New Ideas on the Artificial Intelligence Support in Military Applications

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Abstract: Military decision making demands an increasing ability to understand and structure the critical information on the battlefield. As the military evolves into a networked force, decision makers should select and filter information across the battlefield in a timely and efficient manner. Human capability in analyzing all the data is not sufficient because the modern battlefield is characterized by dramatic movements, unexpected evolutions, chaotic behavior and non-linear situations. The Artificial Intelligence (AI) ingredient permits to explore a greater range of options, enabling the staff to analyze more possible options in the same amount of time, together with a deeper analysis of these options.

Key words: artificial intelligence (AI), AI algorithms, MDMP (Military Decision Making Process), RPD CoA (course of action).

1 Introduction

Military decision should consider information about a huge range of assets and capabilities (human resources combat and support vehicles, helicopters, sophisticated intelligence and communication equipment, artillery and missiles) that may perform complex tasks of multiple types: collection of intelligence, movements, direct/ indirect fires, infrastructure, and transports.

The decisional factor needs an integrated framework capable to perform the critical steps, from capturing a high-level course of action (CoA) to realizing a detailed analysis/ plan of tasks (Hayes, Schlabach 1998, Atkin, 1999, Tate, 2001, Kewley, Embrecht) and one possibility is to be based on different AI techniques, ranging from qualitative spatial interpretation of CoA diagrams to interleaved adversarial scheduling.

Given the logistics consumption and the complexity of time/space analysis, the classic decisional process is time and manpower consuming (Bohman 1999, Paparone 2001) and is dramatically limiting the number and diversity of options able to explore and analyze (Banner 1997).

The military planning process is typically composed on the following steps: *initiation:* corresponds to mission trigger and task reception; *orientation:* includes mission assessment, mission statement and decision maker's planning guidance; *concept development:* includes staff's analysis, friendly and enemy courses of action development and analysis, and decision maker's estimate; *decision:* includes courses of action comparison and selection, course of action approval, decision maker's direction, review of critical assumptions; *plan development:* mainly concerned by synchronization and finalization; *plan review:* includes analysis and revision of plans.

Elaboration, mitigation and evaluation of different CoAs are significant steps in planning process. CoA development and analysis are exercises in which are simulated different situations. Time constrains the process to generate a complete range of CoAs, and evaluate them according to significant point of views, before selecting and executing the optimal one.

2 A review of the possibilities to introduce AI algorithms in military applications

AI based military decision behavior models can be classified into the following groups: models based on neural networks (NN), Bayesian belief networks (BBN), fuzzy logic (FL), genetic algorithms (GA) and expert systems (ES).

2.1 Neural Networks applications

NN philosophy is based on the concept of a neuron as a unit for information storage and mapping input to output. NNs are based on the connection of sets of simple processing elements/ nodes, where a weight is associated to each connection between nodes. Weights are initialized randomly at the beginning, and as the network begins to learn, the weights change. The neuron receives a numerical input vector (binary or part of a continuum) and each element of the input vector is scaled by a weighting constant, which assigns the importance rank to each input. The result of the dot product is used into a squashing function whose output is used as the input to another neuron.

Other types of networks are self-organizing maps (SOMs) in which neurons are connected together in a grid such that each neuron is connected only to its neighbors, receiving input from the bottom and giving output at the top. SOM-like networks excel at picking out features from images. Other network types include recurrent Hopfield networks and stochastic Boltzmann machines.

NNs can be trained to produce specific outputs for specific inputs and also to produce specific answers for specific kinds of inputs. This leads to their most common usage: pattern recognition. Their status as a decision algorithm rests on their ability to classify inputs for which they have not been previously trained. The greatest disadvantage of NNs is that they are exceedingly slow to train because they are usually run on a single processor computer and do not take advantage of their massive parallel processing potential—the potential that nature maximizes in human brains. We see the same problem later in GAs.

NNs are usually used for pattern recognition or classification but they are poor in decision-making applications because they lack computational efficiency and tend to act as a black box unless a laborious query-and-response procedure is undertaken to develop rules after training is complete. NNs have been successfully applied to automatic target recognition (Rogers, 1995), data fusion (Bass, 2000; Filippidis, 2000), agent-based, recognition-primed decision models (Liang, 2001) and determining decisive points in battle planning (Moriarty, 2001).

In Bayesian belief networks (BBN), the architecture is designed in accordance with expert knowledge instead of trained. BNN allow users to develop a level of confidence that a particular object will be in a particular state based on certain available information. Belief networks add probability to facts and inferences that indicates how much credence the fact lends to an inference. In (Starr, 2004), BNN are "directed acyclic graphs over which is defined a probability distribution". Each node in the graph represents a variable that can exist in one of several states. A node could be ground forces with different states (attack, withdrawal, defending). The network is set up to represent causal relationships. For example an enemy intention node might be the parent of a ground forces node. Bayesian networks can be solved using conditional probability methods. Bayesian networks are suitable when variables have a small number of states. They could be useful in multi-resolution models where smaller networks can be connected into larger ones and treated as black boxes. They are not a good choice for maneuver or force allocation because of their scalability limitations (probabilities are difficult to assign).

2.2 Genetic Algorithms

The classic genetic algorithm (GA) begins as a search technique for tackling complex problems. Through the process of initialization, selection, crossover, and mutation, GA repeatedly modifying a population of artificial structures in order to chose an appropriate structure for a particular problem. GAs are useful when the fitness landscape contains high, narrow peaks and wide stretches of barren waste between them, GAs. If the area covered by fitness peaks approaches zero compared to the number of bad solutions in the landscape (good solutions are exceedingly rare) a random problem solver will rarely find a good solution. Real world fitness landscapes correspond to the difficult problems where traditional algorithms fail, and GAs should be applied to these problems.

Some researchers have attempted to use GA in assisting military decisions. Packard (1990) used GAs in time-series prediction. Allen, Karjalainen (1993) used genetic programming (GP) to find new decision rules. Bauer (1994) suggested a decision selection method based on GAs in which one or more variables are defined to determine an attractive strategy, and a GA finds thresholds for these variables, above or below which a strategy is attractive.

GAs design requires only few heuristics and their input and output design is highly configurable and more intuitive. GA's discover the rules that create good solutions, and these rules are often ones that humans would rarely consider. NN input must be in a vector format, and certain input configurations may be better than others; NN outputs must be in a vector format, numbers between 0 and 1. Using heuristics, the designer must convert solutions and input data into a format that may not be either intuitive or optimal. GA's input should be defined as the parameters of a fitness function whose output is a single number. The fitness function has an intuitive interpretation describing how good a solution is.

GA it is fast, flexible, intuitive and transparent, and lends itself to the discovery of a variety of options. GA begins with a seed population of trial solutions and then evolves this population over several generations to find better and better solutions. The process is analogous to natural selection: Solutions are grouped by similarity, combined to form new possibilities, varied to allow for incremental improvement and evaluated against each other to find the best of each generation to pass to the next. This principle can be repeated a fixed number of times or until the solutions stop improving appreciably

2.3 Fuzzy Logic

Fuzzy Logic (FL) architecture consists of a set of fuzzy rules that expressed the relationship between inputs and desired output. In these models inputs are fuzzyfied, membership functions are created, association between inputs and outputs are denned in a fuzzy rule base, and fuzzy outputs are restated as crisp values. Fuzzy rules in such a model could be provided by the decision maker (subjective fuzzy logic) or elicited from raw data (objective fuzzy logic).

Wong, Wang (1992) developed a fuzzy-neural system for decision selection. Yuize (1991) applied fuzzy logic approach to a decision support system. Ye, Gu (1994) developed a hybrid neuro-fuzzy model in which fuzzy logic enhances a neural trading system.

Fuzzy Associative Memories (FAM) proposed by Kosko (1992) is used to determine decision rules. In this method, the weight vector of a network trained by input-output data is considered as the membership function of input-output space.

Benachenhou, (1994) developed a fuzzy rule extraction tool (FRET) that extracts fuzzy rules from input-output data by FAM method, and then uses them in a fuzzy decision support system. A fuzzy rule set derived from sample data is then used as a fuzzy expert system.

Man, Bolloju (1995) implemented a prototype of a fuzzy rule based decision support system. To extract and transfer decision maker's expertise, they employed unstructured interviews with some experienced decision makers. Fuzzy rules representing the commander's decision making process are quite close to the terminology used by the experts and the rules are easily interpretable. The use of FL for knowledge representation has facilitated a high level of abstraction of the experts' knowledge. Moreover, the flexible relationship represented by membership functions and fuzzy rules, between the variables in the model have provided a robust model of the decision making process.

In maneuver planning and force allocation, FL's usefulness comes from its capability to synthesize easy to understand statements from complex data, a kind of fusion. This leads to the judgment that they ought to be closer together. In this case FL allows facts to be translated into judgments quite easily but is not suitable in telling a unit to go to a particular point or a specific coordinate. The performance of global judgments based on FL unless a GA ingredient is added

2.4 Expert Systems

Expert systems (ES) use a knowledge base including a set of rules and an inference mechanism that provides computer reasoning through inductive, deductive, or hybrid inductive- deductive reasoning. Knowledge base rules usually are undertaken through interview with traders. Rules in such knowledge-based systems are represented in the form of computer readable sentences. Checking for consistency and validity of rules is essential for a knowledge-based system, which is complex and difficult in the financial field, even when it is a system with only a dozen rules.

Lee, Jo (1999) developed an expert system based on candlestick analysis to determine the timing of action. In candlestick analysis there are several patterns which can imply future battlefield movements. Various such patterns were used to construct the knowledge base. Several aspects, such as recognition of patterns, formulization of pattern definition, rule generation based on the patterns, performance evaluation of the rules, should be considered, which requires much effort.

3 A comparative analysis of the candidate AI techniques

Regarding the learning capacity of various AI techniques ES, FL, NN, GA can be ordered from low to high. ES and FL as suggested by Zadeh are not capable of learning anything. NN and GA have learning capability, although on average, pure GA usually need a longer learning time (Russo, 1998), but when a priori knowledge is concerned, the order is inverted. GA need no a prior knowledge;

NN need very little; FL and ES need quite detailed knowledge of the problem to be solved.

NNs are capable of learning and can therefore be used when all that is available are some significant examples of the problem to be solved, rather than a solution algorithm. NNs are capable of learning from examples, but what is learned is not easy for humans to understand. Complexity and interactions between the hidden nodes of a NN make it unattainable to understand how a decision is made. The outputs have to be trusted blindly, and this is what does not endear the NN to decision makers.

GAs are affected much less than NNs by the problem of local optima and has far less likelihood than a NN of finding a local optimum rather than a global one; this is likely to correspond to a less significant learning error. Their learning speed is generally slower and they are computationally intensive requiring much processing power.

ES are more flexible to modification than neural or genetic based systems because rules can be adjusted over time, and when the system doesn't perform properly but it is impossible to build in the absence of experts and a priori knowledge. In comparison with FL, more rules are needed in expert systems to cover possible outcomes.

Subjective FL’s linguistic representation is very close to human reasoning. It is much less complex in terms of computational effort. Unlike in ES, overlap or ambiguity between rules can be managed in FL. It is not capable of learning and it is impossible to use when experts are not available.

The objective FL (Takagi, Sugeno, 1985), inherits all the advantages of subjective fuzzy logic, but not the less desirable features. It possesses good learning capacity and can therefore be used when all that is available are some significant examples of the problem to be solved, rather than a solution algorithm. The system generates a fuzzy knowledge base, which has a comprehensible representation. Therefore, one can easily understand how a decision is made. It is independent of experts and it has a low degree of computational complexity. The optimization of a fuzzy model requires some effort in order to arrive at the optimal mix of membership functions and the number of fuzzy rules. Lack of available tools that optimize these functions is the main bottleneck.

4 The use of DSS - CoA in operation planning

CoA design is based on the understanding of the situation assessment, mission analysis, resources status assessment. According on the time available, the decision staff should develop different CoAs that answer to some critical questions (when, who, what, where, why and how), each of them suitable, feasible, acceptable, exclusive, complete. The analysis of these CoAs could be based on war gaming simulations even if some authors considered that war gaming could be a frustrating tool for the military since the selected CoA is never wargamed sufficiently to achieve synchronization. Based on the fact that the staff has to deal with huge volume of information in a very short time period DSS would be helpful in any step of the operation planning process.

DSS-CoA should be based on a detailed investigation of how the staff perform CoAs evaluation, analysis, selection. Since the evaluations of the CoAs according to the different criteria might include uncertainty, ambiguity, fuzziness, subjectivity, is necessary to minimize the risk component introduced during the evaluation process. A graphical and intuitive tool could balance the relative importance of the set of criteria. A stability interval analysis tool could be the answer to the increase of the awareness of the decision-maker about the role of relative importance coefficients.

The design, development, implementation of DSS- CoA is based on formal models of a CoA designed in special processes of knowledge acquisition. The event model uses operational information required by the evaluation and analysis tools and contextual information (socio- political aspects). Even if the event model would have been a lot simpler without this contextual information, this information is critical in the CoAs generation process.

DSS should be integrated to the organization workflow, and should be designed in a way to facilitate the acceptance and the transition. DSS should interact with other information, planning and decision systems.

DSS-CoAs selection support the following functions: description of the event, development/description of possible CoAs, identification of criteria to be used in the evaluation process, evaluation of the CoAs according to the selected criteria, analysis and comparison of these CoAs, and post-execution analysis that are performed sequentially or simultaneously. Decision staff is in charge of describing the events and the capability to support this function should allow the creation of new events, the upgrade of the description of an existing event, the retrieval of old events to trigger the CoAs development or the selection processes. The event description should be based on a framework that include information related to situation review, assumptions about the enemy, enemy forces and CoAs, planning guidance, other consideration aspects, theatre of operation features, and own forces capabilities.

This information is essential to fully understand the problem, essential for a better assessment of the situation.

CoAs facility should include the creation of a new CoA, the update of existing ones, and the verification of CoA feasibility. In this case a model that include information related to action items that describe the actions to be performed by the resources (what, who, how, when) should be used to represent a CoA. As soon as the CoAs description is completed, the planning officer needs a communication channel to trigger the evaluation and selection processes.

The automated evaluation of each CoA is made according to each criterion. Heuristics may be used or subjective assessment may be directly provided by the users. A selection facility must allow automated CoAs comparison and the decision-maker considers different criteria when comparing CoAs. This facility should then, according to different types of situations, propose different criteria to be considered in the evaluation process, and predefined weights and thresholds accordingly. Even if the proposed criteria should be considered, the decision-maker should have the possibility to select those he considers most appropriate for the actual situation. This should be performed in an interactive way. When the criteria are selected, the CoA comparison should be done automatically, using Multiple Criteria Decision Analysis (MCDA) procedure, and different types of results must be presented to the decision-maker. A graph may represent the ranking of the CoAs. It is essential that information about the quality of each CoA should be presented since this graph only indicates only the rank of CoAs. Among the analyses that can be provided to help a decision-maker, there is a dominance check which verifies if a CoA is better than all other CoAs on all the criteria, no matter the value assigned to the different thresholds. A weight stability analysis offer to the decision-maker information on the sensitivity of the criteria when weights changes. A what-if analysis on the model parameters or on the CoAs evaluations allows the decision-maker to foresee the effects of the actual settings on the prioritization of the CoAs. This enables the user to either select any CoA while providing justifications, or ask for more satisfactory CoAs and information.

A post-analysis facility should allow the reconsideration of the relevance of the choice made while the event is completed. Once a CoA has been selected and executed, the commander could then re-evaluate if its decision was the best one or not, and why. This precious knowledge should be archived for reference to future operations. This knowledge will be used to learn from experience.

Finally, the functional facilities must allow the management of the criteria, and the default parameters used within the different decision analysis procedures. This facility must support an analyst in creating new criteria, updating existing ones and associating criteria with generic instances of events. Also, this facility should enable him to set default values for different parameters.

Since the processes of defining events and CoAs, evaluating and comparing CoAs, and selecting the most appropriate one are realized through a team effort, it is important to be able to assign different facilities to different people by defining user’s profiles (event editor, responsible to describe an event; CoA editor, responsible to define and describe appropriate CoAs for a specific event; commander to select the most appropriate CoAs; analyst for managing the criteria and to set the parameters according to the preferences of the decision-maker; system administrator, responsible to define who can have access to the system to do what.

DSS-CoA must have a facility to manage the user's profile, and maintain the databases on event, CoA and criteria and this ingredient could be used by a system administrator to create new users, assign privileges, and update user's profile.

6 Conclusions

The AI ingredient in military decision making offers a strong support capable to create natural sketch-based interfaces that domain experts can use with low training. The users expressed the desire for a single integrated framework that captures CoA sketches and statements simultaneously and capable to provide a unified map-based interface to do both tasks. The interest is to design a framework capable to express CoA sketches equipped with visual understanding.

DSS-CoA offers the inspiration to define a set of facilities appropriate for any DSS developed for the evaluation and selection of CoAs: event management facility; CoA management facility; CoA evaluation facility; CoA comparison, analysis and selection facility; Post-analysis facility; criteria management facility; system administration facility. DSS- CoA users should be aware about the limitations and the level of trust and an explanation facility providing result explanations adapted to the user (background, experience, knowledge, preference) and the context (time available) are important in military decision training.

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