- Déterminer les solutions potentiels permettant d'intégrer les intentions des opérateurs ou des interacteurs humains dans la réplication de jeu de guerre;
- Évaluer les approches possibles d'IA et recommander des solutions pour les systèmes de réplication de jeu de guerre axés sur l'IA.

Méthodologie :

Selon l'analyse du contexte du projet et la définition du système de réplication de jeu de guerre axé sur l'IA, le présent projet permet de catégoriser les approches d'IA ainsi : logique, probabiliste, connexionniste, évolutive et mémorielle. Les approches à base logique comptent les arbres de décision, les méthodes à base de règles, la logique floue et la logique non monotone. La méthode probabiliste typique est représentée par les réseaux de Bayes, tandis que les réseaux de neurones artificiels sont la méthode populaire en ce qui concerne le connexionnisme, et que les algorithmes génétiques constituent l'approche représentative de l'évolution informatique. Le raisonnement par cas est choisi comme méthode spécifique de l'approche basée sur la mémoire. Les concepts, les avantages, les restrictions et les secteurs d'application généraux sont brièvement résumés pour chaque approche établie dans les catégories pertinentes.

La liste suivante présente un groupe d'outils, de systèmes et de logiciels possibles d'IA et de représentation du comportement humain (RCH) pour le raisonnement et la résolution de problèmes concernant la réplication de jeu de guerre :

- Contrôle adaptatif de la pensée – Rationalité;

- Croyance, souhait, intention;
- Apprentissage connexionniste avec induction adaptative de règles en ligne;
- Système d'analyse et de conception intégrées homme-machine;
- Modèle de connaissance de la situation pour l'évaluation du pilote dans la boucle;
- État de l'exploitant et résultat;
- Langage des agents de modélisation des performances;
- Logiciel à base logique;
- Logiciel bayésien et statistique;
- Logiciel de réseaux de neurones.

Les problèmes associés aux réplicateurs de jeu de guerre actuels sont analysés et placés selon les catégories suivantes : identification et évaluation de la tendance et de la situation, découverte de connaissances, planification et prise de décision. Aucun outil, système ou logiciel n'est entièrement capable de résoudre la portée totale des problèmes liés aux réplicateurs de jeu de guerre. Ainsi, le projet propose une solution générique qui offre les caractéristiques suivantes :

- Combine les résultats des sciences humaines pour améliorer la réalité, y compris les réseaux de neurones, la mémoire humaine, l'analogie, la pensée à deux temps et les modérateurs de comportement humain;
- Intègre des outils connus pour gagner du temps de développement;
- Offre de multiple approches pour élargir l'adaptabilité du système;
- Modélise les modérateurs de comportements humains pour caractériser la variabilité et les différences individuelles;
- Fournit l'adaptateur d'approche pour améliorer l'adaptabilité du système.

Résultats :

En terminant, le projet permet de recommander deux solutions possibles : la première étant un ensemble de solutions expérimentales à court terme selon lesquelles des approches et des outils possibles sont suggérés en fonction de la catégorie du problème concernant la réplication du jeu de guerre; et la deuxième étant une solution à moyen et à long terme basée sur une architecture unifiée, intégrée et adaptable.

L'architecture à moyen et à long terme proposée pourrait être utilisée dans divers secteurs des forces générées par ordinateur, par exemple les réplicateurs de jeu de guerre, les opérateurs et interacteurs virtuels, les ennemis virtuels, ainsi que les fonctions cognitives comme la connaissance de la situation, la prise de décision, la planification et la découverte de connaissances, le commandement et contrôle, la recherche et le sauvetage, et la modélisation et la simulation.

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Acknowledgements

We'd like to thank Dr. Kevin Sprague of DRDC CORA for providing valuable example scenarios and relevant materials describing current wargame replications and their inherent problems.

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1 Project Background

1.1 Objectives

The objective of this report is to provide a recommended course of action to the Land Force Operational Research Team (LFORT) with regard to increasing the fidelity of wargame replication for operational research. Current wargame replication techniques do not capture the intent of human interactors and cannot produce plausible replications of in-field and 'live' performance except in very limited scenarios. An Artificial Intelligence (AI)-driven wargame replicator is envisioned to reduce these limitations. The specific objectives of this report are as follows:

- Analyze the current wargame replication system used by the LFORT,
- Propose potential solutions to integrate human operator intent into wargame replications, and
- Assess competing AI approaches and recommend solutions for AI-driven wargame replications.

1.2 Scope

The purpose of this report is to provide a recommended course of action to the LFORT. The scope of this analysis considered the three aspects listed in Section 1.1. Namely, based on the analysis of the current wargame replication system, this report provides a review and makes references to currently available techniques and methods within the AI industry for wargame replications. This report briefly evaluates all of the competing solutions for AI-driven wargame replication. Based on the assessments, it will define a framework using AI approaches to represent human behaviour in wargames, and recommend the courses of action. The domain of application has been scoped by sample use cases, scenarios and details of a prototypical wargame execution provided by the scientific authority. This information is outlined in Section 2, System definition.

1.3 Constraints

The contract start date is approximately 20, Nov, 2009. The deliverables will be submitted to both the scientific authority and technical authority no later than 15 March, 2010. The scoping report is a small effort and is co-funded by both DRDC CORA and CAE PS.

Due to the limited time and budget, it is impossible to provide a comprehensive review of AI approaches and detailed solutions to the current problems. Thus, the main focus of this project was the high-level review of AI approaches, feasibility and potential directions of solutions. Detailed approaches and solutions may be pursued in a future project. Necessarily, all recommendations and scoping are preliminary in nature, and subject to change by further definition activities.

1.4 Assumptions

This section describes some basic assumptions about this work. A modular system is assumed, based on the LFORT way-forward outlined by the Scientific Authority (*Games & Reps 4CAE.ppt*, K. Sprague, 2010). The assumed approach decouples the interactor (gaming), replication (constructive simulation) and analysis functions through the use of a standard, comprehensive data interchange format (such as the Virtual Command and Control Interface Database, or 'VDB').

Also, an existing constructive or virtual simulation synthetic environment (such as CAEn, JCATS or OneSAF) is assumed to be the basis for the proposed replicator solution. The data pertaining to entities and tasks related to scenarios or use cases in the synthetic environment should be accessible to external software modules through standard network protocols, the High Level Architecture (HLA), the Distributes Interactive Simulation (DIS) protocol or a fully feature Application Programmer's Interface (API). Historic data of war games is assumed to be available for the recommended AI approaches to extract information and knowledge from experience.

1.5 Document organization

This report is organized as follows. Section 2 describes the system definition of wargame replicator systems. Section 3 describes the technical approach, including a review of the AI approaches based on logic, probabilistic, connectionism, evolutionary and memory-based categories, and a summary of the available AI and Human Behaviour Representation (HBR) tools. Section 4, heavily based on results from the human sciences, proposes a mid/long-term research and development system architecture. Section 5 is the system scoping consisting of work tasks, milestones, and efforts. The next section of the report, Section 6, presents recommendations for achieving a functional AI-driven wargame replicator, including a set of short-term experiment solutions and a mid/long-term generic solution for research and development. The last two sections consist of acronyms and references.

2 System definition

2.1 High level concept

A wargame is a simulated military operation, carried out to test the validity of a war plan or operational concept[1] (Sprague & Dobias, 2010). Wargame replication refers to the process of repeating the execution of a specific wargame many times to enable statistically valid analysis in an environment that can be sensitive to the impact of random factors, such as the influence of a 'lucky shot' (Sprague, 2010). LFORT uses computer based simulation as the basis for wargaming. With simulation tools, such as the Close Action Environment (CAEn), human interactors can control military forces and enact simulated military operations. However, military subject matter experts are a limited resource, so the number of replications that can be conducted with human interactors is very limited.

Computer driven control of the military forces (often referred to as 'constructive simulation') would enable an unlimited number of replications to be conducted. However, sophisticated Artificial Intelligence (AI) techniques are required in a fully autonomous constructive simulation process to ensure that the intent of the human interactors is captured, and replicated with sufficient fidelity during the computer driven replications.

The high level concept for LFORT wargame replication is as follows:

- Human interactors control synthetic equipment in an interactive simulation environment ('computer game') to execute a number of runs of the experimental scenario;
- The human interactions with the gaming environment and the activities in the gaming environment are logged to an authoritative, standardized data repository;
- If required, further information is elucidated from the human interactors, potentially in an interview process, and this information is added to the record of the wargame execution;
- If required, analysis is performed on the information recorded from the wargame execution and the results of this analysis are also added to the record of the wargame execution;
- An AI-based replicator makes use of the record of the human-interactor driven wargames to capture the intent of the human interactors and produce meaningful, constructive replications of the scenario to the required level of statistical validity;
- The AI-based replicator records the events and outcomes of the replications in the same repository in the same format as the human interactor based executions; and
- Analysis is performed to validate the plausibility of the computer driven replications as compared to the human driven executions, and to extract the experimental outcomes from both the human and computer driven replications.

2.2 Wargame replicator requirements

There are two main dimensions to the wargame replicator requirements. The first dimension is the nature of the wargames that need to be replicated. The second dimension is the information that needs to be derived from the replications themselves. Example experiments outline the nature of the wargames that need to be replicated. Interviews with interactors around some example scenarios provide indications on

[1] Based on Random House Dictionary.

the aspects of human behaviour that might need to be modelled in the wargame replications. Section 2.2.1 outlines an example experiment and Section 2.2.2 outlines an example scenario only (no analysis/results). Detailed actions and decision making information were not recorded for the example experiment (Section 2.2.1), thus only a summary of results appears. It is a useful example in that it describes a problem to be addressed via wargaming, the basic simulation environment and entities, and the recommended 'solution' based on the results. On the other hand, the example scenario (Section 2.2.2) includes a record of decision making for the forces involved, but no analysis or interpretation of the results. It is useful in that it provides a glimpse into the reasons behind the actions taken in the game and also the various factors that contribute to the success or failure or the 'virtual' mission. The information was provided by DRDC CORA and is included for context and reference. Section 2.2.3 outlines some of the replication requirements of the wargame replicator.

2.2.1 Example experiment

The example experimental matrix consists of:

- Two vehicles modeled: 'ALPHA' and 'BETA';
- Two weapon stations: 1-man turret with remote capability, and a remote weapon station (RWS); and
- Five weapon systems: .50 cal Heavy Machine Gun (HMG) ; 40 mm Automatic Grenade Launcher (AGL); Antitank Guided Missile (ATGM); 20 mm cannon; and a Low Velocity (LV) 25 mm cannon (notional).

There are three scenarios in the experiment:

- Irregular Warfare (IW);
    - Scenario 1: Convoy ambush in urban terrain; and
    - Scenario 2: Recce picket objective of a town in mixed urban/open terrain.
- Conventional Warfare (CW);
    - Scenario 3: Fighting Withdraw in open terrain

The experimental matrix of wargames played is shown in Table 1. The 'No. Variations' column is derived from the listed entries in the previous three columns as the following product: (number of weapon stations) x (number of vehicles) x (number of scenarios). The 'No. Replays' column records the number of games that the interactors played per variation (each variation represents one possible equipment option to be tested). The 'No. Games' column records the total number of interactor games played for the entire set of variations, and the 'No. Reps' column records the total number of replications generated for the set of variations.

Table 1: Wargames Played

ID	Priority	Weapon System	Weapon Stations	Vehicles	Scenarios	No. Variations	No. Replays	No. Games	No. Reps
1	HIGH	LV 25mm / C6	RWS, 1-man	Vehicle A, Vehicle B	I, II and III	12	4	48	960
2	MED	LV 25mm / C6 / 2xATGM	RWS, 1-man	Vehicle A, Vehicle B	II and III	8	4	32	640
3	HIGH	AGL / C6	RWS, 1-man	Vehicle A, Vehicle B	I, II and III	12	4	48	960
4	MED	AGL / C6 / 2xATGM	RWS, 1-man	Vehicle A, Vehicle B	II and III	8	4	32	640
5	HIGH	.50 cal / C6	RWS, 1-man	Vehicle A, Vehicle B	I, II and III	12	4	48	960
6	MED	.50 cal / C6 / 2xATGM	RWS, 1-man	Vehicle A, Vehicle B	II and III	8	4	32	640
7	HIGH	C6 / 4xATGM	RWS, 1-man	Vehicle A, Vehicle B	II and III	8	4	32	640
8	HIGH	25mm / C6	2-man	Vehicle BASELINE	I, II and III	3	4	12	240
9X	HIGH	20mm / C6	RWS, 1-man	Vehicle A, Vehicle B	I, II and III	12	4	48	960
				HIGH PR. TOTALS -	---------	59	4	236	4720
				MED PR. TOTALS -	---------	24	4	96	1920

To the accuracy gamed, the overall results for all three scenarios indicate that:

- The weapon system was the BIGGEST factor;
- The vehicle only made a noticeable difference in Scenario 1; and
- The weapon station did not matter.

The specific results for the individual scenarios are now provided.

Figure 1 is the visual view of Scenario 1. The Measures of Effectiveness (MOEs) for that scenario are as follows:

- Convoy Survival Rate: 50%;
- BLUE Residual Combat Strength: 25%; and
- RED Losses: 25%.

The results of Scenario 1 are summarized below:

- BETA faired better then ALPHA;
- In most cases, the weapon stations did not make much of a difference;
- The LV25mm, HMG and AGL each logged (high-ranking) performances comparable to the 25mm cannon of the BASELINE vehicle; and
- The arming distance for the AGL was a negative factor for that weapon in close combat.

Figure 1: Example Wargame: Scenario 1

Figure 2 is the visual view of Scenario 2, with the following MOEs:

- Identification of RED Units: 50%;
- BLUE Residual Combat Strength: 25%; and
- RED Losses: 25%.

The results of Scenario 2 are summarized below:

- ALPHA and BETA performances were comparable to one another;
- In most cases, the weapon stations did not make much of a difference;
- On average, 1-man turret engagements occurred at longer ranges than RWS engagements; and
- ATGM options logged performances comparable to the BASELINE, with the LV25mm not far behind.

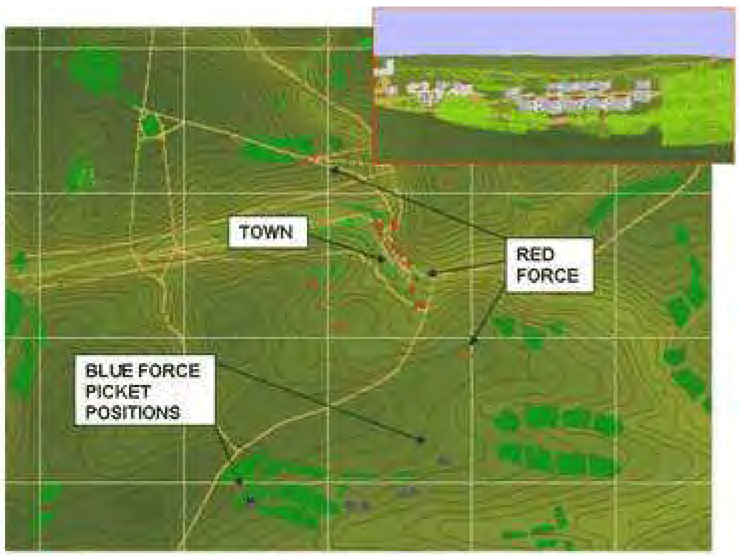

Figure 2: Example Wargame: Scenario 2.

Figure 3 is the screen shot of Scenario 3 with the following MOEs:

- 70% BLUE Residual Combat Strength; and
- 30% of RED Losses.

Rather than list the results of this final scenario, the results of Scenario 3 are shown in Figure 4 as they might be presented to the military sponsor of the wargame.

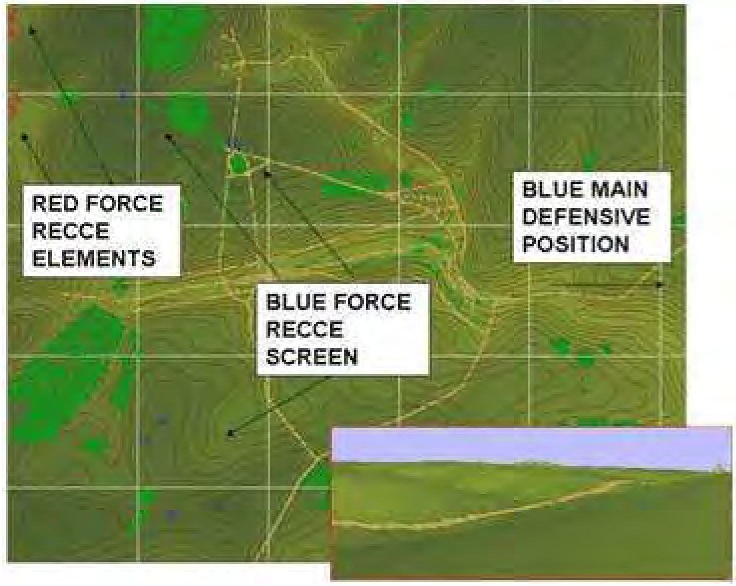

Figure 3: Example Wargame: Scenario 3

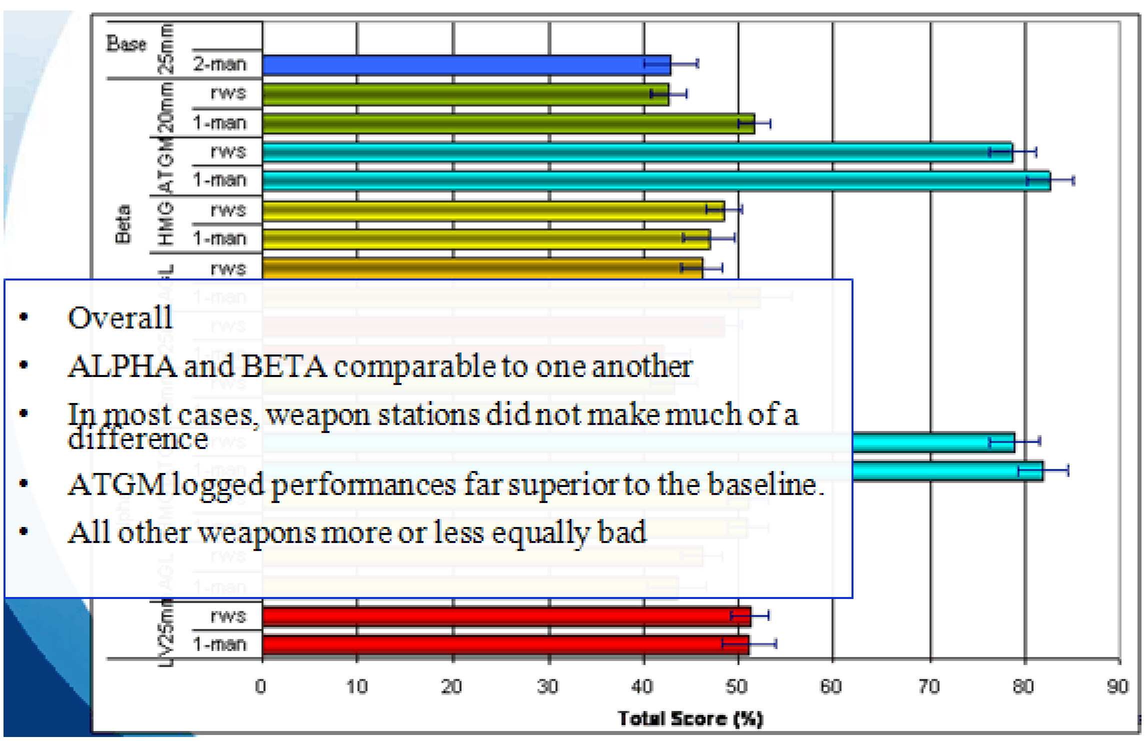

Figure 4: Example Wargame: Scenario 3 results

Finally, this example has the following overall recommendations, based on all three scenarios:

- Best combination overall: NONE were high performers in all three of the scenarios
- Need to combine ATGMs with LV25mm to maximize performance over the three scenarios: BETA vehicle preferred on the basis of Scenario 1 (either station); Require more than a wargame to inform vehicle selection though (CAEn vehicle templates are not complex enough).

2.2.2 Example scenario

The following example scenario (Sprague, 2010) was used to elucidate information on the decision making process from the interactors. This section outlines the scenario and the feedback from the interactors. *ScenarioCutoff_RUN_1.doc* (Sprague, 2010) details the scenario.

The scenario is based in an urban/open terrain with a playing area of 10km by 10km. Blue force has been tasked with clearing the village. Blue force commander's intent is to destroy or capture all members of Red force to remove the current and future threat. Red force's intent is to maximize Blue force casualties, create maximum confusion and to escape to fight in the future. The terrain is a mainly flat urban area with some rolling hills. The village mainly consists of two story buildings with some larger buildings, trees and shrubs. There is a paved road network.

Blue force is a light infantry section of eight (8) soldiers with C7 rifles. Red force is composed of eight (8) soldiers who have trained together as a formed group and have a well-defined set of tactics, techniques and procedures (TTPs) that they follow. Red force is armed with C7 rifles.

Subject matter expert interactors executed this scenario and recorded the details of their decision-making processes during the scenario execution. Examples of this information are listed in the following tables (Table 2) and are provided for reference. The text is drawn from the Blue force commander in the scenario, and records a series of seven (7) major decision points over a span of approximately nine (9) minutes of game time. After a series of weapons fire exchanges by a stationary Blue force on a moving Red force, by the time of the last entry (ID#7), all Red units have been destroyed. However, it is not clear to Blue whether or not there are still Red units at large since they rely on visual detections of an enemy that is constantly changing its position amidst rubble, trees and nearby buildings.

Note that this particular scenario is at least reasonably robust under slight variations in decision-making, since it basically describes a 'shoot-out' along well-defined positions and paths of motion. Case in point, wargames currently have to pay close attention to how a game will be replicated in order to achieve credible results. That is, the replicator capability constrains the complexity of scenarios that can be gamed and analyzed statistically.

Table 2: Decision making feedback from SME Interactors

ID	TIME	SITUATION	GOAL	CONSIDERATIONS / COAs	DECISION	ACTION	RESULT
1	00:00	BLUE Section Deployed as cutoff team for RED forces fleeing from building.	Kill / stop RED from fleeing building	Range, approx. 300m; RED has good cover to withdraw; BLUE also has good cover at location but little freedom of movement; BLUE has little cover in the immediate area;	Engage RED as they become visible.	Engage RED with Direct Fire; Use cover to alternate between being under cover and firing on RED via Assault Groups.	4 RED seen exiting building to covered positions in front of building; BLUE engaged but no RED are believed to have been killed.
2	00:39	Half Section of RED seen exiting Building and have taken up positions in front of building (as per results in #1).	As above (#1).	RED now outside building under less cover; RED now engaging BLUE.	As above.	As above.	A second half-section exits the building; 0 believed killed in action (KIA)
3	01:43	2 BLUE KIA in same assault group; 2 half-sections of RED now outside building using cover; RED continues to engage BLUE.	As above (#2).	Firepower in section is unevenly divided between assault groups.	As above.	Use individual cover/fire movement instead of assault groups.	RED is using fire and movement to withdraw towards woods; 0 RED believed KIA.

ID	TIME	SITUATION	GOAL	CONSIDERATIONS / COAs	DECISION	ACTION	RESULT
4	05:20	RED using fire and movement to withdraw towards woods (as per results in #3)	As above (#3); Plus halt RED withdrawal.	RED difficult to detect; BLUE Direct Fire has been ineffective.	Use Suppressive Fire to halt RED withdrawal.	Put half-section on Suppressive Fire; Target likely RED position at initial cover just outside building.	RED withdraws; Continues; 1 RED believed KIA
5	07:02	RED continues withdrawing towards woods.	As above (#4).	As above (#4).	As above (#4).	Shift Suppressive Fire to follow the RED withdrawal.	RED withdrawal continues.
6	07:45	As above (#5).	As above (#5).	RED moving across more open terrain; Visibility improves.	Use Direct Fire to halt RED withdrawal.	Place all BLUE on Direct Fire; Engage RED when seen.	3 additional RED believed KIA; RED continue to withdraw;
7	09:18	Remaining RED forces continue to withdraw using fire and movement.	As above (#6).	Right-most BLUE soldier has best visibility of RED; RED easily seen and moving across open terrain along final stretch to woods.	Shift BLUE section to better vantage point to engage RED.	Use fire and movement to shift half of BLUE section to the right; Continue Direct Fire.	Majority of RED KIA; Shifting section proved unnecessary as RED becomes visible to all of BLUE as soon as they cross the road.

2.2.3 Replication requirements

The goal of the replicator is to allow the execution of an experimental run to be repeated without human interactors in a fashion that is consistent with the execution of the scenario with human interactors. This is necessary, as military operations deal with many unpredictable factors that are necessarily modelled by random processes. For instance, weapon accuracy and weapon effects are normally modelled using probability tables. The outcomes of a specific scenario are critically sensitive to these probabilistic factors. For instance, the survival of a vehicle crossing open ground will be highly dependant on whether it is detected by enemy forces, whether it is engaged by enemy weapons and how it is damaged by weapon impacts. The future actions of the force are in this fashion strongly influenced by the critical outcomes of a series of events, many of which are random in nature.

Thus, to measure the effectiveness of a piece of equipment, or a specific tactic, many runs across a number of scenarios will have to be executed to produce measurable significance across the many random factors. This is the requirement for repetition. The replicator is complicated by the fact that the execution of the scenario is also sensitive to the intent of the human operators, which may vary in time as circumstances change. For instance, a force commander may order an action that has a low probability of destroying a resource. However, if the resource is then destroyed; the force commander may completely re-plan future actions and employ different tactics or strategies than if the resource was not destroyed.

If warfighter interactors are used to provide this control (in an interactive simulation or ‘gaming’ mode of experimentation), the number of executions that can be performed are strictly limited based on resource availability. This is the Artificial Intelligence (AI) requirement of the replicator. The wargame replicator is required to simulate the intent of the human interactors to produce executions that are consistent with the operations of human interactors in the gaming environment.

2.3 Wargame replicator concept

Current wargame replication systems do not take into account the intent of the interactors and thus courses of action taken by system-controlled entities in a replication may vary greatly from actions that would have been taken by interactor-controlled entities under the same set of circumstances. Therefore, wargame replication needs to somehow incorporate the intent of the wargame players in a meaningful and efficient way, providing a more plausible representation of the behaviours of both the virtualized players and the agents within these wargame simulations.

Figure 5 is the proposed future architecture of the Post-Gaming Analysis Tool (PGAT+) from DRDC CORA. CAEn and JCATS (‘Joint Conflict and Tactical Simulation’) are synthetic environments. The VDB (Virtual Data Base) will store all results of wargame executions for use in three tools: the Post-Wargame Analysis Tool, Aramis (a wargame viewing environment[2]) and a Replication Query Tool.

[2] Aramis is a product of Simfront Corporation. See http://www.simfront.com.

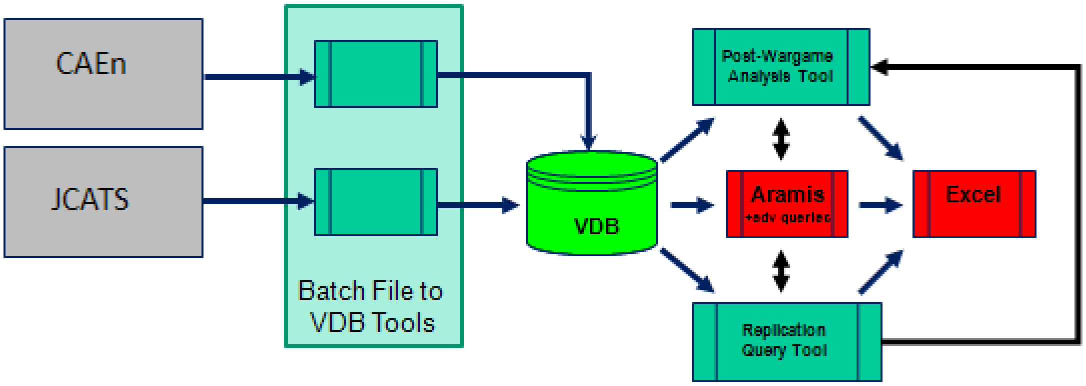

Figure 5: Post-Gaming Analysis Tool (PGAT)

Critically, the VDB is used as the central data repository to decouple interactor driven executions from replicated executions from post game analysis. All systems will read from the VDB and write from the VDB to gain the inputs they require and to store the outputs they produce. In this fashion, the input requirements for the wargame replicator become data requirements for what information must exist in a VDB in order to produce replication for a specific experimental plan. These data requirements may be satisfied by a combination of:

- Interactor drive scenario executions that produce data stored in the VDB;
- Interactor interviews that supplement data stored in the VDB; and
- Analysis and queries that produce analysis results from data, and store these results as further data in the VDB.

The AI-driven wargame replicator can integrate human interactors' intent into the replications (as shown in Figure 6).

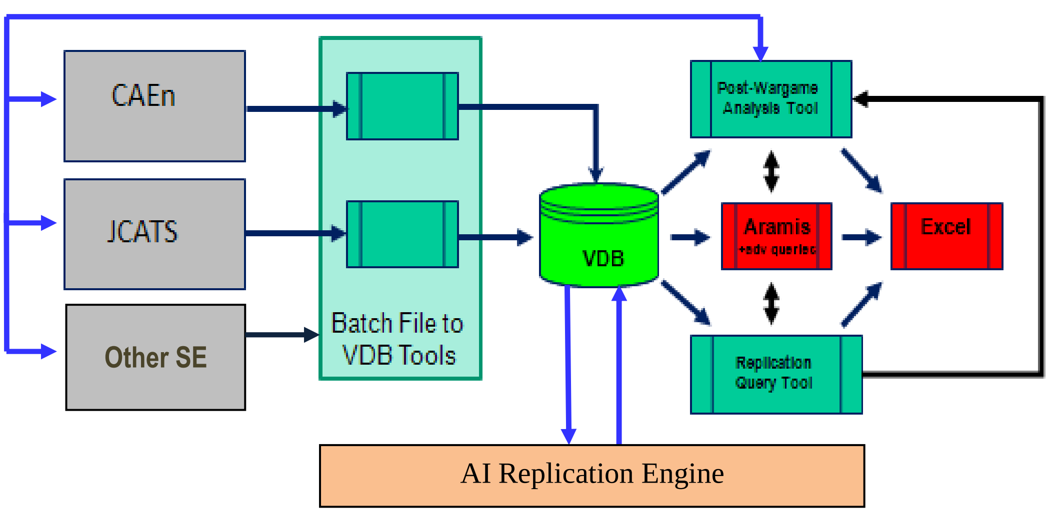

Figure 6: PGAT: AI-Driven Post-Gaming Analysis Tool

The AI Replication Engine integrates the intent of human interactors into wargame replications. It acquires data of the initial wargame from the PGAT database, combines the data with human intentions to form new inputs of the wargame replications. The human intent may be tasks related to situation assessment, planning, decision making and knowledge discovery. Note that additional data, not necessarily stored in the VDB, may be required to run replications. For example, standardized probability tables for detections and weapon accuracy/lethality are also required as inputs. These data do not currently reside in the VDB. Nor do the interview data. Also, quite possibly, the results of certain queries may lie outside the current array of fields supported by the VDB. In any case, the VDB will have to be extended or supplemented in order to support replication. For the remainder of this document, we assume the former (extended).

3 Technical approach

This section reviews the available approaches and tools of Artificial Intelligence (AI) and Human Behaviour Representation (HBR) and proposes a unified human science oriented AI solution for problem solving in wargame replications.

3.1 AI approaches

AI approaches may be roughly categorized as logic-based, probabilistic, connectionism, evolutionary and memory-based approaches.

3.1.1 Logic-based approaches

Logic is the study of reasoning that is used in most intellectual activity. Symbolic logic is one area of logic that studies the purely formal properties of a string of symbols. There are also many branches of symbolic logic, such as propositional logic, predicate logic, temporal logic, modal logic, fuzzy logic and non-monotonic logic. However, propositional logic and predicate logic are two main subfields. One of logic's powerful features is its reasoning ability. It is through its deduction power that logic is the foundation of many artificial intelligence approaches. This section summarizes several typical logic-based approaches that are very useful for problem solving in AI-driven wargame replications, including decision trees, rule-based systems, fuzzy logic and non-monotonic logic.

A **decision tree** (Howard, 1966) is a directed logic structure with the topology of a tree. It is a decision support tool that uses a tree-like graph or model of decisions and their possible consequences. Decision trees have been used in many applications areas, for instance, decision making (Gensure, 2007; Santos, et al., 2008), knowledge discovery (Zhang et al., 1999; Hsu & Wang., 2005), and prediction (East & Sharfstein, 2006). In the AI-driven wargame replicator, decision trees may be used in problems associated with decision making, pattern discovery and planning.

A **rule-based system** is a knowledge-based system that uses IF-THEN rules to represent knowledge (Brownston et al., 1985; Cooper & Wogin, 1988). Rule-based systems are a relatively simple approach that can be adapted to a great number of problems (Russell and Norvig, 2003; Anderson et al., 2004, Ligeza, 2006). The rule-based system itself uses a simple technique: it starts with a rule-base, which contains all of the appropriate knowledge encoded into IF-THEN rules, and a working memory, which may or may not initially contain any data, assertions or initially known information. Rules are of the form: IF some condition THEN some action. There is an inference engine that derives action based on the conclusions obtained from the rule-base.

Rule-based systems have been used in great number of application areas, for example,

- Situation assessment and threat evaluation (Pew and Mavor, 1998; De Jongh, et al., 1994; Lightfoot, 2003; Duke et al., 1989; Tang & Zhang, 2009);
- Strategic planning (Huang, 2009; Liao et al., 2003);
- Decision support (Eom et al., 1998, Eom and Kim, 2005; Metaxiotis, et al., 2004; Momoh et al., 1994);
- Simulating the game strategies in computer games (Rielly, 2005);

- Expert systems (Lindsay et al., 1980; Buchannan & Shortliffe, 1984); and
- Natural language processing.

In the AI-driven wargame replicator, rule-based systems can be used in various levels from situation assessment, threat detection to decision and planning.

Fuzzy reasoning is based on fuzzy set theory and fuzzy logic (Zadeh, 1965, 1968; Kosko, 1993) to specify how well an object satisfies a vague description. The main advantage of fuzzy reasoning is the ability to mimic human decision making to handle vague or imprecise or imperfect concepts.

Fuzzy reasoning also has wide usages, for instance, situation awareness in military applications (Chai, et al., 2007; Jeppesen and Trellue, 1997; Rao, et al., 2008; Liang, 2007; Gonsalves et al., 2000), reconnaissance (Ragsdale et al., 1997), planning (Kewley & Embrechts, 2002), optimal strategy selection to respond to a threat (Smith III, 2002), fuzzy control for UAV, robots, aircraft flight (Guo et al., 2008), electronic equipment, etc. In AI-driven wargame replications, fuzzy reasoning may be used for situation and target value evaluation, reconnaissance, and strategy or tactics selection.

Non-monotonic logic is a formal logic whose consequence relation is not monotonic. Most formal logics have a monotonic consequence relation, meaning that adding a formula to a theory never produces a reduction of its set of consequences. Some recognized non-monotonic reasoning models include the Default Reasoning (Reiter, 1980), the Abductive Reasoning (Peirce, 1958), the Reasoning about Knowledge (Moore, 1984, 1985) and the Belief Revision (Gardenfors and Rott, 1995). Some applications of non-monotonic reasoning consist of situation assessment (Ly et al., 2003), air force threat correlation (Cohen and Laskey, 1986), qualitative physics, databases, learning, logic programming, diagnosis or robotics (Etherington and Kautz, 1994; Nunez et al., 2007), and cognitive functions (Novak, 2008). In an AI-driven wargame replicator, non-monotonic logic is a relevant advanced topic. It can be combined with rule-based systems to support deeper problem solving in wargame replications.

The advantages of logic-based system are as follows:

- Sound logic foundation;
- Able to represent expert's knowledge and thinking patterns;
- Natural knowledge representation, i.e., an IF-THEN rule is like "In such-and-such situation, I do so-and-so" in human thinking; and
- Separation of knowledge from its processing.

Logic-based systems also have some limitations, for example, requiring explicit expert's knowledge and thinking patterns, difficult knowledge acquisition, lack of common sense needed in some decision making, opaque relations between rules, and ineffective exhaustive search strategy.

3.1.2 Probabilistic approaches

The basic idea of probabilistic reasoning is that real world phenomena can be reasonably modeled as probability. Handling uncertainty is the focus of probabilistic reasoning. The foundation of probabilistic reasoning is the well-known Bayes Theorem (Bayes, 1763) that shows how one conditional probability depends on given evidence. The key idea is that the probability of hypothesis H given event e (evidence) depends not only the relationship between *H* and *e* but on the absolute probability of *H* independent of *e*, i.e.:

$$P(H|e) = \frac{P(e|H)P(H)}{P(e)}$$

where $P(H)$ is the prior probability or marginal probability of H, $P(H \mid e)$ is the conditional probability of H, given e, $P(e \mid H)$ is the condition probability of e given H, and $P(e)$ is the prior probability or marginal probability of e.

A Bayesian network, derived from Bayes theorem, is a probabilistic graphical model that represents a set of random variables and their conditional independencies via a Directed Acyclic Graph (DAG) (Pearl, 1988; Murphy, 1998; Russell & Norvig, 2003). It provides a natural tool for dealing with two problems that occur throughout applied mathematics and engineering – uncertainty and complexity – and in particular they are playing an increasingly important role in the design and analysis of machine learning algorithms.

The main advantages of Bayesian networks include:

- Supporting decision making;
- Readily handling uncertain information or incomplete data sets;
- Able to handle different variable types or different sources of knowledge, e.g. subjective beliefs and empirical data;
- Readily facilitating use of prior knowledge or combining expert knowledge;
- A clear semantic interpretation of the model parameters;
- Capable of learning about causal relationships; and
- Flexible applicability for different levels of same problem domain.

Bayesian networks also have some limitations, for instance:

- Quality depending on the quality of the prior beliefs or model;
- No feedback loop;
- Difficult to examine the solutions of the networks;
- NP-hard calculation costs; and
- Difficult to get the probability knowledge in some domains.

Bayesian belief networks have numerous applications in various areas, including situation awareness, (Johansson and Falkman, 2008; Mahoney et al., 2002; Wright et al., 2002; Baumgartner et al., 2008), threat assessment/detection (Ghazi et al., 2004; Suzic, 2005), decision making (Russell & Norvig, 2003; Starr & Shi, 2002; Watthayu & Peng, 2004; Brynielsson, 2006), planning (Vaccaro & Guest, 2004), prediction of terrorist attack (Jha, 2009), pattern recognition, Modelling and Simulation (M&S), knowledge discovery, data/information/text fusion and mining (NASA), gaming, speech recognition, engineering (NASA, General Electric, Lockheed Martin, Hewlett-Packard (HP), Intel, American Airlines), information technology (Microsoft, NASA, etc.), computational biology & bioinformatics, medical diagnosis (BiopSys, Microsoft) & medical image process, and law. The AI wargame replicator can use Bayesian inference at various levels, e.g. situation awareness, threat detection and evaluation, strategy and tactics selection, decision making and planning.

Other approaches associated with probability computing include Naïve Bayes (Bhargavi & Jyothi, 2009; Marhav, 2002; Chia & Williams, 2003; Galli et al., 2009), and hidden Markov model (HMM) (Rabiner, 2989; Marhav, 2002; Cappe et al., 2005; Popken & Cox, 2003; Andersson , 2003, Kelley et al., 2008; Inamura et al., 2006). In addition, a kernel computing-based approach, known as support vector machines (SVM) (Vapnik, 1995; Burges, 1998; Cristianini & Shawe-Taylor, 2000) is also a useful method for classification and regression.

3.1.3 Connectionism approaches

Connectionism is a set of approaches in the fields of artificial intelligence, cognitive psychology, cognitive science, neuroscience and philosophy of mind, which models mental or behavioral phenomena as the emergent processes of *interconnected networks of simple units*. There are many forms of connectionism, but the most common forms use artificial neural network models.

An Artificial Neural Network (ANN) (McCulloch and Pitts, 1943; Grossberg, 1988, Feldman and Ballard, 1982; Hertz et al., 1990; Lawrence, 1994, Bishop 1995), usually called "Neural Network" (NN), is a mathematical or computational model that tries to simulate the structure and/or functional aspects of biological neural networks. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase.The objective of the neural network is to transform the inputs to the network into meaningful outputs. More details of ANN will be discussed in Section 4.

ANN has distinct features over other approaches, including:

- Self-learning & tuning capability;
- Not necessary to extract the thinking patterns of experts;
- Robustness towards noisy data, thus well suited for sensorial data processing;
- Ability to implicitly detect complex nonlinear relationships between dependent and independent variables;
- Availability of multiple training algorithms; and
- No need to assume an underlying data distribution such as usually done in statistical modelling.

ANN, like other methods, also has some limitations, for example:

- Requires a substantial training set;
- Black box nature without explicit explanation;
- Greater computational burden;
- Unable to combine numeric data with linguistic/logic information;
- Incapable of managing imprecise or vague information;
- Difficult to reach global minimum even by complex Back-Propagation (BP) learning; and
- Rely on trial-and-errors to determine hidden layers and nodes.

ANN has also been used in numerous application areas including military target recognition (Himes & Inigo 1992; Ratches et al.,1997; Roth 1990; Zhao & Bao, 1996), wargame threat/situation assessment (Rushing et al., 2004; Madeira et al., 2010), pattern classification (Zhang, 2000; Zhai et al, 2006; Ibrahim et al. 2009), emotion recognition (Khashman, 2008), prediction (Ahmed 2005; Gan et al., 2005), clustering (Liu & Zheng, 1992; Sanchez et al., 2006), function approximation (Zainuddin & Pauline, 2008), speech recognition (Al-Alaoui et al, 2008; Lim et al., 2000), medicine diagnosis (Ozyilmaz & Yildirim, 2003; Ahmed, 2005; He et al.2009), computer vision, speech recognition, biometrics, handwriting recognition, portfolio management, financial forecasting, quality control, fraud detection, etc. In AI-driven wargame replications, ANN’s appropriate application might be best applied at the situation / pattern recognition level.

3.1.4 Evolutionary approaches

Evolutionary computation is a subfield of computational intelligence that involves combinatorial optimization problems with inspirations drawn from biological evolution. Genetic algorithms are the most popular type of evolutionary computational approach.

Genetic algorithms (GA) (Fraser 1957; Barricelli 1957; Holland, 1975; Fogel, 1998, 2006) are a search technique used in computing to find exact or approximate solutions to optimization and search problems. Genetic algorithms are categorized as global search heuristics with the mechanism inspired by evolutionary biology such as inheritance, mutation, selection, and crossover. They are implemented in a computer simulation in which a population of abstract representations of candidate solutions to an optimization problem evolves toward better solutions.

Advantages of genetic algorithms include

- Ability to quickly scan a vast solution set;
- Capable of discarding bad proposals without affecting the end solution negatively; and
- Not necessary to know domain rules and easy to parallelize.

Some disadvantages of genetic algorithms are as follows:

- Possible to evolve into a dead end;
- Quality as good as the evaluation function (often hardest part); and
- No guaranteed convergence even to local minimum.

Some examples of GA’s applications include situation assessment (Gonsalves et al., 2000), strategy generation (Revello and McCartney, 2002), wargame/gaming/strategy selection (Revello & McCartney, 2002; Pew & Mavor, 1998; Watson et al., 2010 ; Brainz, 2010; Periaux et al., 2001; Dworman et al., 2010; Marks, 2010), planning (Guitouni and Belfares, 2003; Allaire et al., 2009; Kewley & Embrechts, 2002; Boukhtouta et al., 2004; Pew and Mavor, 1998), trajectory planning of robotics (Davidor, 1991; Miryazdi & Khaloozadeh, 2002), chemistry & biology (Weber, 1998; Padgett & Saad, 2009; Leardi, 2001), clustering (Fernandez et al., 2010), combination optimization, scheduling, etc. GA may be used for the selection of strategy/tactics/courses of action in AI wargame replications.

3.1.5 Memory-based approaches

Memory-based AI approaches consist of various heuristic search, instance/example-based, case/experience-based, and analogical methods. This section reviews case-based reasoning, a typical method in the memory-based approaches.

Case-based reasoning (CBR) (Schank, 1982, 1990; Riesbeck & Schank, 1989; Kolodner, 1993), broadly construed, is the process of solving new problems based on the solutions of similar past problems. An auto mechanic who fixes an engine by recalling another car that exhibited similar symptoms is using case-based reasoning. Case-based reasoning is a prominent kind of analogy making.

Case-based reasoning has been formalized for purposes of computer reasoning as a four-step process: (1) *Retrieve***:** given a target problem, retrieve cases from memory that are relevant to solving it, (2) *Reuse***:** map the solution from the previous case to the target problem, (3) *Revise***:** if necessary, revise the new solution, and (4) *Retain***:** store the resulting experience as a new case in memory.

Compared to other AI methods, CBR has some apparent advantages, e.g.,

- No need to understand the domain completely;
- Suitable for domains without precise mathematical or algorithm models;
- Naturally reflecting human's thinking in many situations, easy knowledge acquisition; and
- Capable of learning from both successes and failures.

Some limitations of CBR contain:

- Hard to get sufficient cases;
- Hard to define similarity measurement between cases;
- Difficult to validate the systems; and
- A type of inductive reasoning without guaranteed generalization.

CBR has also been used in various application areas, for example, planning and decision support (Liao, 2000; Moriarty, 2000; Lachevet, 2009; Munoz-Avial et al, 1999; Boukhtouta et al, 2004; Pew and Mavor, 1998; Talbot, 2001), situation assessment (Looney, 2003; Pew and Mavor, 1998; Gupta and Mukherjee, 2009), air traffic control (Allendoerfer and Weber, 2004), spatial analysis (Holt and Benwell, 1996), customer services (Acorn and Walden, 1992), design (Maher et al., 1995), clinical problem solving (Kolodner & Kolodner, 1987), education (Brown et al, 1989), legal reasoning, medical diagnosis, scheduling, help-desk support, etc. In AI wargame replications, CBR may be used for solving problems in planning, decision making and problem solving.

3.1.6 Summary of AI approaches

The following Table 3 summarizes these AI approaches, providing brief descriptions, advantages, disadvantages and main applications.

Table 3: Summary of AI approaches

Approach Category	Approach	Description	Advantages	Disadvantages	Main Applications
Logic-based	Decision trees FOL rules (rule-based) Fuzzy logic Non-monotonic logic	Using decision trees, propositional / predicate logic, fuzzy logic or non-monotonic logic for reasoning	• Useful for decision making • Can represent human thinking pattern • Natural knowledge representation • Simple to understand • Easy to get explanation	• Require experts' knowledge explicitly specified • Knowledge acquisition is difficult • Exhausted search • No self-learning / organization ability	• Situation assessment • Decision analysis • Planning • Expert systems • Learning: pattern classification • Prediction • Control
Probabilistic / Kernel	Naïve Bayes Bayesian Networks HMM SVM	Use Bayes Theorem, and / or acyclic directed graph as foundation of inference.	• A sound decision theory • Consist, theoretically solid mechanism for processing uncertain information • Flexible applicability • A clear semantic interpretation of the model parameters • Allowing different variables types • Handling missing data	• Does not support feedback loop • Quality depending on the quality of the prior beliefs or model • Difficult to examine the solutions • Difficult to get the probability in some domains. • NP-hard calculation costs	• Situation / threat assessment • Decision making • Planning • Prediction • Pattern recognition and classification • Knowledge discovery • Information fusion • Data /text mining
Connectionism	Neural Networks	An approach that models mental or behavioural phenomena as the	• Not necessary to extract the thinking patterns of domain experts • Robustness towards noisy	• A substantial training set is required • Black box nature • Large computational	• Threat/situation assessment • Prediction • Pattern recognition

		emergent processes of interconnected networks of simple units (neurons)	data • Ability to implicitly detect complex nonlinear relationships between dependent and independent variables.	burden.	• Target recognition • Emotion recognition
Evolutionary	Genetic Algorithms	A popular search-based evolutionary algorithm to find exact or approximate solutions to optimization and search problems.	• Can quickly scan a vast solution set. • Bad proposals do not affect the end solution negatively as they are simply discarded. • Easy to parallelize	• Possible to evolve into a dead end • Quality as good as evaluation functions • No guaranteed convergence even to local minimum.	• Planning • Situation assessment • Strategy generation • Strategy selection • Optimal route selection • Optimal design
Memory-based	Case-based	A process of solving new problems based on the solutions of similar past problems, including four processes: retrieve, reuse, revise, and retain.	• Can be used in problem domains that are not well understood. • Can re-use previous successfully solutions • Relatively easy to set up a knowledge base. • Adding examples are easier than rules. • Can learn from previous failed examples • Explanation becomes easier.	• Defining the similarity between cases is difficult. • Previous experience may not be validated. • May not have sufficient similar cases. • Validation of the system is difficult.	• Planning • Decision making • Situation assessment • Air Traffic Control • Analysis and design • Problem solving • Scheduling

3.2 AI and HBR Tools

3.2.1 HBR tools

There are many tools and approaches for modelling human behaviour / performance, such as the IPME (Integrated Performance Modelling Environment), GOMS (Goals, Operators, Methods and Selection rules); EPIC (Executive-Process Interactive Control), HOS (Human Operator Simulator), OMAR (Operator Model Architecture), etc. This section focuses mainly on the HBR tools with obvious AI reasoning approaches and functions, including the Adaptive Control of Thought – Rational (ACT-R), Belief-Desire-Intention (BDI), Connectionism Learning with Adaptive Rule Induction On-line (CLARION), Man Machine Integrated Design and Analysis System (MIDAS), Situation Awareness Model for Pilot-in-the-Loop (SAMPLE) and State, Operator And Result (Soar).

3.2.1.1 Adaptive Control of Thought – Rational (ACT-R)

ACT-R is a cognitive architecture mainly developed by John Robert Anderson at Carnegie Mellon University (Anderson, 1990; Anderson & Lebiere, 1998; Anderson et al., 2004). Like any other cognitive architecture, ACT-R aims to define the basic and irreducible cognitive and perceptual operations that enable the human mind. In theory, each task that humans can perform should consist of a series of these discrete operations.

Figure 7 shows the architecture of ACT-R, consisting of the following components:

- **Modules**: including perceptual-motor modules, and memory modules: declarative memory for facts and procedural memory for IF-THEN rules.
- **Buffers**: ACT-R accesses its modules (except for the procedural-memory module) through buffers. For each module, a dedicated buffer serves as the interface with that module.
- **Pattern Matcher.** The pattern matcher searches for a production that matches the current state of the buffers.

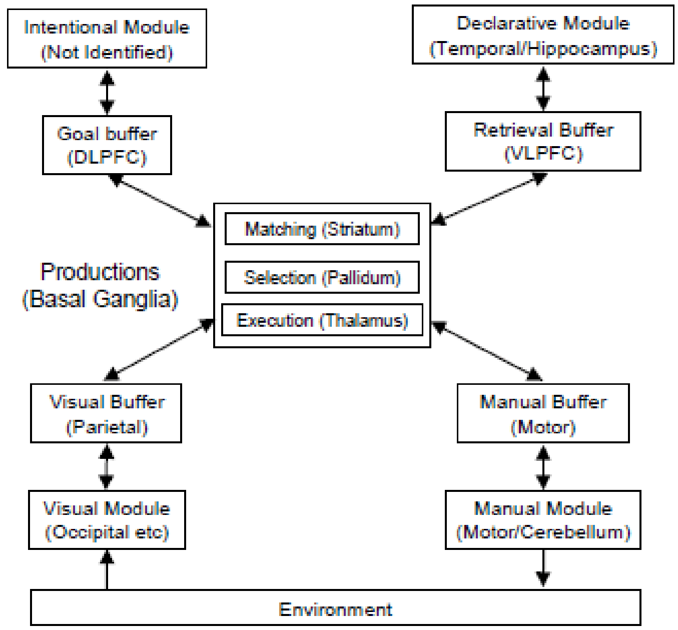

Figure 7: Architecture of ACT-R (Anderson et al., 2004; Chong et al., 2007)

A fundamental characteristic of ACT-R is that it is based on a production system theory. The basic premise of a production system theory is that a cognitive skill is composed of conditional statements known as production rules. A production rule is a statement that describes an action which would be taken if a condition is met, sometimes referred to as a condition-action pair.

The main advantages of ACT-R include a powerful reasoning method, very active user community (primarily psychologists and cognitive scientists), strong training, support, and commitment to “user friendly” software, and is the most well known of current psychology-based systems.

ACT-R also has some limitations, for instance, it is primarily an academic research system, its value for large applied problems has not been clearly demonstrated, it has a debated scientific basis, the perceptual/motor representations are lagging, and there are many parameters affecting performance.

Most applications of ACT-R focus on cognitive experiments, including human-computer interaction, intelligent tutoring systems, experiments for behaviour moderators, experiments of military modelling and simulation, learning and memory, problem solving and decision making, language and communication, perception and attention, cognitive development, and individual differences.

3.2.1.2 Belief-Desire-Intention (BDI)

BDI is based on the Dennett’s theory of intentional systems (Dennett, 1987) and the theory of human practical reasoning (Bratman et al., 1988). Originally developed as a system that can reason and plan in a dynamic environment, BDI meets real-time constraints by reducing the time used in planning and reasoning. BDI is designed to be situated, goal directed, reactive, and social. This means that a BDI agent is able to react to changes and communicate in their embedded environment as it attempts to achieve its goals. Mechanisms for responding to new situations or goals during plan formation for general problem solving and reasoning in real time processes are also included in most BDI systems (Georgeff and Ingrand, 1989; Sardina et al., 2006).

BDI architecture consists of Beliefs, Desires and Intentions. Beliefs represent the information state of the agent. Desires represent the motivational state of the agent. And Intentions represent the deliberative state of the agent – what the agent has chosen to do.

There are some limitations and criticisms of BDI, including doubt surrounding the sufficiency of the three attributes (Rao and Georgeff, 1955), that it is not adaptable for learning behaviour, agents have no ability to interact with other agents, there is no explicit goal representation, no forward planning capability, and that the multi-modal logic underlining BDI has little relevance in practice (Rao & Georgeff, 1995).

Some implementations of BDI consist of Procedural Reasoning System (PRS) (Georgeff & Ingrand, 1989; Guerra-Hernandez et al., 2004; Sardina et al., 2006), Distributed Multi-Agent Reasoning System (dMARS) (d'Inverno et al., 2004), JACK Intelligent Agents (Howden et al., 2001), and CoJACK (Evertsz, et al., 2008) - an extension to the JACK platform that adds a cognitive architecture to the agents for eliciting more realistic behaviours in virtual environments.

3.2.1.3 Connectionist Learning with Adaptive Rule Induction On-line (CLARION)

CLARION, with its root in neural networks, is a hybrid architecture that incorporates models of both implicit and explicit memory for reasoning and learning (Sun et al., 2001). Procedural knowledge, i.e. implicit memory, can be gradually accumulated with repeated practice, and subsequently applied to practiced situations with minor variations (Chong et al., 2007). To deal with novel situations, declarative knowledge is required to assist in the exploration of new situations, thereby reducing time for developing specific skills. It also unifies neural, reinforcement and symbolic methods to perform on-line, and bottom-up learning. Hence, CLARION is able to react in a dynamically changing environment without any pre-existing knowledge installed into the architecture (Sun and Peterson, 1996, 1998).

CLARON is an integrative architecture, consisting of a number of distinct subsystems, with a dual representational structure in each subsystem. Its subsystems include the action-centered subsystem for action control, the non-action-centered subsystem for general knowledge, the motivational subsystem for motivations of perception, action and cognition, and the meta-cognitive subsystem for controlling all other subsystems.

CLARION has been used to implement intelligent systems (Sun et al. 2010). Some application examples include the serial reaction time task, the artificial grammar learning task, the process control task, a categorical inference task, an alphabetical arithmetic task, and the Tower of Hanoi task.

3.2.1.4 Man Machine Integrated Design and Analysis System (MIDAS)

MIDAS is a system for simulating one or more human operators in a simulated world of terrain, vehicles, and other systems (Laughery and Corker, 1997; Pew and Mavor, 1998; Tyler et al., 1998). The primary purpose of MIDAS is to evaluate proposed human-machine system designs and to serve as a test bed for behavioural modelling.

The overall architecture of MIDAS comprises a user interface, an anthropometric model of the human operator, symbolic operator models, and a world model. The user interface consists of an input side (an interactive GUI, a cockpit design editor, and equipment editor, a vehicle editor, and an activity editor) and an outside (display animation software, run-time data graphical displays, summary data graphical displays, and 3D graphical displays). The human operator representation consists of physical representation, perception and attention, updatable world representation, activity representation, scheduler and user interfaces.

MIDAS uses IF-THEN rules to provide flexible problem-solving capabilities. Description activities select from among alternatives. Six generalized decision algorithms are available: weighted additive, equal weighted additive, lexicographic, elimination by aspect, satisfying conjunctive, and majority of confirming decisions.

The advantages of MIDAS include submodels based on current psychological and psychomotor theory and data, task loading modelling consistent with multiple resource theories, potential for military simulations, and a good base for a human behaviour representation. Its limitations consist of insufficient behaviour models, is too cumbersome for most military simulations, and is very labour-intensive for application development.

MIDAS has been used for situation awareness (Shively et al., 1997; Burdick & Shively, 2000), and operator cognition & performance (Gore et al., 2009; Boring et al., 2008; Gore & Jarvis, 2005).

3.2.1.5 Situation Awareness Model for Pilot-in-the-Loop Evaluation (SAMPLE)

SAMPLE is used to represent individual operators, as well as crews of complex human machine systems (Baron et al., 1980; Zacharias et al., 1981, 1994, 1996).

The SAMPLE architecture provides a general framework for constructing models of operators of complex systems, particularly in cases in which the operators are engaged in information processing and controls tasks. SAMPLE draws heavily on modern control theory, which has enjoyed considerable success in the modelling of human control behaviour. The belief-net at the core of the situation assessor of later variants appears to have considerable potential for representing situation awareness. However, procedure development for SAMPLE models would appear to be quite labour-intensive since there seems to be no high-level procedure representation language.

The SAMPLE architecture consists of a system model and one or more human operator models. The system model takes in system dynamics, e.g. ownship, the plant, or a target, which is modeled by partial differential equations of motion (e.g., point mass equations for vehicle trajectory). The system dynamics can be modeled at any level of complexity desired.

A human operator model exists for each crew member. It consists of sensory and effector channels and several processors: an information processor monitoring the system, and situation assessors generating random situation and task procedures. The sensory channels model visual and auditory sensing. Both are based on an optimal control model with no perceptual delay.

SAMPLE has been used in the examination of crew procedures, for example, the evaluation of air traffic alerting systems in a free flight environment.

3.2.1.6 State, Operator And Result (Soar)

Soar is another symbolic cognitive architecture (as shown in Figure 8) created by John Laird, Allen Newell and Paul Rosenbloom at Carnegie Mellon University (Laird et al., 1987; Newell, 1990; Lehman et al., 2010).

The main goal of the Soar architecture is to create a system that is able manage the full range of capabilities of an intelligent agent, from highly routine to extremely difficult open-ended problems. According to the view underlying Soar, such architecture must be able to create representations and use appropriate forms of knowledge (such as procedural, declarative, episodic, and possibly iconic).

Soar is based on a production system, i.e. it uses explicit production rules to govern its behavior (these are roughly of the form "if... then...", as also used in expert systems). Problem solving can be roughly described as a search through a *problem space* (the collection of different states which can be reached by the system at a particular time) for a *goal state* (which represents the solution for the problem). This is implemented by searching for the states which bring the system gradually closer to its goal. Each move consists of a decision cycle which has an elaboration phase (in which a variety of different pieces of knowledge bearing the problem are brought to Soar's working memory) and a decision procedure (which weighs what was found on the previous phase and assigns preferences to ultimately decide the action to be taken).

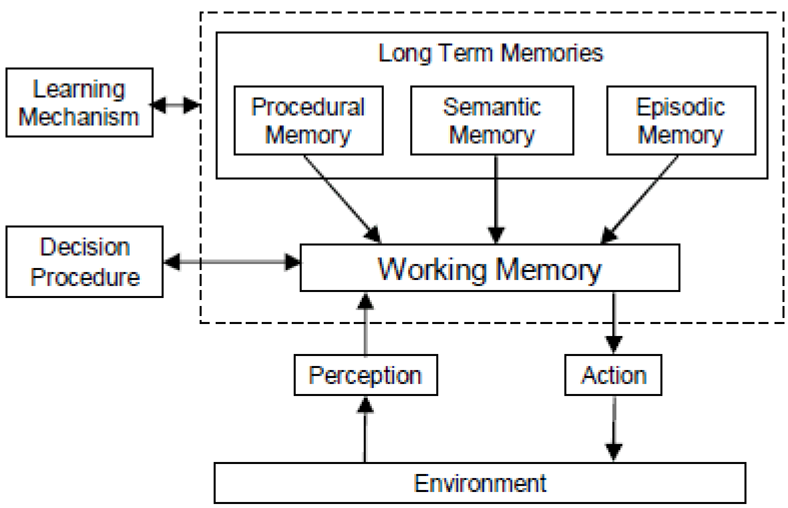

Figure 8: Soar architecture (Chong et al., 2007; Lehman et al., 2010).

Soar is best described at two levels, called the problem space level and the symbol level. At the problem space level, Soar casts all cognitive activity as transformations of states by operators within a state space. In a state space, there is a single current state, which encodes working information about the problem or situation being processed. Cognitive processing occurs by means of operators, which apply to the current state to yield a new current state. In straightforward cases, processing consists of a repeated cycle in which Soar first picks an operator, and then applies it to transform the current state into a new one.

Advantages of Soar (Kieras, 2010) include a well established in AI community, good software support and training, commercial-grade applications developed and sold, freely available, and definite track record of success on large problems (thousands of rules).

Soar also has some limitations, for example, psychological basis of learning and reasoning are not as well developed as others, and reputed to be difficult to program, even with excellent software support. There are many applications with Soar in various application areas, in particular in military modelling and simulations (Pew & Mavor, 1998); for example, the Synthetic Theater of War (STOW-97), Tactical Air-Soar (TacAir-Soar, JCATS, Rotary-Wing Aircraft-Soar (RWA-Soar), Fixed-Wing Aircraft-Soar (FWA-Soar), Special Operation Forces-Soar (SOFSoar), etc.

3.2.1.7 Summary of HBR tools

The following Table 4 summarizes these HBR tools.

.

Table 4: Summary of HBR tools.

Tool	Original Purpose	Memory / KR	Functions	Validating	Notes
ACT-R	Model problem solving and learning	Network or schema-like structures plus productions	• Learning: Weight adjustment learning • Planning: Creating new Planning • Decision making: knowledge-based, Bayesian • Situation Awareness: Overt and inferred	Extensive at many levels	Focusing on single, specific information processing tasks; has not yet been scaled up to complex multitasking situations or high-knowledge domains.
BDI	Problem solving	Object oriented	• Learning: no • Planning: instantiates general plans • Decision making: BDI-based • Situation awareness: overt	n/a	Based on three attributes: Belief, Desire, and Intention.
CLARION	Extending neural networks functions	Neural networks and production rules	• Learning: neural networks-based • Planning: instantiates general plans • Decision making: rule-based • Situation awareness: neural-network-based	n/a	Combining neural networks and production rules.
MIDAS	Evaluate interfaces and procedures	Frames, rules	• No learning • Planning: instantiates general plans • Decision making: knowledge-based, Bayesian • Situation awareness: overt	Full model	Scripted behaviors.
SAMPLE	Evaluate crew procedures, equipment	Objects, Production rules	• Learning: no • Planning: Instantiates general plans • Decision Making: Knowledge-based, Bayesian	Control tasks (OCM)	Has been used in small-scale military simulations.

			• Situation Awareness: overt		
Soar	Model problem solving and learning.	Productions	• Learning: learning by chunking • Planning: can create new plans • Decision making: knowledge-based • Situation awareness: overt and inferred	Extensive at multiple levels	Has been used in military simulations: e.g., synthetic theater of war-Europe [STOW-E], STOW-97, etc.

3.2.2 Other AI tools

3.2.2.1 Language of Agents for Modelling Performance (LAMP)

Language of Agents for Modelling Performance (LAMP) (Guo et al., 2005a, 2005b) is a knowledge representation and reasoning approach to provide intelligent / human-like behaviour for HBR in modelling and simulation tools, such as Integrated Performance Modeling Environment (IPME) or OneSAF. It is able to represent both deterministic and uncertain (Guo et al., 2008) knowledge, as well as supporting semantic-similarity-based associative reasoning, and rule-based abstract deduction.

Figure 9 is a conceptualization of LAMP, encompassing an *InteractiveInterface* to human behaviour representation tools and an *Aspect Network*. The *InteractiveInterface* module receives the data from M&S tools, activates the LAMP engines to get solutions, and sends the results to M&S tools for the next phase of simulation.

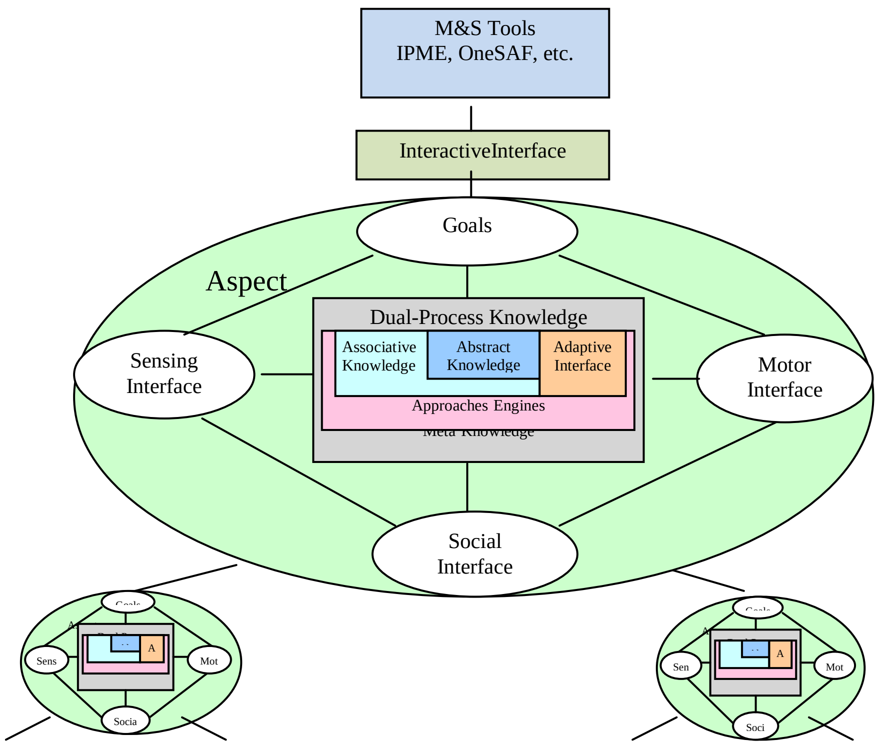

Figure 9: LAMP component organization.

The core of LAMP is an *Aspect Network*, in which each *Aspect* is a knowledge unit with *Goals*, *SensingInterface*, *Dual-Process Knowledge*, *MotorInterface*, and *SocialInterface*. During simulation, M&S tools communicate with LAMP's *InteractiveInterface* to activate the dual-process reasoning sub-system, send data to and get conclusions from the reasoning sub-system, and then apply the reasoning results for the next step of task simulation.

Goals in an *Aspect* describe the solutions or conclusions that can be achieved by this *Aspect. SensingInterface* receives the data from the M&S tool and converts the data into an internal representation. *MotorInterface* transmits the reasoning results to the simulated tasks in an appropriate format. *SocialInterface* provides mechanisms to interact with other *Aspect*s for collaborated resolutions or reasoning.

The kernel of *Aspect* is the *Dual-Process Knowledge* that comprises modules for *Associative Reasoning, Abstract Reasoning, Approach Engines, Adaptive Interface* and *Meta Reasoning.* LAMP integrates dual-process and behaviour moderators (Halford et al., 2006; Evans, 2003, Sloman, 1996, 2002) to enhance reality.

LAMP has been used as the reasoning engine in the Simulated Operators for Networks (SIMON) project in DRDC Toronto. Examples of applications include battlefield reasoning with personality effects, fuzzy logic helicopter flight control, and analogical problem solving in search and rescue.

Compared with other reasoning systems, LAMP's main features include the integration of human dual-process thinking, multiple approaches, human behaviour moderators, human memory and analogical models.

3.2.2.2 Logic-based software

Two general AI programming languages including List Programming (Lisp) (McCarthy, 1960) and Programming in Logic (Prolog) (Warren, 1977) are proposed for generic AI programming. The following provides a list of commercial and free available implementations.

Lisp is the earliest AI programming language. Today, the most widely known general-purpose Lisp dialects are Common Lisp and Scheme. Commercial implementations of Lisp include (online information available on February 5, 2010):

- Allegro Common List, http://www.franz.com/products/allegrocl/
- Corman Common Lisp, http://www.cormanlisp.com/
- LispWorks, http://www.lispworks.com/
- Scieneer Common Lisp, http://www.scieneer.com/scl/.

Some freely redistributable implementations of Lisp consist of:

- Armed Bear common Lisp, http://common-lisp.net/project/armedbear/
- CLISP, http://clisp.cons.org/
- Clozure CL, http://trac.clozure.com/ccl; CMUCL at http://www.cons.org/cmucl/
- Embeddable Common Lisp (ECL) , http://ecls.sourceforge.net/
- GNU Common Lisp, http://www.gnu.org/software/gcl/
- Macintosh Common Lisp, http://www.digitool.com/
- Movitz, http://common-lisp.net/project/movitz/
- Poplog, http://www.poplog.org/

- Steel Bank Common Lisp, http://sbcl.sourceforge.net/.

Prolog (Warrant, 1977) is a general purpose logic programming language associated with artificial intelligence and computational linguistics. Commercial software examples of Prolog include (online information available on February, 5, 2010):

- Amzi Prolog, http://www.amzi.com/
- Arity Prolog, http://www.arity.com/?Tab=products&tab2=prolog
- BinProlog, http://www.binnetcorp.com/BinProlog/
- IF/Prolog, http://www.ifcomputer.com/IFProlog/
- LPA-Win, http://www.lpa.co.uk/ind_pro.htm
- MINERVA Prolog, http://www.ifcomputer.com/MINERVA/
- Quintus Prolog: http://www.sics.se/quintus/
- SICStus: http://www.sics.se/isl/sicstuswww/site/order.html
- Trinc-Prolog: http://www.trinc-prolog.com/
- Visual Prolog: http://www.visual-prolog.com/.

Examples of freely or shareware Prolog implementations comprise (online information available on February, 5, 2010):

- Aquarius Prolog: http://www.info.ucl.ac.be/~pvr/aquarius.html
- B-Prolog: http://www.probp.com/
- BinProlog: http://www.binnetcorp.com/BinProlog/
- CIAO Prolog: http://www.ciaohome.org/
- Cu_Prolog: http://www.freebsdsoftware.org/lang/cu-prolog.html
- EZY-Prolog: http://www.ezy-software.com/
- GNU Prolog at http://www.gprolog.org/
- Open Prolog: http://www.scss.tcd.ie/misc/open-prolog/
- Poplog: http://www.cs.bham.ac.uk/research/projects/poplog/freepoplog.html
- Strawberry Prolog: http://www.dobrev.com/
- SWI-Prolog: http://www.swi-prolog.org/
- Visual Prolog Personal Edition: http://www.visual-prolog.com/.

In addition, there are also several rule-based tools available, e.g., the C Language Integrated Production System (CLIPS) (Girratano and Riley, 1998) at http://www.siliconvalleyone.com/clips.htm, ACT-R at http://act-r.psy.cmu.edu/actr6/ and Soar at http://sitemaker.umich.edu/soar/soar_software_downloads. (Note: Online information available on February 5, 2010.)

3.2.2.3 Bayesian networks software

The following list contains some commercial software of Bayesian belief networks as follows (online information available on February 2, 2010):

- AgenaRisk Bayesian network tool, http://www.agenarisk.com
- BayesBuilder, http://www.snn.ru.nl/nijmegen/index.php3?page=31
- Bayesia, http://www.bayesia.com
- Bayesian network application library, http://www.norsys.com/netlibrary/index.htm
- BNet, http://www.cra.com/bnet
- Causeway, http://www.inet.saic.com/
- DBL Interactive, http://www.decisionbasedlearning.org/
- Dezide, http://www.dezide.com
- dVelox , http://aparasw.com/dVelox
- Hugin, http://www.hugin.com
- MSBNx: BN from Microsoft Research, http://research.microsoft.com/adapt/MSBNx/
- Netica, http://www.norsys.com
- Promedas Bayesian medical decision support, http://www.promedas.nl
- ProBayes, http://www.probayes.com
- Quiddity, http://www.iet.webfactional.com/quiddity.html.

There is a great number of free and open source software of Bayesian belief networks (online information available on February 2, 2010):

- Ace, http://reasoning.cs.ucla.edu/ace
- AIspace, http://aispace.org/bayes
- BANJO: BN in Java, http://www.cs.duke.edu/~amink/software/banjo
- BANSY3, http://www.dynamics.unam.edu/DinamicaNoLineal3/bansy3.htm
- Bayesian Logistic Regression Software, http://stat.rutgers.edu/~madigan/BBR/
- BNJ: Bayesian Network tools in Java, http://bnj.sourceforge.net/
- BN4R, http://bn4r.rubyforge.org/
- BNJ: BN in Java, http://bnj.sourceforge.net/
- BN PowerPredictor: BN based classifier learning, http://webdocs.cs.ualberta.ca/~jcheng/bnsoft.htm
- BNT: BN Toolbox for MatLab, http://bnt.sourceforge.net/
- dlib C++ Library, http://dclib.sourceforge.net/

- FDEP, http://www.cs.bris.ac.uk/~flach/fdep/
- GeNIe & SMILE: BN for Windows, http://genie.sis.pitt.edu/
- JavaBayes: BN in Java, http://www.cs.cmu.edu/~javabayes/Home/ or http://www.pmr.poli.usp.br/ltd/Software/javabayes/
- jBNC: BN classifier in Java , http://jbnc.sourceforge.net/
- JNCC2, extension of Naive Bayes Classifier in Java), http://www.idsia.ch/~giorgio/jncc2.html
- Mocapy: BN in Python, http://mac.softpedia.com/get/Math-Scientific/Mocapy.shtml
- MSBNx: Microsoft Bayesian Network Editor, http://research.microsoft.com/en-us/um/redmond/groups/adapt/msbnx/
- OpenBayes, http://www.openbayes.org
- pebl: BN in Python, http://pebl-project.googlecode.com
- ProBT- free version of the ProBAYES', http://www.probayes.com
- PNL, http://sourceforge.net/projects/openpnl/
- Pulcinella, tool in Common Lisp, http://iridia.ulb.ac.be/pulcinella/Welcome.html
- RISO, http://sourceforge.net/projects/riso/
- SamIam, http://reasoning.cs.ucla.edu/samiam (See also Ace, above)
- UnBBayes, http//unbbayes.sourceforge.net/.

3.2.2.4 Neural networks software

Some available commercial software of Artificial Neural Networks includes (online information available on February 2, 2010):

- Alyuda NeuroIntelligence, http://www.alyuda.com/neural-networks-software.htm.
- BioComp iModel(tm), http://www.biocompsystems.com/products/imodel/
- COGNOS 4Thought, http://www-01.ibm.com/software/data/cognos/
- BrainMaker, http://www.calsci.com/
- KnowledgeMiner, http://www.knowledgeminer.com/
- MATLAB Neural Net Toolbox, http://www.mathworks.com/products/neuralnet/
- MemBrain, http://www.membrain-nn.de/
- NeuroSolutions, http://www.nd.com/
- NeuroXL, NN in Excel, http://www.neuroxl.com/.(NeuroDimension, 2010)
- NeuralWorks Predict 3.0 and Professional II/PLUS, http://www.neuralware.com/index.jsp
- SPSS Neural Connection 2, http://www.spss.com/press/template_view.cfm?PR_ID=165

- STATISTICA, http://www.statsoft.com/products/statistica-automated-neural-networks/
- Synapse, http://www.peltarion.com/products/synapse/ (Peltarion, 2010)
- Tiberius, http://www.tiberius.biz/.

There are also some free software and shareware of neural networks (online information available on February 2, 2010):

- NuClass7, http://www-ee.uta.edu/eeweb/IP/Software/Software.htm
- Sciengy RPF(tm), http://sciengy.kuzmenko.net/
- Sharky Neural Network, http://sharktime.com/us_SharkyNeuralNetwork.html
- Stuttgart Neural Network Simulator (SNNS), JavaNNS (Stuttgart-University, 2010), http://www.ra.cs.uni-tuebingen.de/SNNS/
- Emergent (formerly PDP++) (Aisa et al., 2008; O'Reilly et al., 2000), http://grey.colorado.edu/emergent/index.php/Main_Page
- Neural Lab (Guanajuato, 2010) , http://www.dicis.ugto.mx/profesores/sledesma/documentos/index.htm
- Neuro Laboratory, http://www.scientific-soft.com/?content/products/neurolab/main.htm (Scientific Soft 2010).

3.2.2.5 Description logics software

- Protégé, Protégé-OWL, SWOOP
- Description logic reasoners – FaCT++, Pellet, Racer-Pro, Sim-DL

4 Development roadmap

This section examines some relevant results from human science, including neural networks, human memory models, analogy, dual-process thinking, and human behaviour moderators. Based on the analysis of problems, an integrated and adaptive AI replication engine is proposed for modelling human interactors' intentions in wargame replications.

4.1 Overview of human behaviour representation

An HBR is a computer-based model that mimics either the behaviour of a single human or the collective action of a team of humans (Pew and Mavor, 1998). Figure 10 shows an integrated architecture for an HBR.

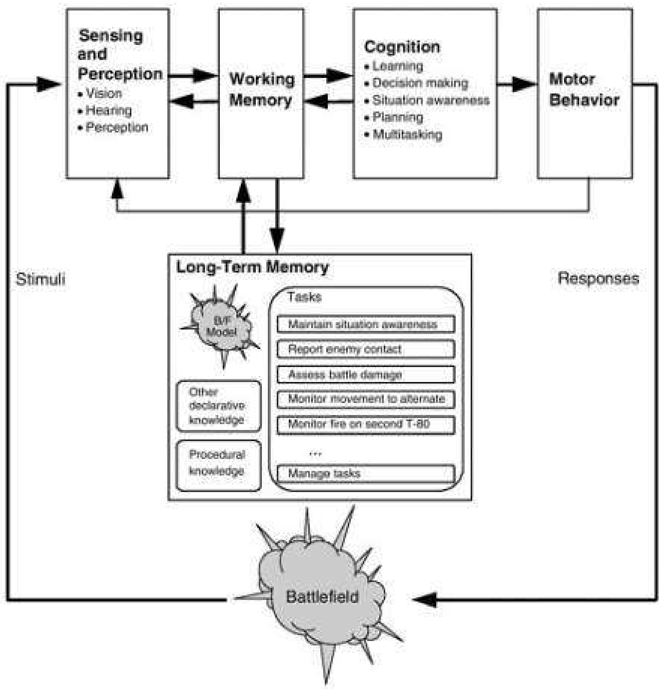

Figure 10: An integrated architecture of human behaviour representation (Pew & Mavor, 1998).

The "Sensing and Perception" module in the architecture acquires the environment data via models of vision, hearing or perception, and then sends the data to a working memory store. There are considered to be two representations of human memory: working memory and long-term memory. Working memory maintains a short-term representation of data from the environment and interacts with long-term memory during retrieval, storage, and comparative activities. There are three kinds of components in long-term memory: declarative knowledge, procedural knowledge and various tasks. In the next step, working memory interacts with the cognitive functions associated with learning, decision making, situation awareness, planning and multitasking. The outputs of the models of cognition are transmitted to "Motor Behaviour" to model the reactions. Finally, the status of the environment, e.g. battlefield, changes and another cycle begins again.

There are many HBR prototypes proposed, for example, Adaptive Control of Thought (ACT-R) (Anderson, 1990; Anderson et al.,2004), State, Operator And Result (Soar) (Laird et al., 1987; Newell, 1990), COGnition as a Network of Tasks (COGNET) (Zachary et al., 1991; Zachary et al., 1996), Executive-Process Interactive Control (EPIC) (Meyer and Kieras, 1997a, 1997b), Human Operator Simulator (HOS) (Glenn et al., 1992), Integrated Performance Modeling Environment (IPME) (MAAD, 2010), Man Machine Integrated Design and Analysis System (MIDAS) (Laughery and Corker, 1997; Banda et al., 1991), Operator Model Architecture (OMAR) (Deutsch and Adams, 1995; MacMillan et al., 1997), Situation Awareness Model for Pilot-in-the-Loop Evaluation (SAMPLE) (Baron et al., 1980, Zacharias et al., 1981, 1994, 1996). A high level review of these systems can be found in Pew and Mavor's book (Pew and Mavor, 1998).

HBR tools have made great contributions to current modelling and simulation initiatives, but there are some limitations. For example, as described by Pew and Mavor (1998): current decision making tools are rigid, predictable, not flexible, not human-like, not variable and not adaptable (Pew and Mavor, 1998).

4.2 Related results from Human Science

This section reviews some results from human science that are significant factors to consider for future HBR methodology and models, including neural networks, human memory models, analogy, dual-process thinking and behaviour moderators.

4.2.1 Neural networks

In neuroscience, a neural network (Barr and Kiernan, 1988) describes a population of physically interconnected neurons or a group of disparate neurons whose inputs or signaling targets define a recognizable circuit (Figure 11). Communication between neurons involves an electrochemical process. The interface through which they interact with surrounding neurons usually consists of several dendrites (input connections), which are connected via synapses to other neurons, and one axon (output connection). If the sum of the input signals surpasses a certain threshold, the neuron sends an action potential (AP) at the axon hillock and transmits this electrical signal along the axon.

The fundamental unit of the biological neural network is called a neuron or nerve cell. Figure 12 shows a schematic of the structure of the neuron. The main body of cell is called "soma" where nucleus is located. It has tree like fine fibers attached called dendrites. These dendrites receive signals from other neurons. "Axon" is the single long fiber which extends from the soma, which branches into strands and sub-strands connecting to many other neurons at the synaptic junction.

Figure 11: Biological neurons.

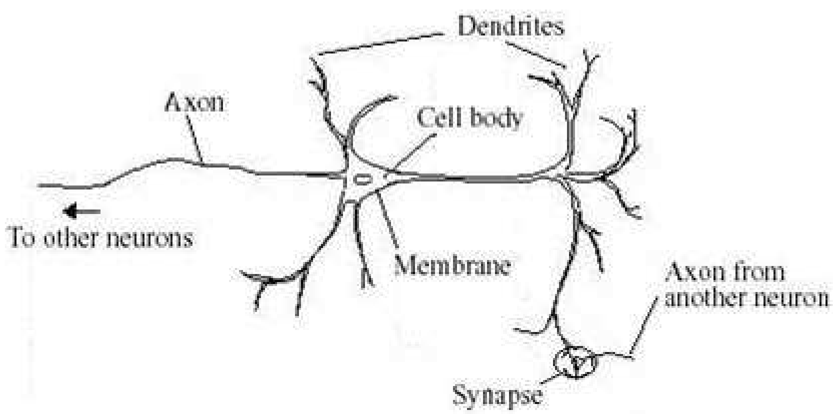

Figure 12: Biological neuron structure.

Each neuron accepts stimuli from other neighbouring neurons and produces an output as soon as the overall effect of the input stimulus exceeds the threshold limit that a neuron can bear. The connection and connection strength among neurons reflect the knowledge pattern of human beings (Barr and Kiernan, 1988). A neural network is a massively parallel distributed processor that has a natural propensity for storing experimental knowledge and making it available for use.

The brain is a collection of about 10 billion interconnected neurons (Dowling, 2001). Each neuron is a cell that uses biochemical reactions to receive, process and transmit information. A neuron's dendritic tree is connected to a thousand neighbouring neurons. When one of those neurons fires, a positive or negative charge is received by one of the dendrites. The strengths of all the received charges are added together through the processes of spatial and temporal summation.

An Artificial Neural Network (ANN), as described in Section 3.1.3, is an information processing paradigm that is inspired by the way biological nervous systems process information. Figure 13 shows an artificial neuron structure. In this diagram, various inputs to the network are represented by the mathematical symbol, *Ij*. Each of these inputs is multiplied by a connection weight represented by *Wj*. In the simplest case, these products are simply summed, fed through a transfer function to generate a result, and then produce an output. This process lends itself to physical implementation on a large scale in a small package. This electronic implementation is still possible with other network structures which utilize different summing functions as well as different transfer functions.

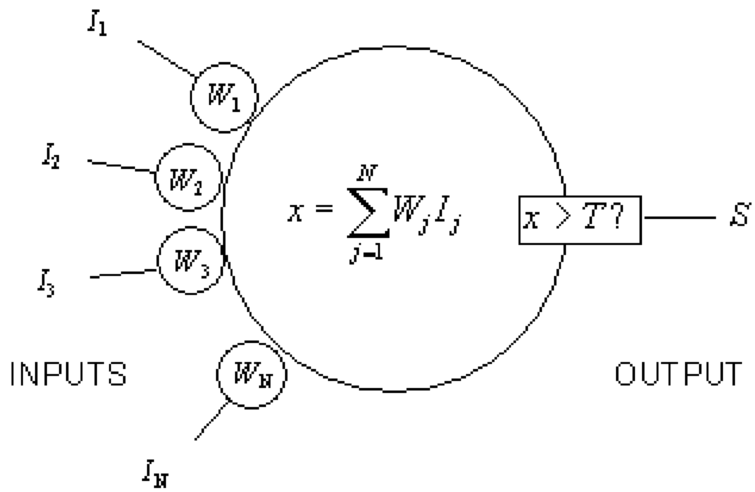

Figure 13: Neuron in artificial neural networks.

These networks are also similar to the biological neural networks in the sense that functions are performed collectively and in parallel by the units, rather than there being a clear delineation of subtasks to which various units are assigned.

4.2.2 Human memory models

In psychology, memory is an organism's ability to store, retain, and recall information (Neath & Surprenant, 2002). Traditional studies of memory began in the fields of philosophy, including the development of techniques aimed at artificially enhancing memory functions. The late nineteenth and early twentieth century placed memory within the paradigms of cognitive psychology. In recent decades, it has become one of the principal pillars of a branch of science called cognitive neuroscience, an interdisciplinary link between cognitive psychology and neuroscience.

From an information processing perspective there are three main stages in the formation and retrieval of memory:

- *Encoding* or registration (receiving, processing and combining of received information);
- *Storage* (creation of a permanent record of the encoded information); and
- *Retrieval, recall* or *recollection* (calling back the stored information in response to some cue for use in a process or activity).

There are many memory models proposed including the Matrix model (Humphries et al., 1989; Pike, 1984), Search of Associative Memory (SAM), Theory of Distributed Associative Memory

(TODAM), MINERVA 2, Scale Invariant Memory and Perceptual Learning (SIMPLE) (Brown et al., 2007), etc. This section reviews three typical models: SAM, TODAM and MINERVA 2.

4.2.2.1 Search of Associative Memory (SAM)

Search of Associative Memory (SAM) model (Raaijmakers & Schiffrin, 1981) is a standard model of memory that employs association. Though SAM was originally designed to model episodic memory, its mechanisms are sufficient to support some semantic memory representations as well (Kimball et al., 2007). In SAM, when any two items simultaneously occupy a working memory buffer, the strength of their association is incremented. Thus, items that co-occur more often are more strongly associated. Items in SAM are also associated with a specific context, where the strength of that association is determined by how long each item is present in a given context. In SAM memories consist of a set of associations between items in memory and between items and contexts. The presence of a set of items and/or a context is more likely to evoke some subset of the items contained within memory. The degree to which items evoke one another—either by virtue of their shared context or their co-occurrence—is an indication of the items' semantic relatedness. The Retrieving Effectively from Memory (REM) (Shiffrin and Steyvers, 1997) is another model in the SAM family.

4.2.2.2 Theory of Distributed Associative Memory (TODAM)

Theory of Distributed Associative Memory (TODAM) is described in a series of articles by Murdock and his colleagues (Murdock 1982, 1983, 1997). TODAM is of interest for two reasons. First, it stores all information in one main memory vector (the length of which is the parameter N). As such, TODAM uses a distributed form of representation: all elements are involved in representing all items. Information is stored using convolution and retrieved using correlation. TODAM thus serves as an existence proof that serial memory phenomena can be modeled successfully using only one memory system which is viewed as a single vector.

Second, TODAM provides an elegant solution to the chaining problem. If an item is not recalled, the link in the chain is missing; in the typical chain model of memory, recall must necessarily stop at this point. This problem has limited development of models of serial order for years. One of the contributions of TODAM is a way around this problem. The result of correlation is a blurry but potentially interpretable vector. The way the model interprets this vector, f'_j, is to compute the dot product between the recovered vector and the possible candidates and if this value is within acceptable limits, then the item is interpreted and produced. One of TODAM's attractive properties is what happens if the blurry vector cannot be interpreted; even if this is the case, f'_j can be used as the cue for the next item and will often lead to successful retrieval of the next item.

4.2.2.3 MINERVA 2

MINERVA 2 (Hintzman, 1984, 1986, 1988) is another recognized memory model. One of the main goals was to explain memory for individual experiences (episodic memory) and memory for abstract concepts (generic or semantic memory) within a single system. This version implements some of the simulations reported by Hintzman.

This version of MINERVA 2 concentrates on schema abstraction, recognition, and frequency judgments and is best thought of as an existence proof: the program proves that it is possible to account for many aspects of memory for individual experiences (i.e., episodic memory) and memory for abstract concepts (i.e., generic or semantic memory) within a single system. This does not prove that there is only a single system; rather, it proves it can be done.

4.2.3 Analogy

Analogy has long been recognized an a important component of intelligence (Halford et al., 2006, Binet & Simon, 1905/1980; Piaget, 1950), playing a significant role in mathematics (English & Halford, 1995; Polya, 1954), science (Tweney, 1998; Holyoak & Thagard, 1995; Dunbar & Klahr, 1989), politics, art, religion, pedagogy, communication, humour , and law (Holyoak & Thagard, 1995). Analogy is now being recognized as a fundamental process in natural reasoning (Halford, 1992; Hofstadter, 2001). Its basic role in reasoning is indicated by the fact that mental models, which are important to some theories of human reasoning (Johnson-Laird, 1983; Johnson-Laird & Byrne, 1991; Polk & Newell, 1995) and cognitive development (Halford, 1993) are essentially based on processes of analogy. Analogy is used to affect transfer between isomorphic tasks (Halford, Bain, Maybery, & Andrews, 1998; Novick, 1988; Reed, Ackinclose & Voss, 1990; Reed, 1987) and is particularly important to transfer between domains (Gentner & Gentner, 1983; Gick & Holyoak, 1983). The literature on analogy has blossomed since 1983 and there are a number of volumes devoted to it (Holyoak & Barnden, 1994; Gentner, Holyoak & Kokinov, 2001). There is also a review by Holyoak worth noting (2005).

A number of computational models of analogy have been developed. These include Analogical Constraint Mapping Engine (ACME) (Holyoak & Thagard, 1989), Structure-Mapping Engine (SME) (Falkenhainer, Forbus, & Gentner, 1989); Copycat (Mitchell & Hofstadter, 1990), Incremental Analogy Machine (IAM) (Keane & Brayshaw, 1988), Structured Tensor Analogical Reasoning (STAR) (Halford et al., 1994; Wilson et al., 2001), Learning and Inference with Schemas and Analogies (LISA) (Hummel & Holyoak, 1997, 2003, 2005). SME, ACME and LISA are summarized by Holyoak (Holyoak, 2005) and an overview of LISA is given by Hummel and Holyoak (Hummel & Holyoak, 2005). Some of these models, ACME, Copycat, STAR and LISA are neural network models, and can also been seen as contributions to the area of symbolic connectionism.

Human mental models for deduction can be based on analogy. A mental model is iconic, meaning that there is some structural correspondence between the model and the content of the problem. As structural correspondence is essentially the defining property of analogies, it is selected or retrieved from memory. As an example of the way analogy could be used to generate a mental model, consider the task of assessing the validity of the inference, $p \rightarrow q$, $\sim p$, therefore $\sim q$. An everyday analog could be used such as: rain implies clouds, no rain, therefore no clouds. This makes it obvious that the inference is not valid, and is a natural way to simplify the problem.

Some examples of applications of analogical reasoning consist of situation assessment Yang et al., 2006; Louvieris et al., 2006), threat assessment / Security: foreign policies (Hehir, 2006; Markman et al., 2003; Knopf, 2002), decision support (Louvieris et al., 2006), and planning (Forbus et al., 2004; Cox & Veloso, 1997; Haign, et al., 1997).

4.2.4 Dual-process thinking

There is evidence that anatomically distinct regions of the human brain are involved in two processes: a low process and a high process. These processes directly affect human reasoning and thinking. In a situation where there was a conflict between valid unbelievable (high process) and invalid-believable inferences (low process), a functional Magnetic Resonance Imaging (fMRI) study showed resolution in favour of valid inferences involving the right inferior prefrontal cortex, but resolution in favour of invalid inferences involving the ventral medial prefrontal cortex (Goel et al., 2000; Goel & Dolan, 2004). Based on the results, two levels of reasoning and thinking have been identified in many contexts and models should recognize that more than one type of reasoning process occurs (Halford et al., 2006). Models that integrate these levels offer the best potential for capturing the flexibility and robustness of thinking. Table 4 summarizes distinctions between levels of cognitive processes.

Table 5: Distinctions between levels of cognitive processes (Halford et al., 2006).

Low Process	**High Process**	**References**
System 1	System 2	Evans (2003)
Implicit	Explicit	Reber, 1967 Clark & Karmiloff-Smith, 1993 Karmiloff-Smith, 1992
Automatic	Effortful/controllable	Hasher & Zacks, 1979
Low processing demands	High processing demands	Logan, 1979 Schneider & Shiffrin, 1977
No volitional or adaptable	Volitional	Evans, 2003
Without training involving external input	Responsive to verbal instructions	Clark & Karmiloff-Smith, 1993
Associative	Rule-based	Sloman, 2002
Driven by learning or innate modules	Based on thinking	Evans, 2003
Similarity based Pragmatic/contextualized	Rule Logic/abstract	Pothos, 2005
Unconscious except for final product	Conscious	Norman, 1986 Reber, 1992 Evans, 2003
Rapid	Slow	Norman, 1986
Parallel	Serial	Evans, 2003
Associative	Relational	Phillips, Halford & Wilson, 1995
Sub-symbolic	Symbolic	Smolensky, 1988
Independent of language	Related to language	Accepted by many authors

Low Process	High Process	References
Independent of general intelligence	Related to general intelligence	Stanovich & West , 2000; Evans, 2003
Evolved early	Evolved late	Reber & Allen, 2000
Shared with other animals	Uniquely human (or uniquely primate)	Evans 2003

Dual processes in reasoning have a number benefits:

- Two systems can be mutually supportive, so System 2 can facilitate recognition of similarity by System 1, which can pre-process information for use by System 2.
- Because System 2 is capacity limited, System 1 is often useful in conditions of high processing load in providing heuristic solution that will be correct most of the time.

Obviously, in the modelling and simulation of human thinking and reasoning, the dual-process approach should also be taken into account.

4.2.5 Human behaviour moderators

A behavioural moderator is a condition that causes a change to an individual physiological state or environment that alters the behaviour of an individual in any way (Pew & Mavor, 1998). A number of performance moderators relevant to military-operator simulation have been identified in literatures (Pew and Mavor, 1998; Ritter and Avraamides, 2000). Pew and Mavor classified behavioural moderators as external and internal moderators. External moderators include physiological stressors (environment (heat, toxins, noise, vibration) or physical workload and fatigue) and cognitive workload stressors. Internal moderators consist of intelligence, expertise level and type, cognitive abilities, personality, and emotions, attitudes and cultural values. They believe that the variables they identified have the potential to impact the performance of soldiers and commanders in the field and therefore should be considered for further development.

The following list contains some example models / references of behaviour moderators:

- Emotion: (Costa & McCrae, 1992; Ortony et al, 1988; Picard, 1997; Henninger et al., 2001, 2002, 2003; Gratch and Marsella, 2001, 2004; McRorie, et al., 2009)
- Personality and Individual difference (Zachary et al., 2005; Eysenck, 1990; Hudlicka and Pfautz, 2002; Silverman and Bharathy, 2005; Read and Miller, 2002; McKenzie et al., 2001, 2003; McRorie et al., 2009; Guo & Cain, 2009)
- Workload and fatigue (Pfeiffer et al., 1979; Hendy et al., 2000; Stokes & Kite, 2000; Weaver et al., 2000; Ma et al., 2009)
- Culture, (Hofstede, 1980; Klein & Klein, 2000; Klein 2004).

4.3 Analysis of problems in current wargame replications

LFORT, with many years of experience of wargame replications, summarizes the features in both the current wargame replicator and a prospective future AI-driven replicator, as shown in Table 6.

Based on the comparison of features between the current wargame replicator and AI-driven replicator, the problems in current wargame replications may be categorized into situation recognition & assessment, planning and decision making.

The following list includes some examples of human intentions related to situation/pattern recognition and assessment:

- Who is the aggressor? Who is on the defensive?;
- What are the high value targets?;
- What is the pattern of force formation (offence + defense)?;
- Is one side retreating?;
- Is on force trying to draw the other into a particular (vulnerable) position, or force them into a particular position? If, so, why?;
- Are there diversionary tactics at play (e.g. enemy suppression to ease mobility)?;
- Are some units dug in – i.e. prefer to fight from fixed positions?;
- Are they defending something (i.e., convoy, building)?; and
- What advantage is one side trying to gain over the other (e.g., high ground, covered positions, buildings, etc.)?

Some instances associated with planning and decision making may be

- Quality or value of courses of action;
- Assess courses of action; and
- Select courses of action.

Obviously, the AI-driven replicator should provide approaches and means to support various human intentions in wargame situation assessment, knowledge / pattern discovery, planning and decision making.

Table 6: Features of Current Replicator vs. AI-Driven Replicator

Feature	Current Replicator	AI-driven Replicator
Input	CAEn game files: routes, aim zones, activities, orders, arcs, speed, rules of engagement, damage taken, entity state CAEn probability tables (see next page)	Aramis game files (common format for supported wargame systems): routes, speed, shots fired, damage taken, entity state. Common probability tables (see below) Time-segmented interactor description of goals, tactics, movement patterns, rules of engagement, etc..
Output	CAEn game files: routes, aim zones, activities, arcs, speed, damage taken, entity state	Aramis game files Additional Information: aim zones, activities, arcs, record of goals, decisions and reasons behind decisions (entity state).
Entity Movement	Constrained to follow exact path defined in game	Based on entity decisions derived from interactor description of movement patterns
Entity Activities	Activity sequence recorded from game. Replicator reuses exact activity sequence of game	Goal-oriented and situation dependent activity sequence provided by interactors
Entity Interactions	As recorded from game with certain limitations	Depend on circumstances as defined by the interactors.
Probability Tables (eg., hit, kill, detect)	Uses CAEn tables	Use external tables common to all wargames. Must decide on a baseline (e.g., JCATS tables).
Terrain	Terrain not taken into account	GIS-based terrain features taken into account, based on interactors description of how terrain enters into decision making.
Exploration of the Space of Possibilities	Limited. Replications strongly polarized to the seed game. No fitness criteria applied.	Robust. Wider possibilities explored by virtue of added decision points. Fitness criteria applied (e.g., culling).
Number of Interactive Games Needed to Support Analysis	At least four (4) depending on the scenario, but more are preferred. Typically 20 replications are produced per game.	Less games should be able to explore more possibilities. Therefore, expect adequacy with fewer games and more replications.
Length/Complexity of Games	Short/Simple. Otherwise, replication results can become nonsensical.	Long/Complex. Entities consistently make similar decisions compared to ‘realistic’ interactors.

4.4 An AI-driven wargame replication system

This section describes a mid/long-term solution to solve all kinds of problems in current wargame replications, which uses a unified memory representation structure, integrates results from human science and provides a mechanism for future adaptability of problem domains.

4.4.1 Objectives

The objectives of the proposed solution are the development of a system that:

- Absorbs results from human science: memory, ANN, analogy, and dual-processes thinking;
- Defines a unified memory representation structure for re-use of knowledge;
- Integrates existing recognized approaches and tools;
- Supports multiple approaches for various problem areas;
- Provides means for modelling human behaviour moderators ;
- Characterizes various cognitive functions: e.g. situation assessment, planning, decision making and learning; and
- Recommends adaptable approaches for various problems in wargame replications.

4.4.2 High level solution

This proposed architecture is shown in Figure 14, which consists of an AI Replication Engine, a Post-Game Analysis Toolkit (PGAT) and a PGAT Interface.

The *AI Replication Engine* provides various AI approaches for problem solving and reasoning in wargame replications. It comprises a *Working Memory, Regular Thinking Layer, Meta Layer and Motor Interface*.

The *Working Memory* component is a sensing interface to acquire external data, and the *Motor Interface* transmits the result of problem solving or reasoning to external PGAT modules for further use.

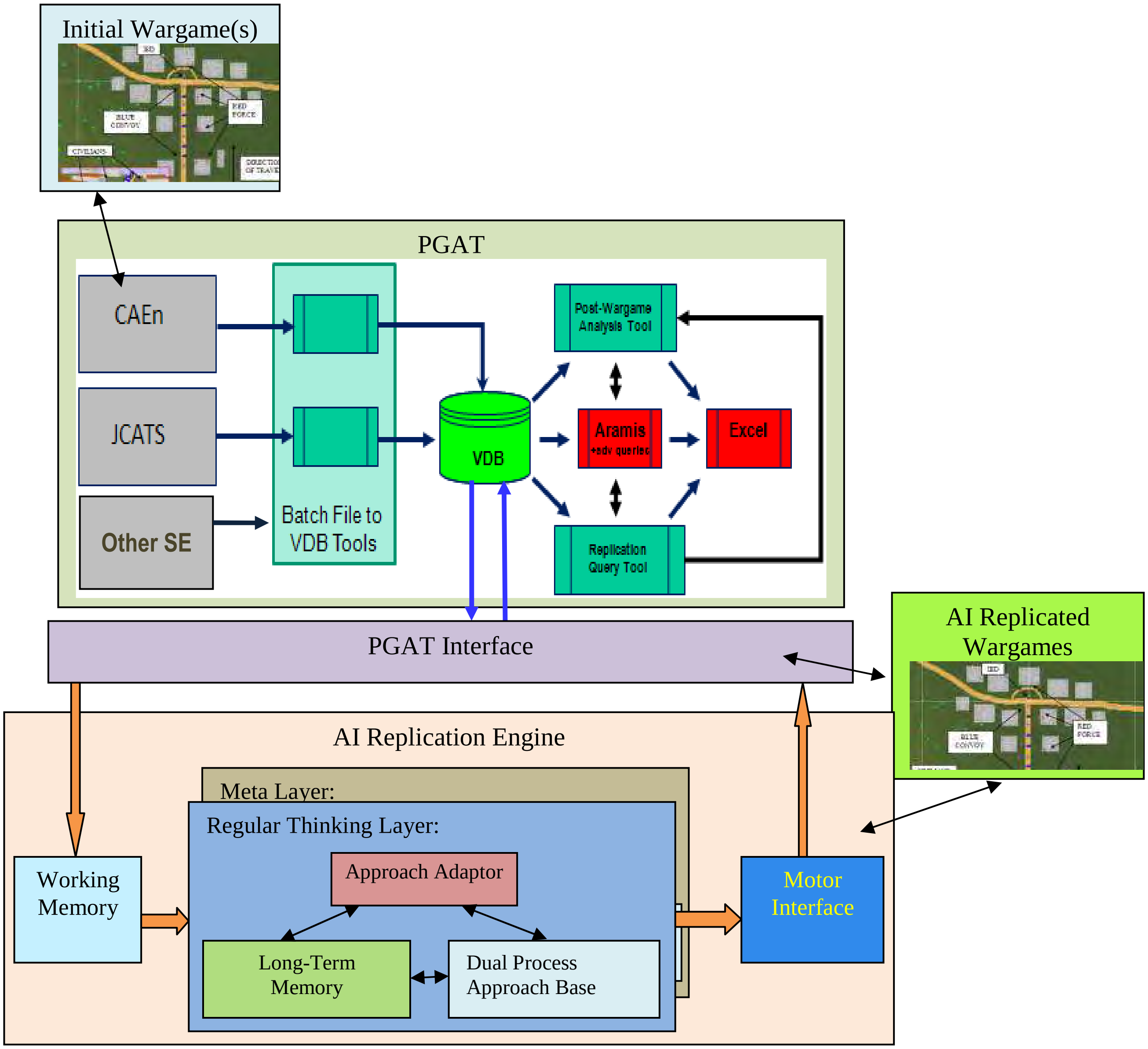

Figure 14: AI-Driven Wargame Replication System.

The *Regular Thinking Layer* is the kernel in the structure with three sub-components: *Long-Term memory*, *Dual Process Approaches* and *Approach Adaptor*. The *Long-Term Memory* is a unified knowledge representation structure defined by combining the features from human science including memory models, analogical models, dual process model and artificial neural networks. The *Dual Process Approach Base* integrates multiple methods related to both abstract and associative levels. Typical examples at the abstract level may be the rule-based reasoning and fuzzy computing, and some representative associative methods include human memory models, Bayesian networks and neural networks. The *Approach Adaptor* is used to recommend better methods for a given problem category. For example, if an interactor wants to assess the value of a fighter, the system checks all methods in the system for evaluating the values of objects, and finds that the Utility method is the best one among three existing approaches in the system: Bayesian networks, Utility and Fuzzy Logic, and then the system selects the Utility method to evaluate the value of a fighter and back the results to the user.

The *Meta Layer* in the architecture is important to support human behaviour moderators. The basic assumption here is that human behaviour moderators, e.g. personality, emotion and workload, affect the process and results of human thinking and reasoning. The *Meta Layer* and *Regular Thinking Layer* work together to enhance the variability and human-like behaviour in the proposed solution. The *PGAT Interface* in the structure is responsible for data transmission and format conversion between PGAT and the AI replication engine. *PGAT*, as explained in Section 2, collects data from wargames in Synthetic Environments, e.g. CAEn, stores the results of simulation to the central database, analyzes data, displays data, provides queries and interacts with the *AI Replication Engine* for intelligent behaviour. By combining the results from the *AI Replication Engine*, a 'template' *Initial Wargame* (or wargames) plus supplementary data (all stored in the VDB), a validated set of *Replicated Wargames* are generated and stored in the VDB for later analysis and visualization via PGAT[3].

4.4.3 Features of the proposed architecture

Compared to other systems, the significant features of the proposed solution include

- Human science oriented representation to enhance reliability and human-like behaviour;
- Re-use of knowledge to increase system efficiency;
- Multiple approaches to widen the system flexibility;
- Human behaviour moderators to characterize variability and individual differences; and
- Learning ability to recommend suitable approaches and enhance adaptability.

4.4.4 Potential application areas

Some potential application areas of the proposed solution consist of

- AI-driven wargame replications;
- Virtual interactors or operators in wargame replications and various CGFs;
- Simulated adversary;
- Virtual training partners: pilots, co-pilots, landing security officers, etc.;
- Cognitive functions for generic problem solving in wargames and CGFs:

[3] Ideally, it would be advantageous to have the AI Replication engine interact directly with the synthetic environment as interactors would to produce new 'games'. However, that is not possible with the current systems employed. Therefore, the AI engine must draw from a generic representation of the synthetic environment based on data in the VDB (entity capabilities, entity intent, events, probability tables, GIS terrain features, etc.). Note that it may be possible to specify an existing 'standard replication environment' (such as JCATS) where artificial interactors generated by the AI engine could play out the replications and generate the required data.

- Situation awareness;
- Decision making ;
- Planning; and
- Knowledge / pattern discovery, or learning .

- Command and control, search and rescue, training, M&S, air traffic control, etc.

5 System scoping

This section provides an estimate pertaining to the overall level of effort and scope related to implementing the proposed AI driven wargame replication system. A work plan is proposed with an initial phase where a detailed conceptual model of the AI driven wargame replication system is developed. Following this definition phase an incremental development effort is proposed that builds from an initial capability to the full objective capability. Significant investigation is still required to fully define the requirements for the wargame replication system. For this reason, the estimates contained in this section should be considered preliminary in nature.

5.1 Work tasks and efforts

Based on the domain cognitive analysis of wargame replications, four (4) main categories of tasks in the mid/long-term solution described in Section 4 are identified. The development effort proposed is an iterative, incremental process involving categories of work indentified as follows:

- Model development: 9 person-months
- System implementation: 19 - 46 person-months depending on selected tools and desired capability
- Application development: 7 person-months
- Verification & validation: 6 person-months

5.1.1 Model development (9 person-months)

More effort is required to define the requirements for the wargame replicator in more detail. Based on these system requirements, a more detailed conceptual model of the system must be developed. Conceptual model development is the first task in the proposed development effort. The following Table 7 describes the main sub-tasks and efforts in model development:

Table 7:Sub-tasks in model development.

Sub-Tasks in Model Development	**Efforts** (person-month)	**Details in Wargame Replicator**
Objectives and scope identification	0.5	Based on analysis of human interactor intent, define goals and objectives; Define the boundaries of the project.
Typical scenario development	0.5	Develop typical scenarios that span the experimentation space that the replicator will need to address, e.g. consisting of both BLUE and RED sides involved in an urban battle.

Identification of requirements	1.0	Based on current and anticipated wargame needs, define detailed requirements of AI-driven replicator.
Cognitive task analysis	0.5	Analyze a collection of previous or existing wargame scenarios; Generalize wargame goals, tasks and activities.
Identification and categorization of user intentions	0.5	Gather, analyze and categorize intentions of human interactors / commanders of wargames.
Component and relationship analysis of interactor intentions	0.5	For each category of problems, identify main components and relationships between them, for example, situation recognition: various components and relationships for recognizing “aggressor” and “defender”, values of targets, pattern of force formation (offence + defense), entity intentions (retreating?, forcing an entity to do something (e.g. to a particular position), tactics recognition (diversionary tactics: e.g. Suppression to ease mobility), unit preferences (prefer to fight from fixed positions), attacking/defending recognition, units’ advantages/disadvantages recognition; For instance, planning & decision making: quality of courses of action, selection course of action; decision evaluation, & decision selection.
Memory structure modeling Declarative memory modeling Procedural memory modeling (tasks and activities)	1.5	 Entities and facts representation (0.5 months): Representation of aim zone, arcs, damage taken, entity state, routes, speed, shots fired, etc.; Goals, decisions, reasons behind decisions; Common Probability Tables: hit, kill, detect, etc.; Terrain DB: entities & features, position relationships, values of entity features to tactics: defending, offending; Procedures / tasks representation (0.75 months): Movement patterns, rules of engagements, production rules, algorithms; Courses of action, activity sequences and tasks.
Dual-process approach identification and evaluation: Abstract Associative	1.0	Identify abstract approaches for rules or patterns in wargame decisions, planning or situation assessments, & unit movements; Identify methods for wargame goal networks, task networks, courses of action, activities, situation elements and relationships networks; associative networks for wargame pattern recognition, knowledge discovery & other cognitive functions.

Modeling of system adaptability	0.5	Application/scenario-type-oriented approach evaluation; e.g. method measurement and comparison for the evaluation of wargame targets.
Protocol development for component interactions	0.5	Define and develop interaction requirements between various AI & wargame components.
Behaviour moderator model development: Factor identification Models categorization Effect exploration Model integration	1.0	Identify various moderator factors of human interactors and virtual operators in wargames, e.g. emotion and personality; Categorize them based on common features and associations; Explore effects of behaviour moderators to wargame interactors performance; Integrate important models.
Options Analysis	1.0	Cross reference the system requirements with the capabilities of existing cognitive modelling and artificial intelligence application and existing ontologies and other knowledge bases to inform which aspects of the system will be formed by the integration of existing applications, and which aspects of the system will have to be developed.
Develop Implementation plan	1.0	Build on the documentation of the system requirements and the conceptual model and develop the implementation plan that provides the detailed work plan for the design, development testing and deployment of the wargame replication system

5.1.2 System implementation (19 – 46 person-months)

The time range in the system implementation may range from 19-46 person-months, depending on the selected tools to be integrated into the proposed solution and the final scope of the system requirements. The following Table 8 shows the sub-tasks, efforts and details in wargame replicator in system implementation. Please note that while the work tasks are laid out in a waterfall fashion in table 8, an incremental spiral development approach is recommended to provide capability in an incremental fashion and for risk reduction.

Table 8: Sub-tasks in system implementation.

Sub-Tasks of System Implementation	**Efforts** (person-month)	**Details in Wargame Replicator**
Requirement specification	1.5 -3.0	From software point of view, develop detailed requirements of AI-driven replicator from the system requirements and conceptual model.
Scope, boundary and risk identification	0.5 -2.0	Analyze and identify software's scope, boundary and risks.

Decomposition of detailed functionality	2.0 – 6.0	Itemize functionality of software modules.
Architecture & system design actor identification Use case development Interaction development Class identification and design Significant algorithms and activities	3.0 – 6.0	Identify human interactors at various wargame unit levels, interactions, external hardware and software, network components, protocols, &connections; Categorize detailed functionality & interactions of system components; Define logic structures of software; Main algorithm developments.
Implementation: Basic memory knowledge base development: declarative & procedural (3 – 4 months) Integrate existing tools (4-14 months) Protocol development for interaction between tools (1 - 2 months) Working memory and motor interface (1 - 2 months)	12.0 – 28.0	Implement various representations of entities relationships and associations: e.g. aim zones, arcs, damage taken, entity state, routes, speed, shots fired, goals, context, decisions, common probability tables, terrains. Realize dynamic procedures and tasks: movement patterns, rules of engagements, production rules, algorithms, courses of action, activity sequences, and other relevant tasks. Choose existing tools to integrate: e.g. Soar, ACT-R, Bayesian, ANN, CBR, LAMP etc.; Integrate the selected tools; Analyze wargame tasks and assign wargame intelligent tasks to various tools. Implement interactions between tools; Analyze data and constraints in interactions between AI replication engine and PGAT; Define data formats and data exchanges between AI engine and PGAT; Develop data structures and integrate them into the system;

Interface to synthetic environment (1 - 2 months) Interface to PGAT (1 - 2 months) Tests (1 - 2 months)		Possibly define and realize an interface to a specified standard synthetic environment to host the 'AI-interactive' games (wargames utilizing artificial interactors), e.g. JCATS; Implement input/output and communication interfaces to PGAT data bases; Verification of the implemented software.

5.1.3 Application integration and configuration (7 person-months)

As increments of the AI driven wargame replication system are developed, they will be integrated with DRDC CORA's PGAT infrastructure, and configured with the necessary data to support the required replications. The sub-tasks, efforts and details in application integration and configuration are shown in Table 9.

Table 9: Sub-tasks in application development.

Sub-Tasks in Application Development	**Efforts** (person-month)	**Details in Wargame Replicator**
Scenario analysis and definition	1.0	Define and develop a group of typical wargame scenarios.
I/O data identification	0.5	Identify data from the wargame scenarios.
Scenario development in SE	2.0	Establish scenarios in synthetic environment: CAEn / JCATS.
Integrate with SE & PGAT for applications	3.5	Complete the scenarios implementation in Synthetic Environment, PGAT and AI replication engine; Implement interactions between PGAT, CAEn/JCATS and AI replication engine.

5.1.4 Verification and validation (6 person-months)

As an ongoing process with the development of replicator increments, and as the last phase of the work effort, Verification and Validation (V&V) is a critical component of the proposed work plan. The sub-tasks of the V&V effort are described in Table 10.

Table 10: Sub-tasks in verification & validation.

Sub-Tasks in Verification & Validation	**Efforts** (person-month)	**Details in Wargame Replicator**
Verification of software system	1.0	Software packages and system testing.
Identification of validation resources	0.5	Classify, recognize and find various human and other resources required by validation.
Scenario identification & selection	1.0	Develop wargame scenarios for validation.
Development of validation process and methods	0.5	Work out methodology for validation of AI-driven replicator.
Validation conduction	2.0	Validate the AI-driven replicator.
Result handling of validation	1.0	Analyze and summarize validation results.

6 Recommendations

6.1 Short-term experimental solutions

There are many HBR and AI tools as described in Section 3, but there is no single tool / approach that has the capacity to span the problem space of wargame replications. However, each tool or approach has its own features and strengths and can be used for some limited range of experiments / tests in wargame replications. Based on the categories of the problems in wargame replications, the following Table 11 recommends some tools or approaches to solve problems in related categories.

Table 11: Recommendation for short-term solutions.

Problem Category	**Approaches / Tools Recommended**	**Efforts for Integration and simple example development** (person-month)
Situation/threat assessment, Pattern recognition/classification	Bayesian tools, neural networks	3.0 – 5.0
	Rule-based tools: ACT-R, Soar, Common Lisp, & Prolog	3.0 – 5.0
	Others: HMM, SVM, fuzzy, K-nearest neighbor, etc	3.0 – 5.0
Planning	Rule-based: Soar, ACT-R	3.0 – 5.0
	Genetic algorithms	3.0 – 5.0
	BDI	3.0 – 5.0
	Others: Bayesian, ANN, CBR	3.0 – 5.0
Decision Making	Decision Trees, Utility, RPDM, Bayesian networks	3.0 – 5.0
	Rule-based: Soar, ACT-R, Lisp, Prolog	3.0 – 5.0
	Others: CBR, fuzzy, ANN, etc.	3.0 – 5.0
Generic Cognitive functions	ACT-R, Soar, LAMP	3.0 – 5.0

6.2 Mid/long-term generic solution

The mid/long-term solution described in Section 4 is a human-science-oriented, knowledge-reusable, integrated and adaptable system. The main purpose of the proposal is to meet the needs of current and future wargame replications. Combining various results from human science makes the system have a solid cognitive foundation. A unified memory structure that supports multiple approaches provides the capability to re-use the same group of knowledge/information/data for different experiments and performance evaluation. Integrating multiple approaches is to extend the categories of problem solving for future wargame replications, e.g. from low-level situation perception/recognition to high-level decision making and planning. Furthermore, modelling human behaviour moderators, and selecting/recommending appropriate approaches are able to improve human-like variability and system adaptability.

The main tasks, efforts and outputs in the mid/long-term solution are summarized in Table 12.

Table 12: Recommendation for mid/long-term solutions.

Task	**Sub-task**	**Efforts** (person-month)	**Outputs**
Unified memory /KR and Feasibility Proof	Feasibility model development	3.0	Memory representation structure development: A re-usable memory representation structure: aim zones, arcs, damage taken, entity state, routes, speed, shots fired, goals, decisions, reasons behind decisions, common probability tables, terrain DB, dynamic procedures: movement patterns, rules of engagements, courses of action, activity sequences, rules, tasks; Integration of memory structure & abstract approach; Wargame application development: Demonstration of initial scenario: typical scenarios plus AI functions for situation assessment or decision support.
	Unified memory development	4.0	
	Initial integration for abstract process approach	3.5	
	Example development	1.5	
Main functionality development	Architecture design	2.0	System architecture development: software logic components, relationships and organization for various wargame entities, COA, decisions, terrains and AI-related components; Typical functions developments: Typical abstract & associative functions development:
	Abstract approaches	7.0 - 12.0	
	Associative	7.0 -	

	approaches	12.0	for pattern recognition, knowledge discovery, situation assessment, planning and decision support: recognizing aggressor, defender, target values, pattern of formation; retreating recognition; adversary intentions (one forces another to do something; defending something), tactics recognition; preferences, advantages evaluation (high ground, covered positions, buildings, etc.); Typical wargame applications development and demonstration.
	Extended applications	4.0 - 6.0	
Advanced adaptable functions	Meta Layer model development	4.0 - 8.0	Adaptive functions development: develop measurements to evaluate various approaches for problem categories in wargame replications; Adaptive applications implementation: build scenarios with advanced adaptability functions; verify & validate the adaptive functions.
	Learning and Adaptive functions implementation	5.0 - 16.0	
Total		41.0 - 68.0	(See Section 4 for details).

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References

[1] Acorn, T., and Walden, S. (1992). SMART: Support management automated reasoning technology for Compaq customer service. In *Proceedings of the Tenth National Conference on Artificial Intelligence*. MIT Press.

[2] Ahmed, F.E. (2005). Artificial neural networks for diagnosis and survival prediction in colon cancer. *Molecular Cancer,* Vol. 4, 29.

[3] Aisa, B, Mingus, B., O'Reilly, R.C. (2008). The Emergent neural modeling system. *Neural Networks,* Vol. 21, Issue 8, 1146–1152.

[4] Al-Alaoui, M.A., Al-Kanj, L., Azar, J. and Elias Yaacoub, E. (2008). Speech Recognition using Artificial Neural Networks and Hidden Markov Models. *Proc. of the 3rd International Conference on Interactive Mobile and Computer Aided Learning (IMCL 2008),* Amman, Jordan.

[5] Allaire, F.C., Tarbouchi, M., Labonte, G. and Fusina, G. (2009). *Journal of Intelligent and Robotic Systems,* Vol. 54, Issue 1-3, 495-510.

[6] Allendoerfer, K.R. and Weber, R. (2004). PlayMaker: An Application of Case-Based Reasoning to Air Traffic Control Plays. *Advances in Case-Based Reasoning,* 476-488, Sprinter Berlin / Heidelberg.

[7] Anderson, D, Bailey, C. and Skubic, M. (2004). Hidden Markov Model Symbol Recognition for Sketch-Based Interfaces. Retrieved Jan 21, 2010, from *https://www.aaai.org/Papers/Symposia/Fall/2004/FS-04-06/FS04-06-003.pdf*.

[8] Anderson, J.R. (1990). *The Adaptive Character of Thought.* Hillsdale, NJ: Erlbaum.

[9] Anderson, J.R. & Lebiere, C. (1998). *The Atomic Components of Thought*. Mahwah, NJ: Erbaum.

[10] Anderson, J.R., Bothell, D. Byrne, M. D., Douglass, S., Lebiere, C., & Gin, Y. (2004). An integrated theory of the mind. *Psychological Review,* 111, 1036-1060.

[11] Andersson, M. (2003). Classification of Aerial Missions Using Hidden Markov Models. *Symbolic and Quantitative Approaches to Reasoning with Uncertainty,* Vol.2711, 125-136.

[12] Barr, M.L. and Kiernan, J.A. (1988). *The Human Nervous System. An Anatomical Viewpoint.* Fifth Edition, Harper International.

[13] Baron, S., Zacharias, G., Muralidharan, and Lancraft, R. (1980). PROCUE: A model for analyzing flight crew procedures in approach to landing. *Proceedings of the Eight IFAC World,* Congress, Tokyo, Japan.

[14] Barricelli, N.A. (1957). "Symbiogenetic evolution processes realized by artificial methods". *Methodos*: 143–182.

[15] Baumgartner, N., Retschitzegger, W. and Schewinger, W. (2008). Application Scenarios of Ontology-Driven Situation Awareness Systems Exemplified for the Road Traffic Management Domain. *Proc. of the 2008 Conference on Formal Ontologies Meet Industry – Frontiers in Artificial Intelligence and Applications*, Vol. 174, 77-87.

[16] Bayes, T. (1763). An essay towards solving a problem in the doctrine of chances. *Philosophical Transactions of the Royal Society London*, Vol. 53, 370-418.

[17] Bhargavi, P. and Jyothi, D. (2009). Applying Naïve Bayes data mining technique for classification of agricultural land soils. *International Journal of Computer Science and Network Security*. Vol. 9 No.8: 117-122.

[18] Binet, A. and Simon, T. (1905/1980). *The development of intelligence in children.* Nashville, TN: Williams Printing Co.

[19] Bishop, C.M. (1995) *Neural Networks for Pattern Recognition*, Oxford: Oxford University Press.

[20] Boring, R.L. Gertman, D.I, Tran, T.Q., & Gore, B.F. (2008). Framework and application for modeling control room crew performance at nuclear power plants. *In the 52nd Annual Human Factors and Ergonomics Annual Meeting*, September 22-26, NY, USA.

[21] Boukhtouta, A., Bedrouni, A., Berger, J., Bouak, G. and Guitouni, A. (2004). A Survey of Military Planning Systems. *Proc. of the 9th International Command and Control Research and Technology Symposium*, Copenhagen, Demark.

[22] Brainz. (2010). *15 Real-World Uses of Genetic Algorithms.* Online available on January 21, 2010, at http://brainz.org/15-real-world-applications-genetic-algorithms/.

[23] Bratman, M., Israel, D. and Pollack, M. (1988). Plans and resource-bounded practical reasoning. *Computational Intelligence,* Vol.4, No. 4, 349-355.

[24] Brown, J. S., Colins, A., & Dugid, P. (1989). Situated cognition and the culture of learning. *Educational Researcher,* 18 (1), 32-42.

[25] Brown, G.D.A., Neath, I., and Chater, N. (2007). A temporal ratio model of memory. *Psychological Review,* 114:539-576.

[26] Brynielsson, J. (2006). Using AI and games for decision support in command and control. *Decision Support Systems,* Vol. 43, Issue 4, 1454-1463.

[27] Buchanan, G.G. and Shortliffe, E.H. (1984). *Rule-based Expert Systems: The MYCIN Experiments of the Stanford Heuristic Programming Project.* Addison-Wesley, MA: Boston, USA.

[28] Burdick, M.D., & Shively, R.J. (2000). A full mission evaluation of a computational model of situation awareness. *Proceedings of the 14th Triennial International Ergonomics Association (IEA) and the Human Factors and Ergonomics Society 44th Annual Meeting*, USA.

[29] Burges, C. (1998). A tutorial on support vector machines for pattern recognition. *Data Mining and Knowledge Discovery*. 2(2):1-47.

[30] Cappe, Olibier, Moulines, Eric, Ryden, Tobias. (2005). *Inference in Hidden Markov Models.* Sprinter.

[31] Chai, H.-M. and Wang, B.-S. (2007). A Fuzzy Logic Approach for Force Aggregation and Classification in Situation Assessment. *Proc. of the International Conference on Machine Learning and Cybernetics,* Hong Kong, China.

[32] Chia, C.W. and Williams, K.E. (2003). A modified Naïve Bayes approach for autonomous learning in an intelligent CGF, *Proc. of the Conference on Behavior Representation in Modeling and Simulation (BRIMS 2003),* Scottsdale, AR, USA.

[33] Clark, A. and Karmiloff-Smith, A. (1993). The cognizer's innards: a psychological and philosophical perspective on the development of thought. *Mind and Language,* 8(4), 487-519.

[34] Cohen, M.S. and Laskey, K.B. (1986). An application of non-monotonic probabilistic reasoning to air force threat correlation. *Proceedings of the Second Workshop on Uncertainty in Artificial Intelligence*.

[35] Colmerauer, A. and Roussel, P. (1992). The birth of Prolog, in *The second ACM SIGPLAN conference on History of programming languages,* p. 37-52.

[36] Costa, P.T. and McCrae, R.R. (1992). Normal personality assessment in clinical practice: The NEP personality inventory. *Psychological Assessment*, (4):5-13.

[37] Cox, M.T. and Veloso, M.M. (1997). Supporting Combined Human and Machine Planning: An Interface for Planning by Analogical Reasoning. In D. Leake & E. Plaza (Eds.), *Case-Based Reasoning Research and Development: Second International Conference on Case-Based Reasoning* (pp. 531-540). Berlin: Springer-Verlag.

[38] Cristianini, N. and Shawe-Taylor, J. (2000). *An Introduction to Support Vector Machine and Other Kernel-Based Learning Methods.* Cambridge University Press, Cambridge.

[39] Davidor, Y. (1991). *Genetic Algorithms and Robotics – A Heuristic Strategy for Optimization.* World Scientific Publishing Co., Inc. River Edge, NJ. USA.

[40] De Jongh, P.J., Carden, K.J. and Rogers, N.A. (1994). Future: A Knowledge-Based System for Threat Assessment. *Interfaces*, 24:76-86.

[41] Dennett, D. (1987), *The Intentional Stance.* MIT Press, Cambridge, MA, USA.

[42] Deutsch, S.E. and Adams. (1995). The operator-model architecture and its psychological framework. *Proc. of the Sixth IFAC Symposium on Man-Machine Systems.* Cambridge, MA: Massachusetts Institute of Technology, USA.

[43] d'Inverno, M., Luck, M., Georgeff, M., Kinny, D. and Wooldridge, M. (2004). The dMARS Architecture: A Specification of the Distributed Multi-Agent Reasoning System. *Journal of Autonomous Agents and Multi-Agent Systems,* 5-53.

[44] Domingos, P. (1997). On the optimality of the simple Bayesian classifier under zero-one loss. *Machine Learning*, 29:103-130.

[45] Dowling, J.E. (2001). *Neurons and networks: an introduction to behavioral neuroscience.* Second Edition, Belknap Press of Harvard University Press, Second Edition.

[46] Duke, E.L. Disbrow, J.D. and Butler, G.F. (1989). A Knowledge-Based Flight Status Monitor for Real-Time Application in Digital Avionics Systems. *NASA Technical Memorandum 101701*. Online available on January 22, 2010, at http://www.nasa.gov/centers/dryden/pdf/88169main_H-1568.pdf.

[47] Dunbar, K. and Klahr, D. (1989). Development differences in scientific discovery processes. In D. Klahr & K. Lotovsky (Eds.), *Complex information processing: The impact of Herbert A. Simon* (pp. 109-143). Hillsdale, NJ: Lawrence Erlbaum.

[48] Dworman, G. Kimbrough, S. and Laing, J. (2010). *An Application of Genetic Programming to Bargaining in a Three-Agent Coalition Game.* Online available on January 21, 2010, at http://opim.wharton.upenn.edu/risk/downloads/archive/arch62.pdf.

[49] East, Therese L. and Sharfstein, Bruce. (2006). Development of a decision tree model for the prediction of the limitation potential of phytoplankton in Lake Okeechobee. *Archiv Fur Hydrobilogie,* Vol. 165, No. 1, pp 127-144.

[50] English, L.D. and Halford, G.S. (1995). *Mathematics education: Models and processes.* Hillsdale, NJ: Erlbaum.

[51] Eom, S. and Kim, E. (2006). A survey of decision support system applications. *Journal of the Operational Research Society,* Vol. 57, 1264-1278.

[52] Eom, S.B., Lee, S.M. , and Somarajan, C. (1998). A survey of decision support system applications. *Journal of the Operational Research Society,* Vol. 49, 109-120.

[53] Etherington, D.W. and Kautz, H.A. (1994). The Fourth International Workshop on Nonmonotonic Reasoning. *AI Magazine,* Vol. 15, No. 3, 83-85.

[54] Evans, J.B.T. (2003). In two minds: dual-process accounts of reasoning. *TRENDS in Cognitive Science,* vol. 6, no. 10, 2003, pp. 454-459.

[55] Evans, J.S.B.T. (2003). In two minds: Dual-processing accounts of reasoning. *Trends in Cognitive Sciences,* 7(10), 454-459.

[56] Evertsz, R.; Busetta, P., Pedrotti, M., Ritter, F. E., & Bittner, J. L. (2008). CoJACK—Achieving principled behaviour variation in a moderated cognitive architecture". *Proceedings of the 17th Conference on Behavior Representation in Modeling and Simulation (08-BRIMS-025).* Online available on January 23, 2010, at http://acs.ist.psu.edu/papers/evertszBPRB08.pdf.

[57] Eysenck, H.J. (1990). Biological dimensions of personality. In L.A. Pervin, editor, *Handbook of personality: Theory and research*, pp 244-276. New York: Guilford.

[58] Falkenhainer,B. Forbus, K.D and Gentner, D. (1989). The structure-mapping engine: Algorithm and examples. *Artificial Intelligence*, 41(1), 1-63.

[59] Feldman, J.A. and Ballard, D.H. (1982). Connectionist models and their properties. *Cognitive Science,* Vol.6, 205-254.

[60] Fernandez, V. Garcia, M.R. Gonzalez, R. and Rodriguez, L. (2010). *Genetic Algorithms Applied to Clustering.* Online available on January 21, 2010, at http://laboratorios.fi.uba.ar/lsi/rgm/comunicaciones/c-AGsclustering-ORLANDO96.pdf.

[61] Fogel, D.B. (1998). *Evolutionary Computation.* The Fossil Record. New York: IEEE Press.

[62] Fogel, D.B. (2006). *Evolutionary Computation: Toward a New Philosophy of Machine Intelligence,* IEEE Press, Piscataway, NJ. Third Edition.

[63] Forbus, K.D., Usher, J. and Chapman, V. (2004). Qualitative Spatial Reasoning about Sketch Maps. *AI Magazine,* Vol. 25, Issue 3, 61-72.

[64] Fraser, A. (1957). Simulation of genetic systems by automatic digital computers. I. Introduction. *Aust. J. Biol. Sci.* 10:484-491.

[65] Gali, L., Loiacono, D. and Lanzi, P.L. (2009). Learning a context-aware weapon selection policy for unreal tournament III. *Proc. of the 2009 IEEE Symposium on Computational Intelligence and Games,* Milano, Italy.

[66] Gan, C., Limsombunchai, V., Clemes, M. and Weng, A. (2005). Consumer Choice Prediction: Artificial Neural Networks versus Logistic Models. *Journal of Social Sciences,* 1(4):211-219.

[67] Gardenfors, P. and Rott, H. (1995). Belief, revision. *Handbook of Logic in Artificial Intelligence and Logic Programming,* Vol.4, 35-132. Oxford University Press.

[68] Gensure, J.R. (2007). Application of structured decision-making tools to defense acquisition. *Defense A R Journal,* Vol. 14, Issue 1, 260-276.

[69] Gentner, D. and Gentner, D.R. (1983). Flowing waters or teeming crowds: Mental models of electricity. In D. Gentner and A.L. Stevens (Eds.), *Mental models* (pp. 99-129). Hillsdale, NJ: Lawrence Erlbaum Associates.

[70] Gentner, D., Holyoak, K.J. and Kokinov, B. (Eds.). (2001). *The Analogical Mind: perspectives from Cognitive Science*. Cambridge, MA: MIT Press.

[71] Georgeff, M. and Ingrand, F. (1989). Decision-making in an embedded reasoning system. *Proc. of the International Joint Conference on Artificial Intelligence,* 972-978.

[72] Georgeff, M., Pell, B., Pollack, M., Tambe, M. and Wooldridge, M. (1999). The Belief-Desire-Intention Model of Agency. Intelligent *Agents V: Agents Theories, Architectures, and Languages.* Online available on January 23, 2010, at http://www.springerlink.com/content/dr028l3v7194328l/.

[73] Ghazi, K.L., Laskey, K., Alghamdi, G., Want, X., Barbara, D., Shackelford, T. and Fitzgerald, J. (2004). Detecting Threatening Behavior Using Bayesian Networks. *Proc. of the Conference on Behavioral Representation in Modeling and Simulation (BRIMS 2004),* Arlington, Virginia, USA.

[74] Gick, M.L. and Holyoak, K.J. (1983). Schema induction and analogical transfer. *Cognitive Psychology,* 15(1), 1-38.

[75] Glenn, F.A., Schwartz, S.M. and Ross, L.V. (1992). *Development of a Human Operator Simulator Version V (HOS-V): Design and Implementation.* U.S. Army Research Institute for the Behavioral and Social Sciences, PERIPOX, Alexandria, VA, USA.

[76] Goel, V., Buchel, C., Frith, C., and Dolan, R.J. (2000). Dissociation of mechanisms underlying syllogistic reasoning. *Neuroimage*, Vol. 12, 504-514.

[77] Goel, V. and Dolan, R.J. (2004). Differential involvement of left prefrontal cortex in inductive and deductive reasoning. *Cognition,* Vol. 93, Issue 3, B109-B121.

[78] Gonsalves, P., Cunningham, R., Ton, N. and Okon, D. (2000). Intelligent threat assessment processor (ITAP) using genetic algorithms and fuzzy logic. *Proc. of the 3rd International Conference on Information Fusion,* Vol. 2, THB1/18-THB1/24.

[79] Gore, B.F., Hooey, B.L., Wickens, C.D., & Scott-Nash, S. (2009). A computational implementation of a human attention guiding mechanism in MIDAS v5. In V.G. Duffy (Ed.): *Digital Human Modeling, HCII 2009*, LNCS 5620, pp. 237-246.

[80] Gore, B.F., & Jarvis, P. (2005). Modeling the complexities of human performance. *Proc. of the 2005 IEEE International Conference on Systems, Man, and Cybernetics*.

[81] Gratch, J. & Marsella, S. (2001). Modeling Emotions in the Mission Rehearsal Exercise. *Proceedings of the 10th Conference on Computer Generated Forces and Behavior Representation(CGF&BR)* , Orlando, FL.

[82] Gratch, J. & Marsella, S. (2004). A Domain-independent Framework for Modeling Emotion. *Journal of Cognitive Systems Research*, Vol.5 (Issue 4), Pages 269-306..

[83] Grossberg, S. (1988). *Neural Networks and Natural Intelligence*. Cambridge, MA: MIT Press.

[84] Guanajuato – University. (2010). *Neural Lab*. Online available on January 24, 2010, at http://www.dicis.ugto.mx/profesores/sledesma/documentos/index.htm

[85] Guerra-Hernandez, A., Fallah-Seghrouchni, A.E. and Soldano, H. (2004). Learning in BDI multi-agent systems. *Proc. of the 4th International Workshop on Computational Logic in Multi-Agent Systems.* Fort-Lauderdale, FL, USA.

[86] Guitouni, A. and Belfares, L. (2008). *Comparison and Evaluation of Multi-Object Genetic Algorithms for Military Planning And Scheduling Problems: Applied to Course of Action Planning*. DRDC Valcartier Technical Report, TR-2003-372.

[87] Guo, R.J. and Cain, B. (2009). Integrating Reasoning with Personality Effects in Simulated Operators. *Proc. of the 2009, IEEE Symposium on Computational Intelligence for Security and Defense Applications (CISDA 2009),* Ottawa, Canada.

[88] Guo, R.J., Cain, B. and Meunier, P. (2005a). Knowledge Representation Supporting Multiple Reasoning Methods for Simulated Operators. *Proceedings of the 2005 Conference on Behavior Representation in Modeling and Simulation (BRIMS 2005),* Universal City, CA, USA..

[89] Guo, R.J., Cain, B. and Meunier, P. (2005b). *Supporting Uncertainty Reasoning in Simulated Operators for Networks,* DRDC Technical Report, TR-2005-268.

[90] Guo, R.J., Cain, B. and Meunier, P. (2008). Representing Uncertainty in Computer-Generated Forces, *International Journal of Computer and Information Science and Engineering*, vol. 2, no. 2, 2008, pp. 90-95.

[91] Gupta, M. and Mukherjee, S. (2009). Towards Situation Awareness in Integrated Air Defence Using Clustering and Case Based Reasoning. *Pattern Recognition and Machine Intelligence*, Vol. 5909, 579-584, Springer Berlin / Heidelberg.

[92] Haigh, K.Z., Shewchuk, J.R. and Veloso, M.M. (1997). Exploiting Domain Geometry in Analogical Route Planning. *Journal of Experimental & Theoretical Artificial Intelligence*, Vol., 9, Issue 4, 509-541.

[93] Halford, G.S. (1992). Analogical reasoning and conceptual complexity in cognitive development. *Human Development*, 35, 183-217.

[94] Halford, G.S. (1993). *Children's understanding: The development of mental models*. Hillsdale, NJ: Erlbaum.

[95] Halford, G.S., Bain, J.D., Maybery, M. and Andrews, G. (1998). Induction of relational schemas: Common processes in reasoning and complex learning. *Cognitive Psychology,* 35(3), 201-245.

[96] Halford, G.S., Ford, M., Busby, J. and Andrews, G. (2006). *Literature Review of Formal Models of Human Thinking,* DRDC CR-2006-206.

[97] Halford, G.S., Wilson, W.H., Guo, J., Gayler, R.W., Wiles, J. and Stewart, J.E.M. (1994). Connectionist implications for processing capacity limitations in analogies. In K.J. Holyoak & J. Barnden (Eds.), *Advances in connectionist and neural computation theory: Vol. 2. Analogical connections* (pp. 363-415). Norwood, NJ: Ablex.

[98] Hasher, L. and Zacks, R.T. (1979). Automatic and effortful processes in memory. *Journal of Experimental Psychology:* General, Vol. 108, 356-388.

[100] He, S., Wu, Q.H., Saunders, J.R. (2009). Breast cancer diagnosis using an artificial neural network trained by group search optimizer. *Transactions of the Institute of Measurement and Control,* Vol. 31, No. 6, 517-531

[101] Hehir, A. (2006). The Impact of Analogical Reasoning on US Foreign Policy Towards Kosovo. *Journal of Peace Research*, Vol.43, No. 1, 67-81.

[102] Hendy, K.C., Farrell, P. S. E. & East, K.P. (2000). An information-processing model of operator stress and performance. In Peter A. Hancock & Paula A. Desmond (Eds.) *Stress, Workload and Fatigue,* 34-79. CRC Press, Boca Raton, FL 33487, USA.

[103] Henninger, A.E., Jones, R.M., and Chown, E. (2001). A Symbolic-Connectionist Framework for Representing Emotions in Computer Generated Forces. *Proceedings of the 2001 Interservice / Industry Training Simulation, and Education Conference (I/ITSEC).* Orlando, FL.

[104] Henninger, A.E., Jones, R.M., and Chown, E. (2002). Behaviors that Emerge from Emotion and Cognition: A First Evaluation. *Proceedings of the 2002 Interservice / Industry Training Simulation and Education Conference (I/ITSEC),* December 2, 2002, Orlando, FL.

[105] Henninger, A.E., Jones, R.M., and Chown, E. (2003). Behavior that Emerge from Emotion and Cognition: Implementation and Evaluation of a Symbolic-Connectionist Architecture. *Proceedings of the Second International Joint Conference Autonomous Agents and Multiagent Systems.* Melbourne, Australia.

[106] Hertz, J., Palmer, R.G., Krogh. A.S. (1990) *Introduction to the theory of neural computation*, Perseus Books.

[107] Himes, G.S. and Inigo, R.M. (1992). Automatic Target Recognition Using a Neocognitron. *IEEE Transactions on Knowledge and Data Engineering.* Vol. 4, Issue2:167-172.

[108] Hintzman, D. L. (1984). MINERVA2: A simulation model of human memory. *Behavior Research Methods, Instruments & Computers, 16,* 96-101.

[109] Hintzman, D. L. (1986). “Schema abstraction” in a multiple-trace memory model. *Psychological Review, Vol. 93,* 411-428.

[110] Hintzman, D. L. (1988). Judgments of frequency and recognition-memory in a multiple-trace memory model. *Psychological Review, Vol. 95,* 528-551.

[111] Hofstadter, D.R. (2001). Analogy as the core of cognition. In D. Gentner, K.J. Holyoak & B.N. Kokinov (Eds.), *The analogical mind: Perspectives from cognitive science* (pp. 499-538). Cambridge: MIT Press.

[112] Hofstede, G. (1980). *Culture's consequences: International differences in work-related values*. Newbury Park, CA: Sage.

[113] Holland, J.G. (1975). *Adaptation in Natural and Artificial Systems.* University of Michigan Press, Ann Arbor.

[114] Holt, A. and Benwell, G.L. (1996). *Case-Based Reasoning and Spatial Analysis.* URISA Journal, Vol. 8, No.1, 27-36.

[115] Holyoak, K.J. (2005). Analogy. In K.J. Holyoak & R.G. Morrison (Eds.), *Cambridge handbook of thinking and reasoning* (pp. 117-142). Cambridge, England: Cambridge University Press.

[116] Holyoak, K.J. and Barnden, J. (1994). *Analogical connections* (Vol. 2). Norwood, NJ: Ablex.

[117] Holyoak, K.J. and Thagard, P. (1989). Analogical mapping by constraint satisfaction. *Cognitive Science,* 13(3), 295-355.

[118] Holyoak, K.J. and Thagard, P. (1995). *Mental leaps.* Cambridge, MA: MIT Press.

[119] Howard, Ronald A. (1966). Decision Analysis: Applied Decision Theory." *Proceedings of the 4th International Conference on Operational Research*. 55-77.

[120] Howden, N. Ronnquist, R., Hodgson, A., and Lucas, A. (2001). JACK Intelligent Agents – Summary of an Agent Infrastructure. *Proc. of the 5th International Conference on Autonomous Agents.*

[121] Hsu, C.-H. and Wang, M.-J. (2005). Using decision tree-based data mining to establish a sizing system for the manufacture of garments. *The International Journal of Advanced Manufacturing Technology,* Vol. 26, No. 5-6, 669-674, Springer London.

[122] Huang, H.-C. (2009). Designing a knowledge-based system for strategic planning: A balanced scorecard perspective. *Expert systems with Applications,* Vol. 36, Issue 1:209-218.

[123] Hudlicka, E. and Pfautz, J. (2002). Architecture and Representation Requirements for Modeling Effects of Behavior Moderators. *Proceedings of the 11th Conference on Computer Generated Forces and Behavior Representation (CGF&BR)*, Orlando, FL.

[124] Hummel, J.E. and Holyoak, K.J. (1997). Distributed representations of structure: A theory of analogical access and mapping. *Psychological Review,* 104, 427-466.

[125] Hummel, J.E. and Holyoak, K.J. (2003). A symbolic-connectionist theory of relational inference and generalization. *Psychological Review,* 110(2), 220-264.

[126] Hummel, J.E. and Holyoak, K.J. (2005). Relational Reasoning in a Neurally Plausible Cognitive Architecture. An Overview of the LISA Project. *Current Directions in Psychological Science,* 14(3), 153-157.

[127] Ibrahim, N.K., Raja Abdullah, R.S.A and Saripan, M.I. (2009). Artificial Neural Network Approach in Radar Target Classification. *Journal of Computer Sciences,* 5(1):23-32.

[128] Inamura, T. Kojo, N. and Inaba, M. (2006). Situation recognition and behaviour induction based geometric symbol representation of multimodal sensorimotor patterns. *Proc. of the 2006 IEEE Conference on Intelligent Robots and Systems.* Tokyo, Japan.

[129] Jha, M. (2009). Dynamic Bayesian Network for Predicting the Likelihood of a Terrorist Attack at Critical Transportation Infrastructure Facilities. *Journal of Infrastructure Systems,* Vol. 15, Issue 1, 31-39.

[130] Jeppesen, D. and Trellue, R. (1997). Unattended ground sensor situation assessment workstation. *Proc. of the Peace and Wartime Applications and Technical Issues for Unattended Ground Sensors.* Orlando, FL. USA.

[131] Johansson, F. and Falkman, G. (2008). A Bayesian network approach to threat evaluation with application to an air defense scenario. *Proc. of the 11th International Conference on Information Fusion*, 1-17, Cologne, Germany.

[132] Johnson-Laird, P.N. (1983). *Mental models.* Cambridge: Cambridge University Press.

[133] Johnson-Laird, P.N. and Byrne, R.M.J. (1991). *Deduction*. Hillsdale, NJ: Erlbaum.

[134] Karmiloff-Smith, A. (1992). *Beyond modularity: a developmental perspective on cognitive science.* Cambridge, MA, USA: The MIT Press.

[135] Keane, M.T. and Brayshaw, M. (1988). The Increment Analogical Machine: A computational model of analogy. In D. Sleeman (Ed.), *European working session on machine learning.* London: Pitman.

[136] Kelley, R., Tavakkoli, A., King, C., Nicolescu, M., Nicolescu, M. and Debis, G. (2008). Understanding human intentions via hidden Markov models in autonomous mobile robots. *Proc. of the 3rd ACM/IEEE International Conference on Human Robot Interaction*, 367-374. Amsterdam, The Netherlands.

[137] Kewley, R.H. and Embrechts, M.J. (2002). Computational military tactical planning system. *IEEE Transactions on Systems, Man and Cybernetics, Part C, Applications and Reviews,* Vol. 32, No.2, 161-171.

[138] Khashman, A. (2008). Application of an emotional neural network to facial recognition. *Neural Computing & Applications,* Vol. 18, No. 4, 309-320.

[139] Kieras, David E. (2010). *A survey of cognitive architecture.* Online available on January 20, 2010 at http://hcc.cc.gatech.edu/documents/83_Kieras_2b_Architecture_Survey.pdf.

[140] Kimball, D. R., Smith, T. A. & Kahana, M. J. (2007). The fSAM model of false recall. *Psychological Review,* Vol. 114, No.4, 954-993.

[141] Klein, H. A. (2004). Cognition in Natural Settings: The Cultural Lens Model. *Advances in Human Performance and Cognitive Engineering Research,* Vol. 4, 249-280.

[142] Klein, H.A., and Klein, G. (2000). Cultural Lens: Seeing Through the Eyes of the Adversary. Presented at *the 9th Conference of Computer Generated Forces and Behavior Representation (CGF&BR)*. Orlando, FL.

[143] Knopf, J.W. (2002). Misapplied Lessons? 9/11 and the Iraq Debate. *The Nonproliferation Review*, Fall-Winter, 47-66.

[144] Kolodner, J. (1993). *Case-Based Reasoning.* Morgan Kaufmann, San Francisco, CA, USA.

[145] Kolodner, J. L., & Kolodner, R. M. (1987). Using experience in clinical problem solving: Introduction and framework. *IEEE Transactions on Systems, Man and Cybernetics,* 17(3), 420-431.

[146] Kosko, Bart. (1993). Fuzzy logic. *Scientific American*, 269(1):76-81.

[147] Laird, John, Rosenbloom, Paul, and Newell, Allen. (1987). Soar: an architecture for general intelligence. *Artificial Intelligence,* 33: 1-64.

[148] Lachevet, K. (2009). Mixed-Initiative Planning in a Distributed Case-Based Reasoning System. *Proc. of the 14th International Command and Control Research and Technology Symposium (ICCRTS),* Washington, DC, USA.

[149] Laughery, K.R. and Corker, K.M. (1997). Computer modeling and simulation of human/system performance. In *Handbook of Human Factors,* second edition, G. Salvendy, et. New York, NY: John Wiley and Sons.

[150] Lawrence, Jeanette. (1994). *Introduction to Neural Network.* California Scientific Software Press.

[151] Leardi, R. (2001). Genetic algorithms in chemometrics and chemistry: a review. *Journal of Chemometrics,* Vol.15, Issue 7:559-569.

[152] Lehman, Jill Fain, Laird, John, & Rosebloom. (2010). *A gentle introduction to Soar, an architecture for human cognition.* Online available on January 19, 2010 at http://www.eecs.umich.edu/~soar/sitemaker/docs/misc/Gentle.pdf.

[153] Liang, Y. (2007). An Approximate Reasoning Model for Situation and Threat Assessment. *Proc. of the 4th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD 2007)*, Vol.4, 246-250.

[154] Liao, S. (2000). Case-based decision support system: architecture for simulating military command and control. *European Journal of Operational Research*, Issue 3, 558-567.

[155] Liao, S.-H., Sun, B.-L. and Wang, R.-Y. (2003). A knowledge-based architecture for planning military intelligence, surveillance, and reconnaissance. *Space Policy*, Vol. 19, Issue 3, 191-202.

[156] Ligeza, Antoni. (2006). *Logic Foundations for Rule-Based Systems.* Springer-Verlag, Berlin Heidelberg.

[157] Lightfoot, J.M. (2003). The applicability of expert systems to a space-based defensive shield. *Space Policy*, Vol.10, Issue 4: 256-264.

[158] Lim, C.P., Woo, S.C., Loh, A.S. and Osman, R. (2000). Speech recognition using artificial neural networks. *Proc. First International Conference on Web Information Systems Engineering*. Hong Kong, China.

[159] Lindsay, R.K., Buchanan, G.G., Feigenbaum, E.A., and Lederberg, J. (1980). *Applications of Artificial Intelligence for Organic Chemistry: The Dendral Project*. McGraw-Hill Book Company.

[160] Liu, J. and Zheng, N. (1992). A new neural network model based approach to unsupervised image segmentation. *ICCS/ISITA'92*, Singapore.

[161] Logan, G.D. (1979). On the use of a concurrent memory load to measure attention and automaticity. *Journal of Experiment Psychology: Human Perception and Performance*, Vol. 5, 189-207.

[162] Looney, C.G. & Liang, L.R.(2003). Cognitive situation and threat assessments of ground battlespaces. *Information Fusion*, Vol.4, No. 4, 297-308.

[163] Louvieris, P., Gregoriades, A., Machanovich, N., White, G. and Papathanassiou, C. (2006). Parsimonious Analogical Reasoning for Smart Decision Support in Network-enabled Environments: Managing Situational Awareness. *Proc. of the 11th Conference of Coalition Command and Control in the Networked Era*, Cambridge, UK.

[164] Ly, T.C., Greenhill, S., Venkatesh, S. and Pearce, A. (2003). Multiple hypotheses situation assessment. *Proc. of the Sixth International Conference of Information Fusion*, 972-978, Cairns, Queensland, Australia.

[165] Ma, L., Chablat, D., Bennis, F. and Zhang, W. (2009). A new simple dynamic muscle fatigue model and its validation. *International Journal of Industrial Ergonomics*, Vol. 39, Issue 1, 211-220.

[166] MAAD. (2010). *IPME*. Online available on January 25, 2010, at http://www.maad.com/index.pl/ipme.

[167] MacMillan, J., Deutsch, S.E. and Young, M.J. (1997). A Comparison of Alternatives for Automated Decision Support in a Multi-Tasking Environment. *Proc. of the Human Factors and Ergonomics Society 41st Annual Meeting*, Albuquerque, NM, USA.

[168] Madeira, C., Corruble, V. and Ramalho, G. (2006). Designing a Reinforcement Learning – based Adaptive AI for Large-Scale Strategy Games. *Proc. of AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*, pp. 121-123. Marina del Rey, California.

[169] Maher, M. L., Balachandran, M. B., & Zhang. D. M. (1995). C*ase-based reasoning in design*. Mahwah, NJ: Lawrence Erlbaum Associates.

[170] Mahoney, W.E. Laskey, K., Takikawa, M. and Levitt, T. (2002). Multi-entity Bayesian networks for situation assessment. *Proc. of the 5th International Conference on Information Fusion,* Vol.2, 804-811, Annapolis, MD, USA.

[171] Markman, A.B., Rachkovskij, D.A., Misuno, I.S. and Revunova, E.G. (2003). Analogical reasoning techniques in intelligent counterterrorism systems. *International Journal of Information Theories & Applications,* Vol. 10, No.2, 139-146.

[172] Marks, R.E. (2010). *Playing Games with Genetic Algorithms.* Online available on January 21, 2010, at http://www.agsm.edu.au/bobm/papers/shu.html.

[173] McCarthy, J. (1960). Recursive Functions of Symbolic Expressions and Their Computation by Machine. *Communications of the ACM*, Vol. 3, Issue 4, 184-195.

[174] McCulloch, W.S. and Pitts, W. (1943). A Logical Calculus of the Ideas Immanent in Nervous Activity. *Bulletin of Mathematical Biophysics,* Vol. 5, 115-133.

[175] McKenzie, F.D., Catanzaro, J. and Petty, M.D. (2001). A Personality-Based Command Decision-Maker: Results and Recommendations. *Proceedings of the 10th Conference on Computer Generated Forces and Behavior Representation (CGF&BR),* Orlando, FL.

[176] McKenzie, F.D., Petty, M.D. and Catanzaro, J. (2003). An experimental application of a trait-based personality model to the simulation of military decision-making. *Information & Security: An International Journal*, Vol.12 (No.1), 75-92.

[177] McRorie, M., Sneddon, I., de Sevin, E., Bevacqua, E. and Pelachaud, C. (2009). A model of personality and emotional traits. *Intelligent Virtual Agents, Lecture Notes in Computer Science,* Vol. 5773, 27-33, Springer Berlin/Heidelberg.

[178] Merhav, Ephraim Y. (2002). Hidden Markov processes. *IEEE Trans. Inform. Theory,* Vol. 48, 1518-1569.

[179] Metaxiotis, K., Psarras, J.E. and Samouilidis, J.-E. (2004). New application of fuzzy logic in decision support systems. *International Journal of management and Decision Making*, Vol.5, No. 1, 47-58.

[180] Meyer, D.E. and Kieras, D.E. (1997a). A computational theory of executive cognitive processes and multiple-task performance. Part i. Basic mechanisms. *Psychological Review*, Vol. 104, Issue 1, 2-65.

[181] Meyer, D.E. and Kieras, D.E. (1997b). A computational theory of executive cognitive processes and multiple-task performance. Part 2. Accounts of psychological refractory-period phenomena. *Psychological Review,* Vol. 104, Issue 4, 749-791.

[182] Miryazdi, H.R. and Khaloozadeh, H. (2002). Application of Genetic Algorithm to Decentralized Control of Robot Manipuilators. P*roc. of the 2002 IEEE International Conference on Artificial Intelligence Systems (ICAIS'02),* Divnomorskoe, Russia.

[183] Mitchell, M. and Hofstadter, D.R. (1990). The emergence of understanding in a computer model of concepts and analogy-making. *Physica D,* 42(1-3), 322-334.

[184] Momoh, J.A., Dias, L.G., Thor, T. and Laird, G. (1994). Rue-based decision support system for single-line fault detection in a delta-delta connected distribution system. *IEEE Transactions on Power Systems,* Vol. 9, Issue 2, 782-788.

[185] Moore, R.C. (1984). Possible-world semantics for autoepistemic logic. *Proceedings of the Workshop on Non-Monotonic Reasoning,* 344-354. Reprinted in M. Ginsberg, et., *Reading on Nonmonotonic Reasoning,* 137-142, Morgan Kaufmann, 1990.

[186] Moore, R.C. (1985). Semantical considerations on nonmonotonic logic. *Artificial Intelligence,* 25:75-94.

[187] Moriarty, D.E. (2000). Determining Effective Military Decisive Points through Knowledge-Rich Case-Based Reasoning. *Intelligent Problem Solving, Methodologies and Approaches,* Vol. 1821, 187-267, Springer Berlin / Heidelberg.

[188] Munoz-Avila, H. Aha, D.W., Breslow, L. and Nau, D. (1999). HICAP: An Interactive Case-Based Planning Architecture and its Application to Noncombatant Evacuation Operation. *Proceedings of the Sixteenth National Conference on Artificial Intelligence and Eleventh Conference on Innovative Applications of Artificial Intelligence*, Orlando, FL, USA. Online available on January 23, 2010, at http://www.cs.umd.edu/~nau/papers/AIC-99-002.pdf.

[189] Murdock, B.B. (1982). A theory for the storage and retrieval of item and associative information. *Psychological Review,* Vol. 89, 609-626.

[190] Murdock, B.B. (1983). A distributed memory model for serial-order information. *Psychological Review,* Vol. 90, 316-338.

[191] Murdock, B.B. (1997). Context and mediators in a theory of distributed associative memory (TODAM2). *Psychological Review,* Vol. 104, 839-862.

[192] Murphy, K. (1998). *A brief introduction to graphical models and Bayesian networks.* Online available on January 20, 2010 at http://people.cs.ubc.ca/~murphyk/Bayes/bayes.html.

[193] Neath, I. and Surprenant, A. (2002). *Human Memory*. 2nd edition. Wadsworth Publishing,

[194] NeuroDimension. (2010). *NeuroSolutions*. Online available on January 24, 2010, at http://www.neurosolutions.com/products/ns/.

[195] Newell, Allen. (1990). *Unified theories of cognition.* Harvard University Press.

[196] Norman, D.A. (1986). Reflections on cognition and parallel distributed processing. In J.L. McClelland & D.E. Rumelhart (Eds.), *Parallel distributed processing: Vol. 2. Psychological and biological models,* 531-546. Cambridge, MA: MIT Press.

[197] Novak, P. (2008). Cognitive agents with non-monotonic reasoning. *Proc. of the 7th International Joint Conference on Autonomous Agents and Multiagent Systems*, 1746-1747.

[198] Novick, L.R. (1988). Analogical transfer, problem similarity, and expertise. *Journal of Experimental Psychology*: Learning, Memory, and Cognition, 14(3), 510-520.

[199] Nunez, G., Cortes, U. and Larrosa, J. (2007). Non-monotonic characterization of induction and its application to inductive learning. *International Journal of Intelligent Systems,* Vol. 10, Issue 10, 895-927.

[200] O'Reilly, R. and Munakata, Y. (2000). *Computational Explorations in Cognitive Neuroscience: Understanding the Mind by Simulating the Brain*. The MIT Press.

[201] Ortony, A., Clore, G.L., and Collins, A. (1988). *The Cognitive Structure of Emotion.* New York, NY: Cambridge University Press.

[202] Ozyilmaz, L. and Yildirim, T. (2003). Artificial neural networks for diagnosis of hepatitis disease. *Proc. of the International Joint Conference on Neural Networks*, Vol.1: 586-589. Istanbul, Turkey.

[203] Padgett, C.W. and Saad, A. (2009). *Genetic Algorithms in Chemistry: Success or Failure Is in the Genes*. Springer Berlin / Heidelberg.

[204] Pearl, J. (1988). *Probabilistic reasoning in intelligent systems: networks of plausible inference.* Morgan Kaufmann.

[205] Peirce, C.S. (1958). *Collected Papers of Charles Sanders Peirce,* v. 7-8, edited by Arthur Burks. Cambridge, MA: Harvard, See v. 8, paragraph 227, from a draft letter c. 1910.

[206] Peltarion. (2010). *Synapse*. Online available on January 24, 2010, at http://www.peltarion.com/products/synapse/.

[207] Periaux, J. Chen, H.Q., Mantel, B., Sefrioui, M. and Sui, H.T. (2001). Combining game theory and genetic algorithms with application to DDM-nozzle optimization problems. *Finite Elements in Analysis and Design,* Vol. 37, Issue 5: 417-429.

[208] Pew, R.W. and Mavor, A. (1998). *Modeling Human and Organizational Behaviour: Application to Military Simulations*. National Academy Press, Washington, D.C., USA.

[209] Pfeiffer, J., Siegel, AI. Taylor, S.E., and Shuler, Jr., L. (1979). *Background data for the human performance in continuous operations.* ARI Technical Report 386. U.S. Army Research Institute for the Behavioural and Social Sciences, Alexandria, VA.

[210] Phillips, S. Halford, G.S. and Wilson, W.H. (1995). The processing of associations versus the processing of relations and symbols: A systematic comparison. In J.D. Moore & J.F. Lehman (Eds.), *Proceedings of the Seventeenth Annual Conference of the Cognitive Science Society,* 688-691, Pittsburgh, PAL Lawrence Erlbaum.

[211] Piaget, J. (1950). *The psychology of intelligence,* (M. Percy & D.E. Berlyne, Trans.) London: Routledge & Kegan Paul.

[212] Picard, R.W. (1997). *Affective computing.* Cambridge, MA: MIT Press.

[213] Pike, R. (1984). Comparison of convolution and matrix distributed memory systems for associative recall and recognition. *Psychological Review,* 91:281-294.

[214] Polk, T.A. and Newell, A. (1995). Deduction as verbal reasoning. *Psychological Review,* 102(3), 533-566.

[215] Polya, G. (1954). *Mathematics and plausible reasoning. 1. Induction and analogy in mathematics.* Princeton, MJ: Princeton University Press.

[216] Popken, D.A. and Cox, L.A. (2003). Model identification and optimization for operational simulation. *Proc. of the Enabling Technologies for Simulation Science VII,* Vol. 5091, 294-303, Orlando, USA. Online available on February 10, 2010, at http://www.dtic.mil/cgi-bin/GetTRDoc?AD=ADA426842&Location=U2&doc=GetTRDoc.pdf.

[217] Pothos, E.M. (2005). The rules versus similarity distinction, *Behavioral and Brain Sciences,* 28(1), 1-49.

[218] Raaijmakers, J. G. W. and Schiffrin, R. M. (1981). Search of associative memory. *Psychological Review* Vol. 8, Issue 2, 98–134.

[219] Rabiner, Lawrence R. (1989). A tutorial on hidden Markov models and selected application in speech recognition. *Proceedings of the IEEE 77* (2): 257-286.

[220] Ragsdale, D.J., Butler, C.D., Cox, B.A., Yen, J. and Pooch, U.W. (1997). A fuzzy logic approach for intelligence analysis of actual and simulated mi8litary reconnaissance missions. *Proc. of the 1997 IEEE International Conference on Systems, Man and Cybernetics*, Vol. 3, 2590-2505.

[221] Rao, M. P. Georgeff. (1995). "BDI-agents: From Theory to Practice". *Proceedings of the First International Conference on Multiagent Systems (ICMAS'95).* Online available on January 23, 2010, at https://www.aaai.org/Papers/ICMAS/1995/ICMAS95-042.pdf.

[222] Rao, N. Kashyap, S.K. and Girija, G. (2008). Situation Assessment in Air-Combat: A Fuzzy-Bayesian Hybrid Approach. *Proc. of the International Conference on Aerospace Science and Technology*, Bangalore, India. Online available on January 22, 2010, at http://nal-ir.nal.res.in/5010/01/INCAST_2008-063.pdf.

[223] Ratches, J.A., Walters, C.P., Buser, R.G. and Guenther, B.D. (1997). Aided and Automatic Target Recognition Based Upon Sensory Inputs From Image Forming Systems. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* Vol. 19, No.9:1004-1019.

[224] Read, S.J. and Miller, L.C. (2002). Virtual Personalities: A Neural Network Model of Personality. *Personality and Social Psychology Review,* Vol.6 (No. 4), pp 357-369.

[225] Reber, A.S. (1967). Implicit learning or artificial grammars. *Journal of Verbal Learning and Verbal Behavior*, 6(6), 855-863.

[226] Reber, A.S. (1992). The cognitive unconscious: An evolutionary perspective. *Consciousness and Cognition: an International Journal*, 1(2), 93-133.

[227] Reber, A.S. and Allen, R. (2000). Individual differences in implicit learning: Implications for the evolution of consciousness. In R.G. Kunzendorf & B. Wallace (Eds.), *Individual differences in conscious experience. Advances in consciousness research,* Vol. 20, 227-247. Amsterdam, Netherlands: John Benjamins Publishing Company.

[228] Reed, S.K. (1987). A structure-mapping model for word problem. *Journal of Experimental Psychology: Learning Memory and Cognition*, 13, 124-139.

[229] Reed, S.K., Ackinclose, C.C. and Voss, A.A. (1990). Selecting analogous problems: similarity versus inclusiveness. *Memory and Cognition,* 18(1), 83-98.

[230] Reiter, R. (1980). A logic for default reasoning. *Artificial Intelligence,* 13:81-132.

[231] Revello, T.E. and McCartney, R. (2002). Generating wargame strategies using a genetic algorithm. *Proc. of the 2002 Congress on Evolutionary Computation,* Honolulu, HI, USA.

[232] Rielly, E.J. (2005). *Baseball: An Encyclopedia of Popular Culture*. Lincoln, NE: University of Nebraska Press.

[233] Riesbeck, C.K. and Schank, R.C. (1989). *Inside Case-Based Reasoning.* Lawrence Erlbaum Associates Inc., Hillside, NJ, USA.

[234] Ritter, F.E. and Avraamides, M.A., (2000). Steps Towards Including Behavior Moderators in Human Performance Models in Synthetic Environments. *Technical Report* No. ACS 2000-1.

[235] Roth, M.W. (1990). Survey of neural network technology for automatic target recognition. *IEEE Transactions on Neural Networks.* Vol. 1, Issue 1:28-43.

[236] Rushing, J. Tiller, J. Tanner, S. and McDowell, D. (2004). Augmenting Wargame AI with Data Mining Technology. *Workshop on AAAI-04,* San Jose, California, USA.

[237] Russell, S. and Norvig, P. (2003). *Artificial Intelligence: a modern approach.* Pearson Education, Inc.

[238] Sanchez, A., Alvarez, R, Moctezuma, R.C. and Sanchez, S. (2006). Clustering and Artificial Neural Networks as a Tool to Generate Membership Functions. *Proc. 16th International Conference on Electronics, Communications and Computers*. Puebla, Mexico.

[239] Santos, J.R., Barker, K. and Zelinke IV, P.J. (2008). Sequential Decision-making in Interdependent Sectors with Multiobjective Inoperability Decision Trees: Application to Biofuel Subsidy Analysis. *Economic Systems Research,* Vol. 20, Issue 1, 29-56.

[240] Sardina, S., de Silva, L., and Padgham, L. (2006). Hierarchical planning in BDI agent programming language : a formal approach. *Proc. of Autonomous Agents and Multi-Agent Systems (AAMAS),* 1001-1008.

[241] Schneider, W. and Shiffrin, R.M. (1977). Controlled and automatic human information processing: I. Detection, search and attention. *Psychological Review,* Vol. 84, 1-66.

[242] Scientific Soft. (2010). *Neuro Laboratory*. Online available on January 24, 2010, at http://www.scientific-soft.com/.

[243] Shank, R. C. (1982). *Dynamic memory: A theory of learning in people and computers*. Cambridge: Cambridge University Press.

[244] Shank, R. C. (1990). *Tell ma a story: Narrative and intelligence*. Evanston, IL: Northwestern University Process.

[245] Shawe-Taylor, J. and Cristianini, N. (2004). *Kernel Methods for Pattern Analysis.* Cambridge University Press.

[246] Shiffrin, R.M. and Steyvers, M. (1997). A model for recognition memory: REM – retrieving effectively from memory. *Psychonomic Bulletin and Review,* Vol. 4, Issue 2, 145-166.

[247] Shively, R.J., Brickner, M., & Silbiger, J. (1997). A computational model of situational awareness instantiated in MIDAS. *Proceedings of the Ninth International Symposium on Aviation Psychology*, pp. 1454-1459. Columbus, OH, USA.

[248] Silverman, B.G. and Bharathy, G.K. (2005). Modeling the Personality & Cognition of Leaders. *Proceedings of the 2005 Conference on Behavior Representation in Modeling and Simulation (BRIMS 2005)*. Universal City, CA, May 16-19.

[249] Smith III, J.F. (2002). Multi-agent Fuzzy Logic Resource Manager. *Intelligent Data Engineering and Automated Learning – IDEAL 2002, Lecture Notes in Computer Science,* Vol. 2412/2002, 231-236.

[250] Sloman, S.A. (1996). The Empirical Case for Two Systems of Reasoning. *Psychological Bulletin,* Vol. 119, No.1, 3-22.

[251] Sloman, S.A. (2002). “Two systems of reasoning,” T. Gilovich & D. Griffin (Eds.), *Heuristics and biases: The psychology of intuitive judgment*, New York, NY: Cambridge University Press, 379-396.

[252] Smolensky, P. (1988). On the proper treatment of connectionism. *Behavioral and Brain Sciences*, 11(1), 1-74.

[253] Sprague, K. (2010). *An Example Wargame*. Internal Communication.

[254] Sprague, K. and Dobias, P. (2010). *Games & Replications*. Internal Communication.

[255] Stanovich, K.E. and West, R.F. (2000). Individual differences in reasoning: Implications for the rationality debate? *Behavioral and Brain Sciences*, 23(5), 645-726.

[256] Starr, C. and Shi, P. (2002). *An Introduction to Bayesian Belief Networks and their Applications to Land Operations*. DSTO Technical Report. Online available on January 22, 2010, at http://www.dsto.defence.gov.au/publications/2655/DSTO-TN-0534.pdf.

[257] Stokes, A.E. and Kite, K. (2000). Op grasping a nettle and becoming emotional. In Peter A. Hancock & Paula A. Desmond (Eds.) *Stress, Workload and Fatigue*, 107-132. CRC Press, Boca Raton, FL 33487, USA.

[258] Stuttgart - University. (2010). *Stuttgart Neural Networks Simulator*. Online available on January 24, 2010, at http://www.ra.cs.uni-tuebingen.de/SNNS/.

[259] Sun, R., Helie, S. and Wilson, N. (2010).*The CLARION Cognitive Architecture: A Tutorial*. Online available on January 24, 2010, at http://www.sts.rpi.edu/~rsun/folder-files/clarion-intro-slides.pdf.

[260] Sun, R., Merrill, E. and Peterson, T. (2001). From implicit skills to explicit knowledge: a bottom-up model of skill learning. *Cognitive Science*, Vol. 25, No. 2, 203-244.

[261] Sun, R. and Peterson, T. (1996). Learning in reactive sequential decision tasks: the CLARION model. *Proc. of the IEEE International Conference on Neural Networks*, 1073-1078.

[262] Sun, R. and Peterson, T. (1998). Hybrid learning incorporating neural and symbolic processes. *Proc. of the IEEE International Conference on Fuzzy Systems*, 727-732.

[263] Suzic, R. (2005). A Genetic Model of Tactical Plan Recognition for Threat Assessment. *Proc. of the Conference on Multisensor, Multisource Information Fusion: Architectures, Algorithms, and Applications*, Vol. 5813, 105-116, Orlando, FL, USA.

[264] Talbot, P.J. (2001). Military Decision Aids – A Robust Decision-centered Approach. *Technology Review Journal*, Vol. 9, No.1, Spring/Summer, 83-86.

[265] Tang, Z.-L. and Zhang, A. (2009). A Method of Knowledge Reasoning for Threat Assessment in the Battlefield. *Proc. of the 2009 International Conference of Information Technology and Computer Science*, Vol. 2, 32-35.

[266] Tweney, R.D. (1998). Toward a cognitive psychology of science: recent research and its implications. *Current Directions in Psychological Science*, 7(5), 150-154.

[267] Tyler, S., Neukom, C. Logan, M. and Shively, J. (1998). The MIDAS human performance model. In the *Proceedings of the Human Factors and Ergonomics Society 42nd Annual Meeting.* Chicago, Illinois. pp. 320-325.

[268] Vaccaro, J. and Guest, C. (2004). Evolutionary Bayesian Dynamic Planner for Game Risk. *Applications of Evolutionary Computing, Lecture Notes in Computer Science*, Vol. 3005, 549-560.

[269] Vapnik, V. (1995). *The Nature of Statistical Learning Theory,* Springer Verlag.

[270] Warren, D.H.D., Luis M. Pereira, L.M. and Fernando Pereira, F. (1977). Prolog - the language and its implementation compared with Lisp. *ACM SIGART Bulletin archive, Issue 64. Proceedings of the 1977 symposium on Artificial intelligence and programming languages*, 109 - 115.

[271] Watson, I., Azhar, D., Chuyang, Y., Pan, W. and Chen, G. (2010). *Optimization in Strategy Games: Using Genetic Algorithms to Optimize City Development in FreeCiv.* Interim Report. Online available on January 27, 2010, at http://www.cs.auckland.ac.nz/research/gameai/projects/GA%20in%20FreeCiv.pdf.

[272] Watthayu, W. and Peng, Y. (2004). A Bayesian network based framework for multi-criteria decision making. *Proc. of the 17th International Conference on Multiple Criteria Decision Analysis*, Whistler, BC, Canada.

[273] Weaver, J.L., Bowers, C.A. & Salas, E. (2000). Stress and teams: performance effects and interventions. In Peter A. Hancock & Paula A. Desmond (Eds.) *Stress, Workload and Fatigue*, 80-106. CRC Press, Boca Raton, FL 33487, USA.

[274] Weber, L. (1998). Applications of generic algorithms in molecular diversity. *Current Opinion in Chemical Biology.* Vol. 2, Issue 3: 381-385.

[275] Wright, E., Mahoney, S., Laskey, K., Takikawa, M. and Levitt, T. (2002). Multi-entity Bayesian networks for situation assessment. *Proc. of the 5th International Conference on Information Fusion,* Vol.2, 804-811, Arlington, VA, USA.

[276] Yang, Q., Abi-Zeid, I. and Lamontagne, L. (1998). An agent system for intelligent situation assessment. *Artificial Intelligence: Methodology, Systems, and Applications, Lecture Notes in Computer Science*, Vol. 1480, 466-474.

[277] Young, Richard M. and Lewis, Richard L. (2010). *The Soar cognitive architecture and human working memory*. Online available on January 19, 2010 at http://www.andrew.cmu.edu/course/85-412/readings/soar.pdf.

[278] Zacharias, G.L., Baron, S., and Muralidharan. (1981). A supervisory control model of the AAA crew. *Proceedings of the 17th Conference on Manual Control*, 301-306, Los Angeles, CA, USA.

[279] Zacharias, G.L., Miao, A.X., Kalhan, A. and Kao, S.-P. (1994). Operator-based metric for nuclear operations automation assessment. *Proc. of the 22nd Water Reactor Safety Information Briefing. NUREG/CP-0140*, Vol. 1, 181-205, Washington, U.S.A.

[280] Zacharias, G., Miao, A., Illgen, C., Yara, J. and Siouris, G. (1996). SAMPLE: Situation Awareness Model for Pilot in the Loop Evaluation. *Proc. of the First Annual Conference on Situation Awareness in the Tactical Air Environment*, Naval Air Warfare Center, Patuxent River, MD, USA.

[281] Zachary, W., LeMentec, J.-C., Miller, L., Read, S., and Thomas-Meyers, G. (2005). Steps toward a Personality-based Architecture for Cognition. *Proceedings of the 2005 Conference on Behavior Representation in Modeling and Simulation (BRIMS 2005)*. Universal City, CA, May 16-19.

[282] Zachary, W. Le Mentec, J.-C. and Ryder, J. (1996). Interface agents in complex systems. *Human Interaction With Complex Systems: Conceptual Principles and Design Practice*, Ntuen, C.N. and Park, E.H., eds. Kluwer Academic Publishers.

[283] Zachary, W., Ryder, J., Ross, L. and Weiland, M.Z. (1992). Intelligent computer-human interaction in real-time, multi-tasking process control and monitoring systems. *Human Factors in Design for Manufucturability*, Helander, M. and Nagamachi, M. eds. New York, NY: Taylor and Francis.

[284] Zadeh, L.A. (1965). Fuzzy Sets. *Information and Control*, Vol. 8, Issue 3, 338-353.

[285] Zadeh, L.A . (1968). Fuzzy algorithms. *Information and Control*, Vol. 12, Issue 3, 94-102.

[286] Zainuddin, Z. and Pauline, O. (2008). Function approximation using artificial neural networks. *WSEAS Transactions on Mathematics*, Vol.7, Issue 6, 333-338.

[287] Zhai, Y., Tomasson, J.A., Boggess, III, J.E., and Sui, R. (2006). Soil texture classification with artificial neural networks operating on remote sensing data. *Computers and Electronics in Agriculture*, Vol. 54, Issue 2:53-68.

[288] Zhang, G. P. (2000). Neural Networks for classification: A Survey. *IEEE Transactions on Systems, Man, and Cybernetics – Part C: Applications and Reviews*, Vol. 30, No.4:451-462.

[289] Zhang, Jianting, Guo, Diansheng, and Wan, Qing. (1999). Geospatial data mining and knowledge discovery using decision tree algorithm – a case study of soil data set of the yellow river delta. In Li, B., et al., (eds.) *Geoinformatics and Socioinformatics. The Proceedings of Geoinformatics'99 Conference*, Ann Arbor, June, pp 1-8.

[290] Zhang, Lei, Wu, Bingfang, and Zhou Weifeng. (2005). Land cover classification using decision tree techniques at mesoscale structure in Three Gorge Dam, China. *Proceedings of the 2005 IEEE International Conferences of Geoscience and Remote Sensing Symposium*, July 2005.

[291] Zhao, Q. and Bao, Z. (1994). Radar target recognition using a radial basis function neural network. *Neural Networks*, Vol. 9, Issue 4:709-720.

List of symbols/abbreviations/acronyms/initialisms

ACME	Analogical Constraint Mapping Engine
ACT-R	Adaptive Control of Thought – Rational
AGL	Automatic Grenade Launcher
AI	Artificial Intelligence
ANN	Artificial Neural Networks
API	Application Programming Interface
ATGM	AntiTank Guided Missile
BDI	Belief-Desire-Intention
CAE	Canadian Aviation Electronics
CAEn	Close Action Environment
CBR	Case-Based Reasoning
CGF	Computer-Generated Forces
CLARION	Connectionist Learning with Adaptive Rule Induction On-line
CLIPS	C Language Integrated Production System
CORA	Center for Operational Research and Analysis
CW	Conventional Warfare
DAG	Directed Acyclic Graph
DIS	Distributed Interactive Simulation
DND	Department of National Defence
DRDC	Defence Research and Development Canada
EA	Evolutionary Algorithm
EPIC	Executive-Process Interactive Control
fMRI	functional Magnetic Resonance Imaging
FWA	Fixed-Wing Aircraft
GA	Genetic Algorithm
GOMS	Goals, Operators, Methods and Selection rules
HBR	Human Behaviour Representation
HLA	High Level Architecture
HMM	Hidden Markov Model
HOS	Human Operator Simulator
HP	Hewlett-Packard
IAM	Incremental Analogy Machine
IPME	Integrated Performance Modeling Environment
IW	Irregular Warfare
JCATS	Joint Conflict And Tactical Simulation
LAMP	Language of Agents for Modelling Performance
LFORT	Land Force Operational Research Team
LISA	Learning and Inference with Schemas and Analogies
LISP	List Programming
LV	Low Velocity
M&S	Modelling and Simulation
MIDAS	Man Machine Integration Design and Analysis System
NASA	National Aeronautics and Space Administration
NN	Neural Networks
OMAR	Operator Model Architecture
OneSAF	One Semi-Automated Forces
OPS	Official Production System

PGAT	Post-Gaming Analysis Tool
Prolog:	Programming in Logic
PRS	Procedural Reasoning System
R&D	Research and Development
RPDM	Recognition-Primed Decision Making
RWA	Rotary-Wing Aircraft
RWS	Remote Weapon System
SAMPLE	Situation Awareness Model for Pilot-In-The Loop Evaluation
SDM	Soar Dynamic Memory
SE	Synthetic Environment
SIMON	Simulated Operators for Networks
SIMPLE	Scale Invariant Memory and Perceptual Learning
SME	Structure-Mapping Engine
Soar	State, Operator And Result
SOF	Special Operations Forces
STAR	Structured Tensor Analogical Reasoning
STOW	Synthetic Theater of War
SVM	Support Vector Machine
TacAir	Tactical Air
TCP	Transmission Control Protocol
TTP	Tactics, Techniques, and Procedures
VDB	Virtual Data Base (or more specifically, Virtual Command and Control Interface Database)

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13. ABSTRACT

The focus of this project was to assess potential improvements to the current wargame replication system used by the Land Force Operational Research Team (LFORT) in DRDC CORA through the integration of human interactors' intentions. The project, based on the analysis of problems in current wargame replication systems, reviews competing Artificial Intelligence (AI) and Human Behaviour Representation (HBR) approaches, tools and systems applicable to the wargame replication domain. For each identified approach, the main concepts, advantages, limitations and application areas are briefly described.

The typical problems in wargame replications are categorized widely as situation / pattern assessment and recognition, knowledge discovery, decision making and planning. There is no single AI or HBR tool that is appropriate for resolving all of these problems. This project proposes a framework-based solution by combining human science results, existing approaches and human behaviour moderators to solve various problems in wargame replications.

L'objectif du présente projet était d'évaluer les améliorations possibles pouvant être apportées au système de réplication de jeu de guerre actuel qu'utilise l'Équipe de recherche opérationnelle de la Force terrestre (EROFT) de RDDC CARO à l'aide de l'intégration des intentions des interacteurs humains. Le projet, en se basant sur l'analyse de problèmes liés aux systèmes de réplication de jeu de guerre actuels, permet d'examiner des systèmes, des outils et des approches possibles d'intelligence artificielle (IA) et de représentation du comportement humain (RCH) applicables dans le domaine de la réplication de jeu de guerre. Pour chaque approche identifiée, les concepts, les avantages, les restrictions et les secteurs d'application généraux ont été brièvement décrits.

Les problèmes typiques de la réplication de jeu de guerre sont placés dans les catégories générales suivantes : reconnaissance et évaluation de la situation et de la tendances, découverte de connaissances, prise de décision et planification. Aucun outil d'IA ou de RCH ne résout entièrement tous les problèmes. Le présent projet propose une solution fondée sur un cadre en combinant les résultats des sciences humaines, les approches existantes et les modérateurs de comportements humains afin de résoudre les problèmes liés à la réplication de jeu de guerre.

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Wargame Replication, Artificial Intelligence, Scoping, Architecture

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