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Literature Survey and Situation Analysis

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On behalf of
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28 March 2000

Executive Summary

This report presents the results of a literature survey on the domain of data fusion and related topics in order to get a better understanding of the process on situation analysis.

This work takes place in the context of a long range project that aims at developing a decision support system (DSS) for Operation Room Officers (OROs) in the HALIFAX class frigate. Given the large volume of incoming data from various sources, the time constraints and the characteristics of the activities taking place in the Operation Room, DREV researchers have investigated for several years the applicability of data fusion techniques for the development of a DSS for OROs. In the open literature the JDL model has been widely used to structure the main activities taking place in the data fusion domain. For several years, DREV researchers have developed systems mainly for multisource data fusion (JDL model's levels 0 and 1). When working on situation and impact assessment (levels 2 and 3), they faced several difficulties and discovered that one main limitation of the JDL model is that not enough attention is given to a fundamental element in the Command and Control (C2) process: the person who makes decision.

In several military domains, researchers have noticed that data fusion techniques cannot provide on their own a complete and satisfactory solution to automate the complex activities taking place in C2 settings. This can be explained by the fact that such settings involve ill-structured problems, uncertain and dynamic environments, conflicting, shifting or ill-defined goals, time constraints, high stakes and pressure. Given the current technology and software development know-how, it is impossible to develop a data fusion system that would efficiently integrate all the functionalities that are pictured in the JDL idealized model without considering the fundamental contribution of human operators. Hence, a data fusion system should be thought of as technological means to support human decisions.

How can such a system be useful to support OROs' decision making process? During the past years the DREV team has emphasized the importance of considering the cognitive aspects of C2 decision making processes, and more specifically of providing means to develop and maintain operators' situation awareness. From the operator's point of view, situation awareness can be informally defined as "knowing what's going on so that you can figure out what to do". In the context of the project for developing a DSS for OROs in the HALIFAX Class Frigat, a Cognitive Task Analysis of the ORO's position (Matthews et al. 1999) has been recently completed and provides relevant observations related to the ORO's cognitive needs: 1) Gaining and maintaining situation awareness is a key issue for OROs; 2) OROs employ a variety of mental pictures and mental models to achieve their cognitive goals; 3) Mission preparation has great significance for establishing mission related mental models; 4) Updating situation awareness when coming on watch is critical for updating ORO's mental models.

These cognitive aspects of the ORO's activities cannot be accounted for in the JDL model. However, they are most important if one wants to develop a decision support

system that will be useful to OROs. Hence, it seems appropriate to adopt a wider perspective by examining how a decision support system can take advantage of data provided by a data fusion system and present them in a way that fits OROs' mental models. This cognitive fit should enable OROs to gain and maintain situation awareness. In this context the Scientific Authority of this contract proposed us to investigate the process of "situation analysis" that can be defined as a process that leads a person or a group of persons to a state of situation awareness.

This document is composed of 3 parts: The master document in which we report the results of the study on situation analysis and our recommendations for future works; Annex 1 which presents a synthesis of works done on Situation and Threat Assessment in the Data Fusion domain; Annex 2 which presents a synthesis on the subject of situation awareness. Numerous references on data fusion, situation assessement and situation awareness have been recorded in an electronic bibliographic data base under the software Endnote™.

Here we summarize the main elements of the master document. We first present the main elements of the widely-used JDL model for data fusion and discuss its limitations when considering the cognitive aspects of the ORO's activities. We then examine the main characteristics of situation awareness which plays a key role in the decision making process. A recent cognitive task analysis for the ORO position has been carried out (Matthews et al. 1999). We mention its main conclusions which emphasize the key role played by situation awareness and mental models for ORO's cognitive activities.
In this context, we introduce the notion of situation analysis as it was defined by the Scientific Authority of the present contract.
Then, we discuss the key elements that influence situation analysis in the context of the Operation Room. We show that situation analysis is a broad process that takes place at several levels at once: at the level of each team member and at a more global level which corresponds to the global situation understanding of the team taken as a whole.
We also propose and discuss generic architectures for a situation analysis support system that could be used to support the work of the ORO's team: operators and their supervisors as well as the ORO himself. From this presentation of the different levels of situation analysis taking place in an Operation Room we conclude that the JDL Data Fusion model may not directly apply to a hierarchically organized team and should be revised considering the notion of situation analysis.
Finally, we present our recommendations for the next steps to be performed toward the creation of a situation analysis support system. More specifically, we recommed that a knowledge engineering approach be coupled with the cognitive task analysis of the ORO and the key members of his team. The knowledge engineering phase of the project should enable knowledge engineers to obtain formal models that match the mental models and pictures enabling an ORO to gain and maintain situation awareness. Such formal models will be used as the key knowledge and data structures on which the situation analysis support system would be built.

Sommaire

Ce rapport présente les résultats d'une revue de littérature sur le domaine de la fusion de données et des sujets associés afin d'avoir une meilleure compréhension du processus d'analyse de situation.

Ce travail se situe dans le contexte d'un projet à long terme qui vise le développement d'un système d'aide à la décision (SAD) pour les Officiers de la Salle d'opérations (OROs) dans la frégate de classe HALIFAX. Etant donné le fort volume des données fournies par diverses sources de données, les contraintes de temps et les caractéristiques des activités qui prennent place dans la Salle d'opérations, les chercheurs du CRDV ont exploré depuis plusieurs années l'applicabilité des techniques de fusion de données pour le développement d'un SAD pour les OROs. Dans la littérature générale le modèle JDL est très utilisé pour structurer les principales activités accomplies dans le domaine de la fusion des données. Depuis plusieurs années, les chercheurs du CRDV ont développé des systèmes qui font la fusion de données multi-sources (niveaux 0 et 1 du modèle JDL). Quand ils ont exploré les niveaux d'évaluation de situation ("situation assessment") et d'évaluation d'impact ("impact assessment") (niveaux 2 et 3 du modèle JDL), ils ont rencontré plusieurs difficultés et découvert qu'une des principales limitations du modèle JDL est de ne pas accorder une importance suffisante à un élément fondamental dans un processus de commandement et contrôle (C2): la personne qui prend les décisions.

Dans plusieurs domaines militaires des chercheurs ont remarqué que les techniques de fusion de données ne fournissent pas de solution complète et satisfaisante pour automatiser les activités complexes qui sont accomplies dans un environnement de C2. Ceci peut être expliqué par le fait que ces environnements sont incertains et dynamiques, que les problèmes sont mal compris, que les buts sont changeants, mal-définis et souvent conflictuels, qu'il y a des contraintes de temps importantes et que les enjeux et la pression sont très importants. Compte tenu du développpement actuel de la technologie et du savoir-faire en dévelppement de systèmes, il semble impossible de développer un système de fusion de données qui intégrerait efficacement les fonctionnalités proposées dans le modèle JDL sans considérer la contribution fondamentale des opérateurs humains. Aussi, un système de fusion de données devrait-il être vu comme un moyen technologique de supporter les décisions humaines.

Comment un tel système peut être utile au processus de prise de décision des OROs? Au cours des dernières années, l'équipe du CRDV a souligné l'importance de considérer les aspects cognitifs des processus de décision en C2 et plus spécifiquement de fournir des moyens de développer et entretenir la conscience de situation ("situation awareness"). Du point de vue de l'opérateur, la conscience de situation peut être informellement définie comme "connaître ce qui se passe de façon à savoir quoi faire". Dans le contexte du projet de développement d'un SAD pour les OROs des frégates de classe HALIFAX, une analyse cognitive de tâches du poste d'ORO (Matthews et al. 1999) a été réalisée récemment et fournit plusieurs observations très pertinentes au sujet des besoins cognitifs des OROs: 1) Former et entretenir la conscience de situation est un facteur clé pour les

OROs; 2) les OROs utilisent un ensemble d'images et de modèles mentaux pour réaliser leurs buts cognitifs; 3) La préparation de mission a une grande importance pour l'établissement des modèles mentaux; 4) mettre à jour la conscience de situation au moment de la prise de quart est critique pour la mise à jour des modèles mentaux de l'ORO.

Le modèle JDL ne peut pas rendre compte de ces aspects cognitifs des activités de l'ORO. Cependant, ils sont très importants si on veut développer un SAD qui sera utile aux OROs. Aussi, il semble approprié d'adopter une perspective plus large et d'examiner comment un SAD peut tirer parti des données fournies par un système de fusion de données et les présenter d'une façon qui s'harmonise avec les modèles mentaux des OROs. Cette harmonisation devrait permettre aux OROs de former et entretenir une conscience de situation. Dans ce contexte, l'autorité scientifique de ce contrat nous a proposé d'explorer le processus d'analyse de situation qui peut être défini comme un processus qui permet à une personne ou à un groupe de personnes d'atteindre un état de conscience de situation.

Ce document est composé de trois parties: le Document maître dans lequel nous rapportons les résultats de l'étude sur l'analyse de situation et présentons nos recommandations pour des travaux futurs; l'Annexe 1 qui présente une synthèse de travaux réalisés dans les domaines de l'évaluation de situation et l'évaluation de menace dans un contexte de fusion de données; l'Annexe 2 qui présente une synthèse de travaux sur le sujet de la conscience de situation. De nombreuses références sur la fusion de données, l'évaluation de situation et la conscience de situation ont été répertoriées dans une base de données bibliographiques sous le logiciel Endnote™.

Ici nous résumons les principaux éléments du document maître. Nous présentons tout d'abord les principaux éléments du modèle JDL pour la fusion de données et discutons ses limitations relativement aux aspects cognitifs des activités des OROs. Ensuite nous examinons les principales caractéristiques de la conscience de situation qui joue un rôle fondamental dans le processus de prise de décision. Une récente analyse cognitive de tâches du poste d'ORO a été réalisée (Matthews et al. 1999). Nous mentionnons ses principales conclusions qui soulignent le rôle fondamental joué par la conscience de situation et les modèles mentaux dans les activités cognitives des OROs. Dans ce contexte nous introduisons la notion d'analyse de situation qui a été définie par l'autorité scientifique du présent contrat.

Par la suite nous discutons des éléments fondamentaux qui influencent l'analyse de situation dans le contexte de la Salle d'opérations. Nous montrons que l'analyse de situation est un large processus qui se déroule simultannément à plusieurs niveaux: au niveau de chaque membre de l'équipe de l'ORO ainsi qu'à un niveau plus global qui correspond à la compréhension globale de la situation qui caractérise l'équipe dans son ensemble. Nous proposons et commentons des architectures génériques pour un système de support à l'analyse de situation qui pourrait supporter le travail de l'équipe de l'ORO: les opérateurs et leurs superviseurs et l'ORO lui-même. De cette présentation des divers niveaux d'analyse de situation qui se déroulent dans la Salle d'opérations, nous concluons que la modèle JDL de fusion de données ne peut pas être appliqué directement à une équipe organisée hiérarchiquement et devrait être révisé en considérant la notion d'analyse de situation.

Finalement, nous présentons nos recommandations pour les prochaines étapes à réaliser en vue de la création d'un système de support à l'analyse de situation. Plus spécifiquement, nous reommandons qu'une approche d'ingéniérie des connaissances soit réalisée en conjonction avec une analyse cognitive de tâches du poste d'ORO et des postes des membres-clé de son équipe. Cette phase d'ingéniérie des connaissances devrait permettre aux ingénieurs de la connaissance d'obtenir des modèles formels qui s'apparentent aux modèles mentaux et des images mentales qui permettent à l'ORO de former sa conscience de situation. De tels modèles formels seront utilisés pour établir les principales structures de données et de connaissances sur lesquelles un système de support à l'analyse de situation pourra être bâti.

Literature Survey on Situation Analysis

1. Introduction

This work takes place in the context of a long range project that aims at developing a decision support system (DSS) for Operation Room Officers (OROs) in the HALIFAX class frigate. Given the large volume of incoming data from various sources, the time constraints and the characteristics of the activities taking place in the Operation Room, DREV researchers have investigated for several years the applicability of data fusion techniques for the development of a DSS for OROs.

The JDL data fusion model (Waltz and Llinas 1990) ordered by the Joint Directors of Laboratories Data Fusion Subpanel is a framework which has been widely used to structure the main activities taking place in the data fusion domain. The revised version of the JDL model (Steinberg et al. 1998) aims at broadening the scope of the model so that it could be applied to both civilian and military application domains. Five levels of data processing are distinguished: Sub-object assessment (level 0), object assessment (level 1), situation assessment (level 2), impact assessment (level 3) and process refinement (level 4). Most of the practical systems that have been developed in the past provide functionalities for levels 0 and 1 of the JDL model: they deal with the difficult problems of multi-source data fusion. Very few systems provide satisfactory solutions for levels 2, 3 and 4.

For several years, DREV researchers have developed systems mainly for multisource data fusion (JDL model's levels 0 and 1). When working on situation and impact assessment (levels 2 and 3), they faced several difficulties and discovered that one main limitation of the JDL model is that not enough attention is given to a fundamental element in the Command and Control (C2) process: the person who makes decision. The naval application domain is very complex and developing complete automatic solutions seems out of reach for the current technology and may be undesirable. In several military domains, researchers have noticed that data fusion techniques cannot provide on their own a complete and satisfactory solution to automate the complex activities taking place in C2 settings. This can be explained by the fact that such settings involve ill-structured problems, uncertain and dynamic environments, conflicting, shifting or ill-defined goals, time constraints, high stakes and pressure. Given the current technology and software development know-how, it is impossible to develop a data fusion system that would efficiently integrate all the functionalities that are pictured in the JDL idealized model without considering the fundamental contribution of human operators. Hence, a data fusion system should be thought of as technological means to support human decisions. How can such a system be useful to support OROs' decision making process? During the past years the DREV team has emphasized the importance of considering the cognitive aspects of C2 decision making processes, and more specifically of providing means to develop and maintain operators' situation awareness.

Several researchers have emphasized the key role played by situation awareness when making decisions in complex settings (Endsley 1995). From the operator's point of view, situation awareness can be informally defined as "knowing what's going on so that you can figure out what to do". In the context of the project for developing a DSS for OROs in the HALIFAX Class Frigat, a Cognitive Task Analysis of the ORO's position

(Matthews et al. 1999) has been recently completed and provides relevant observations related to the ORO's cognitive needs: 1) Gaining and maintaining situation awareness is a key issue for OROs; 2) OROs employ a variety of mental pictures and mental models to achieve their cognitive goals; 3) Mission preparation has great significance for establishing mission related mental models; 4) Updating situation awareness when coming on watch is critical for updating ORO's mental models.

These cognitive aspects of the ORO's activities cannot be accounted for in the JDL model. However, they are most important if one wants to develop a decision support system that will be useful to OROs. Hence, it seems appropriate to adopt a wider perspective by examining how a decision support system can take advantage of data provided by a data fusion system and present them in a way that fits OROs' mental models. This cognitive fit should enable OROs to gain and maintain situation awareness.
In this context the Scientific Authority of this contract proposed us to investigate the process of "situation analysis". Situation analysis can be defined as a process that leads a person or a group of persons to a state of situation awareness.

In Section 2 we mention the contract objectives and give an overview of the accomplished work.
Section 3 presents the main elements of the widely-used JDL model for data fusion and discusses its limitations when considering the cognitive aspects of the ORO's activities.
Researchers have shown that situation awareness plays a key role in the decision making process (Section 4). A recent cognitive task analysis for the ORO position has been carried out. We present in Section 5 its main conclusions which emphasize the key role played by situation awareness and mental models for ORO's cognitive activities.
In Section 6 we introduce the notion of situation analysis as it was defined by the Scientific Authority of the present contract.
In Section 7 we discuss the key elements that influence situation analysis in the context of the Operation Room. We show that situation analysis is a broad process that takes place at several levels at once: at the level of each team member and at a more global level which corresponds to the global situation understanding of the team taken as a whole.
In Section 8 we propose and discuss generic architectures for a situation analysis support system that could be used to support the work of the ORO's team: operators and their supervisors as well as the ORO himself. From this presentation of the different levels of situation analysis taking place in an Operation Room we conclude that the JDL Data Fusion model may not directly apply to a hierarchically organized team and should be revised considering the notion of situation analysis.
In Section 9 we present our recommendations for the next steps to be performed toward the creation of a situation analysis support system. More specifically, we recommend that a knowledge engineering approach be coupled with the cognitive task analysis of the ORO and the key members of his team. The knowledge engineering phase of the project should enable knowledge engineers to obtain formal models that match the mental models and pictures enabling an ORO to gain and maintain situation awareness. Such formal models will be used as the key knowledge and data structures on which the situation analysis support system would be built.

2. Contract Objectives and Review of Accomplished Work

The objectives of the present contract are:

- To survey the relevant literature in relation to situation analysis
- To write a synthetic report on the subject and propose a definition for "situation analysis"
- To propose recommendations for an object-oriented analysis of a situation analysis support system

Here are the main activities that have been performed in order to reach these objectives:

- Literature survey using documents and web searches on the following areas:
  - Data fusion process (several popular DF models (JDL, etc.); an example in the naval domain; advantages, limitations; use of artificial intelligence techniques)
  - Situation assessment process
  - Situation awareness
- Study of the cognitive task analysis of the Halifax-Class Operations Room Officer
- Study of several papers of the DREV team on Data Fusion and situation awareness
- A bibliography base has been built using Endnotes
- Preliminary domain synthesis and presentation to DREV team
- Further literature study and refinement of the domain synthesis
- Report writing and adjustments

3. Data Fusion

Data fusion is an important research and development domain for both military and civilian applications. During the past 20 years much efforts and resources have been devoted to this research area and several systems have been built. However, most of these systems do not fulfill the real needs of their users which are often flooded by data coming from various sources when they would need relevant aggregated information that could help them to make decisions. The JDL data fusion model ordered by the Joint Directors of Laboratories Data Fusion Subpanel is a framework which has been widely used to structure the main activities taking place in the data fusion domain. In its 1992 version which was oriented toward military applications, the JDL model distinguished four levels of data processing: object refinement, situation refinement, threat refinement and process refinement. An overview of this model is presented in Appendix 1 of the present document.

The revised version of the JDL model (Steinberg et al. 1998) aims at broadening the scope of the original JDL model so that it could be applied to both civilian and military application domains.

A general concise definition of the data fusion process is given:

Data fusion is the process of combining data to refine state estimates and predictions.

In the new version of the JDL model, five levels are distinguished: Sub-object assessment (level 0), object assessment (level 1), situation assessment (level 2), impact assessment (level 3) and process refinement (level 4). Let us comment upon those levels in order to emphasize the main elements that are of importance for the data fusion process (Steinberg et al. 1998).

The main activities of level 0 aim at estimating and predicting signal/object observable states on the basis of pixel/signal level data association and characterization. Such a process involves hypothesizing the presence of a signal and estimating its state.

The main activities of level 1 aim at estimating and predicting entity states on the basis of observation-to-track association, continuous state estimation (e.g. kinematics) and discrete state estimation (e.g. target type and identification). Such a process involves associating reports (or tracks from prioir fusion nodes in a processing sequence) into association hypotheses (called here *tracks*). Each such track represents the hypothesis that the given set of reports is the total set of reports available to the system referencing some individual entity.

The main activities of level 2 aim at estimating and predicting relations among entities to include force structure and cross force relations, communications and perceptual influences, physical context, etc. Such a process involves associating tracks (i.e. hypothesized entities) into aggregations. The state of the aggregate is represented by a network of relations among its elements. As the class of estimated relationships and the number of interrelated entities broaden, people use the term *situation* for an aggregate object of estimation.

The main activities of level 3 aim at estimating and predicting effects on situations of planned or estimated/predicted actions by the participants; to include interactions between action plans of multiple players (e.g. assessing susceptibilities and vulnerabilities to estimated/predicted threat actions given one's own planned actions). Such a process involves implementing prediction functions drawing particular kinds of inference from Level 2 associations. Level 3 estimates the impact of an assessed situation, i.e. the outcome of various plans as they interact with one another and with the environment. The impact estimate can include likelihood and cost/utility measures associated with potential outcomes of a player's planned actions.

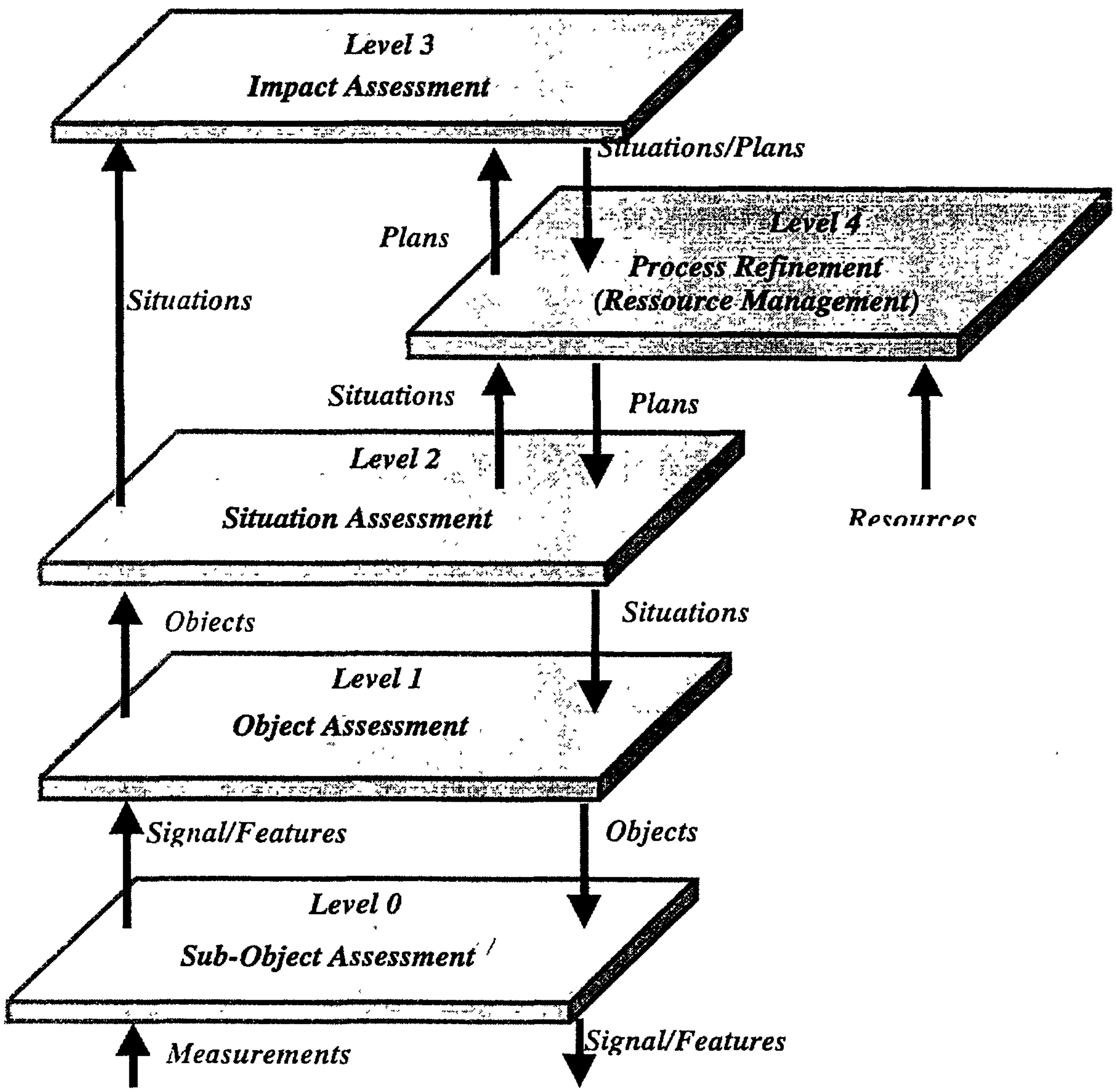

Figure 1 Information Workflow among JDL model's levels (1998)

The main activities of level 4 aim at adaptatively acquire and process data in order to support mission objectives. It is part of the Resource Management process. This involves assigning tasks to resources.

Figure 1 presents an information workflow across the levels of the revised version of the JDL model.
Another important remark (Steinberg et al. 1998) is relative to the importance of estimating the value of entity states on the basis of the context: "A system that integrates data association and estimation processes of all levels will permit entities to be understood as part of a complex situation".
These remarks emphasize situation description and characterization as one of the main goals of the data fusion process. However, most of the practical systems that have been developed until now provide functionalities for levels 0 and 1 of the JDL model: they deal with the difficult problems of multi-source data fusion. Very few systems provide satisfactory solutions for levels 2, 3 and 4. The JDL model presents an ideal view of the functionalities of a data fusion system that should be able to support every activity from data acquisition to resource management. However, building such a system is beyond the capability of current technology and software development methods. Consequently, we can only view a data fusion system as a system supporting an operator who makes decisions and often needs to orient several activities of the data fusion system. Hence, one of the main limitations of the JDL model is that not enough attention is given to the person who makes decision.

4. Situation Awareness

Given the complexity of situations encountered in C2 activities, it has been observed by numerous researchers that decision makers can operate efficiently if they can get a global understanding of the attended situations. Discovery of relationships between objects, as well as patterns or configurations of objects may lead the decision maker to infer the intents of involved player's and act accordingly. Situations being highly dynamic in most cases, decision makers must also be able to follow the evolution of attended situations. All these observations lead to the notion of *situation awareness*. Here is a general definition of SA (Endsley 1987; Endsley 1988):

> *Situation awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future.*

It is necessary to *distinguish the term situation awareness (SA) as a state of knowledge, from the processes used to achieve that state.* These processes, which may vary widely among individuals and contexts, will be referred to as *situation assessment or as the process of achieving, acquiring, or maintaining SA.*

SA as defined here does not encompass all of a person's knowledge. It refers to only that portion pertaining to the state of a dynamic environment. Established doctrine, rules, procedures, checklists, and the like – though important and relevant to the decision-making process – are fairly static knowledge sources that fall outside the boundaries of the term. In addition, SA is explicitly recognized as a construct separate from decision making and performance. *SA, decision making, and performance are different stages* with different factors influencing them and with wholly different approaches for dealing with each of them; thus it is important to treat these constructs separately. Attention, working memory, workload, and stress are all related constructs that can affect SA but that can also be seen as separate from it.

Figure 2 provides a basis for discussing SA in terms of its role in the overall decision-making process. According to this model, a person's perception of the relevant elements in the environment from system displays or directly by the senses, forms the basis for his or her SA. Details of Endsley's model are given in Appendix 2.

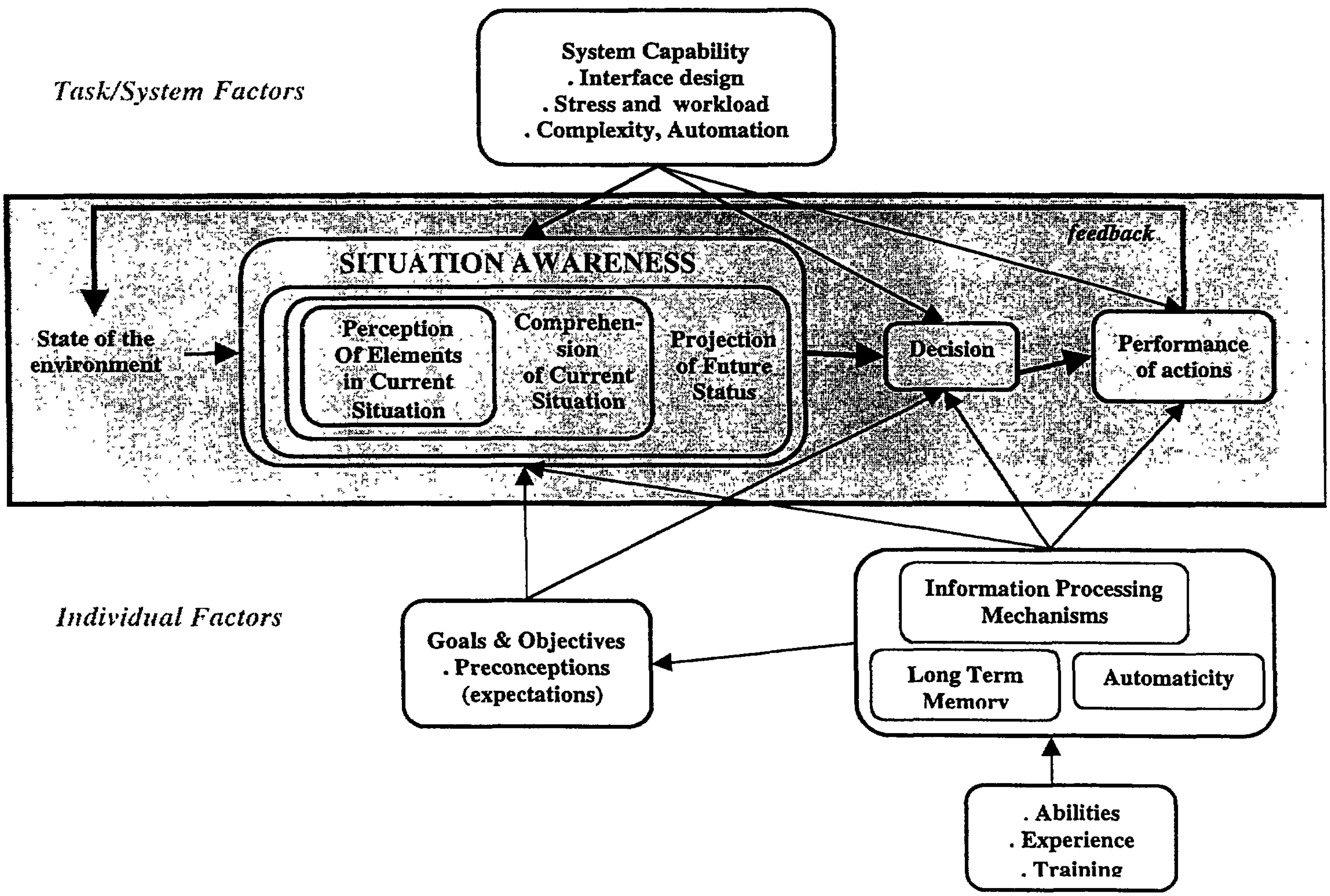

Figure 2: Endsley's model of situation awareness

SA can be shown to be important in a variety of contexts: aircraft, air traffic control, large-systems operations, tactical and strategic systems and many other everyday activities necessitate a dynamic update of the situation to function (Zsambok 1997; Zsambok and Klein 1997).

The need for SA applies in a wide variety of environments. Acquiring and maintaining SA becomes increasingly difficult. Because the state of the environment is constantly changing, often in complex ways, a major portion of the operator's job becomes that of obtaining and maintaining good SA. Operators must do more than simply perceive the state of their environment. They must understand the integrated meaning of what they are perceiving in light of their goals. Researchers in many areas have found that expert decision makers will act first to classify and understand a situation, immediately proceeding to action selection. There is evidence that an integrated picture of the current situation may be matched to prototypical situations in memory, each prototypical situation corresponding to a "correct" action or decision. Experts use pattern-matching mechanisms to draw on long-term memory structures (such as schemas and scripts) that allow them to quickly understand a given situation.

A formal definition of situation awareness is included in several US Navy specifications. It says: "Operator SA is comprised of detecting information in the environment, processing the information with relevant knowledge to create a mental picture of the current situation, and acting on this picture to make a decision or explore further".

Showing the importance of such issues, the Situational Awareness Integrated Product Team (SA IPT) has been formed in the US in response to fleet tactical aircraft aviators ranking situation awareness as a critical mission concern (Garner and Assenmacher 1997). SA IPT held several symposia in order to provide a forum for information exchanges about situation awareness between academia, military researchers and industry (references). We can conjecture that work on situation awareness will have an important influence on the data fusion community in the coming years. This could lead researchers to reconsider the role of data fusion in the context of a broader view of the decision making process based on the ability of the operator to gain and maintain situation awareness.

5. A Cognitive Task Analysis of the ORO's Position (1999)

The naval application domain is no exception. A Cognitive Task Analysis (CTA) of the ORO's position has been recently completed (Matthews et al. 1999) and shows the importance of situation awareness for these decision makers. We sum up in this section the main observations of the CTA that are relevant for our current discussion.

This CTA provides relevant observations related to the ORO's cognitive needs. We mention here some of the main conclusions of this study. Gaining and maintaining situation awareness[1] is a key issue for OROs. OROs employ a variety of mental pictures and mental models to achieve their cognitive goals. Mission preparation has great

[1] A model of situation awareness has been proposed by Endsley (Endsley 1995) who distinguishes three main activities for gaining awareness: perception of current elements of a situation, comprehension of current situation and projection of future status.

significance for establishing mission related mental models. Updating situation awareness when coming on watch is critical for updating ORO's mental models.

For situation awareness several major functional requirements were identified. Information systems should give less data and more "information". There is a need for information acquisition and integration. It is important to have a cognitive match between the available data and the user's mental model(s). A system should help OROs to regain awareness after switches in attention between different areas of focus, and provide alerts to significant changes of unattended areas of the situation.

Background tasks (such as maintaining situation awareness of the evolving operation or dealing with incoming text messages) can be differentiated from foreground or threat-related tasks. OROs need to be able to switch between foreground and background tasks with seamless integration of data. A major ORO function is to manage the overall Operation Room team's threat response rather than to be directly involved in details of responding to particular threats. Common implicit intent and understanding among Operation Room team members has particular significance for communication effectiveness.
Hence, this cognitive task analysis not only shows the importance of situation awareness in the ORO's decision making process, but it also emphasizes the fact that OROs use mental models and pictures in order to get an understanding of the attended situation.

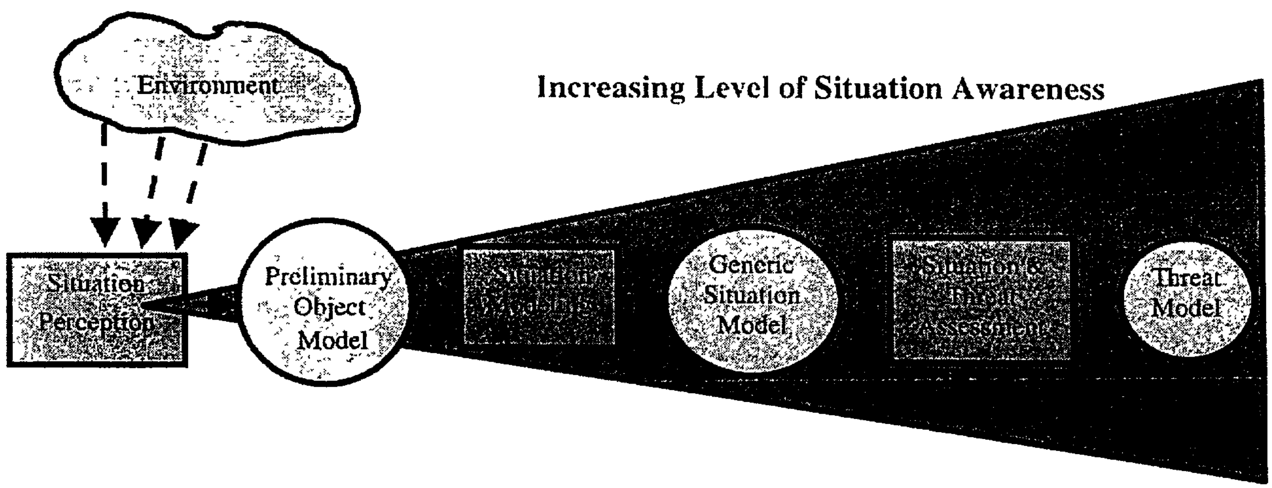

Figure 3: An initial presentation of Situation Analysis

6. Situation Analysis: Initial Definition

During the past years the DREV team has investigated several aspects of the notion of situation awareness and its impact on the development of data fusion systems (Paradis et al. 1997a; Paradis et al. 1997b; Roy and Bossé 1998). They found out that the cognitive aspects of the ORO's activities cannot be accounted for in the JDL model and that mechanisms should be integrated in data fusion systems in order to help users to get and maintain situation awareness. This led the Scientific Authority of this contract to propose the study of the process of *Situation Analysis*.

Situation analysis can be defined as the process that allows a person to gather and structure all the elements and their relations that allow him or her to mentally understand a specific situation and to be aware of its potential consequences.

Figure 3 presents a global view of such a process. This view emphasizes the fact that situation analysis should help the decision maker to increase his or her degree of situation awareness during the whole process of situation analysis. Situation analysis starts from the information obtained through perception and gathered into a *preliminary object model*. Then, a sub-process called *situation modeling* transforms the preliminary object model into a *generic situation model*. Finally a sub-process of *situation and threat assessment* derives a *threat model* from the generic situation model.

This view also emphasizes the primary role played by models: the preliminary object model and the generic situation model. It can be expected that a system will be an efficient aid to gain and sustain situation awareness thanks to the composition of these models and the way the associated information will be displayed to the user. Hence, the importance of the sub-process of situation modeling which manipulates these models. In the rest of this report we will focus on the main elements that can help us further understand the process of situation analysis and its influence on the development of a decision support system for OROs.

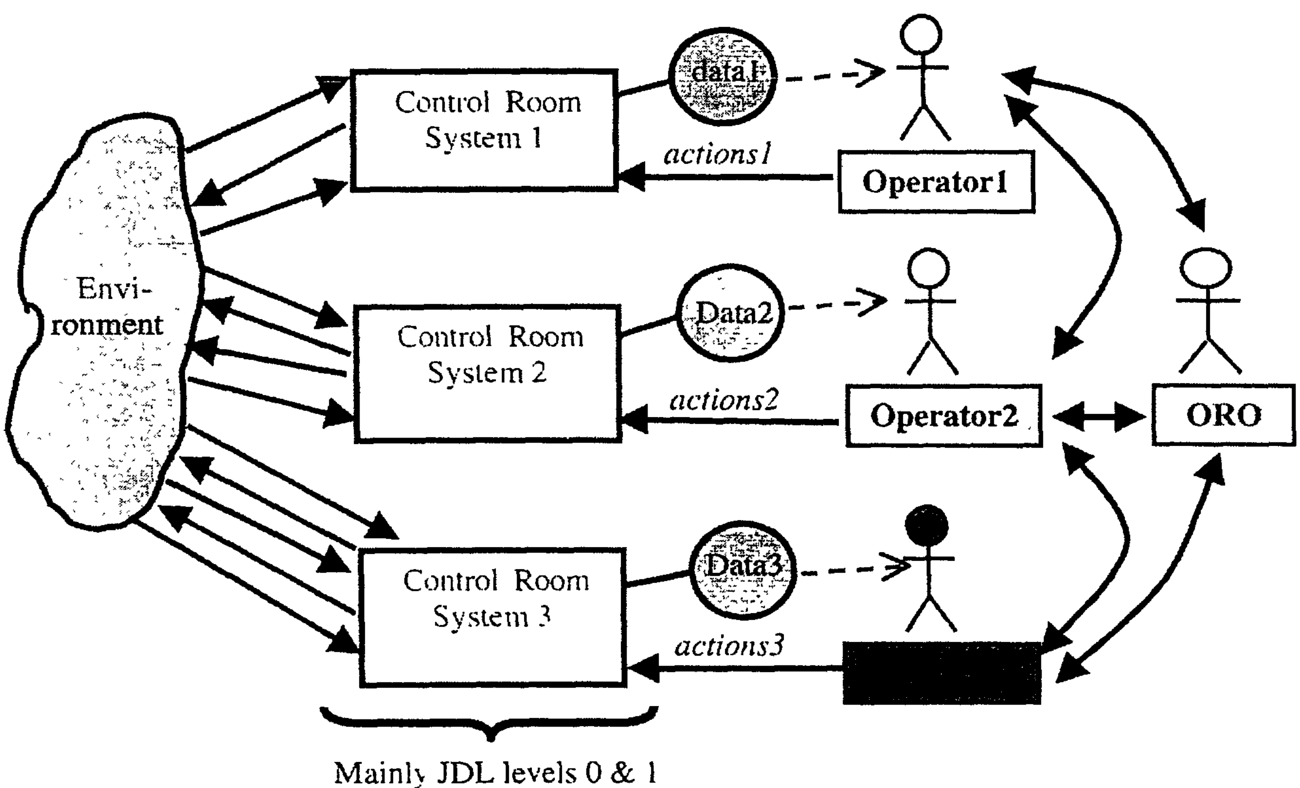

Figure 4: An overview of the main interactions taking place in the Operation Room

7. The Context of Situation Analysis

As a starting point let us present an overview of the interactions that take place in the Operation Room: interactions between operators, existing systems and the ORO. Figure 4 displays a diagram which emphasizes those interactions.

The Operation Room already contains several systems that gather various data about the environment. These systems correspond to JDL Model's levels 0 and 1. They display these data to operators that can perform actions in order to monitor the activities of the systems those systems. In Figure 4 the dashed arrows symbolize the operators' perceptual activities. Operators interact together as well as with the ORO. As a simplification, we did not draw on this diagram the roles of supervisors who supervise a group of operators. However, supervisors would have with operators similar interactions as those displayed between ORO and operators in Figure 4. Whenever necessary, the ORO (or a group supervisor) can go and stand besides an operator and look at specific data on his or her screen. The ORO mentally elaborates a mental picture of the situation by directly observing data, memorizing information obtained from various reports, gathering information from operators and their supervisors and using his experience and intuition. This is the way the ORO currently creates and maintain situation awareness.

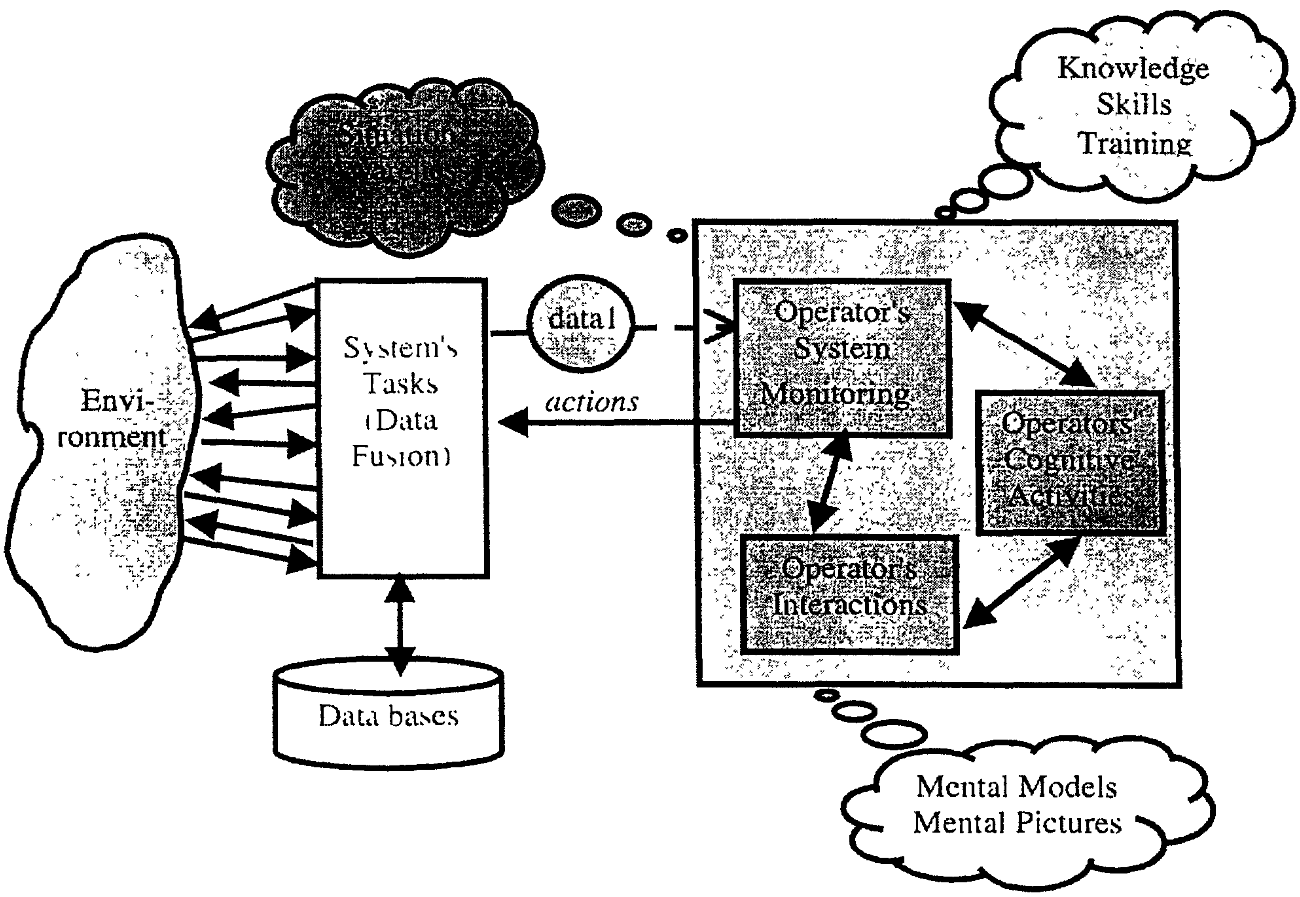

Figure 5: Main elements involved in an operator's analysis of the situation

We should emphasize that every member of the ORO's team develops and maintains an awareness of the situation. However, an individual's situation awareness usually differs from that of another individual for several obvious reasons: differences of the data monitored by each individual given his or her role and specialty; difference of their mental models, difference of their responsibilities in the team which results in the attendance on different aspects of the situation.

Figure 5 emphasizes the main elements that characterize an operator's activities in the Operation Room. We distinguish 3 categories of activities: system monitoring activities, operator's cognitive tasks (reasoning, decision making, mental simulations, etc.) and interactions with other team members. It is clear that all these activities may be carried out concurrently. The main point here is that these activities enable the operator to analyze the attended situation and to gain situation awareness, hence creating and maintaining mental models and mental pictures. Obviously, the operator's knowledge, skills and training influence the way he or she acts and consequently his or her understanding of the situation.

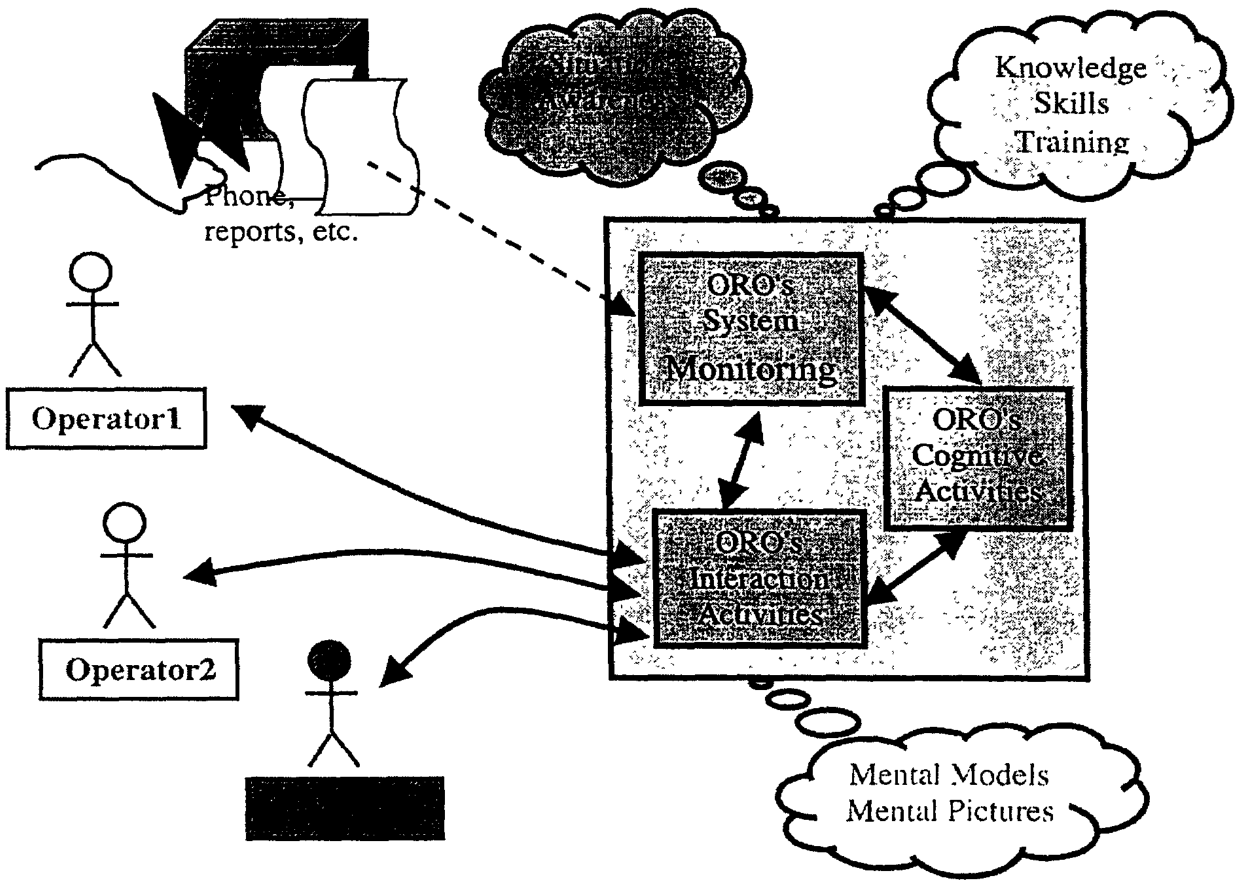

Figure 6: Main elements involved in an ORO's analysis of the situation

Figure 6 presents the main elements that characterize an ORO's activities in the Operation Room. We distinguish 3 categories of activities: system monitoring activities, ORO's cognitive tasks (reasoning, decision making, mental simulations, etc.) and interactions with other team members. The ORO's system monitoring activities refer to his use of phone, reading reports, attending data on screens, etc. The ORO's cognitive activities correspond to creating mental models and mental pictures of the situation, reasoning, decision making, performance of mental simulations, etc. The ORO's interaction activities refer to the various interactions that take place with team members in order to get information, to give orders and ask for advice.

It should be clear now that situation analysis is a broad process that takes place at several levels at once: at the level of each team member and at a more global level which corresponds to the global situation understanding of the team taken as a whole. Ideally, the ORO is the person who would embody this global understanding of the situation. Hence, when studying the process of situation analysis, researchers and developers should be aware of these individual differences of situation understanding and awareness.

8. Toward a System for Supporting Situation Analysis

8.1 Introduction

The preceding discussion sheds new light on the current limitations of data fusion systems. We already mentioned that the JDL model presents an ideal view of the functionalities of a data fusion system that should be able to support every activity from data acquisition to resource management. In practice, researchers and developers have difficulties to deal with the complexity of the activities involved in such a process.

This is not a surprise because there are numerous activities addressing different levels of decision: operational, tactical and strategic. To use an analogy, developing such a data fusion system would be equivalent to designing all the systems of a company at once: operational systems that deal with billing, stock management, sales management, etc., as well as decision support systems for managers and a decision support system for executives. It is impossible to develop all these systems at once because operational systems provide aggregated data that are used by tactical decision support systems that in turn provide information to executive decision support systems.

In an Operation Room, there are systems that are used for different kinds of warfare areas: anti-air warfare, anti-surface warfare, anti-submarine warfare, mine warfare and command and control warfare. Each of these areas is attended by one or several persons of the ORO's team. Each person gains situation awareness in his or her own domain of competence and the ORO gains awareness of the global situation. Hence, the current systems (mainly JDL model's levels 0 and 1) that provide data to the various specialists of the ORO's team are operational systems.

In order to develop a useful decision support system for sub-team supervisors in charge of specific areas (tactical systems), we need to identify which are the relevant elements that compose their understanding of the situation. Hence, these decision support systems will provide a partial view of the situation that fits the cognitive needs of these supervisors.

Considering the perspective of the ORO who must make strategic decisions in the Operation Room, we can say that he has the same position as a company's executive. Hence, the decision support system that will provide an ORO with useful information will need to aggregate the models of the specific situations provided by the decision support systems used by the sub-team supervisors in charge of specific areas. This integrated view of the situation should fit the ORO's cognitive needs (mental models and pictures) in order to support his decision making process.

Consequently, the process of situation analysis must take into account the level of decision that characterizes the users of the decision support system to be built. We distinguish the operational level (operators' activities), the tactical level (activities of operators' supervisors) and the strategic level (ORO's activities). Situation analysis is different at each of these levels. Tactical situation models will be built on the basis of operational situation models and the strategic situation model will be built on the basis of the tactical situation models.

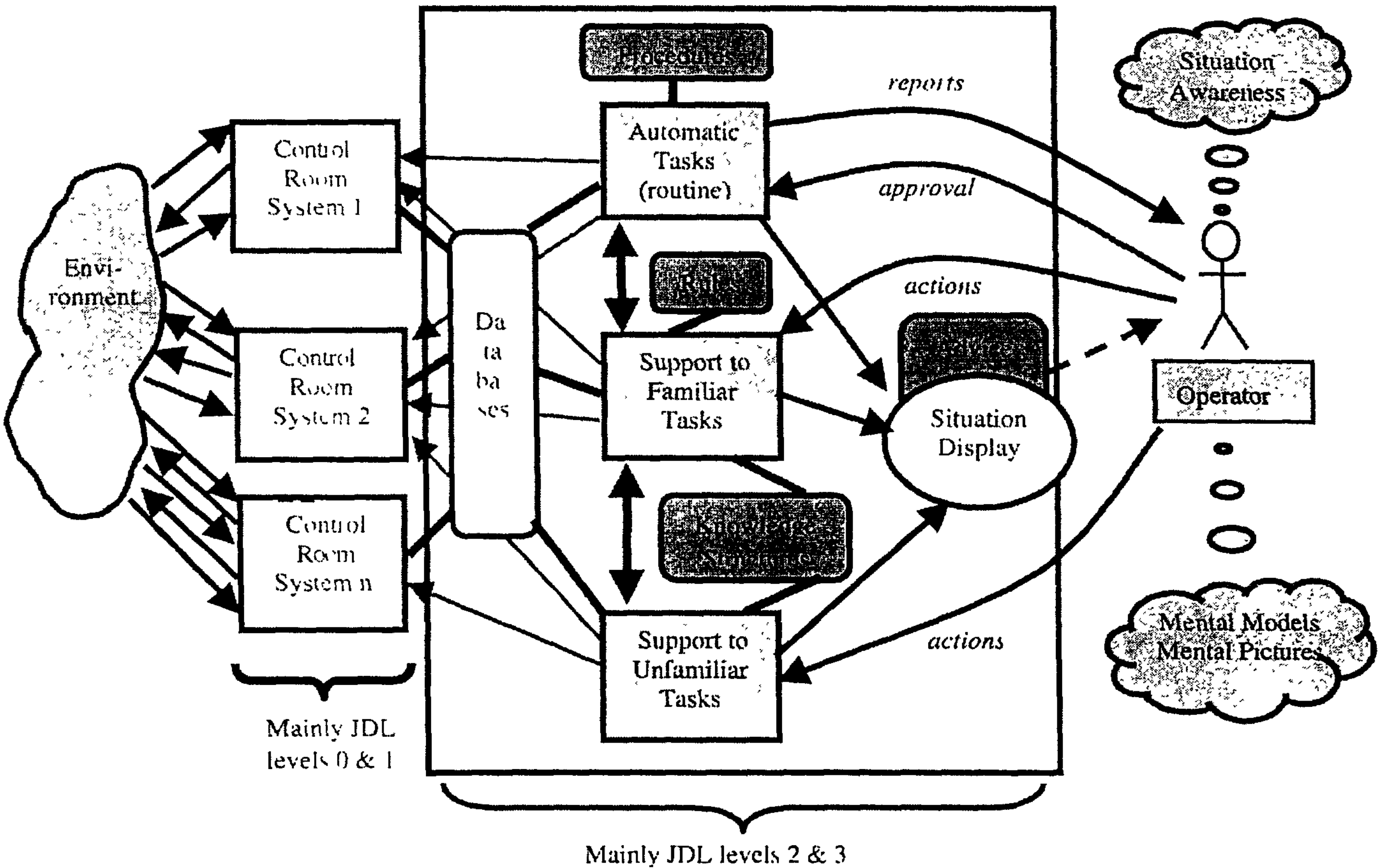

Figure 7: A generic architecture of an operator's situation analysis support system

8.2 Situation Analysis at the Operational Level

At the operators' operational level, a situation analysis support system (JDL model's levels 2, 3 and 4) would have to aggregate data obtained from multi-sensor data fusion systems (JDL model's levels 0 and 1) into a model of the situation which emphasizes the elements needed by the operator to conduct the operations of the system in its specific area.

Figure 7 presents a generic architecture of a situation analysis support system that could be used by an operator. The embedding rectangle symbolizes the situation analysis support system (SASS). The objective of this figure is to illustrate some principles that may be useful to the designers of future situation analysis systems.

- The operator is not in direct contact with the control room systems any more as he was in the Operation Room's current configuration (Figure 4). In Figure 7 we see that the SAS's modules monitor the control room systems (corresponding to JDL levels 0 and 1). As displayed in Figure 7, a single SASS can monitor several control room systems. We suggest that these control room systems record their data in data bases that can be accessed by the SAS's modules.
- The objective of the SASS is to build an image of the situation (called *situation display* in Figure 7) which fits with the operator's cognitive needs. This situation display should correspond to the operator's mental models or at least provide relevant information so that the operator will be able to build his or her mental models of the situation.
- We distinguish three kinds of modules in the SASS's architecture in order to emphasize the fact that only certain activities can be automated. We distinguish three categories of tasks according to the operator's familiarity with them: routine tasks that can be automated, familiar tasks that cannot be completely automated but are known by the operator and unfamiliar tasks that the operator will discover during a course of action. It should be clear that we consider here all the tasks that the operator might have to perform when being on watch in the Operation Room. Although only some of these tasks can be automated, the SASS modules should be able to provide the operator with relevant information so that he or she can build or update his or her mental model of the situation, assess the situation and choose an appropriate course of actions. Hence, each module of the SASS contributes to the creation and update of the *situation display*.
- Let us remark that the three kinds of modules can be distributed in different ways in a real system architecture. This distribution depends on the category of architecture that is chosen (expert system, blackboard system, multi-agent system, etc.) by the designers.
- Automatic tasks correspond to routine activities described by procedures that are well known and can be automated. A module implementing automatic tasks is able to automatically monitor certain functionalities of the control room systems. Usually it will send reports to the controller and require approval for certain actions, when deemed necessary by the system designers. The information gathered by modules implementing automatic tasks contributes to the creation and update of the situation display.
- Modules supporting familiar tasks partly automate tasks that are known by the operator; those tasks requiring the operator's involvement for actions such as choice among several possible alternatives, decisions with incomplete information, orientation of data acquisition systems, etc. One important role of these modules is

to contribute to the creation and update of the situation display. The situation display must present information in a way that will facilitate the operator's decision making process. Hence, the importance of structuring and displaying information about the situation in a way that fits the operator's mental models. Since these tasks are familiar, system designers may implement in the module certain functionalities (rules for example) that will be able to provide advice to the operator with resepct to the attended situation.

- Modules supporting unfamiliar tasks can only gather information and display it in a way that will enable the operator to understand the situation and help him or her to make decisions. It is difficult to design such modules because of the unfamiliarity of the tasks. One way to deal with this difficulty is to try to implement generic knowledge structures that will be able to record any kind of fact characterizing events occurring in the environment. Again, one important role of these modules is to contribute to the creation and update of the situation display. The situation display must present information in a way that will facilitate the operator's decision making process when dealing with unfamiliar tasks.
- The proposed generic architecture also provides ways to make the system evolve. If system designers implement functionalities that will record operator's actions along with the situation states, they will be able to analyze real courses of actions. Such analyses may enable designers to better understand familiar tasks and automate certain of them. In the same way they will be able to analyze the operators actions when dealing with unfamiliar tasks and enhance modules supporting familiar tasks accordingly.

8.3 Situation Analysis at the Tactical and Strategic Levels

Now, let us look at the tactical level (activities of operators' supervisors) and the strategic level (ORO's activities). At these levels, operators' supervisors and the ORO do not deal with operational data, but with aggregated information. As we previously mentioned, they are in the same position as managers and executives in a company. Hence, a situation analysis support system (SASS) for operators' supervisors mainly takes information about the attended situation in the knowledge bases and data bases of the operators' SASSs. The supervisor's SASS modules will aggregate and manipulate information and knowledge provided by the operators' SASSs in order to build an image of the situation display) that fits the supervisor's mental models and pictures.

Figure 8 presents a generic architecture which illustrates how a SASS for an officer (an operators' supervisor in our case) can be developed on top of operators' SASSs. We have not detailed the modules composing the officer's SASS, because they are domain dependent. We do not know if the distinction that we made for the operator's SASS between routine, familiar and unfamiliar tasks still applies to the officer's SAS.

In Figure 8 we also distinguish the officer's SASS from the decision support system. Obviously, they are part of the same system that helps the officer to understand the situation and support decision making. We made this distinction in order to make clear the fact that a situation analysis support system can stand alone without providing advice to the user with respect to the actions that can be performed in order to deal with the attended situation.

The same kind of architecture applies to the strategic level. Hence, an ORO's SASS would take its basic information about the situation into the knowledge bases and data bases of the officers' SASSs. The ORO's SASS modules would aggregate and manipulate information and knowledge provided by the officers' SASs in order to build an image of the situation (situation display) that fits the ORO's mental models and pictures.

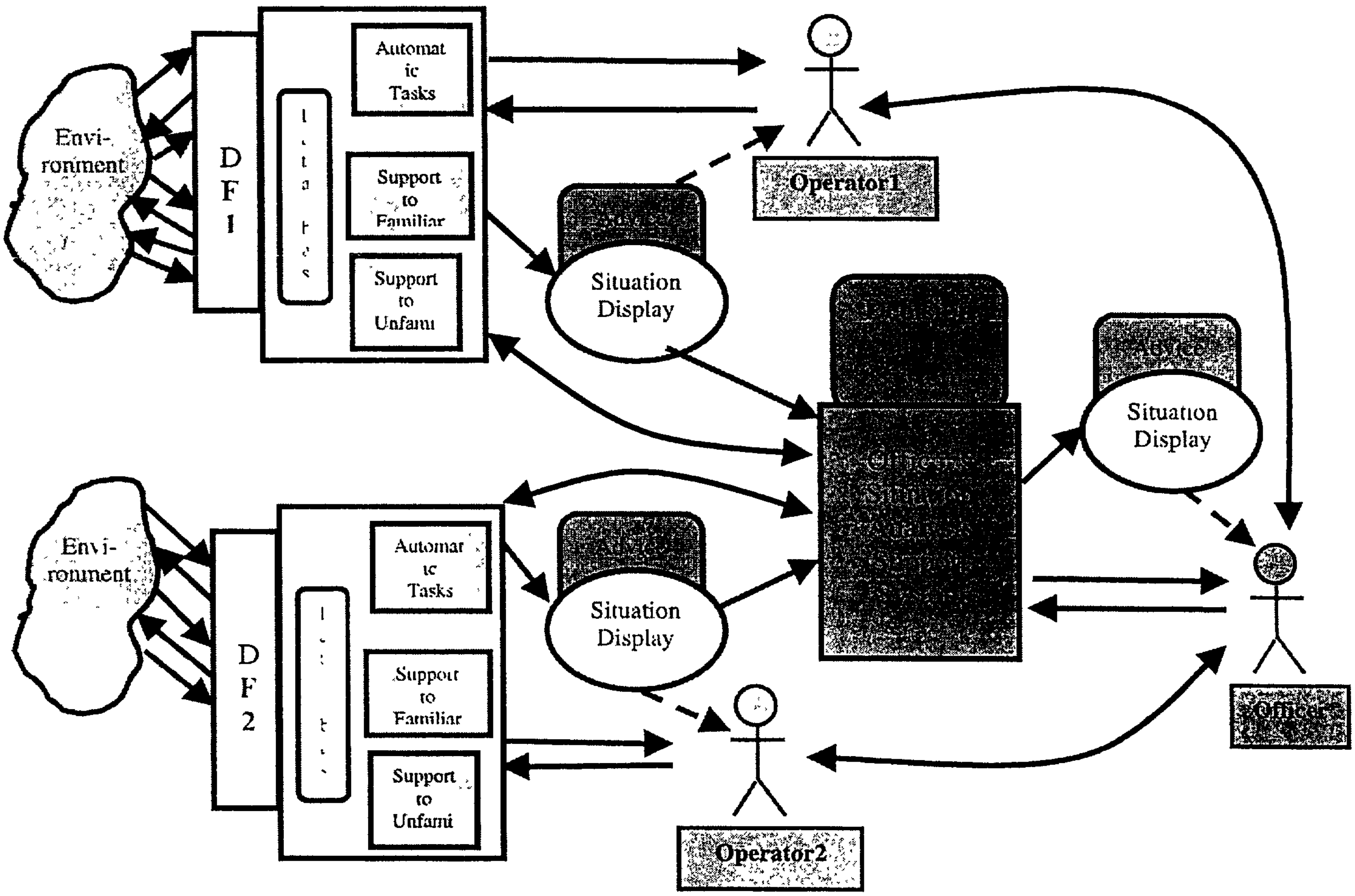

Figure 8: Generic architecture of the Officer's SASS in relation to Operator's SASSs

8.4 Conclusion

In this section we presented generic system architectures that characterize a situation analysis support system. We showed that a SASS architecture will be different depending on the level of situation analysis that we want to automate. We distinguished the operational level (operators' activities), the tactical level (activities of operators' supervisors) and the strategic level (ORO's activities).

Situation analysis is different at each of these levels. Operational SASSs obtain their data from the control room systems (JDL model's levels 0 and 1) and build a situation model that fits the operator's cognitive needs. Tactical situation models are built on the basis of operators' situation models and the strategic situation model are built on the basis of the tactical situation models.

An interesting conclusion of this presentation of the different levels of situation analysis taking place in an Operation Room is that the traditional Data Fusion model (the five levels of the revised version of the JDL model) may not directly apply to a hierarchically organized team. It appears clearly in Figure 7 that the operator's situation analysis support system monitors the control room systems (JDL model's levels 0 and 1). The operator's situation analysis support system mainly covers levels 2 and 3 of the JDL model corresponding to situation assessment and impact assessment. Resource management (JDL level 4) takes place at another level (tactical or strategic level).
In Figure 8 it appears clearly that the Officer's SASS is not in contact with the control room systems (JDL model's levels 0 and 1). The officer's situation analysis support system covers levels 2, 3 and 4 of the JDL model corresponding to situation assessment and impact assessment and resource management. It is clear that only a part of resource management is dealt with at the officer's tactical level. It is also clear that the same considerations apply to the strategic level where the ORO's SASS covers levels 2, 3 and 4 of the JDL model.

Another important conclusion of this discussion is that the various team members do not have the same understanding of the situation, given the level of their interventions and responsibilities. Operators have a specific view of the situation whereas the ORO should have a global understanding of the situation.

We think that the initial definition of *Situation Analysis* proposed Scientific Authority of this contract needs no change in order to take into account the observations made during the present study.

> *Situation analysis is the process that allows a person to gather and structure all the elements and their relations that allow him or her to mentally understand a specific situation and to be aware of its potential consequences.*

We may suggest some complements to that definition.

> *Situation analysis is a cognitive process that should not be confused with the computer-based process of data fusion.*
> *A situation analysis support system is a software that supports a person's situation analysis and should provide a situation display that fits this person's mental models and pictures which are relevant to the attended situation.*
> *If the person works at an operational level, the data that will be fed into his or her situation analysis support system will come from a data fusion system. If the person*

works at a tactical or a strategic level, the data that will be fed into his or her situation analysis support system will not come from a data fusion system but from another situation analysis support system of a lower level (operational or tactical).

9. Recommendations for an Object-Oriented Analysis of a Situation Analysis Support System

9.1 Preliminary Discussion

Given the preceding discussion, it seems too early to give precise recommendations for an object oriented analysis of a SASS. We do not have enough information about the tasks carried out by the different members of the ORO's team, including the ORO himself. We know that other researchers are currently performing work and task analyses of the ORO's position. We recommend that the DREV team wait the results of these analyses in order to better plan and coordinate further activities. However, we can identify several activities that could be carried out in the future in order to prepare the analysis and design of a SASS.

To begin with, we recommend that the DREV team examine the results of the work and task analyses of the ORO's position in order to determine which data sources are used by an ORO in order to build his mental models of the attended situation. We conjecture that an important part of these data are provided by operators and/or their supervisors. If this conjecture is verified by the work and task analyses currently performed, then the generic architectures that we presented in Figures 7 and 8 will apply to the ORO's team. Hence, the DREV team will have to decide which level of situation analysis will be examined in the next phases of the project.

We showed in Section 8 that it would be quite difficult to try to develop a SASS for the ORO right on top of a data fusion system of level 0 and 1 according to the JDL model. It seems more reasonable to develop a SASS for operators on top of these Data fusion systems. Figure 9 presents a general architecture of a system that the DREV team proposed to support the levels 2 and 3 of the JDL model on top of the multisource data fusion systems RM and MSDF (levels 0 and 1 of the JDL model). We think that a SASS for the Operation Room's operators would have similar functionalities and would also be able to display the attended situation in a way that fits the operator's mental model. The architecture proposed in Figure 9 should be modified in order to show the data structures which contain the description of the various elements of the situation. This is important because these structures will provide the basic data that will be used by the SASS designed for the operator's supervisors (and for the ORO).

9.2 Coupling Cognitive Task Analysis and Knowledge Engineering

Situation Analysis aims at allowing a person to mentally understand a specific situation and to be aware of its potential consequences. Research works on situation awareness have shown that people rely on the use of mental models when gaining and maintaining situation awareness. Endsley (Endsley 1995) and various other authors (Zsambok and

Klein 1997) underline the importance of schemas and scripts that structure a person's long term memory and contribute to the creation of his or her mental models of the situation. In the application domain of our study, (Matthews et al. 1999) recently completed a cognitive task analysis of the ORO's position in the Operation Room. They observed that OROs employ a variety of mental pictures and mental models in order to achieve their cognitive goals and to gain and maintain situation awareness. From all these observations we can conclude that identifying the content of a person's mental models relative to situations of interest is a crucial issue when developing a SASS.

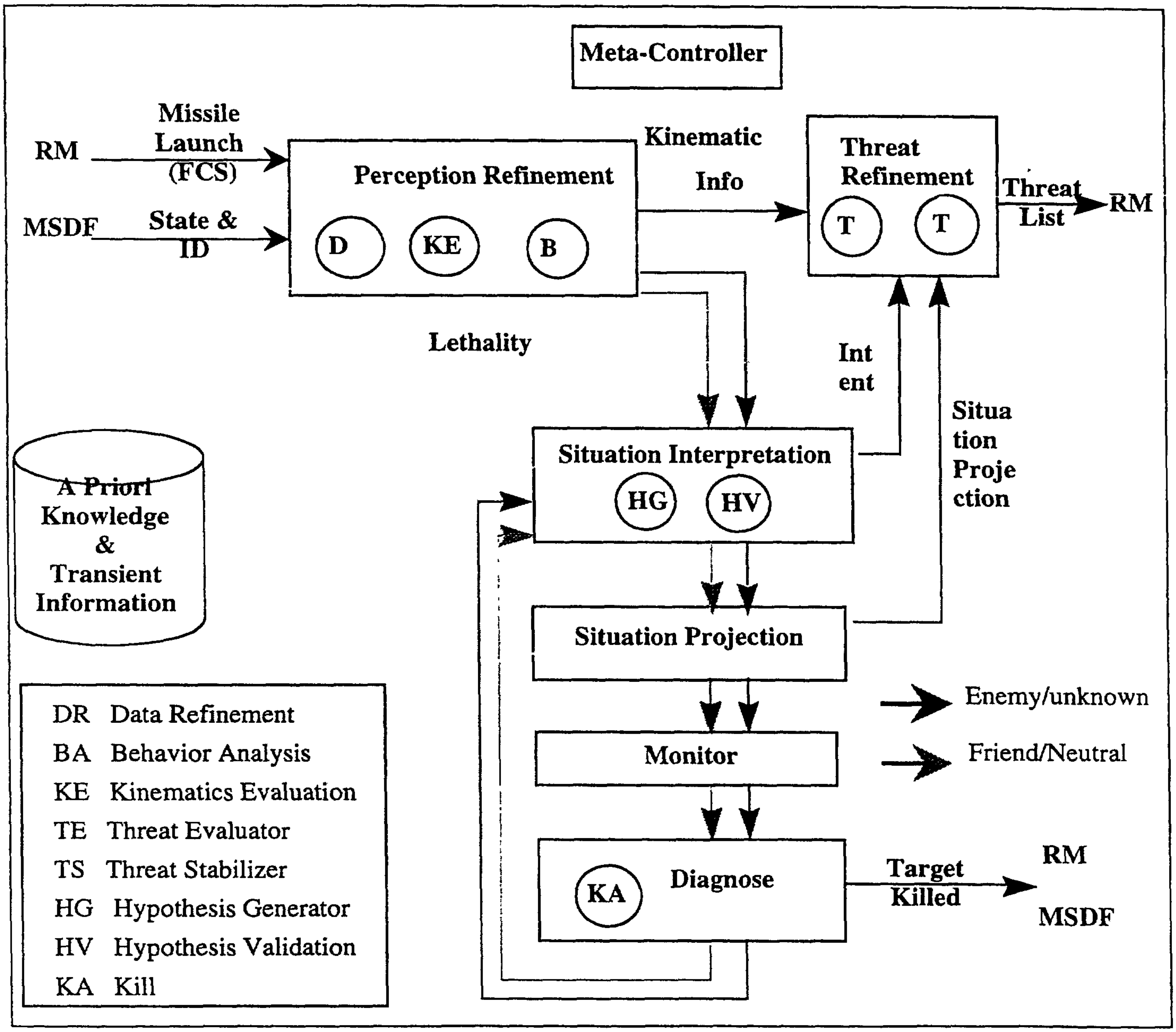

Figure 9: A generic Situation and Threat Assessment System (DREV proposal)

The data structures that represent the elements of a situation and their relationships are at the heart of a SASS. These data structures should allow the SASS to propose to a user a situation display that fits his or her mental models and pictures relative to the attended situation. In order to be able to create those data structures, knowledge engineers should be able to identify which elements make up the mental models of the users of the SASS to be built.

In the context of the creation of a SASS for OROs, it will be necessary to obtain formal models that match the mental models and pictures enabling an officer to gain and maintain situation awareness. Such formal models will be used as the key knowledge and data structures on which the SASS will be built. Hence, it is recommended to carry out a cognitive task analysis coupled with a knowledge engineering approach in order to get at the same time a description of the tasks performed by OROs as well as the content of the key mental models and pictures that are key ingredients in the ORO's decision making process.

We conjectured that an important part of the data used by the ORO are provided by operators and/or their supervisors. If this conjecture is verified, a cognitive task analysis coupled with a knowledge engineering approach should be carried out in order to identify which data structures fit the operators' mental models and which part of these data structures are used to provide information to OROs. From these structures it would be possible to identify which information will be provided to the ORO's SASS.

9.3 Future Work

As it has been shown in the present study, the notion of situation analysis sheds new light on the process of decision making in complex C2 settings by emphasizing the crucial role played by human operators. The difficulty encountered by researchers and developers to build efficient and complete data fusion systems with regard to the JDL model can be explained by the complexity of fully automating processes in which human judgement plays a crucial role. Consequently, we suggested that the JDL model should be revised in order to take into account the human interventions in general and the process of situation analysis in particular. Currently, Levels 2 and 3 of the revised version of the JDL model (1998) are not well-understood. Hence, ***on the theoretical side, the next recommended step*** is to further study the main works that have been performed by several teams on JDL levels 2 and 3 in order to identify their main characteristic elements (concepts, resolution techniques, systems architectures, etc.) and to relate them with the model of situation analysis proposed in the current report. Such a study would provide several outcomes:

- identify the main problems that have been encountered when trying to automate JDL levels 2 and 3:

- identify the main solutions proposed to solve those problems as well as the advantages and limits of those solutions;
- study how the notion of situation analysis may help understand those problems and provide a framework for integrating already available solutions and open directions for new solutions.

On the practical side, the next recommended step is to perform a cognitive task analysis coupled with a knowledge engineering approach of the activities of an ORO as well as of key members of his supporting team. From the perspective of the creation of a SASS, the knowledge engineering work should enable designer to identify the key data and knowledge structures that will be used to create a situation display that will fit the mental models of the SASS's users.

With respect to the identification/representation of an ORO's mental models/pictures, it might be useful to gather various samples of the data/information used by an ORO when trying to gain situation awareness: computer data, information given by operators and their supervisors, maps, drawings, sketches, etc. All these elements may contribute to the creation and maintenance of the ORO's mental models relative to the attended situation;

Thanks to the knowledge engineering phase, knowledge engineers will be able to:
- Develop conceptual model(s) of the situation from an ORO's point of view
- Identify which data/information are needed to generate the situation conceptual model(s)
- Identify ways to enhance the situation model when the ORO is gaining a better understanding of the situation

We can conjecture that a situation model will not be completely generated automatically by a SASS. Given that hypothesis, it will be interesting to characterize how an ORO could orient the SASS in order to get more information in order to adjust the situation model (and display) so that it fits his mental models and pictures in a better way. The SASS will need directions from its user in cases in which the acquired information is incomplete, ambiguous, noisy, contradictory, etc.

Based on these studies and models, the next step would be to develop a base architecture for the SASS and to develop a prototype in order to evaluate the feasibility of the proposed approach.

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11. Abbreviations

C2:	Command and Control
CTA:	Cognitive Task Analysis
DREV:	Defence Research Establishment Valcartier
DSS:	Decision Support System
JDL:	Joint Directors Laboratories
OR:	Operations Room
ORO:	Operations Room Officer
SA:	Situation Awareness
SA IPT:	Situational Awareness Integrated Product Team
SASS:	Situation Analysis Support System

Annex 1: Situation and Threat Assessment in the Data Fusion Process

1. Inroduction

In this document, we give an overview of the process of the situation assessment (SA) and threat assessment (TA) in the context of the data fusion process (DF) (Antony 1995; Waltz and Llinas 1990). Our first objective is to provide a general picture of the main characteristics of the SA and TA processes as they are usually presented in the open literature. Our second objective is to identify in which areas workable solutions have been proposed and in which areas satisfying solutions have not been proposed yet.

The DF process is required within any application where a large amount of data is to be collected and processed as in military intelligence gathering, command and control (C^2), weather prediction applications, etc. In (Hall and Llinas 1997) the process of Data Fusion or Information Fusion is defined as follows: "*The integration of information from multiple sources to produce specific and comprehensive unified data about an entity*".

Data are remotely sensed by different techniques (e.g. radar, sonar, satellite ...). Today, the automation of such a process is becoming more and more crucial, especially in military applications for different reasons:

- The ever-increasing difficulty to identify and track targets, due to the permanent technological improvement;
- Situations and threats are increasingly complex;
- The distributed character of sensed data;
- Due to the increasing amount of data to be processed during short intervals of time (multisensor data), human operators can be overloaded and may make sub-optimal decisions (Pedersen et al. 1999).

Obviously, it may be argued that single-source data can avoid redundant information and therefore reduce the amount of data to be processed. However, redundant data can be of great importance since they validate information in contexts in which one must deal with uncertainty and incompleteness.

In general, the DF process can be divided into two processing levels. At the first level, we deal with numerical processes and products (linear and non-linear estimation techniques, pattern recognition, statistical operations). At the second level, the processing is of a symbolic nature (AI techniques), the products belong to more abstract levels.

In the first part of the present report, we describe three generic models of the DF process that are indicative of the common understanding of this process in the open literature. We also briefly mention some main functions that are associated to the SA and TA processes and show their dependency on the application domain. We also discuss the complexity of the problem solving process in military context.

In the second part, we discuss the practical solutions that have been proposed to manage parts of the DF process. It appears that few systems are able to support the SA and TA processes because of the complexity of the activities involved.

Finally, in the last (third) part, we discuss several techniques that have been developed in the field of artificial intelligence (AI) and applied to the DF domain. The proposed methods, although interesting, have various limitations and do not lead to a complete solution based solely on AI techniques. Recently, multi-agent techniques have been proposed to get various specialised systems collaborate towards a solution to complex problems. Some of these multi-agent techniques have been applied to the DF problem.

In conclusion, we raise several issues that have rarely been addressed in the Data Fusion domain and that can help analysts gain a better understanding of the SA and TA processes.

2. PART 1: Theoretical Data Fusion Models

In this part, we present different DF fusion models described in the literature. The first three sections present three models (including SA and TA processes) from different points of view. Next, we describe the elements and functions required by the SA and TA processes. Finally, we present some theoretical models that are used in military problem-solving to represent the main elements relevant to the SA/TA processes.

2.1 A three-level functional model of DF

A detailed study was ordered by the Joint Directors of Laboratories Data Fusion Subpanel (JDLDFS) in order to define a general framework for DF problems (White and Llinas 1990) (Hall and Llinas 1997). This study has led to the definition of two models. The first model has three levels (see Figure 1):

- Level 1: Estimation of enemy's identity and position;
- Level 2: Situation Assessment (hostile or friendly): "*A process by which the distributions of fixed and tracked entities are associated with environmental, doctrinal and performance data*" (Hall and Llinas 1997);
- Level 3: Threat Assessment (in a hostile situation): "*A structured multi-perspective assessment of the distributions of fixed and tracked entities which result in estimates of (e.g.)* (Hall and Llinas 1997) *:*
    - *expected courses of actions;*
    - *enemy lethality;*
    - *unit compositions of deployment;*
    - *functional networks (e.g. supply, comms);*
    - *environmental effects*".

It is important to mention that processing becomes more abstract as we move to higher levels. At Level 1, products result from single and multi-source processing that involve:

- Tracking (Chang 1994; Desbois 1998; Ding and Hickey 1999; Roy et al. 1999; Roy et al. 1998; Shar and Rong Li 1999). "*A process which generally employs both correlation and fusion component processes to transform sensor measurement into updated states and covariance for entity tracks*" (Hall and Llinas 1997).
- Correlation. "*A decision making process which employs an association technique as a basis for allocating sensor measurements to the fixed or tracked location or entity*" (Hall and Llinas 1997).
- Alignment. "*Processing of sensor measurements to achieve a common time base and spatial reference*" (Hall and Llinas 1997)) and association ("*a process by which the closeness of sensor measurements is completed*" (Hall and Llinas 1997)).

This implies sampling the external environment with multiple sensors and exploiting other available sources. The resulting products are the position and identity estimates of the targets or platforms[1] in the composite battlefield (Chang and Lu 1995; Cowden 1995; Jungert 1999; Zhang and Jiao 1998).

At Level 2, the fusion process involves situation abstraction and situation assessment (Bergeron et al. 1998; Campos and Llinas 1998; Fracker 1988). Situation abstraction consists of the construction of a generalised representation from incomplete data in order to give a contextual interpretation of the distribution of forces determined at the first level. The

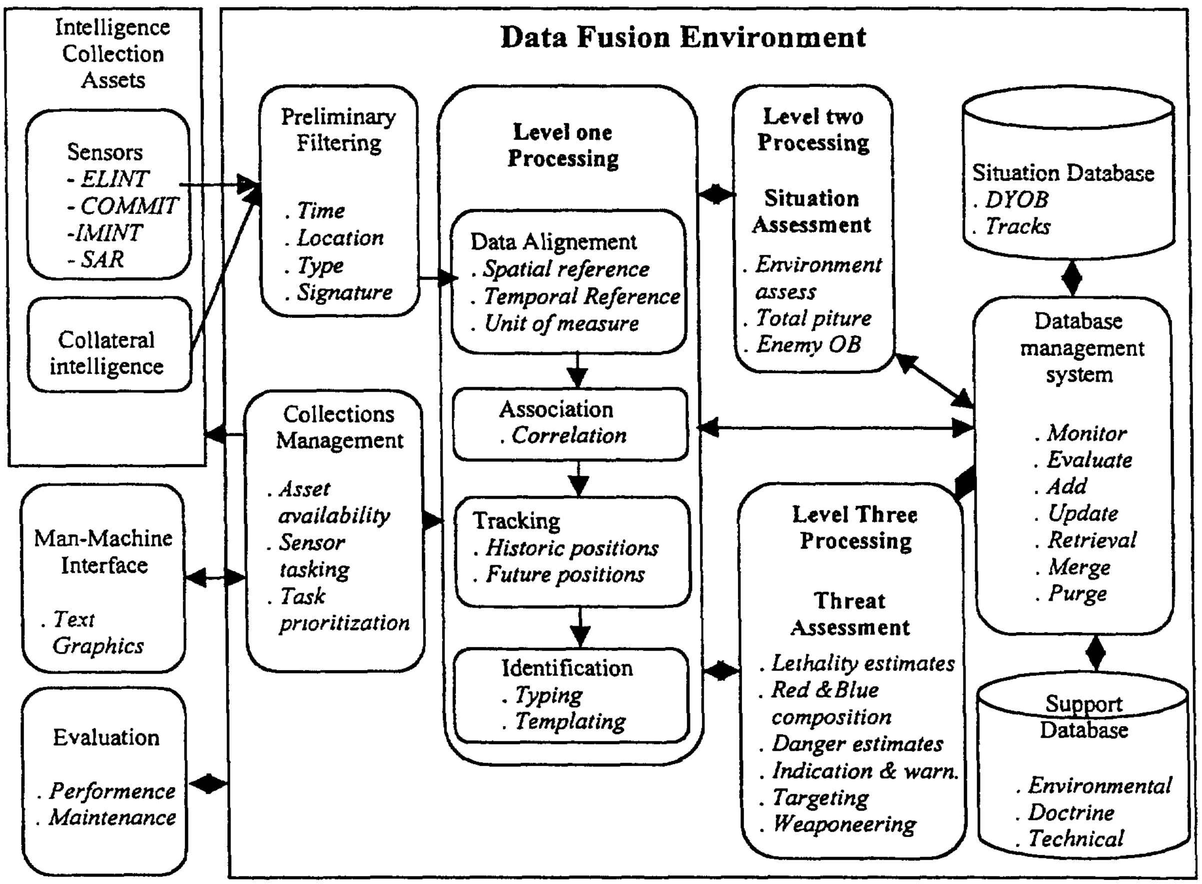

Figure 1. DFS product-oriented model of the data fusion process (White and al. 1988).

uncertainty of the information contained in the modelled situation raises multiple hypotheses about the elements characterising this situation (Cohen 1984; Cohen 1985; Cohen and Grinberg 1983; Decker and Lesser 1994; Li et al. 1999; Rogova and Losiewicz 1999). The situation assessment function refines these hypotheses and selects a finite set of important alternatives for further analysis.

At Level 3, the fusion process involves threat and risk assessment (Bergeron et al. 1998; Hayslip and Rosenking 1989; Paradis et al. 1997), considering the ability of friendly forces to effectively counter the enemy. This assessment must also take into account the vulnerability

[1] Platforms are the raised enemy's structures.

of friendly forces during the confrontation. This level differs from the second one in that the results should provide a true quantification of the enemy's capacities to threaten friendly forces. It should also give estimates about the enemy's intentions. At the second level, the results are limited to the identification of the enemy's behavioural patterns, without interpreting them nor determining their consequences.

2.2 An architectural model of DF

The second model proposed in (White and Llinas 1990) is viewed from a system architecture point of view. The main characteristic of this model is its distributed nature (see Figure 2). Each node corresponds to a set of processing units.

The bus-type elements support the notion of connectivity. As we can see in Figure 2, there are two types of connectivity: interconnectivity and intraconnectivity. The first one connects different processing units with the external environment. The second one connects the processing units of a node. These processing units provide the same functions as those in the first model described in Section 2.1: similar source integration, dissimilar source integration, situation abstraction, situation assessment and threat assessment.

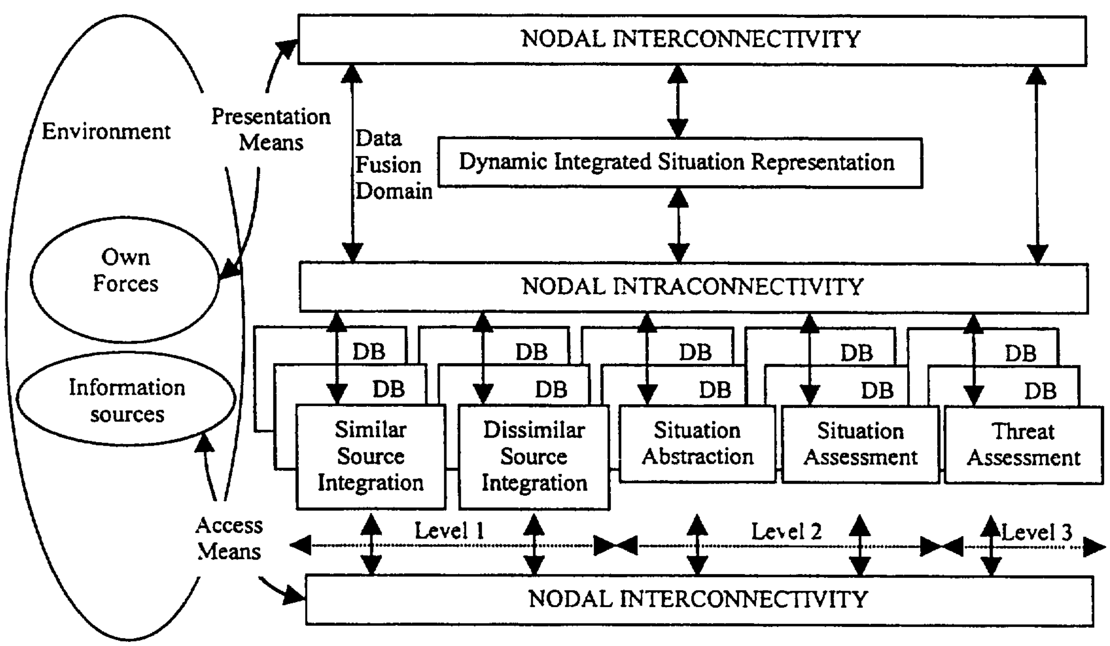

Figure 2. DFS system-architecture-oriented model of the data fusion process.

At the first level. a distinction is made between single and multi-source data fusion. The final processing product is called the "*Dynamic and Integrated Situation Representation*". The relationship between this product and the different processing units is the same as the relationship that can be found between knowledge sources and a blackboard in knowledge-based systems.

A dynamic representation of the assessed situation and the assessed threat is the key element for the decision-making process (Paradis et al. 1999). In fact, decisions are always made with regard to new incoming events. The interpretation of these events can be viewed as a change in the current situation state and the related current TA.

2.3 A four-level functional model

The functional model of DF proposed by (White et al. 1993) is divided into four levels as shown in Figure 3:

- Level 1: this level is characterised by four functions:
  - Detection of objects;
  - Association of the detected objects with other identified objects;
  - Refinement of objects' attributes: position, velocity, etc.;

Classification and identification of detected objects: "*a process by which some level of identity of an entity is established, either as a member of a class, a type within a class, or a specific unit within a type*" (Hall and Llinas 1997).

- Level 2 (situation refinement): this level is an extension of level 1 which aims at enhancing the situation description produced at that level, in terms of completion, consistency, and abstraction. It comprises three functions:
  - Error correction;
  - Ambiguity resolution of the results provided by Level 1.
  - High-level interpretation of all information coming from the different sensors.
- Level 3 (threat refinement): this level identifies the potential intentions of the enemy and estimates vulnerability of friendly forces. The dynamic nature of a situation implies that TA must predict all possible short-term and long-term implications of that situation.
- Level 4 (process refinement): this level is in charge of the optimisation of the system's performances with regard to certain objectives. For example, sensors may collect relevant but redundant information if not controlled. Processing a large amount of redundant information can seriously affect the performance of the whole system. This level aims at controlling the quality of fused data. It also ensures the control of the three other levels in order to orient and focus reasoning activities at each level.

The first stage of Level 2 is an abstraction of the situation which can be a generalisation or a specialisation of the situation. Generalisation aggregates or abstracts information in order to provide a situation awareness with respect to higher-level entities such as activities. For example, a corn field will be associated to farming activity. Specialisation, on the other hand, results from a top-down reasoning process that aims at deducing or inferring subordinate elements or entities. For example, a farming activity in a region suggests the existence of tractors. Generalisation and specialisation allow the definition of structural, organisational, and functional relationships among the different elements of a field. Situation abstraction attempts to provide a complete representation of the situation. The second stage of Level 2 is the SA that gives a dynamic representation of the situation in terms of links between the observed events and the states of entities and organisations.

A system architecture based on the four-level model described above may be centralised or distributed. Distributed DF systems vary considerably with respect to the actual distribution of data, processing and control. The distribution of each of these three elements allows concurrent processing in the system. Centralised systems have the advantage of accessing data that are physically stored in the same place.
In a distributed context, data are located in different places. So, information may be lost because of local processing and communication. A detailed description of distributed systems can be found in (Manyika 1994). The main drawback of centralised systems is the possibility of a general breakdown of the system because of the failure of a major component. Blackboard-based architectures are widely used for the design of distributed systems

(Jagannathan et al. 1989). These architectures allow a centralised control and communication between spatially distributed knowledge-based systems.

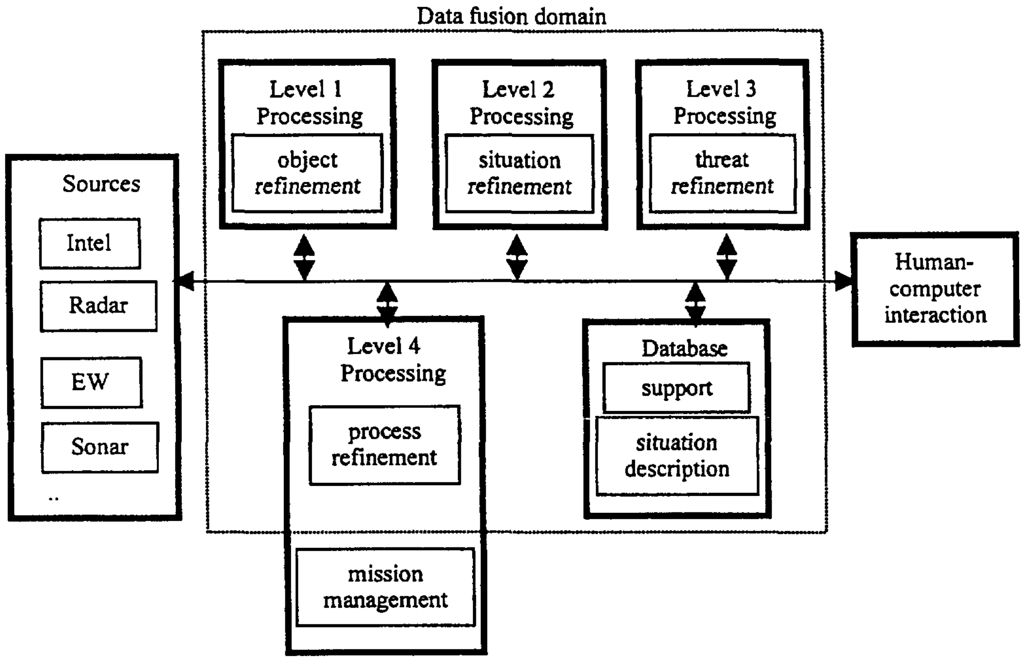

Figure 3 : High-level functional model of the data fusion process (Antony 1995).

2.4 The Joint Directors of Laboratories Model Revision

The model described in section 2.3 is widely used to categorise data fusion functions. However, data correlation and combination and inference are also needed in a wide range of non-military applications. In non-military applications, names such as threat assessment or threat refinement should be changed. Furthermore, there is no standard interpretation of the JDL model's levels. They have variously been used as referring to the kinds of association or estimation processing involved, the kinds of entities being characterised and the degree to which the data used in the characterisation have already been processed. Finally, separating the functions of data fusion into levels has led several persons to associate an implicit order to them: first do level 1, then level 2,3 and finally level 4.

The revised version of the JDL model aims at redefining the levels in order to solve such problems. The new version of the model has five levels (Steinberg et al. 1998):

- Level 0 – Sub-Object Data Assessment: estimation and prediction of signal/object observable states. This level involves hypothesising the presence of a signal and estimating its state. Level 0 processing includes signal detection from a time-series of data and feature extraction from images.
- Level 1 – Object Assessment: this level focuses on objects aiming at estimating and predicting their states on the basis of observation-to-track association, continuous state estimation and discrete state estimation.

- Level 2 – Situation Assessment: estimation and prediction of relations among entities. The relations can be represented as a network. This network allows associating tracks and other information into aggregations. Any type of relation can be considered according to the mission or application: it might be physical, organisational, functional, informational, perceptual, etc.
- Level 3 – Impact Assessment: estimation of the impact of the assessed situation. This level takes into account the impact of the planned course of actions for each participant, so that it is possible to determine interaction of an action with the other actions, and its interaction with the environment.
- Level 4 – Process Refinement: it involves planning and control rather than estimating. This level essentially manages the assignment of tasks to resources.

In conclusion, the main functions of the first two levels are detection and estimation of signals or objects. The next two levels aggregate these objects into situations thanks to the identification of relations between objects. Finally, the last level deals with control aspects such as planning actions with respect to available resources.

2.5 Functional requirements for SA and TA

In the last section, we presented a general overview of a functional architecture for the DF process. The definition of a class of architectures for SA and TA is a more difficult task because these processes are relatively ill-defined (see (Hall and Garga 1999) for a description of the pitfalls in Data Fusion and how to avoid them). In this section, we identify the main characteristics that SA and TA processes are expected to have, by defining the elements and functions that they should include (Waltz and Llinas 1990, p.28-33).

2.5.1 Elements and functions of the SA process

Before abstracting or assessing a situation using data acquired from Level 1, countermeasure activities must be assessed, for example, the force disposition/location/deployment in an environmental or socio-political context or both (see Figure 4). Such an organisational description leads to the definition of a set of functions required in a SA process. Figure 5 presents an overview of the relevant functions for the SA process in the environmental or socio-political context.

Ideally, the SA system must yield results that a) reflect the true situation and b) provide a basis for event-activity prediction and thereby a basis for optimal sensor management. The SA process is therefore concerned with what is happening and which events or activities are going to happen. It focuses on the behavioural aspects of the relevant elements contained in the area of interest.

The highest level, represents the *"struggle of motives assessment function"* (Figure 5). This function means that each collection of data in a SA process may have different interpretations and implications in the decision-making process. Note that ideally, the SA analyst should be applying the concept of shifting perspectives in order to develop an optimal viewpoint of the situation. He or she has to examine data from different points of view.

These functions may be refined at several levels of detail. For example, a fighter pilot's estimation of a situation is not the same as that of a commander in land battle in terms of time-criticality and complexity.

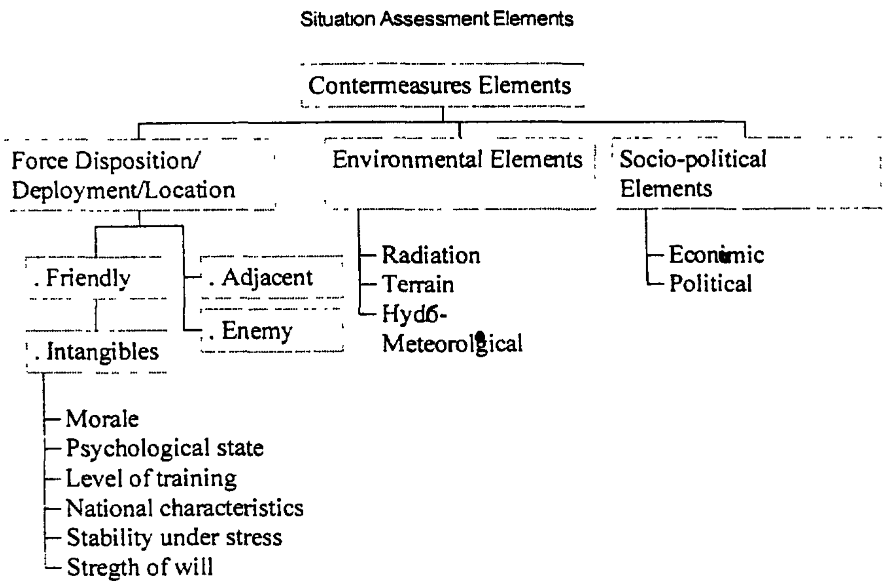

Figure 4. Elements of the SA

In general, SA is clouded with uncertainty because of the difficulty to estimate the enemy's intent. For this reason, different situation-estimating countermeasures must be taken by friendly commanders. These countermeasures are called CC&D techniques:

- Concealment: methods to prevent sensors from observing deployments, capabilities, intentions.
- Cover: methods (e.g. camouflage and avoidance) to deny the adversary the intelligence data needed for carrying out its operations.
- Deception: injection of false or misleading data.
- Ambiguity: Generating situations that have multiple interpretations (especially concerning intent).

As we can observe in this brief overview, the types of SA functions proposed in (Waltz and Llinas 1990, p.28-33) are very much dependent on the kind of application domain that is considered. For example, the functions presented in Figure 5 will not apply to the tasks of the Operations Room Officer (ORO) in the HALIFAX class frigates.

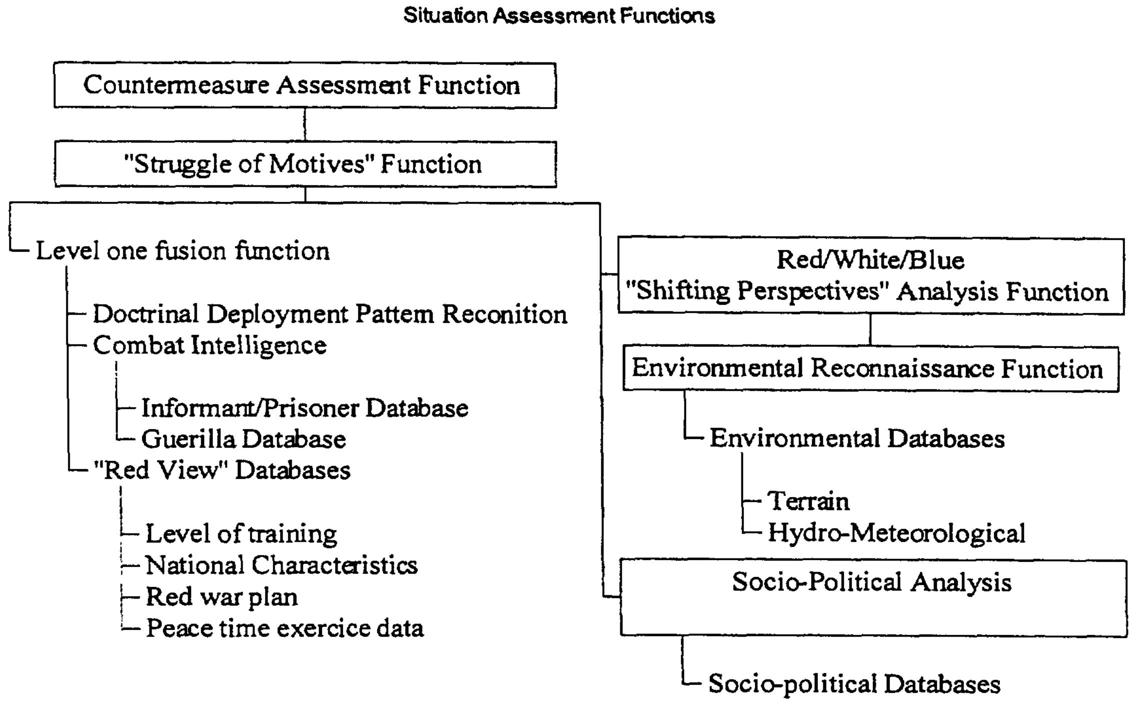

Figure 5. Situation Assessment Functions

2.5.2 Elements and functions of the TA process

For each situation, the SA process must be followed by a TA process. This process qualifies the situation quantitatively as much as possible, in order to estimate the enemy's effective capabilities, its intentions, and the scope of the threat. There are some similarities between the elements of the SA and TA processes, such as the counter-measure activities. Figure 6 shows the elements of TA according to (Waltz and Llinas 1990, p.28-33).

TA is a process where different elements are quantified in order to determine the enemy's capacities, vulnerability and intent:

- *Strength*. Enumeration of the number and size of the enemy units.
- *Composition*. Structure of enemy forces, organisation and weapons.
- *Location and disposition*. Description of the geographical location of the enemy, including the fire support elements, command and control facilities, air, naval, missile forces.
- *Availability of reinforcement*. Description of the enemy reinforcement capabilities in terms of ground, air, naval, missile …; communication and transportation means.
- *Movements and activities*. Description of the latest known enemy activities in the area.
- *Logistics*. Description of levels of supply ability: capacity of beaches, ports, airports …
- *Operational capability to launch missiles*. Relevant factors: characteristics of missile systems, launch rates, size and locations of stockpiles …
- *Serviceability and operational rates of aircraft*. A total aircraft inventory by type, performance and characteristics of operational aircraft, …

- *Operational capabilities of combatant vessels*. Description of the number, type and operational characteristics of ships, boats, ...
- *Technical characteristics of equipment*. Description of the technical characteristics of major items of equipment in the enemy inventory.
- *Electronics intelligence*. Intelligence-gathering capability using electronics devices.
- *Nuclear and CB weapons*. Types and characteristics, delivery capabilities, employment policies and techniques ...
- *Significant strengths and weaknesses*. An estimate of the significant enemy strengths and weaknesses can be developed from the facts presented in the preceding list.

As for the SA, TA has also a set of required functions as shown in Figure 7. Although more generic than the SA functions, we can observe that the TA functions proposed in (Waltz and Llinas 1990, p.28-33) need to be adapted to each application domain.

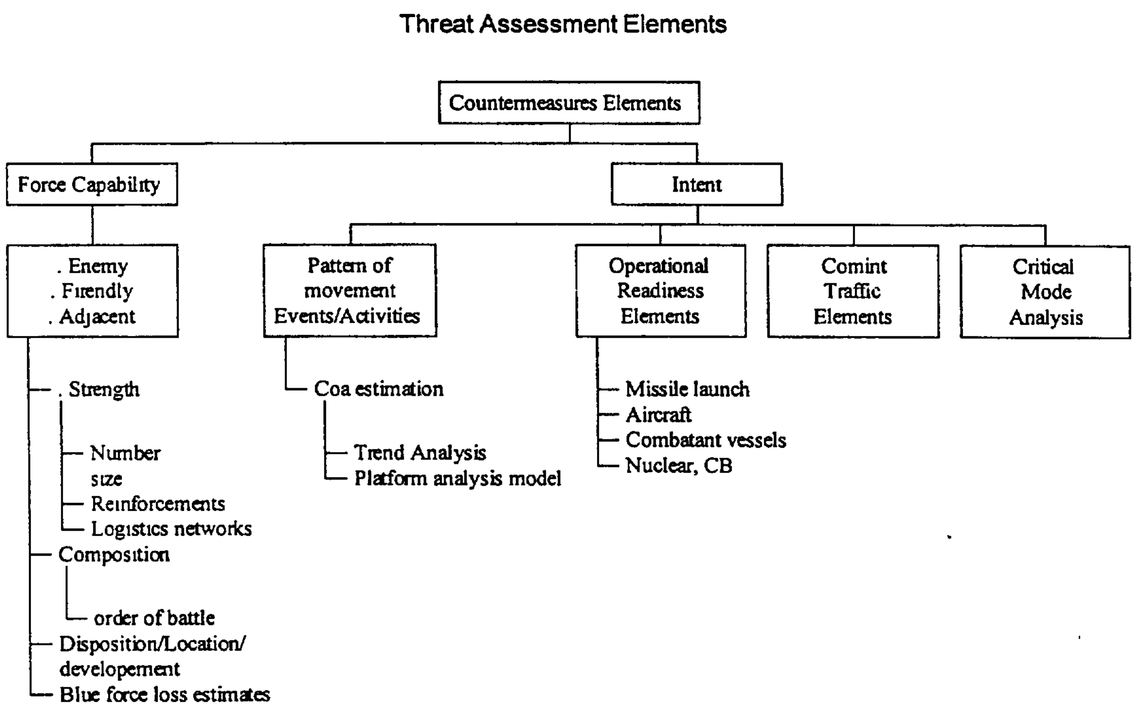

Figure 6. The elements of TA.

2.6 The military problem-solving process

As we stated before, the situation and threat assessment processes are based on multiple-perspectives and contexts. In a real context, we can have a situation, where two commanders have two opposite viewpoints on the problem to be solved, because they follow two different theories or have different understandings of the situations. A well-defined prôblem-solving process may help these commanders to concentrate on the enemy rather than to try to agree on the situation.

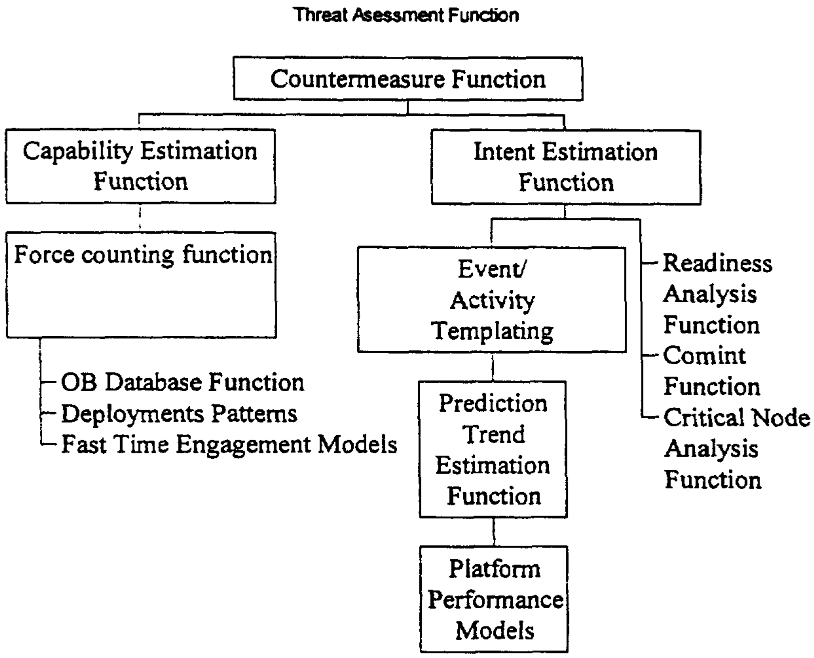

Figure 7. Functions of TA.

Several researchers (Reitman 1965) have described this problem in an abstract way by using a state transition model. There are many types of state-transitions as shown in Figure 8 from (Dieterly 1980). Nodes correspond to states and links correspond to transitions from an initial state to a final state. Dashed-line nodes and links respectively correspond to unknown states and unknown transitions.

Each of these situations leads to different difficulties. Furthermore, there are situations where one action may lead to different states, or multiple actions may lead to the same end state (see Figure 9). The combination of cases presented in Figures 8 and 9 leads to 40 possible problem situations. In (Reidelhuber 1984) a model of tactical decision making is presented. This hierarchical model integrates various Command, Control and Communication (C^3) functions with battlefield state estimates and can be considered as an elaboration of the concepts given in Figures 8 and 9.

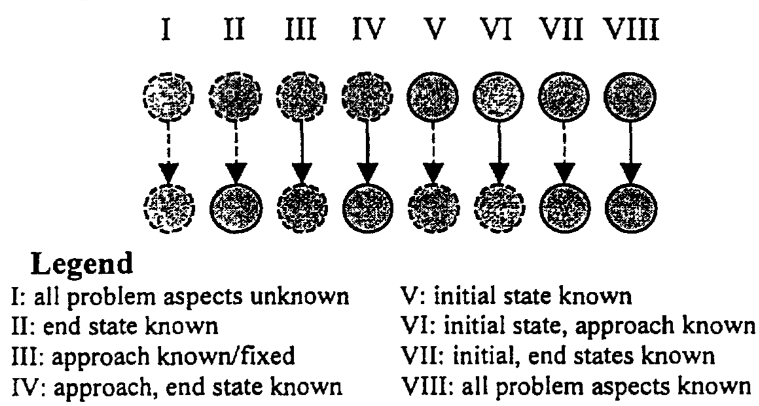

Figure 8. Decision-problem model.

Another relevant decision-making model is the SHOR (Stimulus-Hypothesis-Option-Response) model (Whol and al. 1984) which aims at dealing explicitly with both information input uncertainty and consequence-of-action uncertainty in military problem solving.
Let us now look at particular applications in order to see how data fusion is practically put into work.

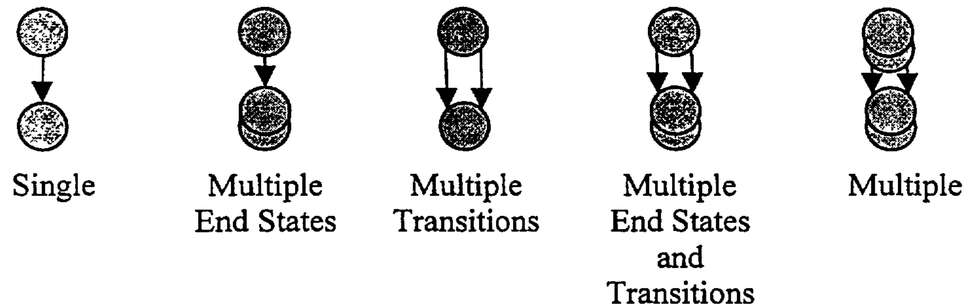

Figure 9. Dieterly 's classes of conditions.

3. PART 2: Practical Solutions

In this part, we briefly review some real-world architectures where a DF process takes place. We will describe the required functions of such architectures. We will also discuss some implementation issues related to the use of knowledge-based and expert systems techniques.

3.1 Real-world Architectures

In general, in practical systems, the DF process only represents a small portion of the overall system (15-20 %). In (Ballard and Rippy 1994), a system for performing situation assessment in Next-Generation Army Helicopters is developed which is composed of three subsystems: recognition, assessment and prediction. In (Bass 2000), the author discusses the cyberspace intrusion detection issue, and its relation to the data fusion process. With intrusion detection systems, designers face the challenge of combining data from different heterogeneous sources into a coherent "*picture*" which aims at improving the process of evaluation of the cyberspace security. It is important to notice that in cyberspace intrusion detection systems, sensors are different because the environmental dimension is different. Instead of trying to detect a missile launch and its supersonic flight in the atmosphere, cyberspace sensors observe information flowing through electronic networks. The decision system for cyberspace intrusion detection is based on a so-called OODA model (Observe, Orient, Decide and Act) which is widely used in military information operations. The decision support process for situational awareness (Chalmers 1997; Drake and Atwell 1997) is tightly coupled with the DF process. This cyber-fusion process requires the use of different techniques ranging from processing algorithms and statistical estimations to heuristic methods such as expert systems, to assess situations and threats in cyberspace.

These examples show that in a functional architecture, the DF process is only a small portion of the system. Such an architecture would include the following functions (Waltz and Llinas 1990, p. 23):

- *Communication*: the system is never isolated from the rest of the environment. Entities located in the environment must be able to communicate with the system so that it can update its representation of the environment and of the current situation as well as the threat related to this situation (Greeway et al. 1996). In addition, human operators must be able to communicate with the system, either to interpret information or to update information resulting from the decision making process.

- *Data-base management*: data captured from the external environment may be voluminous and of different natures. These data give way to several interpretations because of their incomplete nature. Hence, we may have to manage several potential ongoing scenarios as combinatorial problems.
- *Person-Machine Interface*: Continuous changes observed in the external environment lead to continuous interactions between human operators and the system. Very often, these interactions require time-constrained responses that vary according to the type of application in which the DF process takes place. In order to ensure good quality interactions, the system interface must be carefully designed.

This list of components is not exhaustive. A system may have other functions depending on the application needs. From a computational point of view, the DF cannot be separated from the other components of the system. Consequently, the DF system can be constrained by external events causing sub-optimal performances. For example, if the sensors are momentarily inaccessible, the DF process may be blocked, thus preventing the system from obtaining optimal results. The interdependencies between the system's components require in some cases, the use of parallel processing techniques at the first level in order to avoid system blockage. These techniques may also be required in a time-constrained-response context, such as in the military aviation domain (Pipe 1992), where pilots can delegate control to the computer onboard the aircraft. They can thus preserve "*situation awareness*" when events change faster than human recognition.

3.2 Implemented Systems

In this section, we only describe knowledge-based and expert systems techniques. Generally, the goal of such systems is to produce an estimate of the hostile force's structure or order of battle. The Expert System for Intelligence Analysis Support (ESIAS) project proposes one of the most comprehensive systems, at least in its conceptual treatment of the SA problem. The work reported in (King and al. 1986; Ruoff 1988) emphasises three aspects of this system: the development of ESIAS and the Situation Assessment knowledge-based system (KBS), the explanation facility of ESIAS and a system called DECision Aid Development and Evaluation (DECADE), which is a development environment for database-system-based aids for situation assessment. The goal of this work was to develop an environment to build efficient aids that evaluate threat capabilities and actions, infer threat intentions and predict undetected and future situations. The authors used a technique called "*conceptual knowledge modelling*" to develop the Command, Control, Communication and Intelligence (C^3I) conceptual knowledge model which is composed of two components:

- The C^3I conceptual structure model (CS model),
- The C^3I situation assessment behaviour model (SAB model).

The SAB model presents both the functional and the procedural views of the SA process. The CS model is used to define requirements, whereas the SAB model provides a high-level, implementation-independent model of the procedural knowledge to be represented in the knowledge base. These views are then extended to provide a detailed view of the SA process also point out that much of the research and development works on the data fusion process have been concentrated on Level 1.

4. PART 3: AI Technology

In this part, we discuss the benefits and drawbacks of AI-based technologies in the DF process. We review multi-agent techniques that are useful for the DF process. We end this part with a discussion about the human factors in the DF process and a conclusion.

4.1 Role of Artificial Intelligence in the DF process

Artificial intelligence techniques are widely used in many application domains where different aspects are to be addressed at once and where the use of mathematical methods seem to be insufficient, or even impossible. Data fusion is such a domain. The main AI applications used to solve DF problems are: expert systems or knowledge-based systems (KBS), natural language processing (NLP), planning or plan recognition, learning, and intelligent assistance. Other techniques used in the AI domain are also worth mentioning, such as pattern matching techniques which aim at searching for the best or an acceptable solution for a problem in a context where several solutions are possible.

Data Fusion levels 2 and 3 processing involve combinatorial complex problems that are difficult to tackle even with modern-day computers. For this reason, KB approaches can lead to solutions that are satisfying but knowingly sub-optimal. Sometimes, AI techniques are combined with numerical techniques in DF experiments (Level 1), because reasoning strategies typically depend on the quantitative values of various parameters. In (Huang and Lodaya 1990) the authors investigate the performance of an automated decision-making aid based on expert system technology. This system which is used to assist Airborne Early Warning (AEW) operators during the threat assessment task, combines AI techniques and numerical algorithms.

4.1.1 Main techniques provided by AI technology

The following AI techniques may be applied to the DF process (Waltz and Llinas 1990, p. 427):

- Expert systems and knowledge-based systems (KBS) may be used to recover deficiencies of Level 1 algorithms (Cowden 1995; Shahbazian et al. 1998). The KBS may apply contextual knowledge and knowledge about algorithm performance to select and invoke the best algorithm for the current problem. Knowledge may also be combined with numerical methods, in order to improve their adaptability. For Level 2 and Level 3, KBS techniques provide a broad range of reasoning and inference strategies to overcome the combinatorial aspect of the problems (Bergeron et al. 1998; Chaudhri and DesJardins 1999; Dörfel and Distelmaier 1997; Hayslip and Rosenking 1989; Ranze 1999; Ruoff 1988; Yang and Sun 1999). They also allow a multi-level inferring strategy in SA and TA. This gives the possibility of top-down and bottom-up reasoning in the hierarchy of hypothesised threats (potential threats). Further, situation and threat estimating performance can be improved in distributed or headquarters-type fusion centres by applying decision and analysis support with communicating or co-operating KBSs. The main advantage of knowledge-based systems is their use of human knowledge to solve also point out that much of the research and development works on the data fusion process have been concentrated on Level 1.

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- Natural language processing methods can be powerful fusion support tools for message-based systems. They can help human operators when analysing and filtering messages and textual alarms produced by the system, especially, in a context where responses to such messages are time-constrained.
- Military operations are always guided by a plan or a set of plans. These operations are complex, involve multiple resources and goals and require significant coordination. Classical plan recognition approaches are based on a predictability assumption. This means that they assume that the planner's model of the world (representation of the environment) as well as the effect of an action in that world are complete. This assumption does not hold in a military DF context. The planner may lack the effectiveness required to achieve a goal. There may be no sequence of primitive actions that achieve the goal. In such a context, classical planning models are usually unsuccessful. The condition for successful planning is called the effectiveness condition. In a military context, we may have either a predictability assumption or an effectiveness condition violation or both. The problem of how to plan, when at least one of these conditions is violated, is referred to as the reactive planning problem. In this case, the system must take into account constraints on the time left for re-planning. Hayslip and Rosenking (Hayslip and Rosenking 1989) proposed a system architecture composed of several planners concurrently operating at different time scales. The system is composed of five co-operating expert systems that communicate through a blackboard. This work was part of the REACT (Grumman's Rapid Expert Assessment to Counter Threats) system designed to aid pilots in air combat to make decisions at low altitude and hilly terrain. The plan recognition methods are primarily applied at Levels 2 and 3.
- At Levels 2 and 3, estimating or predicting future behaviour is of main importance (Ballard and Rippy 1994). However, the ability to estimate such behaviours is limited because of the complex nature of processes and behaviours that can be encountered in combat or even in peace time. Ideally, more robust fusion systems would be able to adapt to extreme behaviours. Machine learning techniques could also be applied to problems at Level 1.
- Intelligent assistance aims at supporting human operators when achieving various tasks. In DF systems, these aids can be thought of as alerting functions, often called indication and warning functions (I&W). Modern human-computer interface design techniques perform similar attention-focusing functions (Achille et al. 1997; Bachelder and Hansman 1997; Dörfel and Distelmaier 1997; Fechtig et al. 1997; Hoffmann et al. 1998; Huijsing and Meijer 1997; Kuperman et al. 1999; Osgood and Adams 1997; Rhodenizer et al. 1997). Methods in this area differ from others in that special features for interacting with humans and for improving human performance are included. Such methods should be based on the creation of cognitive models. For example, such systems can maintain a model of the profiles of user groups so that the system can adjust to each user's problem-solving approach. The only drawback of intelligent assistance is that it is difficult to apply it in a time-critical context.

- Pattern matching techniques are widely applicable to DF problems, especially in the context of Level 1 object identification strategies. Neural networks are also used for tracking problems (Kuh 1998; Whittington et al. 1993) which is an application of sensor data fusion. Pattern recognition methods are also used at Levels 2 and 3 (Freeman et al. 1997; Rogova and Menon 1998) as well as fuzzy logic techniques (Niekerk et al. 1999; Shastri and Wendelken 1999; Yang and Sun 1999).

4.1.2 Limitations of AI techniques

Although many AI techniques are useful in the DF process, many implementation issues must be dealt with, given the complexity of tasks at Levels 2 and 3. Whatever the technique used in a computerised system, the design of such a system depends on the size of the problem, on the data error characteristics and on the reliability/uncertainty of the applied knowledge.

Other DF-specific factors that influence AI-based solutions are (Waltz and Llinas 1990, p. 442):

- *Real-time processing requirements*. For each level of DF process, we must select the right time granularity for the system. The shortest response time at each level determines the most time-critical part of the process. The FUTURE system (De Jongh et al. 1994) is an example of a real-time knowledge-based system that was used to help African Navy identify threatening events early.
- *Time-varying data and solutions* (temporal variance). In (Bonissone and Aragones) the authors present a system that was used in a naval scenario for ship identification and in a tactical aerial situation, providing the pilot with information about the intent of potential threats.
- *Combined symbolic and numerical functions.* Each of these functions requires a specific programming language. That raises the issue of inter-language functionality. When it is impossible for a language to call another, each process must be executed separately, and the data and results have to be communicated through a shared-memory base.
- *Large data / knowledge requirements.*
- *Significant levels of uncertainty in data and knowledge.*
- *Human operator foibles and idiosyncrasies.*

AI techniques have made good progress during the past ten years. They often provide interesting solutions to difficult and well-defined problems. However, in a DF process, many different techniques may be required to tackle the variety of DF activities. Various sub-systems need to collaborate in order to build a solution. Blackboard architectures have been proposed in the eighties to make several processes (called knowledge sources) co-operatively build solutions to complex problems. In such an architecture, the shared memory (the blackboard) appears as a bottleneck that may impair the whole system's performance. This problem can be handled using *multi-agent systems.*

4.2 Multi-agent techniques

A detailed definition of a multi-agent system is out of the scope of this report. Simply put, a multi-agent system is composed of several agents that must co-operate via communication or other modes of interaction in order to solve a common problem. Each agent participates in the resolution of the problem. The basic assumption is that the sum of the agents' individual capabilities and their interaction ability, will bring better solutions, than merely the sum of their individual capabilities (each agent working alone).

Such techniques are especially well-suited for applications which include heterogeneous and distributed aspects. In general, in such applications, data and processing control are decentralised, and each agent will have a set of responsibilities associated with a domain in the environment where agents are supposed to evolve. Decentralisation can be physical (agents are at different locations) or functional (e.g. hierarchical design of a system).

This is the case of the DF domain applications (Bastos-Filho et al. 1998; De Jongh et al. 1994; Zhongyan et al. 1999). Hence, multi-agent techniques seem to be well-adapted for distributed problem solving within the DF process (Linderman 1999). In (Carver et al. 1993; Carver et al. 1995), the authors address the problem of how a set of co-operating agents must operate in order to converge towards an acceptable solution with a minimum amount of time and communication, and what reasoning capabilities are needed to support such a co-operation. This is in the context of a new distributed problem solving (DPS) testbed, DRESUN, that simulates a distributed set of RESUN interpretation systems and solves DVMT[2]-like aircraft monitoring problems. DRESUN is composed of a set of agents, called RESUN, that have interaction capacities. DRESUN's main goal is to ensure the global consistency of local agents' solutions. To do so, one must address the distributed coordination problem (Decker and Lesser 1993) which aims at scheduling tasks[3] over a set of distributed agents working on sets of inter-related problems. In such a context, uncertainty is still a problem, since agents cannot have complete information about the environment. The more uncertainty we have about the environment, the more uncertainty we get in coordination relationships. Uncertainty in these relationships can be evaluated as the necessary amount of communication needed to reach a solution to the problem. For example, in an aircraft monitoring scenario, two agents are responsible for two intersecting regions. Each agent can only receive information about its own region. The goal of the system is to identify the aircraft that are moving through the regions of interest, to determine their types and to track them through the regions. Received data may be uncertain because of noise. In addition, agent A's sensors may fail, while agent B's sensors are still operating. Hence, agent B can inform agent A about what is going on in the intersection region.

As an extension to the DRESUN testbed, a study on distributed coordination problem has led to the definition of five coordination mechanisms needed in a distributed situation assessment (DSA) context (Carver and Lesser 1995). These coordination mechanisms deal with updating non-local viewpoints, communicating results, handling simple redundancy, handling soft and hard coordination relationships.

In general, there is an overlap between agents' areas of responsibilities. In order to coordinate their actions and plans, agents must be able to change (by themselves or with the help of the system designer) their areas of responsibilities. Hence, it is possible to make changes in the planned tasks and to exchange roles between agents if necessary. This point has to do with the notions of organisation and reorganisation of a group of agents (Decker and Lesser 1995). To analyse the performance of a particular organisation, it is important to know which

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[2] DVMT stands for Distributed Vehicle Monitoring Testbed.

[3] See (Decker and Lesser 1994) for a description of a modelling framework TAEMS used to represent an abstract task environment.

portion of the set of tasks each agent is likely to process. Hence, agents organisations may be static or dynamic.

Often system performance can be significantly improved thanks to dynamic reorganisation of a group of agents. Therefore meta-level communication between agents about their local loads can, with a small communication cost, pinpoint the true costs and the benefits of the various organisational structures, allowing an informed organisational decision to be made. Instead of an agent making decision about restructuring or load balancing by assuming the average load of the group, the agent knows the actual load for its neighbouring agents.

4.3 Human factors in DF process

The evolution of computer-based systems that display intelligent behaviour has had profound effect on their design and on the way they interact with users (Waltz and Llinas 1990, p. 451). In designing such systems, one must focus on the following factors:

- Problem specification,
- Task analysis,
- Task allocation (person-machine),
- Determination of human informational needs,
- Application of human factors principles to interface design.

The key element to be considered in the design is the cognitive characteristics of the person-machine interaction at the cognitive level. This depends on the type of communication that takes place between the person and the machine. Such a communication may take several forms such as asking questions, presenting choices, recommending strategies, etc.

4.4 Conclusion

In this part, we discussed the benefits and drawbacks of the use of AI techniques in the Data Fusion process. The main techniques provided by AI technology are Expert Systems, Natural Language Processing, Plan Recognition, Machine Learning, Intelligent Assistance and Pattern Matching. The use of one or more of these techniques must deal with a number of requirements such as real-time constraints, dealing with uncertainty into the data, time-varying data and symbolic and numeric data combination. In a distributed context, where data is collected from different sites, traditional architectures such as the blackboard architecture appear as a bottleneck having a bad influence on the whole system performance. Multi-agent techniques which are a sub-part of the Distributed Artificial Intelligence (DAI) domain are well-adapted to deal with distributed and data-intensive requirements.

In the next section, we present a research programme which aimed at using knowledge-based systems to support the Data Fusion process in a Naval application.

5. PART 4: Data Fusion: A Naval Application

5.1 Introduction

This report is a summary of a research programme conducted by the Exercise Analysis Group at the Command and Control (C2) Department at DRA Postdown (DRA 1989) that investigates the ways in which new technologies can be used to support various aspects of surface ship command and control in the naval domain.

One of the major shortfalls in the ability to build and organise good C2 systems is the lack of adequate models of the whole system including the human element. For this reason, a research programme is in progress in ARE Postdown that studies the use of knowledge-based systems for solving problems in the time-critical areas of naval battle management. The purpose of this programme is the development of decision support systems capable of providing tactical advice to the combat management team of a naval ship or a group of ships. Knowledge-based Data Fusion Technology Demonstrator System (TDS) has been designed in order to investigate the functional and technical aspects associated with knowledge-based technology and the operational issues that ensue from its use. TDSs interact with the ship's live equipment in a multi-threat environment. The selected strategy was to gradually increase the complexity of scenarios presented to the TDSs in terms of numbers and variety of consorts, density of information and combination of threats. TDSs must provide automated support to the air, surface and sub-surface picture compilers and supervisors.

The prime objectives of the research programme are (Byrne et al. 1989b):

- To investigate the technical, time-scale and financial risks associated with the use of this technology;
- To identify the role of automated decision support within naval combat management and ascertain the adequacy of knowledge-based technology to provide such a support;
- To specify the requirements for the knowledge-based components of a combat management system;
- To explore the manning issues entailed by the use of this technology.

In the following sections, we present the C2 model and will discuss the importance of automating parts of this process. We will also discuss the problems that may arise from such an automation. We will next propose some partial solutions to these problems, such as the use of parallel processing methods and knowledge-based systems and techniques that can reason under uncertainty. Finally, we will emphasise the importance of human factors in C2 systems and will present a user-machine interface that meets the requirements of such factors.

It should be noted that all the information collected from the referenced documents can also be found in (Miles 1988).

5.2 The C2 model

An important problem of command and control in the naval context is related to the real-time decisions that must be made in order to accomplish a planned mission. A mission involves the participation of a large number of ships, aircraft and even submarines which form the Naval Task Group. Sometimes, the term "tactical" is used to distinguish between real-time decisions and higher-level command and control decisions made for whole oceans and continents.

In (Miles 1988) a four-stage model of command and control is presented:

- *Perception* – sense events occurring in the real-world of interest[4].
- *Assessment* – assess what is happening.
- *Decision* – decide how to act in order to achieve mission goals.
- *Direction* – direct resources.

The perception of occurred events combines various types of sensor data in order to form a more intelligible representation called the "tactical picture". This process of combination is called "Data Fusion" (DF). The results of the data fusion must be used cleverly in order to assess what is happening in the world of interest. This process is called "Situation Assessment" (SA). Decisions should be made successively so that the mission goals can be pursued. These decisions concern the "Resource Allocation" or re-allocation and aim at executing a planned course of actions. They also imply the "Resource planning" if measures are to be taken to anticipate future situations. Thus, the stages of naval C2 are data fusion, situation assessment, resource allocation and resource planning. In the following sections, we give only a description of the first two stages that are of interest to us.

5.2.1 Tactical Data Fusion

This process consists of the representation of a coherent tactical world picture based on a combination of sensor data, plans and intelligence. The idea behind the tactical picture is to give a tactically significant vision of the objects in the world of interest to a warship: where they are, what they are and where they are going. Concretely, building a tactical picture is detecting, locating, tracking and possibly classifying objects (Byrne et al. 1989a).

Data fusion can be viewed as a two-stage process:

- Stage 1 – Assemble all data that refer to each individual domain object. Multi-sensor data arrive through different channels from group of ships, aircraft and possibly submarines operating collectively. Sources of evidence include sensors (Radar, IFF (Identification Friend or Foe), ECM (Electronic Counter Measures), ESM (Electronic Support Measures), Active Sonar, Passive Sonar), data links (ship to ship, aircraft to ship, shore to ship), intelligence (electronic, communications, human), and other useful information such as plan and command information (e.g. flight plans for aircraft), environmental data (weather, oceanographic information, etc.), equipment database (weapon systems, etc.).

- Stage 2 – Combine assembled data for each object to estimate or infer most likely values for interesting parameters. The main required platform[5] parameters in a model are position, velocity, identity, capability, mission and allegiance. Allegiance assessment which determines whether a contact has friendly, neutral or hostile allegiance is a particular aspect of the data fusion problem and is characterised by the need to provide an assessment based on existing information. This excludes the option of delaying an assessment until further information is available or until conflict of information is resolved. Any information (evidence) about the contact can be indicative of its allegiance. Evidence may take the following forms (Hirst 1989): geographic position of the contact, transponder response (IFF, electronic emissions detected by ESM), visual

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[4] "World of interest" in the naval application consists of a volume of space including the airspace used by aircraft and the ocean space used by submarines.

[5] Platform: object of interest ; aircraft, ship, submarine…

identification, threatening and hostile behaviour, and other factors such as human intuition, track history or intelligence reports.

5.2.1.1 Scope of data fusion

The results of tracking and image recognition are used as inputs to the data fusion system. The output of a data fusion system may be directly used by humans or may be input into a situation assessment level. Situation assessment is also considered by some people to be a part of the data fusion process. Indeed, drawing high-level conclusions from the results of the merging of input data is also a fusion process. Data fusion is first a problem of correlation which consists in finding which pieces of information refer to the same real-world object, and secondly a problem of classification (Jungert 1999; Zhang and Jiao 1998), i.e. estimating and inferring attributes of the object from the assembled evidence. Figure 10 shows the scope of the data fusion problem (Miles 1987b).

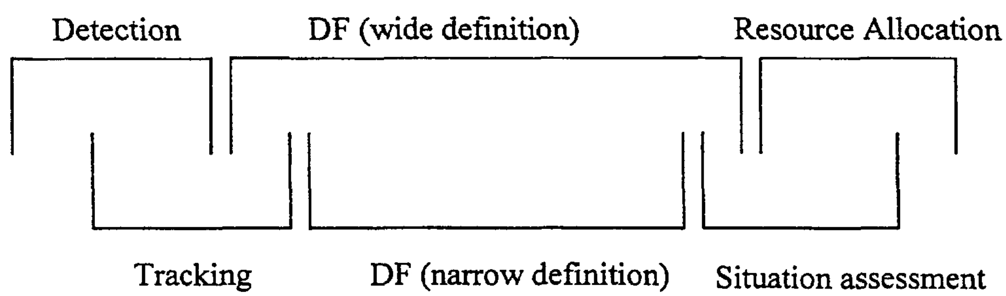

Figure 10. Two definitions of the data fusion process.

This figure shows that the "wide definition" of data fusion includes tracking and situation assessment, whereas the "narrow definition" includes only correlation tasks.

5.2.1.2 Multi-platform data fusion

Assuming that a data link and voice communications are available, it will be possible to collect sensor data from other platforms to form a tactical picture over a much wider area than the one perceived directly by own ship. This is called multi-platform data fusion. Because of the large volume of data produced by active and passive sensors, data links are required to support multi-platform data fusion. Even with data links, the amount of data transferred over a period of time (bandwidth) will be limited. The multi-platform data fusion is a two-level correlation hierarchy. At the first level, are correlated the tracks from different platforms (multi-tracks). At the second level, are correlated the multi-tracks in order to identify platforms or groups of platforms.

5.2.1.3 Conclusion

To conclude, we can state that an intelligent data fusion system in a naval environment should (Lakin and Miles 1989):

- Effectively cope with the large quantity of input data that is available for warship now, and the one that will be available in increasing amounts in the future.
- Include and make full use of non-real-time and encyclopaedic information as well as real-time sensor data.
- Achieve the reaction times necessary to rapidly respond to changing situations.
- Relieve human operators of routine low-level tasks.

5.2.2 Situation Assessment

Situation assessment builds on the tactical picture produced by data fusion in order to form a consistent view of it. This is done by identifying and prioritising potential threats in the environment of a single ship or a group of ships in terms of deployments, capabilities, resource allocation, effectiveness of own and opposing forces. Environmental factors such as the weather and the geographic and oceanographic conditions affect these assessments. The political situation and the rules of engagement also influence the judgements made.

Situation assessment feeds back conclusions to the lower levels in order to fill in unknowns. For example, an aircraft may have been assessed as hostile, but others nearby may have no data to support their allegiance. By assessing the group as a formation, the allegiance can be propagated to all the members of the group.

5.2.2.1 Assessed elements

Those aspects of the tactical situation which could be assessed are:

- *Threats*. They can be classified as direct, indirect and potential. "Direct threats" are observed hostile units in the act of attacking. "Indirect threats" are estimates of attacks that observed hostile units are likely to make according to intelligence about the weapons they carry. "Potential threats" are an assessment of threats which may be encountered according to intelligence only. Potential threats can be assessed on a much longer time scale and there is less need for machine assistance. Rules for threat assessment merge the currently perceived deployment of enemy units with encyclopaedic intelligence data on enemy weapon systems and tactics to generate attack scenarios. Parameters to be estimated include the type of attack, its imminence, the number of units involved, likely targets, etc.
- *Engagements.* They may determine the next course of actions. Unfortunately, information relative to this assessment is difficult to obtain in the required time scale.
- *Weapon systems geometry*. Evaluate the possible conflicts from the positioning of various weapon systems and produce alerts if dangerous situations which may cause accidents are discovered.
- *Weapon states.*
- *Rules of engagement (ROE) and/or exclusion zone (EZ) infringements.*
- *Sensor coverage.*
- *Weapon coverage.*
- *Adherence to plans*. Constantly monitor whether the plans are being followed and, if not, alert the command about the discrepancies. For friendly groups, any discrepancy between the observed situation and the planned one can alert the user. For neutral groups, any uncharacteristic behaviour or deviation from an expected plan should alert the command or invoke a reassessment of identity and mission.

- *Each side perception of the other*. The outcome of this assessment can help determine whether active sensors must be used. This may give away more information to the enemy than provide information to own forces.
- *Defence screen*. Its aim is to alert the command as soon as possible about any weak areas such as those caused by units changing station, equipment failures and losses during actions.

The main goal of situation assessment is to build a complete *high-level* description of what is happening now, given the present position, and to predict what is likely to happen in the future. Unfortunately, only an incomplete *detailed-level* picture of the current situation is available. Three complementary strategies are suggested to bridge the gap between these two levels of knowledge:

- Groups formation
- Plan recognition
- Prediction.

5.2.2.2 Groups formation

Group formation views situation assessment as an extension of the data fusion process. The aim of this process is to create a higher-level view of the tactical picture from those produced by the data fusion process for individual objects, so that further inferences on identity, allegiance, function and mission become possible. The following levels of groups, ordered from lowest to highest, have been defined:

- Vehicles.
- Spatial Groups – groups of vehicles formed by spatial cluster analysis.
- Functional Groups – groups of vehicles of the same hostility carrying out similar functions such as hostile ships performing an anti-surface role. A vehicle may belong to several Functional Groups.
- Interacting Groups – groups of Functional Groups which have similar objectives such as attacking the same target. There are two important categories of Interacting Groups: Defensive Groups and Attack Groups.
- Own/Enemy/Neutral Groups – Own Group is the group of all friendly Interacting Groups, and Enemy Group is the group of all hostile Interacting Groups. Neutral Group is the group of all neutral vehicles.
- Tactical World State – ties Own Group and Enemy Group together.

In general, the set of vehicle data formed by fusing data from all sources will be incomplete and therefore the attempt to form all the functional and interacting groups of interest will not be successful.

5.2.2.3 Plan recognition and prediction

At a higher level, some elements of the tactical plan being executed by unknown units may be identified. These elements may be used to infer the missions of units whose presence was previously unexplained. Thus some parts of the situation assessment may be seen as a "plan recognition" activity. The idea is to form a description of patterns which are accepted to exist and then match those patterns against the available data. If a good match can be found, then details of the pattern which are not present in the data can be inferred with some confidence (prediction). This process is called plan recognition and it aims at predicting unknown conclusions due to incomplete data. The plan recognition will obviously fail when behaviours that are outside the scope of the stored plans are observed. If conclusions cannot be inferred from incomplete data, the prediction can also be made by simulation.

5.3 Why is it important to automate in C2?

One view of the automation in C2 is that it should be capable of providing the right information at the right time, to the right person, in the right form, so that it can be assimilated and processed in a time-critical situation.
In designed worlds, such as in industrial processes and air traffic control, the domain elements are assumed to be co-operative. In real hostile world such as military surveillance and situation appreciation, the elements are unco-operative. Thus, a large amount of disparate data is collected. The use of more powerful and more sophisticated sensors and the provision of high bandwidth data links will generate an even greater volume of data to be processed. The high data output rates (avalanche of information) to human resources result in an overload of information for decision makers (man-intensive systems). To give an idea about the system's performance, it has to cope with up to 100 messages per second from various data sources. In addition, in current C2 organisations, there is a great deal of message traffic in natural language which places huge demands on human resources just to assimilate the facts and update the databases (Miles 1987a).

The main objectives of automation in C2 is to:

- free the operators from doing low-level tasks and allow them to concentrate on higher-level tasks such as decision making and planning.
- handle the slow response rates due to human interventions. This slowness results either from the user's inability to interpret large amounts of data in the required time or from his incapacity to react in time. This problem is related to the system interface design.

5.4 What are the problems engendered by automation in C2?

The automation in C2 raises several questions. First, what are the models that should be used to deal with the real-time requirements and how is it possible to ensure that such models are well-suited to fulfil such requirements. Second, what is the impact of such an automation on system users. Should they trust it? How can they interact with the system? Does this interaction affect the operators' methods of work? Is the task appropriately distributed among the operators and the machines?

In the following sections, we will argue why purely algorithmic approaches in automated C2 are insufficient and inadequate. We will also discuss the psychological impact of such an automation on the user.

5.4.1 Inability of algorithmic approaches to deal with symbolic and numeric data

Data fusion is a critical process in naval C2 since it aims at providing the operations room staff with accurate tactical pictures, based on disparate real-time and non-real-time data. Because of the large amount of data and their incomplete and fragmentary nature, real-time data are an issue for C2. Although algorithmic techniques are widely used in data fusion processes, they are unable to cope with information of different nature (symbolic and numeric). In addition, new communication and intelligence systems will increase the disparity of data types, particularly the non-real-time categories.

5.4.2 Inability of algorithmic approaches to represent high-level knowledge

The naval C2 scenarios tend to become increasingly complex because of the sophistication of sensors, weapon systems and communication technologies. Information sources include not only real-time data but also information provided by human intelligence, encyclopaedic and operational plans, etc. The inability of algorithmic approaches to deal with symbolic and numeric data makes them inadequate to encode high-level knowledge necessary in high-level processes such as situation assessment, human messages processing, reasoning and explanation facilities.

5.4.3 Inability of algorithmic approaches to provide high-level support for operators

Whatever the level of decision making may be, it requires high-level knowledge that can provide a global view of the tactical picture or the current situation. The encapsulated knowledge in algorithms is not rich enough to give such a global view, and even if it did, the available knowledge could not be used to explain how such a view was built. For all these reasons, algorithmic approaches offer little support for decision makers. Yet, this support would be very valuable, especially in a time-critical context where actions cannot be delayed and decisions must be made just in time.

5.4.4 Psychological aspects

Automated decision support tools must be provided with facilities that can guarantee user acceptance. A key factor is the design of the user-computer interface (see Section 6). Another way to increase the user's confidence in an automated tool is to show that the system can solve real problems.

5.5 Solutions

In the following sections, we present solutions to the problems discussed in Sections 4 and 5. These solutions are basically related to the real-time operational performances of parallel computing techniques, the high-level knowledge representation capabilities of knowledge-based systems and finally, the technical means to handle uncertainty.

5.5.1 Parallel processing techniques

To meet the real-time requirements, parallel-processing-based approaches have been investigated. These approaches attempt to provide short-term and long-term solutions for C2 systems.

Connectionist architectures have also been studied:

- A first type of connectionist architecture uses local representations. Each element represents a specific concept and each link represents a specific type of relation. The elements are connected into a semantic network.
- Another type of architecture uses neural networks and tries to recognise patterns through their dynamic behaviour. These methods are still limited because of their slowness in simulation.

A more likely future solution may be a form of what are generally called "Massively Parallel Architectures", one of which is the NETL machine (Fahlman 1979). The NETL machine uses a semantic network to represent real-world knowledge. This representation is very general. In principle, it would be possible to represent the entire knowledge about the military world, both encyclopaedic and real-time. However, this would require a very large number of nodes and links. Searching through the network could become very time consuming on a conventional computer. Yet, the NETL machine uses a simple processor for each node and each link of the semantic network, making it possible to do the search with total parallelism.

5.5.2 Use of knowledge-based systems and expert systems

Conventional computing techniques have shown little success in formulating, maintaining and interpreting a tactical picture resulting from data fusion. Hence, there is an increasing interest in the possible use of knowledge-based systems in general and expert systems, in particular. These systems can be used to deal with unstructured problems and they have some abilities to explain their reasoning.

However, the real-time processing requirements must be kept in mind and one must be sure that the knowledge-based model can be combined with parallel processing techniques (see Section 5.1). In this study it was showed that in a rule-based system there are set of production rules which are independent. The static analysis identified the set of rules which access the same type of data. The dynamic analysis showed that rules belonging to different sets and firable at the same time can be processed in parallel.

At the data fusion level (see Section 2.1), rules may be used in a forward-chaining reasoning to handle the multi-sensor data correlation problem. With regard to the situation assessment (see Section 2.2), rules are required for:

- Group Formation:
    - Forming and maintaining groups;
    - Correlating group evidence;
    - Inferring group parameters and propagating to individuals.
- Plan Recognition and Prediction: this would normally be organised as a backward-chaining task in a rule-based structure, in contrast to the forward-chaining nature of the data fusion activity.

In addition, knowledge-based systems can gain the user's confidence by providing explanation facilities (see Section 5.5.2.4).

5.5.2.1 Architectures

In the research programme undertaken by the ARE (Admiralty Research Establishment of Postdown), a blackboard-based expert system was used to perform data fusion. The main data structure stored in the blackboard is a hierarchy of hypotheses. Each hypothesis represents a possible conclusion for the group of hypotheses situated at a lower level. Input data are posted as new hypotheses on the blackboard. Experts are represented by a set of rules, called knowledge sources, that manage the hierarchy of hypotheses. A scheduling mechanism is used in order to ensure that the most appropriate knowledge is applied (opportunistic reasoning). SPL International was sponsored to design and build a general purpose blackboard framework which is now called MXA (Multiple eXpert Architecture). MXA includes various features:

- A language for expressing rules;
- A hypothesis structure;
- An inference engine, i.e. the knowledge source control program;
- Explanation generation capabilities.

Scheduling is the process that, given the current state of the blackboard and any available input data, determines which knowledge source is to be invoked next. In MXA, the scheduling of knowledge sources uses a rule-based approach. The rules for scheduling are held in Meta-Knowledge Sources and hypotheses are described by declarations.

In order to evaluate different systems' performances, the blackboard architecture was compared to other architectures (Miles 1989):

- A production system using ART (on Symbolics 3600 LISP machine).
- A hybrid production system / imperative programming approach using MUSE (on Sun 4 Workstation).
- The MXA blackboard architecture using Ada (on Microvax 3500 workstation) rather than an AI toolkit because of the real-time performance required.

Let us point out that the different machines used to test these architectures have an equal performance.

5.5.2.2 Levels of knowledge

The heart of the data fusion system is a knowledge-based system which formulates a coherent tactical picture by fusing together in real time all the available information on board a ship that has been conveyed from disparate sources. Using a knowledge-based approach, demonstrators have been developed which are capable of generating an on-going tactical picture not only from a wide variety of simulated data types, but also from data recorded at sea during naval exercises. While the first generation of demonstrators addresses only the first-level task of picture compilation through multi-platform multi-source data fusion, the second generation includes the second-level task of tactical situation assessment and the third-level task of formulating an appropriate response. Because knowledge involved in the situation assessment process is more complex, the knowledge acquisition and encapsulation of naval expertise into rules are not straightforward. Interviews have been used to elicit this knowledge.

5.5.2.3 Knowledge types

The knowledge-based system that was used in the data fusion and the situation assessment processes, identified five categories of knowledge sources:

- The tactical picture;
- Geographical and meteorological information;
- Tactical knowledge;
- Encyclopaedic knowledge;
- The expertise of the expert.

The database must not only represent information relative to tracked platforms, but also higher-level information, such as patterns of behaviour, necessary for the situation assessment process. In order to create a more intelligent C2 system, a multi-level data representation is required (see Figure 11 for a simplified example).

To support the situation assessment process, a more complex multi-level blackboard-data representation has been designed. A bottom-up presentation of the hypotheses hierarchy is given below (Lakin et al. 1989):

- Tracks, Plans & Reports
- Possible correlations
- Multi-sensor tracks
- Possible correlations
- Vehicles
- Spatial vehicle groups
- Functional vehicle groups
- Interacting Vehicle groups
- Hostile/Friendly/Neutral groups

Rules

IF fast track
THEN aircraft or missile

IF radar & ESM on same bearing
THEN possibly same target

IF radar type A
THEN platform X or Y

IF scanning
THEN surveillance or acquisition

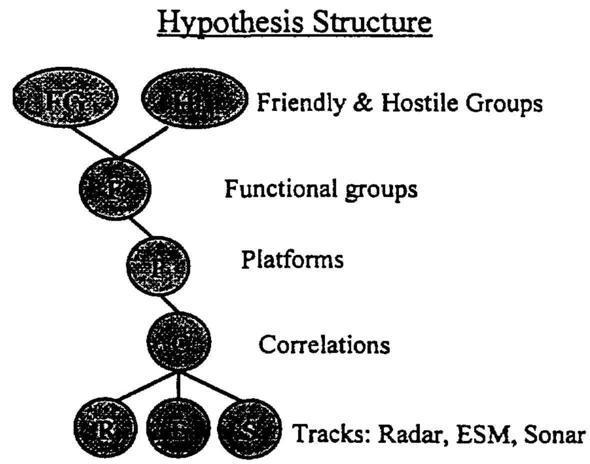

Figure 11. A simplified example of the hypothesis structure and the rules that support this structure.

Hypotheses are about:

- Correlations between tracks from different sensors
- Platforms with estimated parameters from accumulated evidence
- Groups of functionality related to platforms

In order to predict the future from the current situation, a history or script is required for each platform. Moreover, in order to discard out-of-date data and make knowledge more flexible, a time limit is set for these data, beyond which they are no longer considered for correlation. This would allow for data to be retained as long as required depending on their importance.

5.5.2.4 Explanation ability

Explanation is defined as something that makes one's view more coherent and intelligible. Reasoning can be regarded as maximising the explanatory connectedness or coherence of one's belief.

In (Hirst 1989) explanatory structures, called e-structures, were defined to show how the presence of a fact can be explained. For example, the fact that an IFF transponder response is friendly can be explained by the fact that the contact is friendly, because there is a rule that specifies that if the contact is friendly then the response of IFF is friendly. There may be several competing e-structures for a given fact.

In general, the approach requires principles for:
- Determining the possible e-structures;
- Choosing the best explanation from competing e-structures.

The criteria for choosing the best e-structure and thus providing the best explanation are not yet well defined. However, some general principles such as "preferring e-structures that provide the most possible explanations", simplicity, conservation and plausibility have been stipulated.

A mere comparison of e-structures will give rise to ambiguity because of the possibility of a combination of conflicting propositions. Hence, there is a need for further levels of explanation. An alternative approach would be to assign a penalty value to each explanation, based on the plausibility of the additional propositions involved. Thus, unlikely or non-preferred explanations will be given a high number and preferred explanations a low number.

Explanation-based reasoning allows one to draw inferences from incomplete information by using default rules, and from conflicting information by invoking competing explanatory structures with different explanatory power.

5.5.2.5 Problems

Despite all the advantages of using a knowledge-based approach in the data fusion and situation assessment processes, many problems still remain. In the following, we present some of the questions that K-B approaches should address (Anderson et al. 1989):

- How can we deal with the complexity of thousands of separate functions required in naval command and control system?
- How can we deal with inaccurate and uncertain information (explosion of possibilities)?
- Knowledge-based systems are slow. What can we do in a situation where real-time tracking functions are required?
- Knowledge-based systems should be able to provide concise information in an acceptable time so that actions are not delayed. Which tools are needed to provide such capability?
- Creating knowledge-bases demands experts' involvement. It is difficult to get the naval officers involved. How can we solve this problem?
- How can we manage the maintenance of the rule base given that the system has to deal with new threats and scenarios and unforeseen situations that will modify the stored knowledge? In the military domain, it is very difficult to update the knowledge base in a laboratory or a factory because knowledge emerges when the system is fielded? (Miles 1987a).
- If the system is intended to reason about battle situations, how can we make sure that it will be effective or even useful in a future conflict, given the difficulty to predict what is likely to happen?
- Given that knowledge is acquired over a long period of time, how can we deal with the time-critical aspects of the command and control system?
- How can we upgrade the knowledge-base, while keeping the system running, as required during critical periods such as war?
- If all ships were equipped with knowledge-based systems, there is a danger that the conclusions of one system, based on tenuous data, be taken as firm conclusions by another, unless the reasoning is also transferred. Can current data-links manage such a level of communication?
- The knowledge-base will contain the warfare policy, the rules of engagement and the tactical doctrine of the Royal Navy. In principle, any user could view, through the medium of the explanation facility, the entire knowledge base. What level of explanation is adequate for which user?

- If we incorporate knowledge into a computer system and rely on its expertise, then how can we avoid the danger of having it defeated by the enemy's superior human intelligence?
- Knowing that the main goal of using a knowledge-based system is to let men concentrate on high-level tasks that require human intervention, such as decision making, then who would be the operational users of these automated decision support tools?
- If the lower levels of the team are to disappear, how do we train people to assume higher responsibilities?
- Is it possible for the user to assist the machine with his more up-to-the-minute knowledge in real-time context?

It is difficult to give precise answers to all of these questions. The solutions depend on various contextual and environmental constraints and as well as their correlations.

5.5.3 Reasoning under uncertainty

Parallel processing techniques meet the real-time processing requirements and knowledge-based systems are able to manage high-level knowledge. Yet, the problem of dealing with uncertain information remains (Cohen 1985; Li et al. 1999; Rogova and Losiewicz 1999). The data is generally incomplete, inaccurate, ambiguous, conflicting and subject to deliberate interference and deception by the enemy. For example, sometimes we may have poor positional information (uncertainty of positional data increases rapidly with time for fast moving objects), but a good identity information. This leads to considerable ambiguity. In the absence of certainty, it is important to combine and correlate data from different sensors in order to strengthen available pieces of evidence. It is also important to correlate information received by the same sensor at different times in order to maintain interference-free measures. Many of the early expert systems attempted reasoning with uncertainty. The methods used to handle uncertainty are of two types: numerical methods (probability theory, Shafer-Dempster theory of evidence) and non-numerical methods (endorsements, default reasoning). We review these methods in the following sub-sections.

5.5.3.1 Numerical Uncertainty Schemes

The objective of numerical uncertainty schemes is to use a standard method to represent uncertainty (e.g. probabilistic methods) and a standard method to combine uncertainty values when conclusions are drawn from sub-conclusions or a combination of evidence . Numerical schemes are difficult to apply in real-world problems and, in some cases, may not contribute in a significant way to the analysis of results, compared to a simple logical approach. There are perhaps two contexts where a numerical approach can be used:

- When the statistics of the input evidence are well-known;
- When a large number of test examples are available.

Another problem with numerical uncertainty schemes is the difficulty of explaining the reasoning to humans. Uncertainty is usually expressed by humans in words rather than in numerical quantities.

5.5.3.2 Symbolic Uncertainty Schemes

Cohen and Grinberg have invented a method for representing symbolic uncertainty, called the "theory of endorsements" (Cohen 1984; Cohen 1985; Cohen and Grinberg 1983). These authors suggest a method of inference that retains a set of endorsements for all the factors that contribute to belief or disbelief in a hypothesis. Endorsements are rules that can be directly translated into statements of uncertainty about the hypothesis (which appears in the conclusion of the rule), thus providing built-in explanations.

5.6 Man-machine interface issues

In the previous sections, we discussed the importance of automating various functions of the C2 processes and the potential problems that may result from such an automation. C2 is a difficult task because it deals with a large amount of real-time information in an unpredictable environment. For this reason, human intervention is always required and computer solutions are insufficient. Whatever the solutions may be, it is necessary to have appropriate user interfaces. In the next sub-sections we review several factors that must be taken into consideration for the interface design.

5.6.1 Human factor

The human factor is the most important issue. It pertains to the kind of relationship that must be established between the machine and the user:

- Who is allowed to use the system, given that part of its information is of a confidential nature. To which extent can the user query the system?
- Given the real-time nature of the missions, what kind of user-machine interactions are possible? What is the role of the user and the machine regarding each other?
- The Command and Control process involves both men and machines and an important amount of communication between them. This leads to the definition of C^3I (Command, Control and Communication Intelligence).
- What should the system present to the user? In many situations, the action plan should not be predictable by the enemy. Therefore, the system should present to the user a set of solutions that will hide the plan details until the last moment when the user chooses a specific solution. Each time the user selects an option, he must be informed of its consequences and must be able to explore those options that the system apparently did not consider (WHAT-IF capability).

5.6.2 User-machine interactions

The following list includes several kinds of possible user-machine interactions:

- *User input data.* All kind of data that the user may communicate to the system by different ways.
- *User requests for information.* All kind of requests for data, explanations and alerts.
- *User decisions/overrides.* The user must be able to communicate his decisions to the system and override the system's decisions when necessary.
- *Machine output data.* The machine must be able to communicate all its decisions or alarms to the user.
- *Machine requests for information.* In order to make a decision, the machine may need additional data or explanations.

- *Machine requests for decisions.* When the machine is unable to make a decision, it may leave it to the user.
- *User changes to databases.*
- *User changes to parameters.*
- *User changes to plans.*
- *User changes to rules.*

The user-machine interactions lead to the definition of three categories of systems:

- *Autonomous* – basically a black box with minimal interaction.
- *Supportive* – provides an interactive framework for the task with some built-in knowledge.
- *Collaborative* – performs the task and provides for flexible human interaction including control.

5.6.3 Role-based models

The different kinds of possible interactions between the user and the machine imply role definitions. (Miles 1988, p. 215) defines five roles:

- *Monitoring role.* The user may control the inputs and outputs of the system. To do so, he or she needs the following elements:

  - Top-level output conclusions;
  - Intermediate levels of conclusion;
  - The input evidence;
  - Explanation of the reasoning leading to any conclusion at any level;
  - Explanation of the reasoning behind the current strategy of inference;
  - A commentary on significant new conclusions;
  - A commentary on the current inference.

- *Correction role.* This role is an extension of the monitoring role. During the monitoring task, the user may want to add his own ideas to the domain model. It is therefore important that the system accepts manual input while maintaining the logical consistency of the model. The system must check whether conflicts arise once it has updated the knowledge-base. The explanation enables the user to recall the reason for which he made the change.
- *Take-over a low-level task.* In this role, the user has the responsibility for performing the task and the system adopts a background monitoring role. This is the opposite of the monitoring role.
- *High-level decision making.* Users may want to be involved in high-level decisions such as changing the deployment of resources. The system should allow for this by adopting an advisory role, for example by setting out the possible options. It should also be able to predict the outcome for any selected course of action.
- *Control of resources.* Explicit control may be provided by allowing the users to adjust scheduling priorities, particularly when overload conditions arise.

5.7 Man-Machine Interface in the DF and SA laboratory demonstrator

Whatever the complexity of a C2 system may be, its enhanced capabilities can only be fully exploited if a clear, user-friendly interface is provided. The function of the TDS (Technology Demonstrator Systems) is to capture data from various sources, build them into a tactical picture and present the picture to the operator in a suitable form using texts and graphics. The symbols used to represent platforms change according to the type of the assessed platform. Colours are also used to show platforms' allegiance: Red (hostile), Blue (friendly), Green (neutral) and White (unknown).

The operator can click on any object for information (identity, speed, etc.). If further information is needed, knowledge-based system capabilities are exploited to explain why the system believes a specific fact. For example, the system may estimate that an aircraft is hostile although the operator had no information about its allegiance. The system must be able to explain its reasoning: given its behavioural patterns, the aircraft may be assigned to a group of platforms, in which case it takes the same allegiance as the group.

In the next sections, we present the three phases of the ARE (Admiralty Research Establishment of Postdown) programme on user-machine issues.

5.7.1 Phase one

The functionality of phase one demonstrator (Montgomery and Byrne 1989) was limited to a single platform, multi-sensor data fusion. This system had a simple interface with four colours: Red (hostile), Blue (friendly), White (unknown), Green (neutral). The symbols were oriented as to depict the course of the platforms. Velocity was represented by an arrow whose length was proportional to the speed of the platform.

This system had several limitations. The simulated scenarios were slower than desired because of the embedded control codes which were sent to the graphics hardware by the display rules. In addition, the limited use of colours (only four colours were available) was a source of ambiguity.

5.7.2 Phase two

The data fusion demonstrator included a wider spectrum of input data and support data-links (Montgomery and Byrne 1989). The multiple-window environment was also adopted in order to increase flexibility in the presentation of simultaneous information. A high resolution, large screen, video projector was added.

5.7.3 Phase three

This phase (Montgomery and Byrne 1989) dealt with situation assessment. The blackboard hypothesis hierarchy was expanded to cover both data fusion and situation assessment, the strategy for situation assessment being the group formation. A graphical solution was adopted to show functional and interacting groups. Also, a text window was used to show the additional details of the assessment: a threat list and a check list of defensive and offensive courses of action.

This user-machine interface for situation assessment was not straightforward. It proved to be much more thought-provoking than expected and required much more feedback from the users group. The system's difficulty in presenting the results of the situation assessment was reflected in the comments received about the user-machine interface. Users criticised several aspects of the interface: the kind of symbols used to represent groups of platforms, the items of the threat list, and the options they were given to respond to the threats. In fact, the interface was not customised to support any specific role. Moreover, the warfare officers should have the option of altering the threat list and this was not the case.

5.8 Simulations

Scenarios based on simulated data were used to test the environment. The purpose was not to implement a full scale system, but to have a situation assessment system for two representative operational environments under warfare conditions. The data were gradually updated as real data, recorded during missions, were introduced. One of the scenarios was a one-hour sequence from a four-day NATO maritime exercise. This example showed how to correlate the detections of different ships by triangulation. The system's interface displayed information relative to an object selected on the screen and used different symbols and colours.

The ultimate objective of data fusion is to combine data from several sources. This requires a very large knowledge-base. Also, the demonstrators' representation mode implies the use of a very large number of rules. This is why only a subset of the knowledge-base was included in the demonstration prototype.

5.9 Conclusion

To conclude, we can say that architectures for real-time knowledge-based C2 applications must meet two important criteria: a natural way of acquiring and representing knowledge, and real-time performance.

Because in this model the levels of Data Fusion are not sharply separated, a knowledge-based approach can be used not only for high-level processes, such as situation and threat assessment, but also for lower levels, such as correlating the results of the data fusion process (Cowden 1995).

The facts relative to both the low and high levels of the C2 process in a knowledge-based approach show the importance of having a global view of the situation in order to build what is called a "Situation Awareness".

6. Discussion

In conclusion, let us remark that in the specialised literature, the DF process is usually decomposed into levels which are similar to those presented in the three models that we briefly described above. Researchers agree to distinguish 3 levels: a first level, where data are acquired from multiple sources, filtered and processed in order to characterise the situation to be analysed; a second level, often called "situation / abstraction assessment", which deals with the elements and relationships that characterise the situation and that are relevant for the decision process; a third level, often called "threat assessment", which aims at qualifying the situation in terms of possible threats and the way to counter them.

Level 1 (data acquisition, filtering and consolidation) has been widely studied and supported by several tools. Level 2, the situation assessment, is more difficult to tackle since there are many ways of interpreting data in a given context. The incompleteness of the information obtained from the acquisition/consolidation level results into uncertainties that make the situation assessment process a complex activity to automate. Getting an acceptable analysis of the situation in "quasi-real-time" is also an important challenge, especially when the number of elements to be considered increases. Consequently. threat assessment (Level 3) also becomes difficult to model and automate.

It is difficult to provide generic solutions to the SA process, because understanding a situation seems to be highly domain-dependent. Think for example of how the various elements (and their relations) that characterise a situation can be identified, or how the elements that will enhance the person's understanding of a situation can be distinguished. In practice, however, people (in our case the operation Room Officer) are skilled enough to "apprehend" complex situations and to make decisions in consequence. This suggests that getting a better understanding of how specialists apprehend and analyse situations could provide a means to improve the characteristics of the systems developed to support the DF process. Interestingly enough, we have found in the open literature a few works that deal with the cognitive aspects of the SA processes.

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ANNEX 2: Overview of Works on Situation Awareness

1. Introduction on Situation Awareness

In this Section, we present an overview of several recent works done on Situation Awareness. Let us remark that we found in the literature two terms: *situation awareness* and *situational awareness*. "Situational awareness" gives better results when doing web searches.
Research on awareness in the military domain originated in the study of military aviation where pilots interact with highly dynamic, information-rich environments. More recently, researchers have expanded their interests to other environments where situation awareness plays a major role, such as commercial aviation, air traffic control and anesthesiology. All these contexts share the characteristics of dynamism, complexity, high information load, variable workload and risk (Gutwin and Greenberg 1999).

Awareness is knowledge about the state of some environment, a setting bounded in time and space. (Gutwin and Greenberg 1999).
There are several definitions of situation awareness in the literature.
Situation awareness is "the up-to-the minute cognizance required to operate and maintain a system" (Adams et al. 1995).
Here is the definition of situation awareness given by Endsley (Endsley 1987; Endsley 1988) and which is widely used in the literature.

> *Situation awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future.*

Another definition of situation awareness is included in several US Navy specifications: "Operator Situation awareness is comprised of detecting information in the environment, processing the information with relevant knowledge to create a mental picture of the current situation, and acting on this picture to make a decision or explore further".

Showing the importance of such issues, the *Situational Awareness Integrated Product Team* (SA IPT) has been formed in the US in response to fleet tactical aircraft aviators ranking situation awareness as a critical mission concern (Garner and Assenmacher 1997). SA IPT held several symposia in order to provide a forum for information exchanges about situation awareness between academia, military researchers and industry (Annual Symposia on Situational Awareness, 1996-1999).

On the web we can find the *SABRE Bulletin Board* where people interested in issues related to situational awareness can exchange ideas
(http://users.ox.ac.uk/~pemb0595/wwwboard/faq.html)

It is beyond the scope of the present document to review all the works dealing with situation awareness. We summarize here certain key areas.

Situation awareness is recognized as a major issue by the human factors community which is primarily concerned with techniques for training people (see for example (Bass et al. 1997)) and the ergonomics of person/machine interfaces. Numerous papers are found on these subjects (see bibliography). For example, the Third Symposium on Situational Awareness (1998) was devoted to performance measurement techniques and various issues of situation awareness in relation to interfaces (spatial awareness interfaces, cognitive interfaces, intuitive interfaces, multi-modal interfaces). So-called "moderators of situation awareness" include cognitive abilities, motivational states and technological advances. Several authors have emphasized the fact that introducing new technology of greater complexity in the operators' workplace may result in decrease of operators' situation awareness.

Numerous works deal with the creation or enhancement of various kinds of devices (displays, sensors, googles. etc.) in order to enhance operators' awareness in various domains. For example, you can look at the proceedings of the Second Symposium on Situational Awareness (1997) and at a large proportion of references obtained after a web search on "situational awareness". Certain training systems are especially built in order to help operators to enhance their skills relative to situation awareness; debriefing systems (Bass et al. 1998), intelligent tutoring systems (Bass 1998). Other systems are built in order to cooperate with operators in order to help them to create and maintain situation awareness such as the cockpit assistant system CASSY (Onken 1997).

Most works have been targeted to situation awareness of individual persons. However, in most organizations several activities are performed by groups of people. Hence, team situational awareness becomes an important issue. Until recently, few works have been done on this subject. Some recent works address the problem of understanding team situational awareness in order to train team members (Stout and Salas 1997). Gutwin and Greenberg (Gutwin and Greenberg 1999) define *workspace awareness* as the "up-to-the-moment understanding of another person's interaction with the shared workspace". This is a specialized kind of situation awareness, awareness about what is going on in the workspace environment (including team members) by opposition to awareness of the exterior situation. Awareness of an environment is created and sustained through the "perception-action cycle" which involves 1) perception as a way to gain knowledge about the environment and 2) the exploration of the environment directed by that knowledge in order to gain more knowledge.

Methods for measuring situation awareness are also an important issue. An example is SAGAT (Situation Awareness Global Assessment Method) proposed by Endsley (Endsley 1987) which provides an immediate snapshot of the user's situation awareness and an overall measure of awareness drawn from a summation of the snapshot scores.

Several authors have shown the importance of mental models and mental pictures as a way of gaining and maintaining situation awareness (Endsley 1995) (Matthews et al. 1999) (Lipshitz and Shaul 1997) (Mulgund et al. 1997). These models could be obtained thanks to a *cognitive task analysis* (Gordon and Gill 1997). Klein (Klein 1993) identifies four classes of such analyses: questionnaires and interviews, controlled observation, critical incidents and analytical methods.

Other researchers examine how situation awareness models can provide principles to develop decision support systems that go beyond the traditional data fusion model in order to take into account operators' cognitive needs (Chalmers 1997) (Paradis et al. 1997b) (Paradis et al. 1997a). We can conjecture that work on situation awareness will have an important influence on the data fusion community in the coming years. This could lead researchers to reconsider the role of data fusion in the context of a broader view of the decision making process based on the ability of the operator to gain and maintain situation awareness.

In the next section we review the Endsley's foundatinal paper on situation awareness.

2. Summary of the Paper "Toward a Theory of Situation Awareness in Dynamic Systems" By Mica R. Endsley, Human Factors, 1995, 37(1), 32-64

Because this paper is a very important one for anyone who wants to understand the cognitive mechanisms underlying situation awareness, this summary has been done by editing excerpts from Endsley's original paper.

2.1 Introduction

The range of problems confronting human factors practitioners has continued to grow over the past 50 years. The operator's situation awareness (SA) will be presented as a crucial construct on which decision making and performance in such systems hinge.

Endsley's goal is to show (a) the importance of SA in decision making in dynamic environments and the utility of using a model of decision making that takes SA into account, and (b) a theory of SA that expands on prior work (Endsley 1987; Endsley 1988). True SA involves far more than merely being aware of numerous pieces of data. It also requires a much more advanced level of situation understanding and a projection of future system states in light of the operator's pertinent goals.

SA can be shown to be important in a variety of contexts: aircraft, air traffic control, large-systems operations, tactical and strategic systems and many other everyday activities call for a dynamic update of the situation to function effectively.

The need for SA applies in a wide variety of environments. Acquiring and maintaining SA becomes increasingly difficult. Because the state of the environment is constantly changing, often in complex ways, a major portion of the operator's job becomes that of obtaining and maintaining good SA. In analyzing the decision making of tactical commanders, Kaempf, Wolf, and Miller (Kaempf et al. 1993, p. 1110) reported that "recognizing the situation provided the challenge to the decision maker", confirming SA's criticality.

Operators must do more than simply perceive the state of their environment. They must understand the integrated meaning of what they are perceiving in light of their goals. Researchers in many areas have found that expert decision makers will act first to classify and understand a situation, immediately proceeding to action selection.

There is evidence that an integrated picture of the current situation may be matched to prototypical situations in memory, each prototypical situation corresponding to a "correct" action or decision. experts use pattern-matching mechanisms to draw on long-term memory structures that allow them to quickly understand a given situation.

There is a need to more explicitly incorporate the concept into human factors design efforts. A theory of SA that clearly defines the construct and its relation to human decision making and performance is needed to fulfill this mission.

2.2 A model of situation awareness

The present objective is to define a common ground for discussion using the information that is available in order to provide a starting point for future work on SA. Klein (Klein 1989) stated that a desired theory of situation awareness should explain dynamic goal selection attention to appropriate critical cues, expectancies regarding future states of the situation, and the tie between situation awareness and typical actions.

A model

Figure 1 provides a basis for discussing SA in terms of its role in the overall decision-making process. According to this model, a person's perception of the relevant elements in the environment from system displays or directly by the senses, forms the basis for his or her SA.

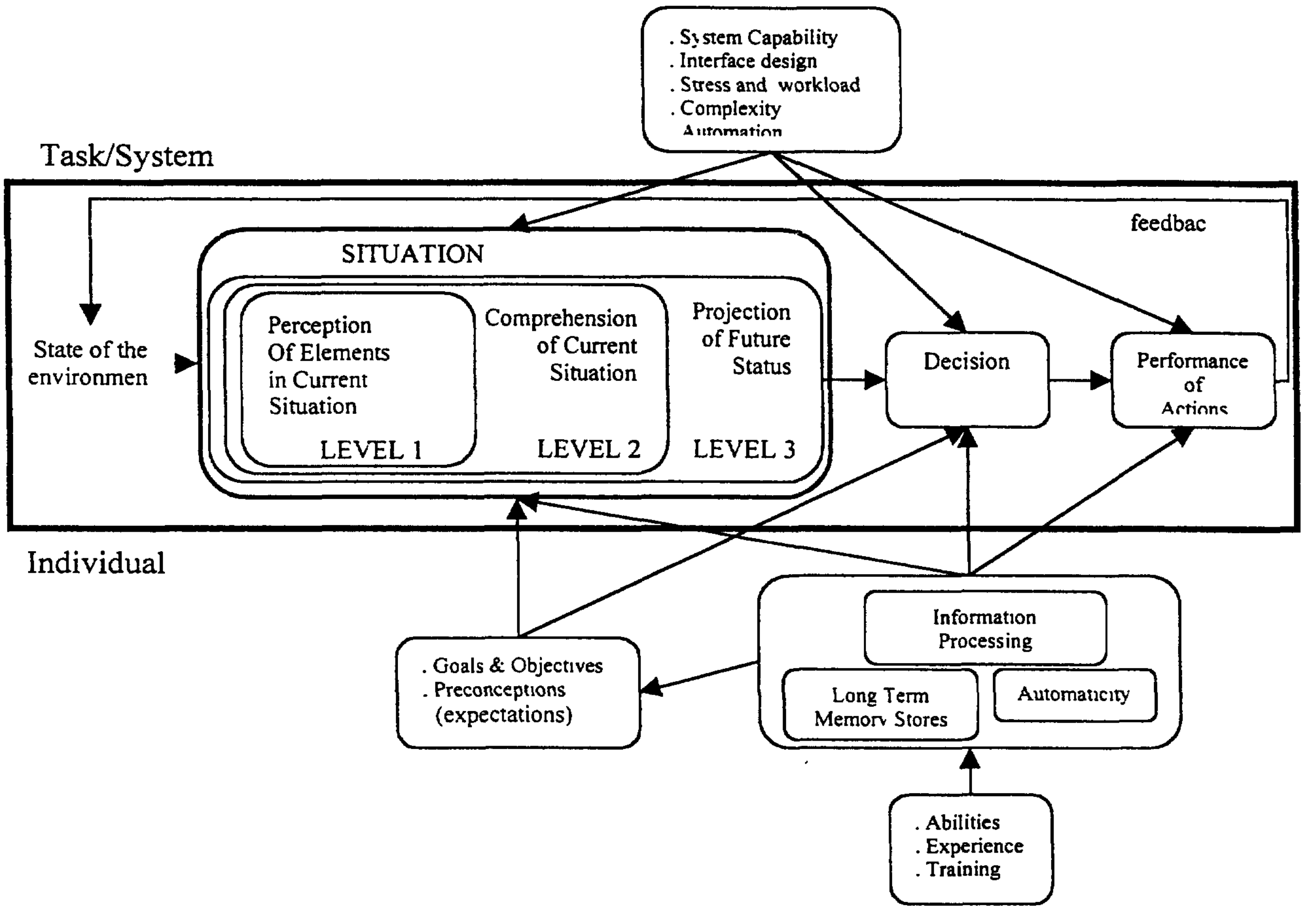

Figure 1. Model of situation awareness in dynamic decision

Several major factors are shown to influence this process. First, individuals vary in their ability to acquire SA. This is hypothesized to be a function of an individual's information-processing mechanisms, influenced by innate abilities, experience, and training. In addition, the individual may possess certain preconceptions and objectives that can act to filter and interpret the environment in forming SA.

SA will also be a function of the system design in terms of the degree to which the system provides the needed information and the form in which it provides it. Other features of the task environment, including workload, stress, and complexity may also affect SA.

Definitions and terminology

It is first necessary to ***distinguish the term situation awareness, as a state of knowledge, from the processes used to achieve that state***. These processes, which may vary widely among individuals and contexts, will be referred to as ***situation assessment or as the process of achieving, acquiring, or maintaining SA***.

SA as defined here does not encompass all of a person's knowledge. It refers to only that portion pertaining to the state of a dynamic environment. Established doctrine, rules, procedures, checklists, and the like – though important and relevant to the decision-making process – are fairly static knowledge sources that fall outside the boundaries of the term.

In addition SA is explicitly recognized as a construct separate from decision making and performance. ***SA, decision making, and performance are different stages*** with different factors influencing them and with wholly different approaches for dealing with each of them; thus it is important to treat these constructs separately.

Attention, working memory, workload, and stress are all related constructs that can affect SA but that can also be seen as separate from it.

Here is a general definition of SA (Endsley 1987; Endsley 1988):

Situation awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future.

Level 1 SA: Perception of the Elements in the Environment

The first step in achieving SA is to perceive the status, attributes, and dynamics of relevant elements in the environment.

Level 2 SA: Comprehension of Current Situation

Comprehension of the situation is based on a synthesis of disjoined Level 1 elements. Level 2 SA goes beyond simply being aware of the elements that are present to include an understanding of the significance of those elements in light of pertinent operator goals.

Level 3 SA: Projection of Future Status

The ability to project the future actions of the elements in the environment – a least in the very near term – forms the third and highest level SA. This is achieved through knowledge of the status and dynamics of those elements and comprehension of the situation (both Level 1 and Level 2 SA).

SA therefore, is based on far more than simply perceiving information about the environment. It includes comprehending the meaning of that information in an integrated form, comparing it with operator's goals, and providing projected future states of the environment that are valuable for decision making.

Elements

From a design standpoint, a clear understanding of SA in a given environment rests on a clear elucidation of the elements in the definition – that is, identifying which things the operator needs to perceive and understand. These are specific to individual systems and contexts, and as such are the one part of SA that cannot be described in any valid way across arenas.

Time

SA is highly temporal in nature. That is, SA is not necessarily acquired instantaneously but is built up over time. Thus it takes into account the dynamics of the situation that are acquirable only over time and that are used to project the state of the environment in the near future.

Space

SA is highly spatial in many contexts. Spatial information is highly useful for determining exactly which aspects of the environment are important for SA. An operator's SA needs to incorporate information on that subset of the environment that is relevant to tasks and goals. Within this boundary, the elements may be further subdivided into levels of importance for SA or may assume a relevance continuum. Elements may vary in their relevance across time, although they do not generally fall out of consideration completely.

Team SA

It is possible to talk about SA in terms of teams as well as individuals. In many situations several individuals may work together as a team to make decisions and carry out actions. In this case one can think of the overall team's SA, whereby each member has a specific set of SA elements about which he or she is concerned, as determined by each member's responsibilities within the team.

Some overlap between each team member's SA requirements will be present. It is this subset of information that constitutes much of team coordination. Higher levels of SA may not be directly presented on displays, but may be communicated verbally, or if the team members possess a shared mental model, each team member may achieve the same higher-level SA without necessitating extra verbal communication.

Link to Decision Making

In addition to forming the basis for decision making as a major input, SA may also impact the process of decision making itself. There is considerable evidence that a person's manner of characterizing a situation will determine the decision process chosen to solve a problem.

Other evidence suggests that even the way a given problem is presented (or framed) can determine how the problem is solved.

Link to Performance

The relationship between SA and performance, though not always direct, can also be predicted. In general, it is expected that poor performance will occur when SA is incomplete or inaccurate, when the correct action for the identified situation is not known or not calculated, or when time or some other factor limits a person's ability to carry out correct action.

2.3 Human Properties Affecting and Underlying SA

This discussion first focus on characteristics of the individual, including relevant information-processing mechanisms and constructs that play a role in achieving SA. In combination, the mechanisms of short-term sensory memory, perception, working memory, and long-term memory form the basic structures on which SA is based (Figure 3).

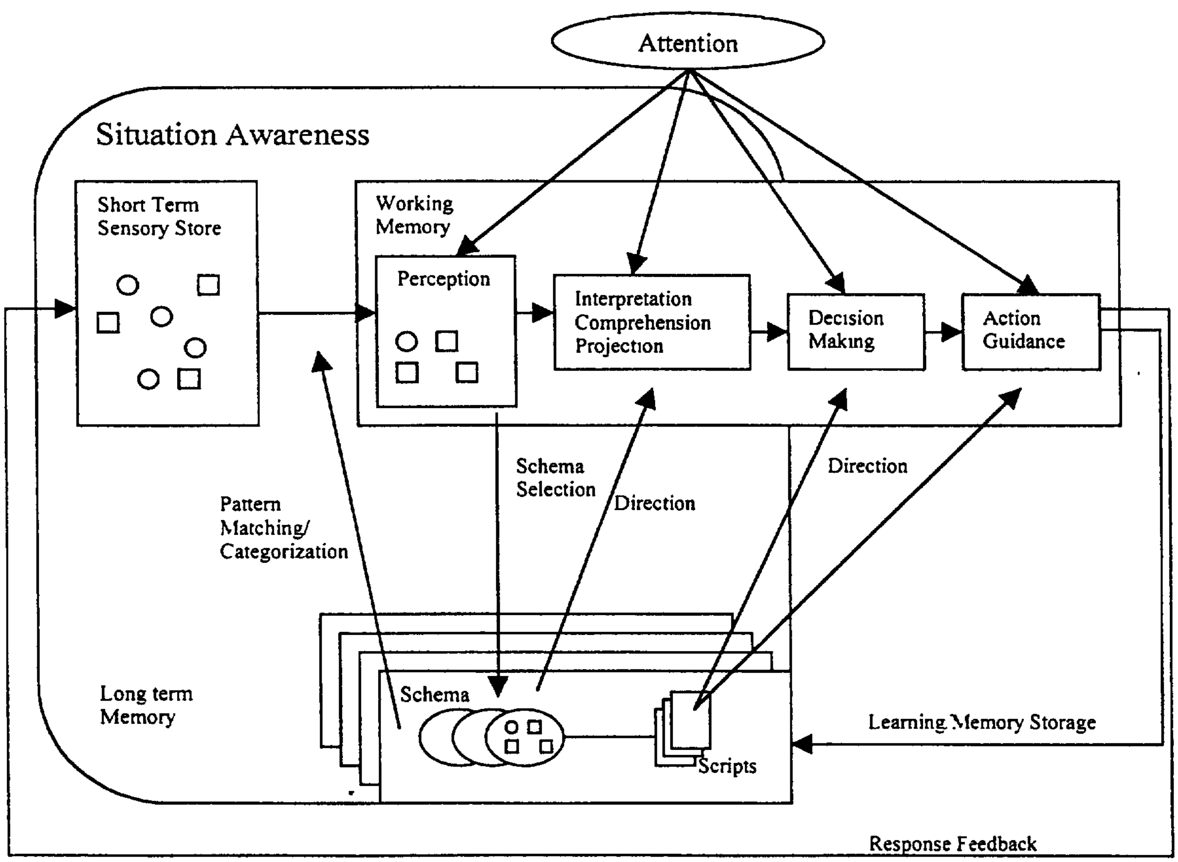

Figure 3. Mechanisms of SA.

Preattentive Processing

According to most research on information processing, environmental features are initially processed in parallel through preattentive sensory stores in which certain properties are detected such as spatial proximity, color, simple properties of shapes, or movement, providing cues for further focalized attention. Those objects that are most salient, based on preattentively registered characteristics, will be further processed using focalized attention to achieve perception. Cue salience, therefore, will have a large impact on which portions of the environment are initially attended to, and these elements will form the basis for the first level of SA.

Attention

The development of attention in the perception process acts to present certain constraints on a person's ability to accurately perceive multiple items in parallel and, as such, is a major limit on SA. In complex and dynamic environments, attention demands resulting from information overload, complex decision making, and multiple tasks can quickly exceed a person's limited attention capacity. Operators of complex systems frequently employ a process of information sampling to circumvent this limit.

Working memory also plays an important role, allowing one to modify attention deployment on the basis of other information perceived or active goals.

People are active participants in determining which element of the environment will become a part of their (level 1) SA by directing their attention based on goals and objectives and on the basis of long-term and working memory.

Because the supply of attention is limited, more attention to some elements (resulting in improved SA on these elements), however, may mean a loss of SA on other elements once the limit is reached, which can occur rather quickly in complex environments.

Limitations of attention may be circumvented to some degree through the development of automaticity.

Perception

The way in which information is perceived is directed by the contents of both working memory and long-term memory. Advanced knowledge of the characteristics, form, and location of information, for instance, can significantly facilitate the perception of information.

One's preconceptions of expectations about information will affect the speed and accuracy of the perception of that information. Repeated experience in an environment allows one to develop expectations about future events.

Long-term memory stores also play a significant role in classifying perceived information into known categories or mental representations as an almost immediate act in the perception process.

The classification of information into understood representations forms level 1 SA and provides the basic building blocks for the higher levels of SA. The cues used to achieve this classifications are important to SA. With higher levels of expertise, people appear to develop critical cues in the environment that allow them to make very fine classifications.

Working memory

Once perceived, information is stored in working memory. Most of a person's active processing of information must occur in working memory. New information must be combined with existing knowledge and a composite picture of the situation developed (level 2 SA). Projections of future status (level 3 SA) and subsequent decisions as to appropriate courses of actions must occur in working memory as well.

Long-term memory

Long-term memory structures can be used to circumvent the limitations of working memory. The exact organization of knowledge in long-term memory has received diversified characterization. including episodic memory, semantic networks, schemata, and mental models. This discussion will focus on schemata and mental models that have been discussed as important for effective decision making in a number of environments.

Schemata provide coherent frameworks for understanding information, encompassing highly complex system components, states, and functioning.
A script – a special type of schema – provides sequences of appropriate actions for different types of task performance. Ties between schemata and scripts can greatly facilitate the cognitive process because an individual does not have to actively decide on appropriate actions at every turn but will automatically know the actions to take for a given situation based on its associated script.

A related concept is the ***mental model***. "Mechanisms whereby humans are able to generate descriptions of system purpose and form, explanations of system functioning and observed system states, and predictions of future states".

Mental models can be described as complex schemata that are used to model the behavior of systems.

A ***situation model*** (i.e. SA) can be matched to schemata in memory that depict prototypical situations or states of the system model. These prototypical classifications may be linked to associated goals or scripts that dictate decision making and action performance. This provides a mechanism for single-step, "recognition-primed" decision making described earlier. This process is hypothesized to be a key mechanism.

A ***well developed mental model*** provides (a) knowledge of the relevant elements of the system that can be used in directing attention and classifying information in the perception process, (b) a means of integrating the elements to form an understanding of their meaning (level 2 SA), and (c) a mechanism for projecting future states of the system based on its current state and an understanding of its dynamics (level 3 SA).

The key to using these models to achieve SA rests on the ability of an individual to recognize key features in the environment – critical cues – that will map to key features in the model.

In cases in which scripts have been developed for given prototypical situation conditions, the load on working memory for generating alternative behaviors and selecting one among them is even further diminished.

A major advantage of this mechanism is that the current situation needs not be exactly like one encountered before. This is a result of categorization mapping.

Of prime importance is the fact that this process can be almost instantaneous because of the superior abilities of human pattern-matching mechanisms. When an individual has a well-developed mental model for the behavior of particular systems or domains, the model will provide (a) for the dynamic direction of attention to critical cues, (b) expectations regarding future states of the environment (including what to expect as well as what to not expect) based on the projection mechanisms of the model, and (c) a direct, single-step link between recognized situation classifications and typical actions.

Schemata and mental models are developed as a function of training and experience in a given environment. With experience, recurrent situational components will be noticed along with recurrent associations and causal relationships.

Default information

Holland et al. (Holland et al. 1986) explanation includes "Q-morphism" in which default information for the system is provided in a higher layer of the model. These default values may be used by individuals to predict the system performance unless some specific exception is triggered, in which case the appropriate transition function for that more detailed classification will be used.

This feature allows people to operate effectively on the basis of often limited information.
In addition, default values for certain features of a system can be used if exact current values are not known.

This provision of mental models allows experts to have access to reasonable defaults that provide more effective decisions than those of novices who simply have missing information (or poorer defaults).

Confidence level

Another important aspect of SA concerns a person's confidence level regarding the SA. The confidence level associated with information can influence the decisions that are using that information. One could hypothesize a degree of uncertainty associated with validity of features used to make the mapping from the real world to categories in the model.

Automaticity

A form of automaticity can be acquired. Automatic processing tends to be fast, autonomous, effortless. In relation to SA, automaticity poses an important question, however. To what degree do people who are functioning automatically have SA ?

Logan (Logan 1988) provided a detailed discussion of automaticity in cognitive processing that he maintained occurs through direct-access, single-step retrieval of actions to be performed from memory. When processing in this way, an individual appears to be conscious of the situational elements that triggered the automatic retrieval of information from memory (SA), but he or she probably will not be conscious of the mechanisms used in arriving at the resultant action selection.

As expressed by Dreyfus (Dreyfus 1981), the individual knows the *what* but not the *how*. If asked to explain why a particular decision was made, an individual will usually have to construct some rationale using logical processes to provide an explanation of the action he or she actually chose in an automatic, non-analytic manner.

The state of the situation itself , however, can still be verbalized as it is in awareness.

In addition, the degree to which automatic processing occurs without any attention or awareness has been questioned. An example of the possibility of decision making without conscious SA is that of a person driving home from work follows the same predetermined path, stops at stoplights.

The major implications of the use of automatic processes are (a) good performance with minimal attention allocation, (b) significant difficulty in accurately reporting on the internal models used for such processing and possibly on reporting which key environment feature were related, and (c) unreliability and inaccuracy of reporting on processes after the fact. Based on this discussion, automaticity is theorized to provide an important mechanism for overcoming human information-processing limitations in achieving SA and making decisions in complex, dynamic environments.

Goals

SA is important as needed for decision making regarding some system or task.

Goals form the basis of most decision making in dynamic environments. More than one goal may be operating simultaneously, and these goals may sometimes conflict. In most systems, people are not helpless recipients of data from the environment but are active seekers of data in light of their goals. In what Casson (Casson 1983) has termed a top-down decision process, a person's goals and plans direct which aspects of the environment are attended to in the development of SA.

Simultaneously with this top-down process, bottom-up processing will occur. Patterns in the environment may be recognized that will indicate that new plans are necessary to meet active goals or that different goals should be activated. In this way a person's current goals and plans may change to be responsive to events in the environment. The alternating of top-down and bottom-up processing allows a person to perform effectively in a dynamic environment. This process also relates to the role of mental models and schemata.

A person's current goal(s). selected as the most important among competing goals, will act to direct the ***selection of a mental model.*** The selected goals will also ***determine the frame*** (Casson 1983). ***or focus, on the model that is adopted.*** Plans are then devised for reaching the goal using the projection capabilities of the model. When scripts are available for executing the selected plan. they will be employed. When scripts are not available. actions will have to be devised to allow for plan completion. As an ongoing process, an individual observes the current state of the environment, with his or her attention directed to environmental features by the goal-activated model and interpreted in light of it.

When these expectations match what is observed, all is well. When they do not match, this signals to the individual that something is amiss and indicates a need to change goals or plans because of a shift in situation classes, a revision of the model, or selection of a new model. This process can also act to change current goal selection by altering the relative importance of goals.

When goals are incompatible, their associated priority level for the identified situation class determines which shall be invoked. Similarly, plans may be altered or new plans selected if the feedback provided indicates that the plan is not achieving results in accordance with its projections, or when new goals require new plans. Through learning, these processes can also serve to create better models, allowing for better projections in the future.

Summary

To summarize the key features of SA in this model, a person's SA is restricted by limited attention and working memory capacity. Where they have been developed, long-term memory stores, most likely in the form of schemata and mental models, can largely circumvent these limits by providing for the integration and comprehension of information and the projection future events (the higher levels of SA), even on the basis of incomplete information and under uncertainty.

The use of these models depends on pattern matching between critical cues in the environment and elements in the model. Schemata of prototypical situations may also be associated with scripts to produce single-step retrieval of actions from memory. SA is largely affected by a person's goals and expectations which will influence how attention is directed, how information is perceived, and how it is interpreted. This top-down processing will operate in tandem with bottom-up processing in which salient cues will activate appropriate goals and models. In addition, automaticity may be useful in overcoming attention limits; however, it may leave the individual susceptible to missing novel stimuli that can negatively affect SA.

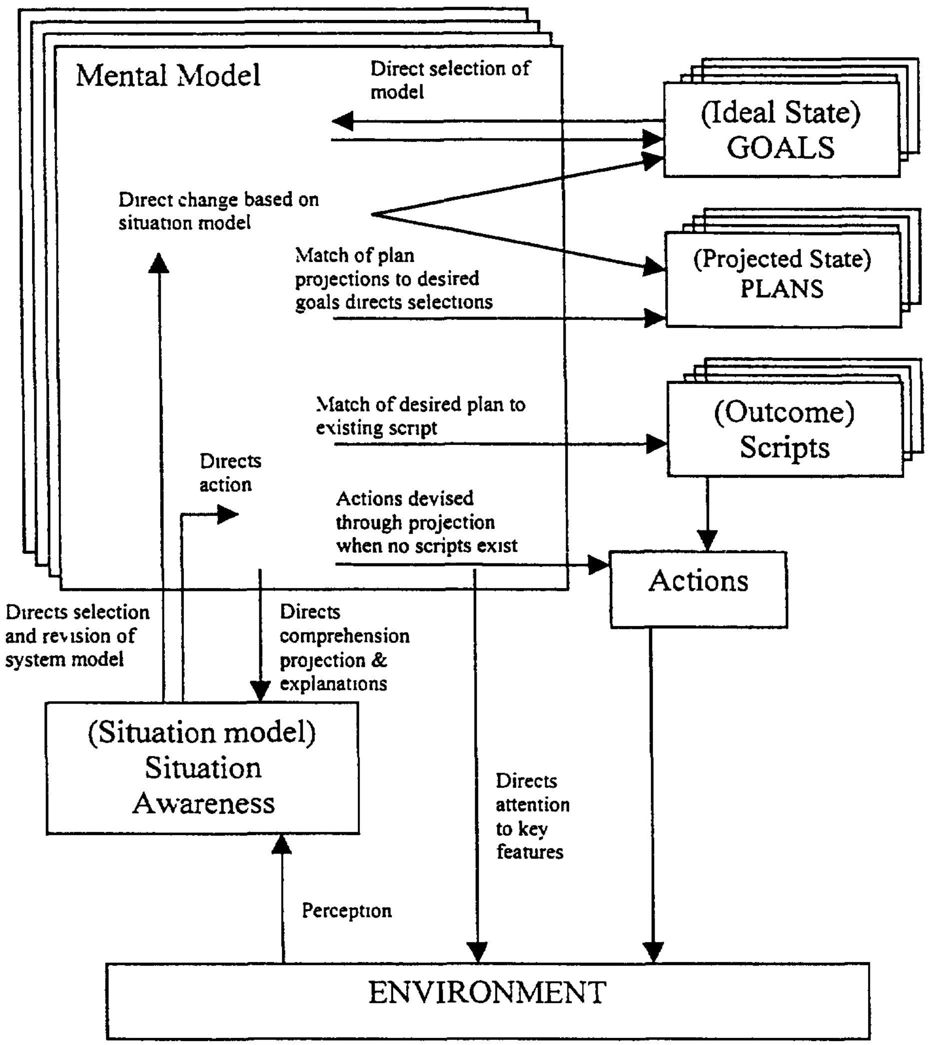

Figure 4. Relationship of goals and mental models to situation awareness.

2.4 Task and System Factors

A number of task and system factors can also be postulated to influence an individual's ability to achieve SA.

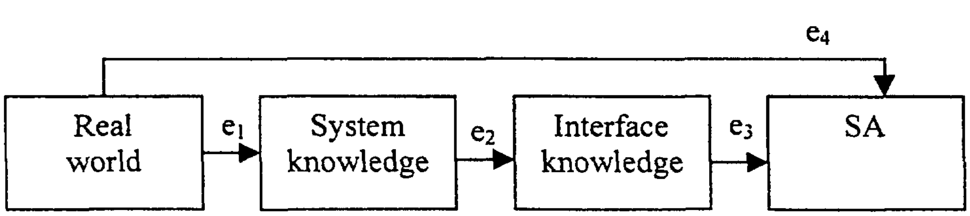

Figure 5. Situation awareness inputs.

System Design

In this process, transmission error, defined as a loss of information, can occur at each transition. First of all, the system may not acquire all the needed information (e_1).

Of the information acquired by the system, not all of it may be displayed of the operator (e_2). Finally, of the information displayed by the system and that directly acquirable from the environment, there may be incomplete or inaccurate transmission to the human operator (e_3 and e_4). because perceptual, attention and working memory constraints, as discussed earlier.

The first external issue influencing SA, therefore, is the degree to which the system acquire the needed information from the environment. The second major issue involves the display interface for providing that information to the operator.

Interface design

The way in which information is presented via the operator interface will largely influence SA by determining how much information can be acquired, how accurately it can be acquired, and to what degree it is compatible with the operator's SA needs. Determining specific design guidelines for improving operator SA through the interface is the challenge fueling many current research efforts.

- The degree to which displays provide information that is processed and integrated in terms of level 2 and 3 SA.
- The degree to which information is presented in terms of the operator's major goals will positively affect SA.
- Considering that mental models and schemata are hypothesized to be key tools for achieving the higher levels of SA in complex systems, the critical cues used for achieving these mechanisms, need to be determined and made salient in the interface design. In particular those cues that will indicate the presence of prototypical situations will be of prime importance.
- Designs need to take into consideration both top-down and bottom-up processing. In this light, environmental cues with highly salient features will tend to capture attention away from current goal-directed processing.
- A major problem for SA occurs when attention is directed to a subset of information and other important elements are not attended to, either intentionally or unintentionally. A preferred design will provide global SA – an overview of the situation across the operator goals – at all times, while providing the operator with detailed information related to his or her immediate goals, as required.
- Although filtering out information on relevant SA elements is hypothesized to be detrimental, the problem of information overload in many systems must still be considered.
- One of the most difficult and taxing parts of SA is the projection of future states of the system. This is hypothesized to require a fairly well developed mental model.
- The ability to share attention between multiple tasks and sources of information will be very important in any complex system. System designs that support parallel processing of information should directly benefit SA.

The value added by the SA concept is a means of integrating these constructs in terms of the operator's overall goals and decision behavior. As such, this provides several advantages in the design process:

- The integrated focus of SA provides a means of designing for dynamic, goal-oriented behavior with its constant shifting goals.
- It provides a means of moving from a focus on providing operators with data to providing operators with information.
- It provides a means of incorporating into the design a consideration of the interplay of elements, whereas more attention to some elements may come at the expense of others.
- This integrated level of focus provides a means for assessing the efficiency of a particular design concept that an examination of underlying constructs (attention, working memory, etc.) does not provide.

A few major design issues, however, poses a serious challenge to SA across numerous systems to warrant special consideration: stress, workload, complexity, and automation.

Stress

Several types of stress factors exist that may act to influence SA, including (a) physical stressors – noise ... and (b) social psychological stressors. Stressors can affect SA in a number of different ways. The first is that under various forms of stress, people tend to narrow their field of attention to include only a limited number of central aspects. Premature closure, arriving at a decision without exploring all information available, has also been found to be more likely under stress. Complex tasks with multiple input sources appear to be particularly sensitive to the effects of stressors.

A second way in which stress may affect SA is through the decrements in working memory capacity and retrieval. The degree to which working memory decrements will affect SA depends on the resources available to the individual operator.

In many dynamic systems, high mental workload is a stressor of particular importance.

Complexity

A major factor creating a challenge for operator SA is the increasing complexity of many systems. System complexity is hypothesized to negatively affect both operator workload and SA through factors such as an increase in the number of the system components, the degree of interaction between these components, and the dynamics or rate of change of the components.

Automation

A lack of SA has been hypothesized to underlie the out-of-the-loop performance decrement that can accompany automation. Although some of this problem may result from a loss of manual skills under automation, SA is also a critical component. Operators who have lost SA may be slower to detect problems and also will require extra time to reorient themselves to relevant system parameters in order to proceed with problem diagnosis and assumption of manual performance when automation fails.

2.5 Errors in Situation Awareness

From an operational point of view, there is major concern about situations in which the operator has poor SA, thus increasing the probability of the undesirable performance to investigate the factors that can lead to breakdowns in the SA portion of the decision making process.

Level 1 SA. At the very lowest level a person may simply fail to perceive certain information that is important for SA in the assigned task (incomplete SA). In the simplest case, this may result from a lack detectability or discriminability of the physical characteristics of the signal in question, from some physical obstruction preventing perception.

In many cases in which SA is incomplete, the relevant signals or cues are readily discernable but not properly perceived by the subject. Furthermore, some people appear to be better than others at dividing their attention across different tasks. This problem is compounded by the addition of stress, which can affect the information input stage through premature closure, changes in factors attended to, and deterioration of the scanning process.

Level 2 SA. SA errors are most often the result of an inability to properly integrate or comprehend the meaning of perceived data in light of operator goals. This misreading of cues can occur for several reasons. A novice will not have the mental models necessary for properly comprehending and integrating all of the incoming data or for determining which cues are actually relevant to established goals. In other cases, a person may incorrectly select the wrong model from memory, based on a subset of situational cues, and use this model to interpret all perceived data. However, if the wrong mental model is initially selected, based on a subset of cues, a representational error may occur. These errors can be particularly troublesome.

Even when a person has selected the correct model with which to interpret and integrate environmental stimuli, errors can occur. Certain pieces of data may be mismatched with the model or not matched at all, resulting in a failure to recognize a prototypical situation. In addition, SA errors could occur from overlying on the default values embedded in the model.

When no model exists at all, level 2 SA must be developed in working memory. An inability to perform this integration in an accurate, timely manner – resulting from insufficient knowledge or working memory limitations, particularly under stress – can also lead to inaccurate or incomplete SA.

Level 3 SA. Finally, level 3 SA may be lacking or incorrect. Even if a situation is clearly understood, it may be difficult to accurately project future dynamics without a highly developed mental model.

General factors. A few general underlying factors may also lead to SA errors at all three levels. People who have trouble with distributed attention may be having trouble in maintaining multiple goals.

A second major type of error affecting SA relates to the role of habitual schemata (or automaticity). While the habitual schema is operating, the person either is not receptive to the non-habitual cues or does not generate the appropriate higher-level SA from the perception of the cues because the appropriate schema is suppressed.

Detection of SA errors. A real issue concerns how people know when their SA is in error. Very often they may be completely unaware of how much they do not know or of the inaccuracy of their internal representation of the situation.

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