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PARSIMONIOUS ANALOGICAL REASONING FOR SMART DECISION SUPPORT IN NETWORK-ENABLED ENVIRONMENTS: MANAGING SITUATIONAL AWARENESS

Topics: Cognitive Domain Issues, C2 Modelling and Simulation, Network Centric Metrics

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Parsimonious Analogical Reasoning for Smart Decision Support in Network-enabled Environments: Managing Situational Awareness

Abstract

How information is managed and exploited to support commanders' intuitive decision making during the execution of a plan is a key consideration in the development of a true networked enabled capability (NEC). While the benefits of NEC are laudable i.e. better networks, better information sharing and situational awareness, better decisions, better actions and better effects, commanders and their staff are nevertheless faced with an overwhelming amount of data; in practice, this can often lead to inconsistent perspectives and tempo stagnation impeding decision and operational effectiveness. Therefore reducing the information volume requirement and servicing commanders' critical information requirements (CCIRs) through parsimonious information fusion is fundamental to maintaining situational awareness (SA) in the battlespace and achieving decision effectiveness. This paper outlines and demonstrates an analogical reasoning approach for smart decision support in NEC which employs soft Case Based Reasoning (CBR) techniques incorporating Critical Success Factors (CSFs). The effectiveness of this approach is illustrated using a war-gaming case study implemented on a Computer Generated Forces (CGF) test-bed.

1 Introduction

Effective decision making constitutes the most important factor of modern warfare. Decision making however is directly related to information availability. Information, despite its importance in this process it poses obstacles when is either unavailable or available in large quantities. Lack of information creates uncertainty which in its turn increases the operational risk of military missions. On the other hand, information overload deteriorates effective decision making. Human Decision makers have limited cognitive capacity that when reached it impairs their decision making capability. According to Miller (Miller, 1956) our information processing capacity is limited to seven plus or minus two distinct information items. The actual range has been doubted but the fact that the human information processing capacity is limited reached a consensus. Hence, in order for information to be able to be exploited by the decision maker it is important that is fused into chunks that do not exceed this range. Inherently, information processing increases the mental workload of the decision maker which in effect reduces its situation awareness (SA) (Gregoriades et al, 2005). SA is defined as the ability to perceive the mental cues from the environment, comprehend them and project possible scenarios that can emerge from them (Endsley et al, 2003). SA research originally was conducted for fighter pilots. Subsequent work on SA focused on commercial aviations (Robinson, 2000), air traffic control (Durso et al, 1998) medicine (Xiao et al, 1997) and military command and control (Artman, 1999).

Endsley et al (2003) warn socio-technical systems designers of the importance of maintaining SA in such systems and draw the attention on the things that could inhibit SA. One of the most important strains of SA is information overload. Too much information at any point in time hinders adequate SA of human operators. Overloading divides decision maker's attention among numerous stimuli which results in increased demand for cognitive resources. Generally, if stimuli do not compete for the same modality (visual, auditory) then the operator would be able to handle the situation with adequate SA. On the other hand, if the stimuli compete for the same modality then the operators SA will quickly become outdated and his decision making capability will be reduced. Additionally, when too much information is available then information scanning capability is reduced. This is due to the effect of attentional tunnelling (Endsley et al, 2003) where decision makers lock their attention on certain aspects of the environment they are trying to process, and ignore other important stimuli.

This paper illustrates the development of a decision support tool that relates to Endsley's design principles for SA which dictate for the mitigation for information overload, reduction of display density, enhance the ability of the commander to comprehend the meaning of data and finally assist in developing projections of the status of important data in the near future. The concept is based on fusion of vast amount of information from the environment into meaningful attentional directives/cues that describe the situation. These directives act as precursors based on which Critical Success Factors (CSFs) of any given situation are assessed. CSFs by definition are specific for each situation and describe the key aspects that if tackled satisfactorily will maximise the likelihood of realising military intent (Louvieris, 2004). Therefore, it is essential for successful decision making to identify the CSFs specific to the situation in hand early in the decision making process in order to provide a decision edge that delivers military advantage. Assessment of CSFs is performed based on observed information acquired from the environment and its quantification through probabilistic models that embed prior knowledge of the domain and powerful inference capabilities. These models are expressed in Bayesian Belief Networks (BBN) format.

The purpose of this paper is to outline a novel approach for maintaining SA of military commanders and improving decision effectiveness throughout the execution of military scenarios. It incorporates the use of Critical Success Factors (CSFs) to reduce the complexity by de-cluttering and speeding up the military decision making process. The underlying concept of the approach is based on the principles of analogical reasoning and its realisation through Case-Based Reasoning (CBR). The application of Bayesian networks enables real time quantification of CSF success likelihood based on events that emerge in the environment.

2 Situation Awareness and Data fusion

The term SA is most commonly used in the Human-Computer Interaction (HCI) community (Endsley et al 2001). The concerns of this community are to design computer interfaces so that a human operator can achieve SA in a timely fashion. From this perspective, SA is a cognitive process that occurs in the mind of the operator. In almost any fairly complex system, such as military aircraft and nuclear reactors, manual tasks are being replaced by automated functions. However, human operators are still responsible for managing SA. This raises new kinds of problems due to human limitations in maintaining SA. The SA literature gives many examples of incidents and accidents due to reduced SA caused by human out of the loop situation.

SA is also used in the data fusion community where it has been more commonly referred to as "situation assessment". Data fusion is an increasingly important element of diverse military and commercial systems. The process of data fusion uses overlapping information to detect, identify and track relevant objects in a region. The term "data fusion" is used because information originates from multiple sources. Briefly, data fusion is the process of combining data to inform states based on which to make predictions (Wald, 1998).

SA is the process of being aware of everything that is happening in the environment of your interest and the relative importance of each entity belonging to that environment. Situational awareness can be broadly described as a person's state of knowledge or mental model of the situation. SA is important for effective decision making and performance in any complex and dynamic environment. Especially in the military domain SA constitutes a key component for effective and timely decision making. According to Endsley et al (2003), SA is the process of perceiving relevant information from the environment, comprehend their meaning and project their future status. This supports three distinct levels of processing: the perception, the comprehension and the projection (figure 2). The Endsley's model however, assumes that these mental processes are sequential in nature which is a simplified view of cognition that inherently is a non serial process. Researchers in the area of SA have identified a close link between Endsley's model and the Joint Development Laboratory (JDL) (Franklin 1998; Steinberg 2004; Steinberg 1998) model for data fusion. Inherently the JDL model as depicted in figure 1 is composed of five distinct levels associated with three cognitive processes, looking, thinking and anticipating that directly link to Endsley's SA model.

- Level 0: Estimation of States of Sub-Object Entities (e.g. signals, features)
- Level 1: Estimation of States of Discrete Physical Objects (e.g. vehicles, buildings)
- Level 2: Estimation of Relationships among Entities (e.g. aggregates, cuing, intent, acting on)
- Level 3: Estimation of Impacts (e.g. consequences of threat activities on one's own assets and goals)
- Level 4: Human computer interaction and decision making (approaches that aim to improve human performance via reducing human error, response time and improved decision making).

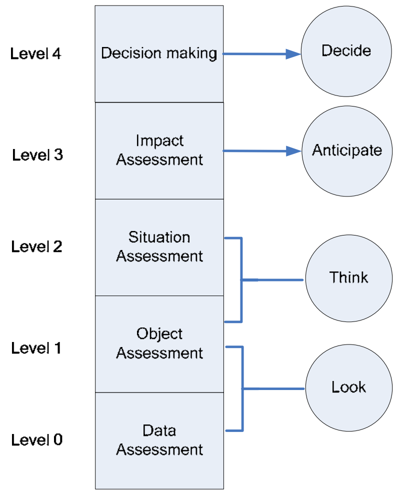

Figure 1. The JDL model

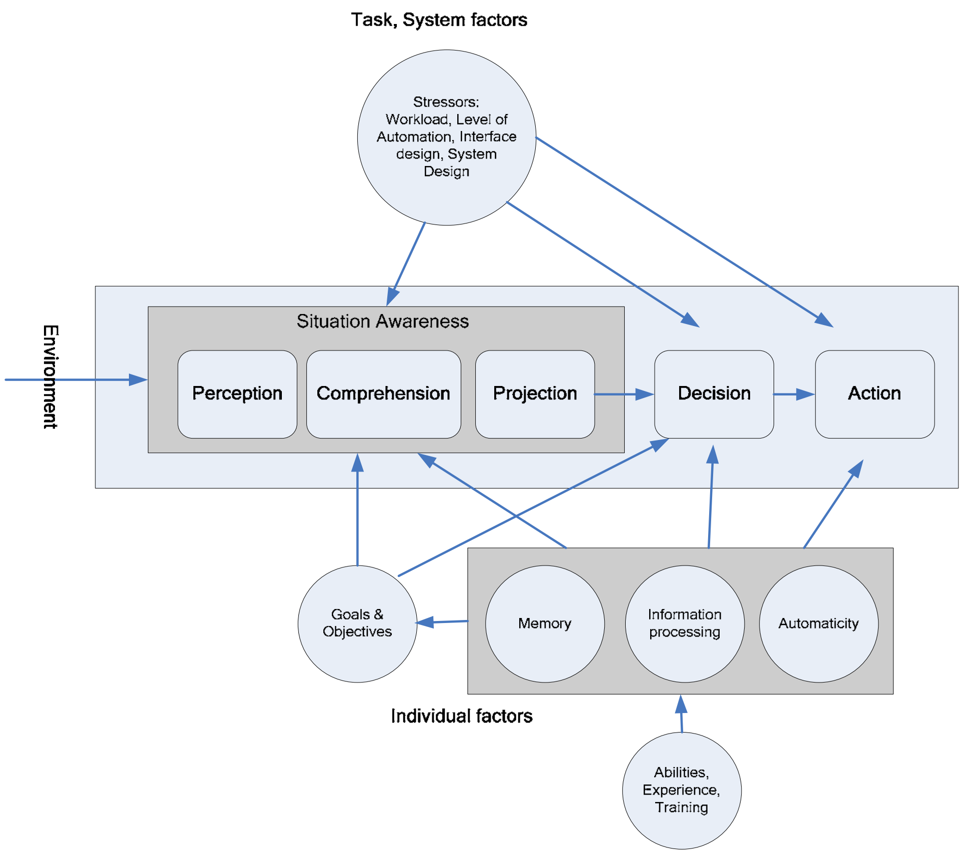

Figure 2. Endsley's model for SA

SA has numerous influencing factors; categorised into two main groups, the individual and the task/system. The former describe the inherent properties of the human agent while the latter focus on the characteristics of the task and the system of use (Endsley, 200). Studies have shown that SA is highly dependent on mental workload (Franklin et al, 1990) (Endsley et al, 2003). Mental workload (Endsley et al, 2002) in turn is influenced by time on duty, task complexity, system design and the environmental conditions (Gregoriades et al 2005). Mental workload is defined as the demand for information processing inherent in operational task execution. In such a process, data is assimilated into information chunks based on which reasoning is performed. To mitigate this, frameworks such as the JDL aim to reduce the cognitive load of the human decision makers by providing them with information needed to maximise the likelihood of making the right decision. Within the context of the JDL model, this paper aims to de-clutter the situational picture through the use of CSFs.

In analogy to the Boyd's OODA (observe, orient, decide, act) (Boyd 1987) model, SA is directly related to the orientation task which define the process of placing observations into context. The common property of these approaches is the need for fusing the data obtained from different sources to infer about the context and behaviour of objects within the environment. Considering the above it is evident that SA is a precursor for satisfactory decision making. Hence, automated support for SA acts beneficially to decision making.

3 Military Decision Making

Decision making is defined as the cognitive process of selecting a course of action among multiple alternatives. Every decision-making produces a final choice. It can be an action or an opinion. Therefore decision-making is a reasoning process which is based on the knowledge and experience of the decision maker. However, there is a constant pressure on commanders to make the right decision on time. This requirement is not always possible when the information based on which decisions should be made is not available, or there is too much of it. Decision making in military operations, due to the nature of the domain, it is often characterized by time pressure and dynamically evolving scenarios. Automated decision support often fails to recognize these critical aspects of the problem (Louvieris et al, 2005), having been designed under the assumption of low time pressure in relatively static scenarios. Decision support tools have concentrated on helping the decision maker generate options, propagate their various consequences, and evaluate the relative merits of a given option. They attempt to overcome the limitations and biases that a human decision maker experience while generating, propagating, and evaluating decision options. Dealing with complex systems does not come naturally despite the advanced cognitive skills that humans seemingly possess. The limit to our cognitive capabilities is evident from the volume of human errors that are committed in such complex environments. The principle component of this limitation is the difficulty in dealing with the temporal aspects of the system. On the other hand spatial configurations of the system can be perceived the relative ease.

Klein (1998) argues that decision making behaviour of experts under high time pressure is highly based on SA. His work suggests that expert decision makers under these conditions do not generate or evaluate options, but only assess the situation. Once the situation is assessed, the reaction strategy and resulting decision is almost automatic. This is SA-centred decision making (sometimes called recognition-primed decision making- RPD) and has been widely accepted as the most appropriate representation of actual human decision making in high-tempo, high-value situations (Klein 1998; Klein 1997) such as the military. Our approach supports this philosophy by providing the required automation to support commander's SA in time and information dependent conditions.

4 CSFs and their Elicitation

Military Critical Success Factors (CSFs) are the key areas on which commanders should concentrate and that should be monitored for the successful realisation of intent (Louvieris, 2004). CSFs were originally introduced by Rockart (1979) and are defined as the limited number of areas in which results, if satisfactory, will ensure successful performance for the organization. Within the military context the CSFs definition has been modified to reflect the uncertainty in military outcomes. Hence, CSFs are defined as those few critical areas in which results, if satisfactory, will maximise the likelihood of effect-based success (Louvieris et al , 2005).

CSFs are the “corner stone” of our approach. They play an important role in determining commanders’ critical information requirements (CCIRs). CSFs facilitate the efficient pull-through and parsimonious fusion of critical information to support commanders’ intuitive decision making and can be used to de-clutter information and thus speed up answering the estimate. Moreover, as CSFs are elicited from SMEs who are best able to define the CSFs most suitable to support their intuitive decision making processes in accordance with the Naturalistic Decision Making (NDM) paradigm.

5 Method

The method is based on the principles of analogical reasoning (Gentner 1983; Falkenhainer, 1989) where unfolding scenarios are compared with past scenarios to identify similar instances based on which the most appropriate strategy for tackling the problem is retrieved. A computational technique that mimics the above inherently human-oriented problem solving strategy is Case-based Reasoning (CBR). CBR method is characterised by five distinct stages namely: retrieval, reuse, revise, review and retain. Each of these stages is dependent on a representation of the problem in the case-base. This constitutes the case representation which could be addressed with numerous techniques according to the problem definition (Kolodner 1993).

The underlying methodology is described in the following distinct stages:

1. Data acquisition
2. Information interpretation
3. Scenario characterisation
4. Scenario retrieval
5. Scenario Simulation

Data acquisition is concerned with the continuous monitoring of entities actions in a Synthetic Environment (simulator), and the population of data structures based on state transitions of the monitored entities. Information interpretation utilises the acquired data and convert these into meaningful information to be analysed. Based on this information a scenario specification is produced that can explicitly describes the situation. This is the case representation in CBR terms. Cases contain a set of features that uniquely characterise each situation. Scenario retrieval employs a similarity metric to quantify the most similar instance of a scenario from a set of past scenarios stored in the case-base. This process systematically compares features from the current and past scenarios to assess the overall similarity of the among each scenario instance in the case base. Together with the most similar scenario the method retrieves the CSFs that are associated with each. The last phase concentrates on the simulation of the retrieved scenario in the synthetic environment and the assessment of the CSF associated with that. During this phase the commander’s attention is drawn on the CSF that characterise the mission’s success. The state of each CSF is informed regularly based on fused data from the simulator. This enables the commander to maintain SA and hence plan subsequent stages of the mission.

6 Scenario Modelling and Retrieval

Since scenarios constitute the main building block of our approach it was important to model them accurately. The formal representation of scenarios should include only information (features in CBR terms) that would contribute towards the adequate classification of possible scenarios. However, due to the richness in information embodied in military scenarios, it was impossible to come up with a case representation that would model it all. To overcome this we based our approach on the principles of recognition RPD. The salient features, required by this approach, that uniquely define each scenario, were identified based on domain analysis. The initial work resulted in the development of an entity relational model that acted as an ontology that represented the knowledge of the domain. However, due to the complexity of that initial model we pursued in developing a meta-model that simplified the knowledge structure by converting it into a tree-like taxonomy of scenario entity's features. The tree structure reduced the richness and complexity of the initial domain knowledge model but still it was complex enough that required further refinement. The structure was subsequently converted into a one dimensional vector by fusing branches of the taxonomy into single nodes (figure 3).

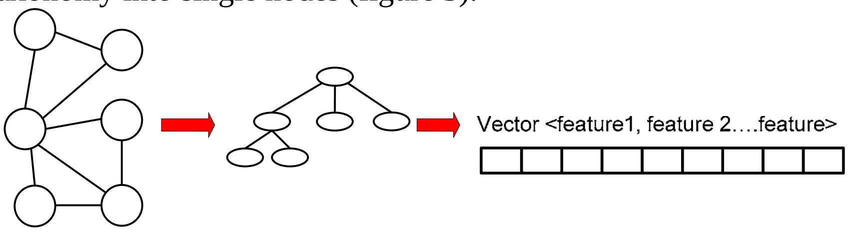

Figure 3. Evolution of the case representation

Elements of the vector constitute the features that describe a scenario. This vector structure comprises the high level representation of scenarios in the case-base. This representation is generic enough to classify emerging scenarios among a number of scenario categories. Once this categorisation has been achieved, additional features are used to further discriminate scenarios within each classification. Essentially, the scenario representation is composed of two parts, the former describes the generic features of a case and the latter the specific ones. Generic features are based on the METTTC mnemonic (Field Manual, 2001) (figure 4) architecture used by the army, which describes scenarios based on six components: Mission, Enemy, Terrain, Troops, Time Available and Civil considerations. Mission is described as the essential tasks for the fulfilment of the mission. Enemy feature describe the strengths, location, activity and capability of the enemy. The Terrain describes obstacles and possible avenues. Troops portray the psychological and training level of the forces. Time available indicate the available time for planning, preparing and executing the mission. Finally civil considerations describe the political, cultural and national properties of the scenario. Tasks, terrain, are described in categorical data while enemy strength, capability, troop's quantity in numerical terms. Scenario specific features enable the discrimination among scenarios belonging to the same category. This is achieved through an additional set of properties that forms the second part of the scenario representation structure.

The most important task in an analogical reasoning process is the identification of the most similar past case from the case-base. This is the similarity assessment, and can be performed in a variety of ways depending to the problem specification. Broadly speaking, similarity calculation is divided into two categories, the first is based on the computation of the distance between cases and the second is related more to the representation/indexing structure of the cases and how the index can be traversed to reach the most similar case (Pal et al, 2004). In our case the similarity assessment is achieved through the application of the K-nearest Neighbourhood (KNN) paradigm which belongs to the first category of similarity metrics. The KNN classifier is based on non-parametric density estimation techniques (Jain 2002) and categorises cases based on their relative geometric distance that express their level of similarity in a two or more dimensional space. The letter k denotes the number of the most similar cases to the case in question. Distance is calculated in various ways.

Our approach employs the Euclidean metric as explain in equation (1). The algorithm compares each feature in the case base with the analogous feature of the target case. Each feature is assigned a different importance weighting. The weighted result is calculated using the weightings vector and the distance of each stored case features from the target case features. The overall similarity is computed using the control algorithm depicted in (3).

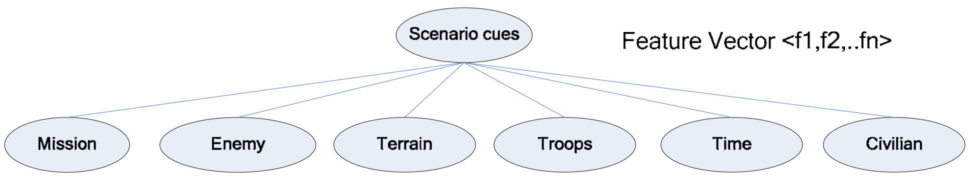

Figure 4. Simplified METTTC model

The structure of the case representation is defined as a set of numeric and symbolic features that together make up the case vector. For the numeric features the Euclidean distance is employed while for the symbolic an exact matching scheme is used. If the symbolic description of the target case feature is identical to the corresponding feature of a case in the case-base then this feature comparison is assigned the score of one, otherwise zero (See equation 2).

Case = $\{f_1 \ldots f_n\}$. The Euclidean distance *d* is calculated using the formulae:

$$d(x,q) = \sqrt{\sum_{i=1}^{n} w_i^{\,2} \times f(a_i^x, a_i^q)^2} \qquad (1)$$

where w_i is the parameterized weight value assigned to feature i ,

and $f(a_i^x, a_i^q)$ is the difference function :

$$f(a_i^x, a_i^q) = \begin{cases} \left|a_i^x - a_i^q\right| & \text{if feature } i \text{ is numeric} \\ 0 & \text{if feature } i \text{ is symbolic and } a_i^x = a_i^q \\ 1 & \text{otherwise} \end{cases} \qquad (2)$$

A high level specification of our implemented KNN algorithm is depicted below:

$\forall$ *(Case* C_i *in the CaseBase K [*$C_1 \ldots C_n$*]) {*

$$ND = \sqrt{\sum_{i=1}^{n} (TF_i - CF_i)^2\, WF_i^{\,2}} ; \forall F_i \in C_i \qquad (3)$$

$$SD = \sum_{i=1}^{n} WF_i ; \forall F_i \in C_i \middle| CF_i \neq TF_i$$

$$Dissimilarity = Dissimilarity + ND + SD$$

$$Similarity_{C_i} = \frac{1}{1 + \sqrt{Dissimilarity}}$$

}

where TF_i*=Target case feature*$_i$ *;* CF_i*=casebase case feature*$_i$ *;ND=numeric distance;SD=symbolic distance;*

7 CSF quantification using BBNs

CSFs constitute the most important elements of the assisted SA method. Therefore it is important to assess their fulfilment throughout the execution of scenarios. However, because of the inherent uncertainty that characterise, the military domain, due to incomplete or inaccurate information, it was necessary to employ probabilistic techniques for their quantification. For this we employed the Bayesian Belief Networks (BBN) technology. BBNs are based on the concept of Bayesian probability, and they provide a decision theory of how to act on the world in an optimal fashion under circumstances of uncertainty. They also offer a language and calculus for reasoning about the beliefs that can be reasonably held, in the presence of uncertainty, about future events, on the basis of available evidence. BBNs are useful for inferring the probabilities of future events, on the basis of observations or other evidence that may have a causal relationship to the event in question (Jensen, 2001). The two main components of BBN are the topology and the conditional probability tables (CPT). The topology corresponds to the qualitative part of the model where the various dependencies of the variables that characterised the domain are explicitly defined. These relationships are expresses as directed acyclic graphs. Variables can have any number of states, so the choice of measurement scale is left to the analyst's discretion. The CPT which corresponds to the quantitative part describes the prior knowledge between the various causal dependencies in terms of conditional distributions. Bayesian Networks can be used in two main types or reasoning: bottom-up/diagnostic and top-down/predictive. The former infers the most likely cause given evidence of an effect. While the latter, "top down", deduces the probability that a certain cause would have given a specific effect.

BBNs provide an efficient factorisation of the joint probability distribution (JPD) over a set of variables with defined states. The JPD provide a probability for each possible combination of values of all variables. If the JPD is known, the posterior probabilities given an observation can be calculated. However, the calculation of the JPD becomes intractable with the increase of the variables included in the model. The key to efficient representation of JPD is to reduce the number of probabilities that are involved. This is achieved with the introduction of conditional independence. This states that a variable is independent of all its non-descendants given its parents. This factors the JPD into several component distributions that is easier to compute because they depend on smaller set of variables. This property is realised with the use of directed acyclic graphs and their corresponding CPTs.

Each CSF is modelled by a BBN model and according to the situation the most appropriate BBN model is retrieved from the case-base and used during the scenario simulation to assess the CSF of interest. CSF BBN models topologies were constructed based on SMEs input while the CPTs were generated using generated data from the simulator and prior knowledge provided by domain experts. The SMEs input was parameterised using the principles of Noisy-Max (Henrion, 1987) were child nodes are considered as independent from each other, hence required reduced set of input probabilities to fully populate the BBN model's CPTs. Data generated from the simulator was used to further refine the SMEs generated CPTs, to escape from the problem of biasing the prior knowledge with experiences from a limited number of SMEs but also to act as a validation.

8 Case study: Application of an analogical reasoning technique to maintain commanders situation awareness

A case study is used to illustrate the application of the method in supporting commander's SA. In this example we use the generic features (METTTC) of the case representation for scenario discrimination. Observations of the state of each of the salient cues enable the system to generate a specification of the target-case that explicitly describes the scenario in hand. The target-case is subsequently compared with all the past scenarios in the case-base and returns the most similar case from which the solution part (CSF) is reused to support the decision making process. Consequently, the scenario is loaded in the simulator together and the retrieved CSF from its solution part. These are continuously assessed based on acquired information from the simulator and possessed through a Bayesian inference engine. A narrative description of the scenario used to illustrate the concept is presented below

Scenario: Breach through a minefield

The objective in this scenario is to cross a minefield that is defended by enemy tanks (red diamonds in figure 5). In order to achieve this, the enemy units ought to be destroyed prior to the deployment of the engineering vehicles that would clear the minefield. The friendly units (blue squares) initially advance to positions, according to the schematic diagram of figure 5. The friendly units successfully destroy the enemy tanks and the engineering elements start to clear the minefield. Once this task is completed, the remaining friendly tanks are able to traverses the minefield through the cleared path.

Throughout the execution of the scenario three CSF are monitored: relative strength, logistics and manoeuvrability. However, for this case study we shall elucidate only on the relative strength CSF. This is a comparative measure of fire power among friendly and enemy forces. It is presented using the traffic light paradigm. The number embedded in the highlighted colour denotes the degree of confidence of the tools assessment, which is due to the inherent uncertainty that characterise the domain. Hence, a high degree of confidence gives the decision maker greater assurance of the assessed result. The measurement of CSFs fulfilment is based on fused information obtained from the simulated scenario entities. Fire power of the friendly and enemy units is calculated based on a table of predefined scores for each entity. The final result is subsequently discretized and entered in a Bayesian model as evidence concerning a specific state of an input node. This input is subsequently propagated down the network and in combination with the prior knowledge embedded in the model in terms of probability distribution it quantifies the probability that the CSF of interest is satisfied or not. The fusion of observed data and information together with the quantification of CSFs continue throughout the execution of the scenario.

Initial results from the approach have been encouraging since the tool successfully recognises the scenario and fishes out the correct CSFs. The results produced from the assessment of CSFs throughout the scenario execution followed the reasoning that was embedded in the BBN models. The scenario CSFs were developed and validated with the assistance of SMEs. Overall the method assists decision makers to orientate their thinking processes based on events that emerge in the environment of interest, the scenario. Essentially, CSFs act as critical cues against which commander's attention is drawn to support decision making. The reduced volume of information through information fusion eases the perception and comprehension processes of the decision maker and hence increases the effectiveness of the decision making process. Furthermore, CSFs and their quantification provide a method for narrowing down the commander's choice set of possible projected scripts that ought to be examined prior to converging on a decision.

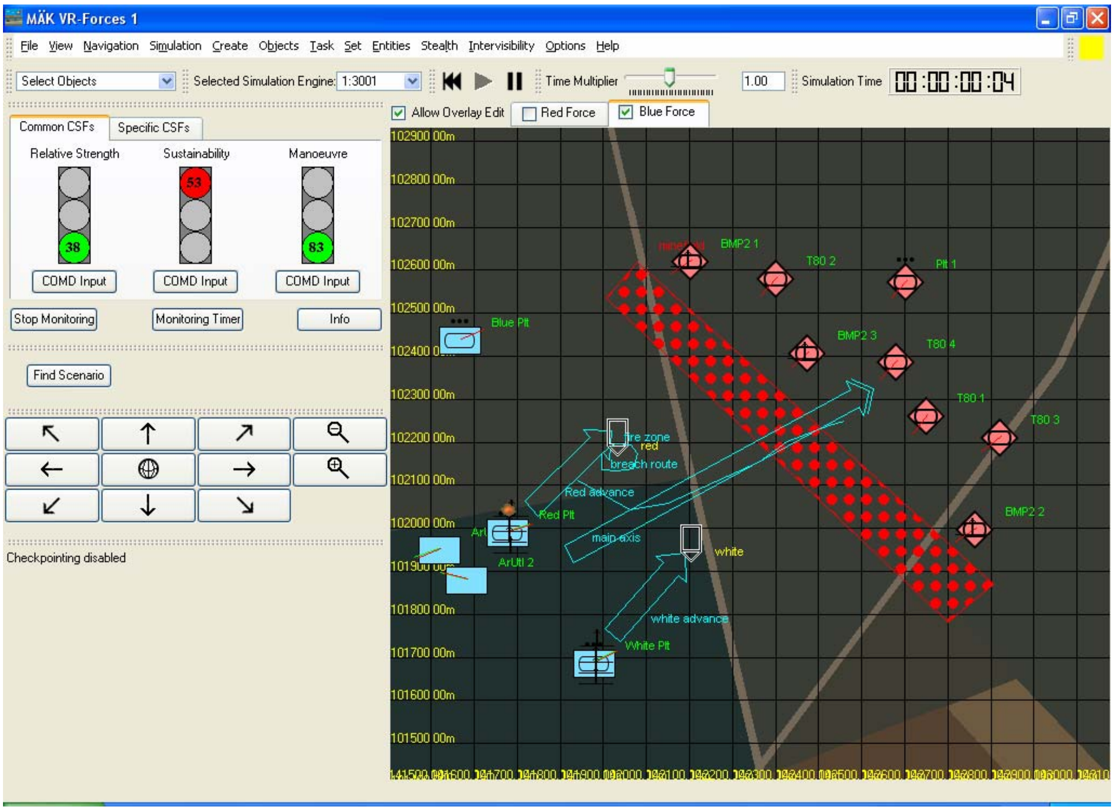

Figure 5. CGF graphical user interface for SA and decision support

9 Conclusion

This paper has described the initial outputs of the DIF DTC[1] sponsored programme of work and illustrates a decision support system that can potentially improve commander's SA. This in return, is expected to improve decision making and operational performance. Inherently the approach is based on the principles of analogical reasoning and its derivative, cased-based reasoning. CSFs are viewed as a parsimonious set of principal components that meet the Commander's CCIRs through which scenario SA is maintained and decision effectiveness is enhanced.

Whilst this decision support system has been researched and developed using an SME assisted participative approach, we are currently working on the next stage of the project which is concerned with a rigorous scientific evaluation and validation using Intelligence (G2), Operations and Planning (G3), and Logistics (G4) SMEs. The validation involves employing a 'scenario walk-through' analysis approach; whereby, each SME is assigned the task of identifying and evaluating the CSFs (knowledge labelling) associated with a specific CGF generated scenario. In the first part of the experiment, the task is completed without any CSF-enabled SA and decision support. During this process the SMEs are able to stop the simulation at any point they consider important to enable them to assess the situation. After their assessment, SMEs are able to resume the simulation. This approach is similar to Endsley's SAGAT[2] method (Endsley, 1987). The second part of the experiment uses the SA and decision support tool to pinpoint the CSFs related with the same scenarios together with their corresponding estimates throughout the execution of the scenario. The data generated in both cases are collected and statistically analysed for comparative significance and goodness of fit estimate. This set of evaluation and validation experiments are an essential precursor to a further set of forthcoming experiments necessary to secure customer buy-in.

[1] Data & Information Fusion Defence Technology Centre (DIF DTC) Consortium, UK

[2] Situational Awareness Global Assessment Technique (SAGAT)

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