NFFP3+
Concepts and Methods

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Abstract

This report documents the first phase of the NFFP3+ project. Different concepts and methods, that are considered to be of interest when fusing data from airborne sensor network during ground surveillance, are presented and discussed. The report then suggests what concepts could be implemented in the second phase of the NFFP3+ project.

Contents

1 Introduction

In order to support and encourage research within the aeronautical area, the Swedish government, represented by the Swedish Defence Material Administration (swe.: Försvarets MaterielVerk, FMV), started a research program called the National Aeronautical Research Program (swe.: Nationella Flygtekniska Forskningsprogrammet, NFFP) (cf. decision 2000-11-30, Fö2000/264/ES). Partners in the program are the Swedish Government, Saab AB and Volvo Aero Corporation. As an additional partner from the industry is Ericsson Microwave Systems AB (cf. decision 2004-01-29, Fö2004/88/MIL).

The program is now in a transition phase, going from phase three over to phase four, referred to as NFFP3+ (see NFFP 522, 2004; FT/R-2004:045, 2004). Participants in the NFFP3+ project are the University of Skövde, Chalmers University of Technology and Ericsson Microwave Systems AB (EMW) (see FT/R-2004:045, 2004).

1.1 Aim

The aim of the NFFP3+ project is to conduct a study about how sensor data from airborne ground surveillance sensors can be used to create and maintain fused common ground situation picture (see FTP/R-2004:045, 2004).

1.2 Motivation

The motivation for the above aim is the focus on network based defence (NBD) (swe.: Nätverksbaserat Försvar) in Sweden. With principles such as information and decision superiority as cornerstones within NBD, the importance of being able to grasp and understand information concerning a certain area of interest or Commander's Intent is high. Airborne sensors that perform ground surveillance tasks are considered to be an important base component due to their relatively large surveillance capacity. However, forming this common ground area picture is a complex problem as it requires the fusion and combination of information from numerous disparate sources, ranging from airborne multi-sensor systems to databases and intelligence, where numerous information fragments might relate to a single object of interest.

In order to investigate the feasibility of creating a common ground area picture from airborne ground surveillance sensors, the NFFP3+ project is divided up into two projects with separate aims:

1. Create a common ground area picture by using fusion methods.
2. Apply alternative interpretation methods for model-based estimation

The first project will be conducted by University of Skövde and EMW and is reported in this document. The second project will be conducted by Chalmers University of Technology and EMW.

The first project is divided up into two phases (where the results from the first phase are documented here). The aim of the first phase is to investigate different concepts and methods for fusing information from airborne ground surveillance sensors with more stationary information in databases, such as geographical data. Of special interest here is to fuse information on different levels of granularity, e.g. single object versus groups of objects.

The second phase involves choosing concepts and methods to implement, in order to test and evaluate them with regards to the goals of NBD. The chosen concepts are documented in this report. The results of phase two and the whole NFFP3+ project should be a suggestion for a long term research project, most likely a doctoral project that should be conducted during the NFFP4 phase.

The document is structured as follows: first the area of fusing data, information and knowledge will be described followed by a more detailed discussion of concepts and methods related to our area of interest. We then suggest concepts to be implemented and tested in phase two.

2 Fusion and the JDL model

Concepts used in the fusion field vary considerable (see for example Wald, 1999). In this report we adopt parts of the terminology defined in Svensson (2003), which in turn is used by the Swedish research and development community for NBD. The terminology relies partially on the Joint Directors Lab (JDL) model (see Figure 1). Svensson (2003) has adopted the following terminology:

- Sensor data fusion (or sensor fusion or data fusion)
    - Deals with creating a target ***situation description*** based on data received from sensors
    - Involves primarily target tracking, but also target identification based on sensor data
- Multi-sensor fusion
    - More than one sensor is employed to create target tracks or a situation picture
    - The purpose is to combine information from several sensors in order to obtain greater robustness, precision, and range from the sensor systems
- Multi-sensor multi-target fusion
    - Is sometimes used to emphasise the use of several sensors to create and maintain a target situation picture containing many different perceived targets which may perhaps also appear and disappear randomly
- Information fusion
    - Employs, in addition to all available target information, other kinds of intelligence data, as well as other relevant kinds of data.
    - This is all fused during *situation assessment* into a higher-level ***situation model***.
    - Interpretation of the situation – threat, vulnerability, tactics etc. - is performed in the *impact assessment* process.
    - The *resource management process* provides feedback to the sensors as well as to the assessment process.

For an introduction to what a sensor is and the basic concepts related to it see Looney (2001). The following is taken from Looney (2001):

- **Sensor:** Transduces received energy into a usable form
- **Sensor system:** Captures, preprocesses and stores the above
- **Active sensor:** Transmits signal and receives its reflection from objects
- **Passive sensor:** Receives emission or reflection of ambient energy, e.g. heat (IR) or light.
- **Seeker sensor:** Searches a large area
- **Tracker sensor:** Scans a smaller area at a higher resolution for detecting location or range velocity of a target
- **Sensor report:** Is a set of sensor readings from a sensor
- **Clutter:** Is undesired energy that degrades the desired signals from objects of interest
  - **Surface clutter:** trees and shrubs, ground or sea, or man-made structures
  - **Volume clutter:** rain, birds and insects

For further overview on different sensor types see Looney (2001) or Warston et al. (2004). Observe that the source of data into the fusion process is not limited to senors. Source of data could be for example intelligence reports or newspaper articles. Extracting information from, for example, free-text reports belongs to the area of Information Extraction (IE) (See Appelt & Israel, 1999, for introduction). Hecking (2004) discusses how it is possible to extract information from free-form battlefield reports.

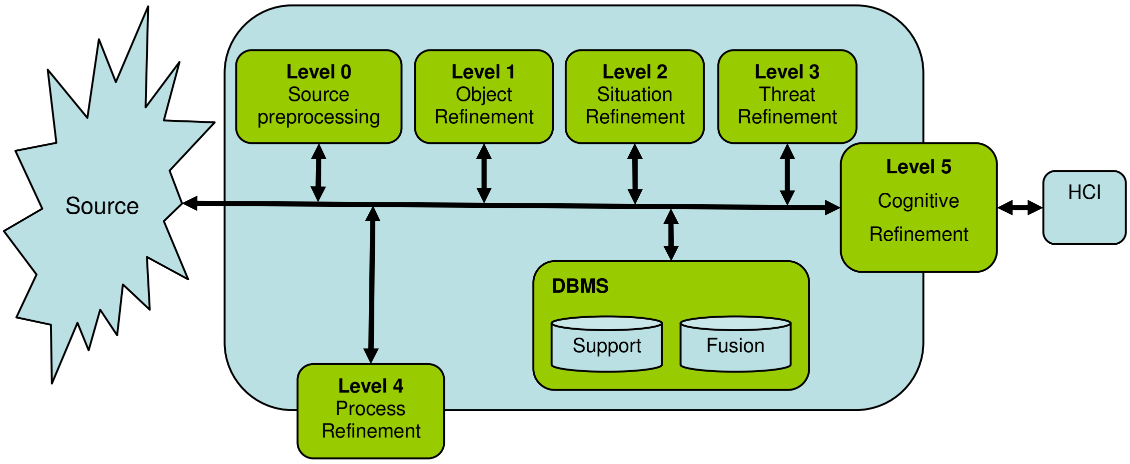

Figure 1 The Joint Directors of Laboratories (JDL) data fusion model (Adapted from Hall & McMullen, 2004)

The JDL model (see Figure 1) was established in 1986 as an effort to establish a terminology related to data fusion (Llinas & Hall, 1998; Hall & Liinas, 2001). The model was designed to be a functional model opposed to, for instance, the Observer-Orient-Decide-Act (OODA)[1] model which is a process model (Steinberg & Bowman, 2001; Hall & McMullen, 2004). The difference is that a functional model only *defines* the functions of the model but does not state anything about the *interactions* within the model. A process model, however, *specifies the interaction* among the functions in a system. In this context, the JDL model has been useful to associate processes to the refinement of “objects”, “situations”, “threats” and “processes”. With regards to the terminology in Svensson (2003) Level 0 and Level 1 can be considered to be sensor fusion processes while the upper levels refer to information fusion processes.

2.1.1 Level 0 – Source preprocessing

Level 0 focuses on preprocessing the data for the other levels. This is performed in order to not overwhelm the system with raw data. This preprocessing is usually performed at the specific sensor and is therefore individual to each sensor (Hall & McMullen, 2004).

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[1] For more info see: http://www.webster-dictionary.org/definition/Military%20Strategy%20%28John%20Boyd%29

2.1.2 Level 1 – Object refinement

Level 1 has been primarily of focus in the research community and numerous techniques have been investigated in order to achieve fusion at this level. Here data, e.g. from level 0, is fused to determine the position, velocity, attributes, characteristics, and identity of an observation. According to the taxonomy in Hall and McMullen (2004) there are four main categories of functions within level 2 (see also Figure 2).

The first is *data alignment* where data from different sources are aligned, both spatially and temporally. This can also include other types of data manipulation/conversion in order to compare data from different sources (e.g. units conversion) (Hall & McMullen, 2004).

The second category is *data/object correlation*. Here the problem of interest is to associate a number of observations from one or more sources to a single observation. An example of this is when observation A observed at time T1 by sensor S1 and observation B observed at time T2 by sensor S1 relates to the same object. The same is valid in the case of two (or more) different sensors. The general model to solve this is by setting up a number of hypothesis that could explain the data, the hypothesis are then evaluated using some form of quantitative measurement such as probabilistic metrics, similarity measures, distance calculations, and likelihood functions (Hall & McMullen, 2004).

The third category of functions focuses on *estimations of position and velocity*. Here the focus is on trying to track an object and predict its next position using a state vector. An estimation problem must be defined by specifying the state vector, observation equations, and equations of motion among others. This is referred to as the system model. When the system model has been specified, optimization criteria must be chosen. This criterion specifies which state vector best fits the observed data. This can be calculated using Mean Square Error (MSE) or Weighted Least Squares (WLS). The selection of this criterion depends upon the a priori knowledge about the observational process. Next would be to decide on the optimization approach, i.e. to actually find the values of the state vector that satisfy the optimization criteria. Here a form of hill-climbing algorithm can be adopted. The last design choice is if the processing should be performed online using sequential methods or offline in batch mode. In the category of sequential methods we find the

Kalman filter (Hall & McMullen, 2004). We will be discussing the tracking subject further in section 3.3.

The fourth category focuses on estimating the *identity of an observation*. Techniques used for identity fusion range from well-known statistical-based methods such as classical inference, Bayesian methods (discussed in section 3.1) and Dempster-Shafer method (discussed in section 3.2), to techniques in pattern recognition, e.g. templating, cluster algorithms (discussed in section 3.4), neural networks, or knowledge based techniques. In some cases the identification process relies on feature vectors created by a feature extraction process. This process takes the raw data (e.g. an image) and extracts features from it to simplify the identification process. Features that could be extracted are for example geometrical features such as lines, polygons, circles, structural features, statistical features, and spectral features (Hall & McMullen, 2004; O'Brien & Irvine, 2004).

It is important to realize that despite the above categorization of functions, they are closely related to one another and usually complement each other in order to achieve fused results. For example, positional information can be of value for establishing identity of an observation and vice versa. In addition, the estimation of identity is closely related to Level 2 as both use pattern recognition techniques.

2.1.3 Level 2 – Situation refinement

Level 2 involves refining our estimates and understanding of a situation. It focuses on understanding the relationships among observations, their relationship to the environment and aggregation of, both in time and space, in order to be able to infer more abstract reasoning. In Figure 2 decomposition of Level 2 can be found (Hall & McMullen, 2004). The level is decomposed into four categories of functions, object aggregation, event and activity aggregation, contextual interpretation, multi-perspective assessment. Further, the functions therein are included.

Object aggregation considers aggregating objects in time and space, i.e. Level 1 identifies a single object and on Level 2 we try to understand the relation among a number of objects. By analyzing the geographical proximity between objects it is possible to investigate if the objects in question are related in some way. Other ways might include communication channels, i.e. we could group observations that are communicating on the same frequency.

Event and activity aggregation is another type of reasoning about situations, where events and activities are analyzed in time, i.e. a certain action may require a number of events and a number of (seemingly unrelated) events may lead to a certain action. Jakobson, Lewis and Buford (2004) describe an interesting approach where they integrate the two techniques of temporal event correlation (EC) and case-based reasoning (CBR) in order to achieve understanding of situations.

The third category of functions refers to being able to reason about the *context of observations*. That is, the environment and weather can constrain observations in different ways, for example a car is most likely to use a bridge to cross a river and a snow storm might prevent traffic.

The fourth category is a rather military point of view where in order to understand a situation one must be able to see the situation from *different perspectives*, e.g. both a neutral point of view, own point of view and from the adversarial point of view. Hall and McMullen (2004) however state that this can also be transferred to other areas, e.g. failure conditions of an airplane is considered from a different point of view if the plane is on the ground or in the air.

2.1.4 Level 3 – Threat refinement

The JDL introduces Level 3 for processing of threat refinement, i.e. to understand the consequences of certain actions with regards to the current situation. An example of this is to predict when machinery might break down based on running it in certain operating conditions. The key functions identified by Hall and McMullen (2004) are aggregation and estimation of force capabilities, prediction of enemy indent, identification of threat opportunities, estimation of implications, and multi-perspective assessment. The functions here bear a strong resemblance to the functions of Level 2 except that on Level 3 the focus is on prediction, i.e. understanding future relationships and predicting the effect of certain events and actions. This is interesting with regards to understand Commander's Intent.

The algorithms that support the functions on level 2 and 3 are mainly pattern recognition algorithms such as cluster analysis, neural networks, decision trees, and parametric templates, and automated reasoning algorithms such as expert systems, blackboard systems, logical templates, case-based reasoning, and intelligent agents (Hall & McMullen, 2004).

2.1.5 Level 4 – Process refinement

Hall and McMullen (2004) define Level 4 as a meta-process. The process monitors the data fusion process and tries to optimize the process by controlling the sensor resources in order to achieve improved fused results. Specific functions include scheduling of sensors, prioritizing tasks, predicting position of objects and relocate sensors in order to achieve optimal/near-optimal results. In order to perform this optimization the quantitative measures of performance (MOP) or measure of effectiveness (MOE) are computed and used as objective functions in the optimization process. An example could be measuring percentage of correctly identified targets and idle sensor time.

Xiong and Svensson (2003) focus on sensor management from a multi-sensor perspective. Sensor management aims at improving data fusion performance by controlling sensor behaviour, i.e. process refinement. According to Xiong and Svensson (2003) sensor manager is responsible for answering questions like:

- Which observation tasks are to be performed and what are their priorities?
- How many sensors are required to meet an information request?
- When are extra sensors to be deployed and in which locations?
- Which sensor sets are to be applied to which tasks?
- What is the action or mode sequence for a particular sensor?
- What are the parameter values that should be selected for the operation of sensors?

Basically the purpose of sensor management is to optimize fusion performance by managing the sensor resources. It can therefore be considered as a decision making task, taking viewpoint from decision theory, determining the most appropriate sensor action to be taken in order to achieve maximum utility. According to Xiong and Svensson (2003) the problems within this area fall into three categories, namely sensor deployment (where to place the sensors in an optimal manner), sensor behaviour assignment (adapt to a dynamically changing situation), and sensor coordination (coordinating numerous, perhaps, heterogeneous sensors).

Xiong and Svensson (2003) mention that the concept sensor management has started to become a non-relevant concept due to the complexity and the dimensionality of its underlying tasks. Ronnie, Johannson and Xiong (2003) suggest the concept *perception management* as an "… appropriate concept referring to controlling and improving data acquisition from the external world to obtain information with greater content, higher utility, and lower uncertainty" (Ronnie, Johannson & Xiong, p. 232, 2003). Of interest here is that by using the concept perception management they imply (which they also point out) that data acquisition is an integral part of an artificial intelligent system. The reason for this is the close relation to the agent metaphor (Russel & Norvig, 2003). This is interesting when considering that it is beneficial to automate the OODA loop.

Of the number of approaches mentioned in Xiong and Svensson (2003) two were considered to be of special interest for this work. These are *behaviour-based artificial intelligence* and *cooperative sensor behaviour*. These areas are considered very interesting. The reason for this interest is that the dynamics of the sensor system, and its relation to the targets being observed, can be compared to the dynamics of two competing populations in biology. An action performed by the opponent needs to be responded by a counter-action. This counter-action can be in the form of relocation sensors, or adding more sensor resources in order to observe an area of interest. Buason and Ziemke (2003) have in a series of experiments investigated artificial competitive co-evolution of two robotic species, where the neural control system of the robots is evolved. One robot evolves the behaviour of a prey while the other evolves the behaviour of a predator. With minimal influence from the designer, the dynamics of the system gives space for arms races to arise between the two competing populations. The basic approach of competitive co-evolution in adaptive robotics is described in detail in Nolfi and Floreano (2000). In addition, the area of cooperative adaptive robotics has also been under investigation (see Cao, Fukunaga & Kahng, 1997). It is our belief that it should be useful to adapt ideas from adaptive robotics, such as competitive co-evolution and cooperative robotics, to the area of process refinement (and threat refinement), working towards the goal of having autonomous reactive fusion system.

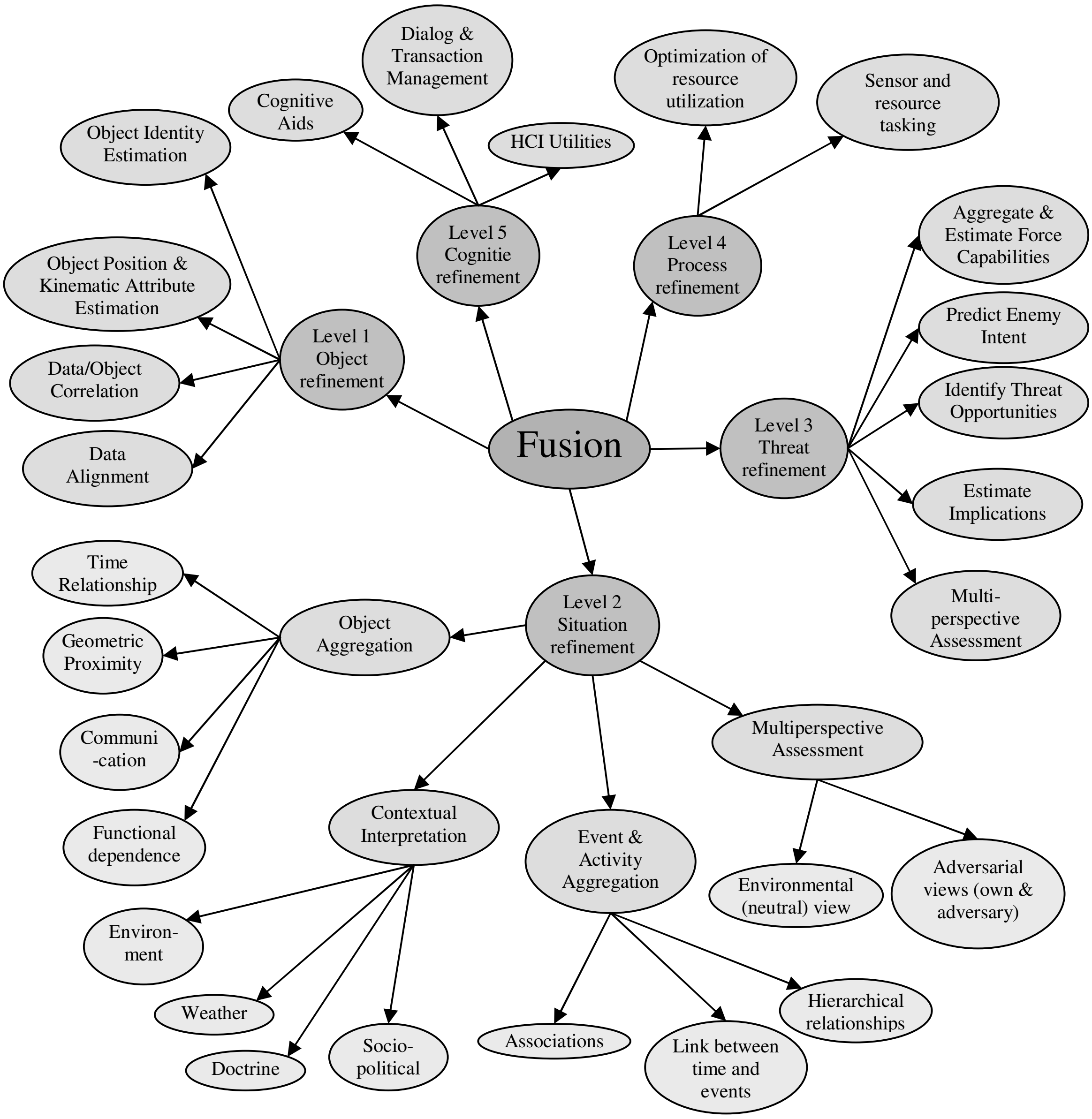

Figure 2 Functional decomposition of the JDL model based on taxonomy from Hall and McMullen (2004). Based on the five levels of the JDL model (excluding level 0) different functions (or category of functions) are identified. We chose to include only a further decomposition of level 2 functions.

2.1.6 Level 5 – Cognitive refinement

According to Hall & McMullen (2004) human-computer interaction (HCI) research in the fusion domain has mainly considered interaction between the user and a geographical information display (based on a geographical information system) through menus and dialogs. However, the current research interest in this area is growing, and techniques such as gesture recognition and natural language interaction are currently of interest. Hall & McMullen (2004) further point out a new research area, referred to as *cognitive aids*. This area focuses on developing different end user aids, in order to avoid, for example, cognitive biases (e.g. all Icelandic words end on "ur") or to draw focus of attention to a certain subject.

2.1.7 Summary

The above discussion has focused on the levels of the JDL model, presenting a terminology of the fusion area, exemplifying functions and algorithms to achieve fused results. This, however, is not nearly a complete list of the functions/algorithms that are required (or can be used) for performing fusion. Hall and McMullen (2004) state that supplementary support functions may account for as much as 80% of the total software in a data fusion system. Examples of such functions are numerical libraries including different types of statistical algorithms and models, data alignment including algorithms for coordinate and time-based transformations, data preprocessing including signal, image and test processing and database management including storage and retrieval approaches.

For a overview of techniques used in the fusion area see (Zuidgeest, 1996; Hinman, 2002; Hall & McMullen, 2004)

3 Fusion Techniques

In this chapter we will explain techniques that are often referred to in the area of fusion.

3.1 Bayes

Bayesian networks (also referred to as belief network or probabilistic network) are a data structure that is represented as a directed graphical model with no cycles. Each node in the graph is associated with quantitative probability. Each node has a conditional probability distribution, quantifying the effects that a parent node has on a child node (Russel & Norvig, 1995). By using Bayesian networks it is possible, by applying Bayes' rule (see Equation 1), to mathematically explain how new evidence can affects ones belief.

$$P(Y \mid X) = \frac{P(X \mid Y)P(Y)}{P(X)}$$

Equation 1: Bayes' rule

Kevin Murphy has written a Bayesian Net Toolbox (BNT) in Matlab (Murphy, 2001)[2]. The toolbox is open source and supports many kinds of probability distribution nodes, exact and approximate inference, parameter and structure learning, and static and dynamic models.

3.2 Dempster-Shafer

The *Dempster-Shafer theory*, also referred to as the *theory of belief functions* or *theory of evidence*, is a generalisation of the Bayesian theory of subjective probability. The Dempster-Shafer theory is based on two ideas: the idea of obtaining degrees of belief for one question from subjective probabilities for a related question, and Dempster's rule for combining such degrees of belief when they are based on independent items of evidence (Shafer, 1990, 1992)[3]. That said it is possible to state that Dempster-Shafer theory differs in three ways from the Bayes approach (Shafer, 1990, 1992)[4]:

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[2] The software can be accessed at http://www.ai.mit.edu/~murphyk/. Kevin Murphy has also written a short introduction to the Bayes' Rule and Bayesian Networks that can be accessed on the previously mentioned web page.

[3] Homepage of Glenn Shafer: http://www.glennshafer.com

[4] Johan Schubert recommends some references about different aspects of Dempster-Shafer theory at http://www.dbai.tuwien.ac.at/marchives/fuzzy-mail98/0279.html

- Evidence is represented as a belief function instead of probability density function.
- Dempster-Shafer does not require priori probability (and assumes ignorance)
- Evidence can be combined

The theory has been under much debate but has received increasing acknowledgement. One of the arguments for not applying Dempster-Shafer in applications is it's computational complexity, where the Dempster's rule of combination is known to be NP-complete (Orponen, 1990; Haenni & Lehmann, 2003). A comparison of Bayesian and Dempster-Shafer theory can be found in Hoffman and Murphy (1993). Among those that have applied and extended the theory is Schubert (1995, 2001, 2003)[5].

When working with different and multiple events, with evidence relating to one or more events, it is required that they are sorted into groups where all evidence in one group refers to the same event. This can be done by Dempster-Shafer clustering (Schubert, 1995, 2001) using the conflict of Dempster's rule in Dempster-Shafer theory as a distance measure. By doing so all evidence in each group that belongs to a certain event can then be fused separately. Schubert has also been investigating attracting evidence, as opposed to conflicting evidence described above (Schubert, 2003).

Wu, Siegel, Stiefelhagen and Yang (2002) stated that the uncertainty management and inference mechanisms in the Dempster-Shafer theory are analogous to human reasoning process. They use the Dempster-Shafer theory to fuse information from multiple cues, tracking user's focus of attention.

Adrian O'Neill has implemented a Dempster-Shafer Engine, a system which implements features of the Dempster-Shafer theory. It is possible to download the software at: http://www.quiver.freeserve.co.uk/dse.htm. In addition O'Neill provides an example which illustrates the mathematical context of the theory. The example can be found at http://www.quiver.freeserve.co.uk/binaries/dempster.pdf.

[5] For extended publication list of Schubert's work see http://www.foi.se/fusion

3.3 Target Tracking

There is a difference between tracking a target in the air and tracking a target on the ground. In the air there are no hard spatial constraints while on the ground the terrain limits the manoeuvrability of the target and also degrades the quality of the measured data (Ke, 1999). In his literature survey, Ke (1999) introduces the subject by discussing terrain factors that limits ground targets motion patterns. These factors include different road types, elevation, land types (e.g. forests, waters, swamps), weather (rain can influence terrain), and man-made constructions (e.g. tunnels and bridges). Ke (1999) also discusses different types of targets and classifies those according to their behavioural pattern into on-road vehicles, off-road vehicles and walking objects.

Peters (2001) gives an introduction to standard data fusion algorithms on level 1, i.e. algorithms for target tracking and classifying. The algorithms explained are the Kalman Filter, the Interacting Multiple Model (IMM) filter, the Probabilistic Data Association Filter (PDAF), the Munkres algorithm for Nearest Neighbour (NN) association, and Multiple-Hypothesis Tracking (MHT). Also some track-level fusion algorithms are described such as Covariance Intersection.

The Kalman filter[6] is a set of mathematical equations that provides an efficient computational (recursive) means to estimate the state (position and velocity, for example) of a process. The filter is very powerful in several aspects supporting estimations of past, present, and even future states, and it can do so even when the precise nature of the modeled system is unknown (Welch & Bishop, 2004).

The *Kalman filter*, however, assumes that the posterior density at every time step is linear Gaussian and, hence, parameterized by a mean and covariance. If the assumptions hold, the filter is an optimal solution in tracking domains (Arulampalam et al., 2002). On the other hand, if the process to be estimated and (or) the measurement relationship to the process is non-linear, other types of filters should be used (Arulampalam et al., 2002; Welch & Bishop, 2004). One of those filters is the Extended Kalman Filter (EKF). This filter is based upon the Kalman filter, and tries to linearize the estimation around the

[6] Good overview page with links to other sources can be found at http://www.cs.unc.edu/~welch/kalman/index.html

current estimate using the partial derivates of the process and measure functions (Welch & Bishop, 2004). However, according to Arulampalam et al. (2002), if the true density around the estimates is non-Gaussian (and non-linear), then a Gaussian can never describe it well. In those cases filters such as the particle filter will yield an improvement in performance. Observe that this benefit is only valid in non-linear, non-Gaussian systems.

Particle filter[7], also referred to as sequential Monte Carlo methods, use numerical methods to achieve the filtering and are therefore not limited to Gaussian systems. Measurement noise and process noise from sensors are seldom Gaussian, and by assuming Gaussian noise in these cases the performance could degrade significantly. The idea behind particle filters is to approximate the state probability density function using particles with weights spread out in the state space. A region in the state space with many particles that have high weights has higher probability than state space with few particles with low weights (Arulampalam et al., 2002).

Downloadable implementations

There exist a number of filtering libraries. Klaas Gadeyne, a Phd student at the Department of Mechanical Engineering, Katholieke Universiteit Leuven, has developed a Bayesian Filtering Library[8] in C++ that contains Sequential Monte Carlo methods, Kalman filter and Particle filter among others. The Australian Center for Field Robotics (ACFR) has developed a class library (Bayes++)[9] in C++ implementing a wide variety of numerical algorithms for Bayesian Filtering of discrete systems. Bayes++ can be considered to be more standardized as it uses Boost[10] to provide compiler independence, and a common build system. As a final example we mention a Matlab toolbox[11] written

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[7] See also discussion on the pros/cons together with some references at: http://www.ee.mu.oz.au/staff/doucet/FAQ.html

[8] The library can be found at http://people.mech.kuleuven.ac.be/~kgadeyne/bfl.html

[9] The library can be found at http://www.acfr.usyd.edu.au/technology/bayesianfilter/Bayes++.htm

[10] Free peer-reviewed portable C++ source libraries, see http://www.boost.org/

[11] The library can be found at http://www.ai.mit.edu/~murphyk/Software/Kalman/kalman.html

by Kevin Murphy which supports filtering, smoothing and parameter estimation for linear dynamical systems.

3.4 Cluster Analysis

Clustering[12] is the classification of observations into groups (clusters) based on similarity. Clustering is considered to be a form of unsupervised classification opposed to supervised classification (or discriminant analysis) where the patterns are known apriori (Jain et al., 1999; Everitt et al., 2001).

When clustering it is of importance to identify how 'close' two observations are to each other. The measurement is commonly referred to as *dissimilarity*, *distance* or *similarity* with the general term being *proximity* (Everitt et al., 2001). A commonly used distance measure when working with continuous data is Euclidean distance.

$$d_{ij} = (\sum_{k=1}^{p} (x_{ik} - x_{jk})^2)^{\frac{1}{2}}$$

Equation 2 Euclidean distance

When measuring the proximity between group of individuals there are a number of techniques to be used. These techniques specify the two points within the groups in the Euclidean space that should be measured. The most common techniques are *single linkage* and *complete linkage* (Jain et al., 1999; Everitt et al., 2001). We would also like to mention *average linkage* and *centroid* (Everitt et al., 2001).

[12] For shorter introduction to clustering algorithms see for example:

- http://www.statsoftinc.com/textbook/stcluan.html
- http://www.quantlet.com/mdstat/scripts/mva/htmlbook/mvahtmlnode77.html

Table 1 explains these different techniques.

Table 1 Different techniques for measuring distances between clusters

Distance	Explanation
Single linkage	Find the smallest distance between any two individuals (also referred to as nearest neighbors distance)
Complete linkage	Find the furthest distance between any two individuals (also referred to as the furthest neighbors distance)
Average linkage	Distance is calculated by averaging the distance between all pairs of individuals in the two clusters.
Centroid linkage	The center of gravity is calculated within each cluster and the distance is measured between these centroids.

Different approaches can be used to cluster data. Jain et al. (1999) provide taxonomy over different approaches (see Figure 3).

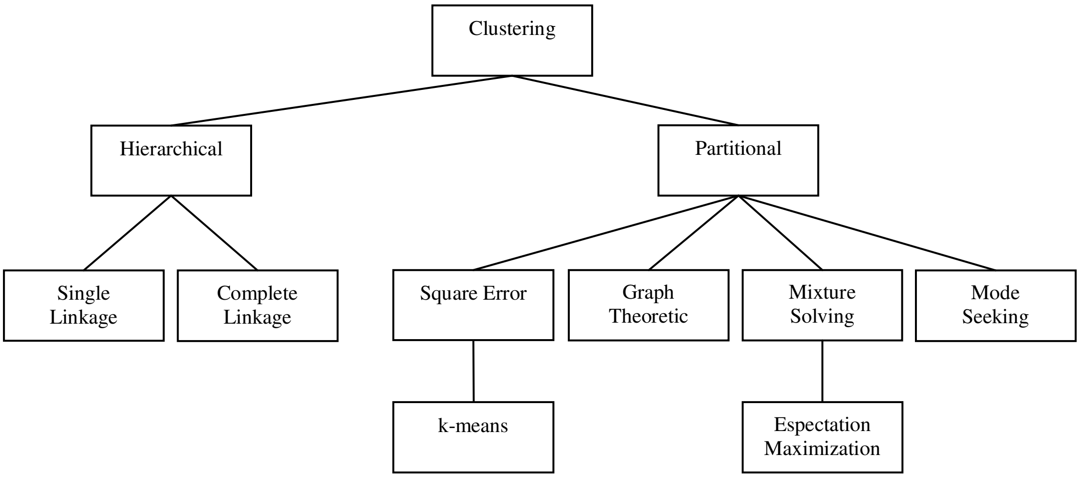

Figure 3 A taxonomy of clustering approaches (Adapted from Jain et al., 1999). Other taxonomies however exists, for example Everitt et al. (2001) implies that all clustering is hierarchical and categorizes it into agglomerative and divisive techniques.

We will not go into details of the above taxonomy (for those interested see Jain et al., 1999). The hierarchical approach (also referred to as hierarchical agglomerative) starts by treating each observation as a cluster. It then continues clustering until a certain stop criterion is achieved or all observations are included in a single cluster. The partitional approach starts with all observations in a single cluster and then splits the cluster up into smaller clusters. The k-means algorithm, for example, starts with a single cluster, and splits that cluster up into k clusters. The problem is to know how many the output clusters should be. However, the k-means algorithm requires less computation on large data sets.

The above description of clustering has focused on hard clustering, i.e. each observation can only belong to a single cluster. However, it is possible to perform a fuzzy clustering where a certain observation can belong to one or more clusters based on a degree of membership (Jain et al., 1999; Everitt et al., 2001).

4 Higher level fusion

We have chosen to name the title of this chapter "Higher level fusion". Although our focus is on Level 2 fusion, i.e. situation assessment (based on our aim of creating and maintaining a fused common ground area picture), the other levels (Level 3, 4 and 5) quickly become intervened. Before we continue discussing the details of higher level fusion (mainly Level 2) we will elaborate on the concept of information. Opposed to the often limited view of fusion in the area of military operations Bloch et al. (2001) try to dissect it at a domain independent level. As a starting point they discuss the two types of information: descriptive and normative. Descriptive information includes real world observations (i.e. how the world is), and knowledge (i.e. how the world is in general). Normative information, on the other hand, focuses on an ideal world and includes preferences (i.e. how the world should be) and regulations (i.e. how the world should be in general). Further they discuss reasons why to perform fusion, based on the type of information. According to Bloch et al. (2001) the four main reasons for performing fusion is based on the motivation of *creating* and *updating* a model of a real world, and *creating* and *updating* a model of an ideal world. They also point out the importance of using suitable data structures to represent information in an efficient and practical way. Information may be:

- *Explicit* (including all information) or *partial* (only part of the information is used due to the amount in question).
- *Numerical* or *symbolic* (or a combination where a numerical value is given a symbolic representation).
- *Defective*, that is it can be ambiguous, uncertain, imprecise, incomplete, vague or inconsistent.

- *Generic*, referring to universal rules, or *factual*, referring to a certain case.
- *Scaleable*, that is in certain situations information needs to be attached to a scale when, for example, measuring uncertainty.

As the JDL model is a functional model, it lacks the human perspective when creating model of the current situation. An alternative or a complement to this could be the Endsley model (Endsley, 2000). The Endsley model (see Figure 4) is commonly referred to in the literature of situation awareness in the context of data fusion (Wallenius, 2004; Salerno et al., 2004). Endsley defines *situation awareness*, a term originated from aircraft piloting, as "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" (Endsley, 2000). Further, situation awareness is the state of knowledge that is the result of a process, *not* the process itself. The process to achieve situation awareness is often referred to as *situation assessment* (Endsley, 2000; Salerno et al., 2004; Moulin et al., 2000). Endsleys definition of situation awareness has been criticised for its individual perspective (e.g. Wallenius, 2004). This can be related to the origin of the concept (i.e. from aircraft piloting).

Salerno et al. (2004) explore both the JDL model and the Endsley model and suggest a framework that uses both of these models.

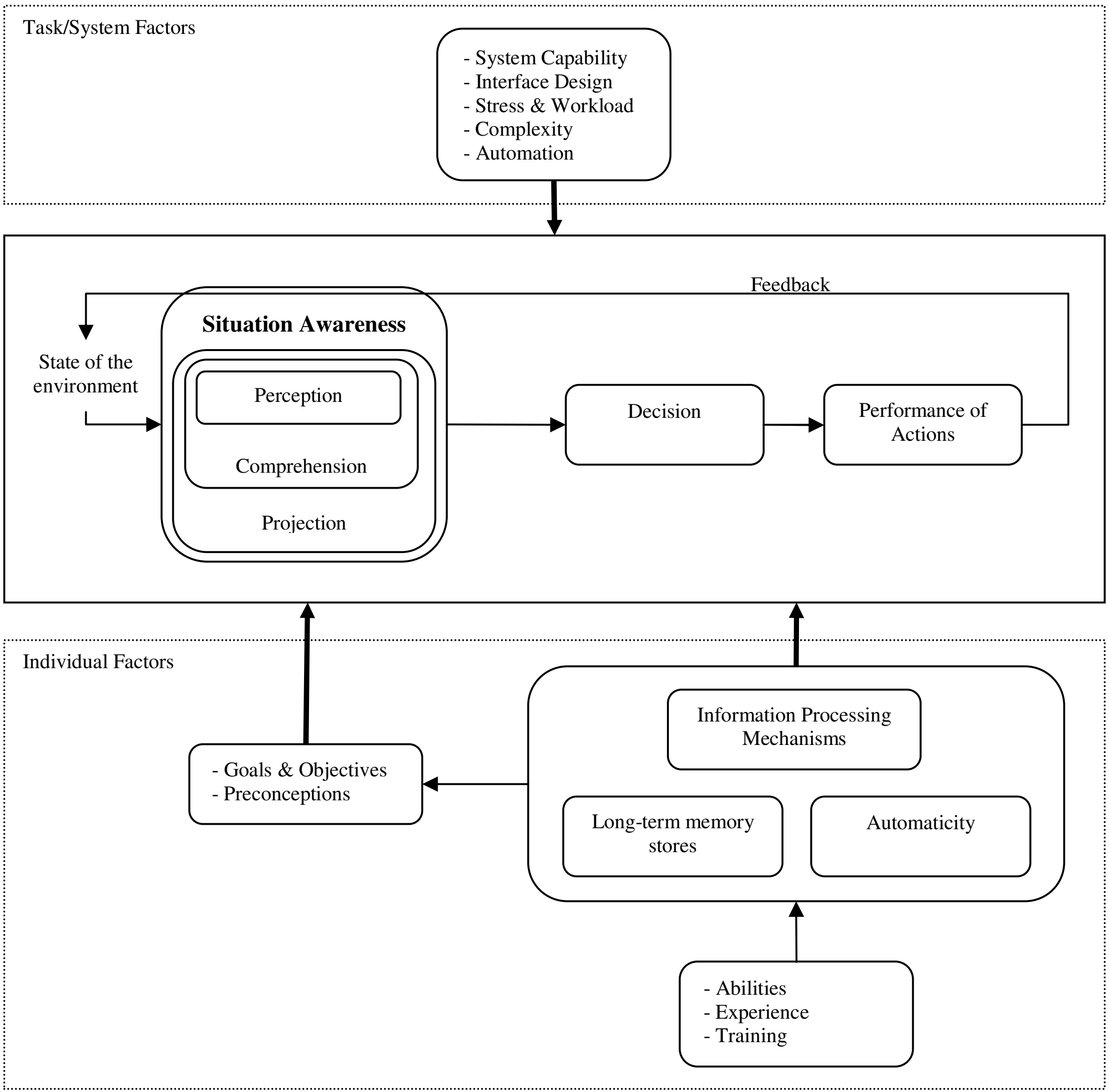

Figure 4: Endsley's model of situation awareness. For more details see Endsley (2000) (adapted from Endsley, 2000).

As an example of another model than the one presented by Endsley is explained in Steinberg and Bowman (2001). The model was not given any name in Steinberg and Bowman (2001) but we will be referring to it as the Waltz model (Waltz, 1998 in Steinberg & Bowman, 2001). Waltz extended the work of the philosopher Karl Popper. The model is based on that a person (or an information system) perceives physical stimuli, building up the persons own perceptual state. This perceptual state can in turn include an estimation of the physical, informational and perceptual state. This model can be seen as an attempt to model the cognitive perception process of a person.

5 Fusion and Geospatial Information

Cantwell, Schubert and Svensson (2000) propose in their report a strategic research activity in the area of Information Fusion during the period 2001-2005. This includes cooperation between the Swedish Defence Research Establishment (FOA) and universities. Their purpose is to develop a methodology that enables information superiority in CC (Command & Control) systems in the Swedish defence. They propose that the focus should lie on the following areas:

- Management of uncertainty
- Information acquisition (and the control of it)
- Fusion architectures with focus on:
    - Situation Assessment (Level 2)
    - Threat Assessment (Level 3)
    - Management of resources (Process Refinement) (Level 4)

They present a overview over the areas of situation assessment (including intelligence management, aggregation problem, and correlation), threat assessment and management of resources. It is clear from their overview that there are certain areas that need to be attended to in order to enable information superiority in CC. In addition they present an overview of research groups that are working within the area of uncertainty, e.g. Bayesian probability theory and Dempster-Shafer, and present a number of international research programs, e.g. Nato DFD (Data Fusion Demonstrator), EUCLID (EUropean Cooperation for the Long term In Defence)[13], and CASE_ATTI (see section 6.1.3). One of the aspects that Cantwell et al. (2000) discuss is the spatial aspect during aggregation and correlation. Geographical distance is important when trying to correlate a number of observations to, perhaps, a single object, or trying to aggregate a number of objects into a single unit. The distance between objects can imply that the objects belong to the same unit (however deciding how "far" the distance between objects in a unit is, is of course

[13] The project finished in 1998, parts of the results can be found at http://public.logicacmg.com/~grace/

debateable). In addition, if the observations are separated in time, one has to include the kinematical properties of the objects, e.g. can a unit or object move this far during a certain time frame. Cantwell et al. (2000) state that the terrain limits the choice of possible routes for ground based vehicles, based on the type of vehicle. In addition, if the vehicles belong to a unit, the size of the unit is also a factor that needs to be considered in this equation. Further they state that methods for extracting information about accessible routes in a terrain from geographical databases does exist to a certain level but needs to be developed further.

In recent years there has been an increased interest in using the road network data to aid and improve fusion (Gustafsson et al., 2002; Gattein & Vannoorenberghe, 2004; Gong et al., 2004). For example, Gong et al. (2004) use the road network to find optimal paths for emergency vehicles in a dynamic disaster environment. Interesting here are the factors that are used when deciding the dispatching of ambulances to patients, such as patient priority, cluster information and distances. Factors considered from patient location to hospital include waiting time estimates, hospital capacity, injury type, and distance. Routes between points consider damage or congestion information on roads and alternative routes whenever needed. Clusters of patients are considered with relation to the revised priority value (RPV), i.e. cluster of patients are prioritised in the dispatch policy.

Snell (2004) discusses interesting ideas concerning using geographical data in the decision making of a Network Enabled Capability (NEC). He states that geographical analysis is separated from the decision makers resulting in an information flow which is fragmented (Snell, 2004). The NEC concept is related to the Network Centric Warfare (NCW, in Swedish NBF). It is based on the following tenets:

- Information is shared
- Situational awareness and commander's intent is available to all levels
- Operations are effects based and synchronised
- Decisions should be collaborative

A core theme in the NEC concept is *shared awareness*. It is an extension of situational awareness referring to achieving awareness in a network by exchanging data and information. Snell (2002) adopts the following definition of situational awareness:

> Situational awareness is the assimilation of current and historical information to form a mental model of what is going on and what is likely to happen in the future in order to support timely decision making.

The essentials to achieving shared awareness are to understanding Commander's intent and also the intent of other battle space participants. The latter can be achieved by understanding the participants Course Of Action (COA).

However, shared awareness is not achieved only by having access to the proper information as it is mainly based in the cognitive domain. Systems cannot provide awareness, they can only support the user in the process of achieving awareness. A possible aid in achieving awareness is to understand the geographical environment. The terrain, for example, is a key factor in determining the type of operation and potential movement of troops. This process, i.e. studying and analysing the terrain is called Intelligent Preparation of the Battlefield (IPB). IPB uses information such as basic infrastructure data (e.g. roads, forest etc.), weather patterns, and population information. According to Snell (2004) the data used in IPB is produced manually (e.g. from maps). This manual process suffers, according to Snell (2004), from a number of disadvantages:

- Fixed level of detail – no zooming in to detailed mapping or imagery
- No control over what is displayed
- Manually commenting on the map is time consuming
- Difficult to reproduce or copy a commented map
- Maps soon get cluttered and information easily misread or disregarded
- There is a limit to the information that can be added
- Not designed for dissemination from HQ.

The IPB process, despite the above disadvantages, is well established. As a means of improving the IPB process, Snell (2004) suggests using Geographical Information

Systems (GIS) in the IPB process. GIS visualize and manipulate geographical or spatial data. The data is stored as raster data (i.e. as an image of a map) and as vector data (i.e. data stored in the form of points, lines and polygons usually encoded in a coordinate system such longitude/latitude or Universal Transverse Mercator grid). According to Snell (2004) vector data is often considered to be “intelligent data” as it is possible to query the data based on their mathematical and geometrical association. An example of queries could be “how far is the road from …” or “what are the possible routes to …”.

As Snell (2004) points out, people that make critical geographical decisions in the context of C2 have been unable to benefit from GIS. The reason for this is that a certain level of expertise is required to perform geographical analysis. Snell (2004) therefore suggests the use of Geographical Decision Support (GDS) systems to distribute the capability of GIS into the hands of more people, using simple “point and click” methods. This involves embedding spatial data into the GDS, removing the requirement that the user has a detailed understanding of the data. The data that should be embedded should include raster data, vector data, digital elevation models and imagery. The last data is included to enhance the visualization aspect. Snell (2004) gives the following examples of geospatial support that can be gained by using GDS:

- Visibility/line-of-sight analysis
- Sensor footprint
- De-confliction of complex three-dimensional scenarios
- Shared environmental picture
- Deployment routing
- Routing analysis and movement timing
- Terrain analysis
- Ballistic trajectory analysis and de-conflicting
- Effect planning
- Asset management and scheduling

With similar arguments as in Snell (2004), Choi, Joo and Cho (2002) propose a new framework suitable for military applications. The framework uses assumption-based truth maintenance system, spatio-temporal reasoning and uncertainty processing in order to support intelligence preparation of the battlefield (IPB). By using spatio-temporal operators (e.g. distance is an operator that can take values such as far, close, between, near and very_near) they are able to generate components of doctrinal templates and situation map. They demonstrate concepts such as mobility corridors from terrain's effect analysis and weather effects analysis on operation.

If one takes airborne sensor networks as an example, one of the challenges is how to effectively fuse uncertain and noisy information for better battlefield situation assessment (Yu et al., 2004; FT/R-2004:045, 2004). Part of the problem is the enormous amount of information available and the risk of overloading the operator's cognitive capabilities. We will describe here an approach suggested by Yu et al. (2004). The approach includes aiding in classifying and aggregating forces by using Dempster-Shafer theory and doctrinal templates.

Their basic assumption is that lower level fusion problems have already been solved. As an example, an Unmanned Aerial Vehicle (UAV) scans an area and the output from the sensors on the UAV is a list of possible types of targets. Each item on the list is associated with an uncertainty value. The problem is then to reason about this uncertainty. Further each sensor has a so called confusion set, where different types of targets are listed each associated with different confidence levels. That is, a low resolution sensor might confuse two different types of targets if they are similar in shape, therefore the sensor in question has similar confidence values associated with these target types. This information, i.e. the confidence levels, is then converted over to Dempster-Shafer belief functions in order to be able to reason about targets, possible in conflict with other information from other sensors. Yu et al. (2004) then uses doctrinal template to identify aggregates (i.e. units). A template could be as simple as stating that four vehicles of the same type form a unit of some sort. The first step here is to identify which vehicles could belong to the same unit. Yu et al. use an agglomerative clustering algorithm for this, calculating the distances between the vehicles. Then, given a cluster of vehicles, a matching process is performed, trying to find the corresponding template. This process bares certain similarity with case-based reasoning (For an introduction to case-based reasoning see Aamodt & Plaza, 1994). However, the vehicles are associated with uncertainty based on the confidence levels from the confusion sets. That is, two or more templates could match to a cluster of vehicles. Here Yu et al. (2004) uses the conflict in Dempster-Shafer theory, trying to minimize the conflict between a template and a cluster of vehicles. Finally, a cluster of vehicles could partially match a template (e.g. the template contains four vehicles while the cluster only contains three vehicles).

An interesting point that they made in their conclusion is the future work on inclusion of spatial data in the process. This point is further discussed in Glinton et al. (2004). In Glinton et al. (2004) they state that a key prerequisite to higher-level fusion is the use of context, terrain information provide this context for ground operations. An example is given in the context of IPB and finding out COAs, i.e. a river that is not passable can be considered as an obstacle that limits possible COAs. Glinton et al. (2004) put their focus on automated terrain analysis, supporting the IPB process by identifying, for example, mobility corridors. They present an approach for this, representing the mobility corridors as graphs, using Voronoi diagrams as starting point. In order to represent 'resistance' in certain mobility corridor, the network is also presented as electronic circuit adding resistance to the path that is proportional to the length of the corridor and inversely proportional to its width (Glinton et al., 2004). The basics of this approach are based upon the Ohm's law of electrical circuits.

Looney and Liang (2002) point out that situation awareness can lead to an operational advantage, but the danger of overloading the operator with information can lead to that the *fog of war* becomes the *glare of war*, delaying critical decision. Looney and Liang (2002) present a clustering algorithm, called the *centralized means* (N.B., in a later article this algorithm is referred to as *the uniform k-centralized mean* (Looney & Liang, 2003)), to cluster feature vectors. This algorithm is a variation of the k-means algorithm and provides, according to Looney and Liang (2002) a better initial seeding and better clustering with slightly more computation cost (Looney & Lang, 2002; Looney & Lang, 2003). When the clusters have been obtained, a case-based reasoning process is used to infer situation awareness. Both Yu et al. (2004) and Looney & Lang (2002) are on the same track concerning the processes within situation assessment, i.e. using clustering algorithm to identify clusters and then use some form of case-based reasoning, creating a model. Yu et al. (2004) are however including Dempster-Shafer to handle uncertainty while Looney and Lang (2002) only handle simple beliefs. In addition, the spatial context is of more focus in Yu et al. (2004) as is further demonstrated in Glinton et al. (2004). Looney and Lang (2002) focus more on the optimization of the clustering algorithm and a more extensive case-based reasoning process where cases can be updated and/or added to the case base.

6 Fusion Systems

A number of fusion systems have been implemented in a number of interesting domains such as transportation management (Dailey, Harn & Lin, 1996) and industrial recycling appropriate (Karlsson et al., 2002). In the latter, fusion was used to find out if electrical motors could be repaired and reused or if disassembly was appropriate. Karlsson et al. (2002) at the University of Linköping created a toolbox of fusion methods for investigating this. The toolbox consisted of nine different methods including fuzzy logic with triangular and Gaussian shaped membership functions, fuzzy measures with triangular and Gaussian shapes, Bayes' statistics, artificial neural networks, multivariate analysis, a knowledge based system, and a neuro-fuzzy system. The methods were tested for extracting features from images taken of the motors and fused with information in databases.

We will present three systems that in some way demonstrate fusion at a certain levels and are relevant to our work. For an overview of other fusion systems we suggest Nichols (2001) and Hall and McMullen (2004) and the references therein.

6.1.1 GTSIM

GTSIM is a Ground Target SIMulator that has been developed at Ericsson Microwave Systems (EMW) to be used as a simulation framework for testing and developing sensor data- and information fusion methods and concepts (Warston & Persson, 2004). GTSIM is built in a distributed manner to demonstrate the capabilities of creating a ground surveillance picture from spatially dispersed, heterogeneous multisensor system. The design methodology of the simulator is based upon that during surveillance, the sensor that presents the best quality of data about a certain target, is responsible for collecting and fusing all available information about the target in question for the ground surveillance picture. If the responsible sensor is then lost, a new negotiation is started to select the best sensor from a pool of available sensors. The best sensor can change from time to time depending on different parameters (Warston & Persson, 2004).

The simulator uses CORBA to communicate between different parts of the system (demonstrating its distributed nature). The world state simulation uses a digital terrain database for placing targets in a realistic environment (Warston & Persson, 2004).

6.1.2 IFD03

The Swedish Defence Research Agency (FOI) has developed a concept demonstrator called InfoFusion Demonstrator 03 (IFD03). The demonstrator provides a research platform for integrating and testing methods related to fusion of for example multisensor-multitracking, force aggregation, and multisensor management. The simulator is of a centralized nature, opposite to GTSIM. In addition, IFD03 relies on COTS software, integrating Matlab, the simulation framework FLAMES and the terrain modelling system TerraVista Pro. The concept is discussed in Hörling and Svensson (2003) and system design and fusion methods are described in Schubert, Mårtenson and Sidenbladh (2004). Experience of using the simulator is documented in Ahlberg et al. (2004). The analysis module has three main tasks (Schubert et al., 2004):

- force aggregation using Dempster-Shafer clustering and Dempster-Shafer template matching
- ground vehicle tracking using probability hypothesis density particle filtering
- sensor allocation using random set simulation

6.1.3 CASE_ATTI

CASE_ATTI (Concept Analysis and Simulation Environment for Automatic Target Tracking and Identification) is a system that has been developed at the Defence Research Establishment Valcartier (DREV) in Canada. It is documented in Roy, Bossé and Dion

(1995)[14] and has been used at CMIF (Center for Multisource Information Fusion, USA) (Chou, 2001). DREV has also worked on a project called ACTIF (Advanced Concepts on Tactical Information Fusion), however documentation concerning this project was not found[15]. Further, Bossé and Roy (1998) describe the effort that Canada and the Netherlands have been working on in the domain of multi-sensor data fusion. They briefly describe the Canadian CASE_ATTI test bed and the Dutch MT3 test bed. In addition they present generic multi-sensor data fusion system architecture (see Figure 5). This architecture includes the basic functions of the JDL model. Cheaito, Lecours and Bossé (1998) describing identity fusion using Dempster-Shafer theory in the context of this test bed.

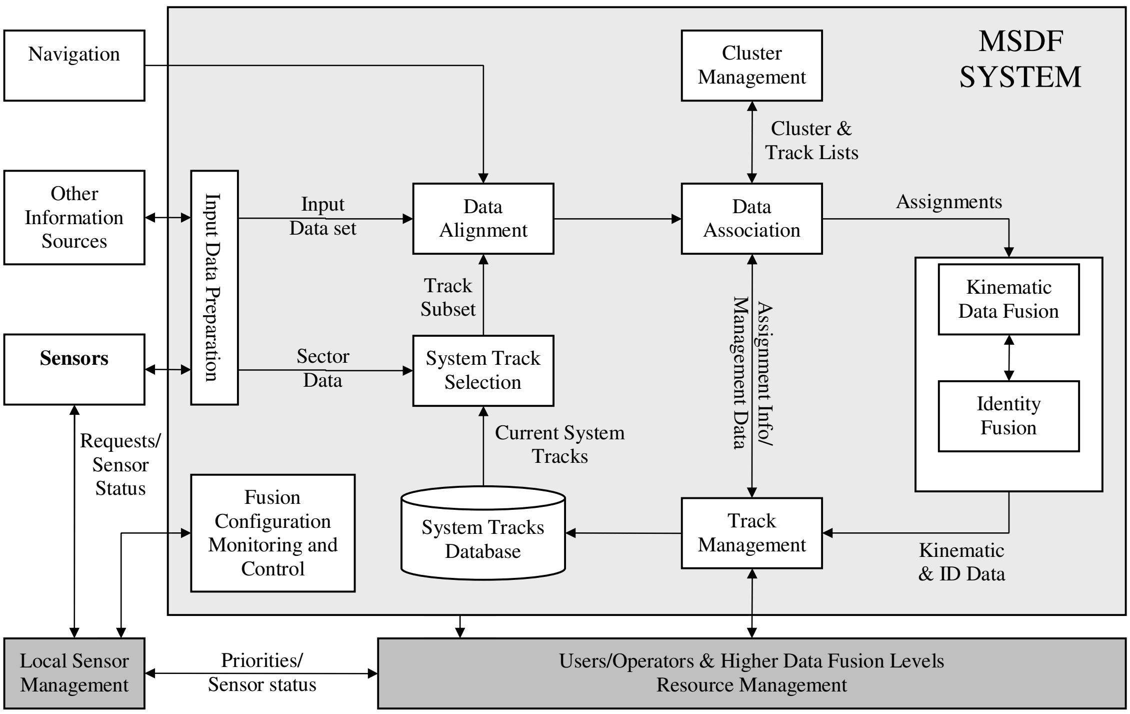

Figure 5: A generic multi-sensor fusion architecture (adapted from Bossé & Roy, 1998).

[14] For an overview of CASE ATTI se http://www.drev.dnd.ca/poolpdf/e/137_e.pdf

[15] For an overview of ACTIF se http://www.drev.dnd.ca/poolpdf/e/111_e.pdf

7 Limitations in fusion

Hall and Steinberg (2001) identify a number of areas within the area of data fusion that require more attention. Based on the JDL model they go through each level and discuss problems and limitations. According to Hall and Steinberg (2001), the level that seems to include active research but little progress is Level 2 in the JDL model, i.e. situation assessment. Motivating this they state that there are only few operational systems that support this level, and prototype systems only address toy problems. They further state that:

> A key problem for Level 2 and Level 3 processing is the lack of cognitive models for performing situation assessment. Current cognitive models are pathetic. Researchers simply do not know how to model the reasoning process to perform a Gestalt-type of situation assessment. (Hall & Steinbrerg, p. 21-5, 2001)

Additionally, Hinman (2002), states that a literature survey indicates that the majority of research and research applications has focused on level 1 fusion. The reason for this, Hinman states, is that physical properties of an object can “easily be measured and comprehended”, while relationships amongst objects are “poorly understood”.

Hall and Steinberg (2001) summarize the research needs in the following figure.

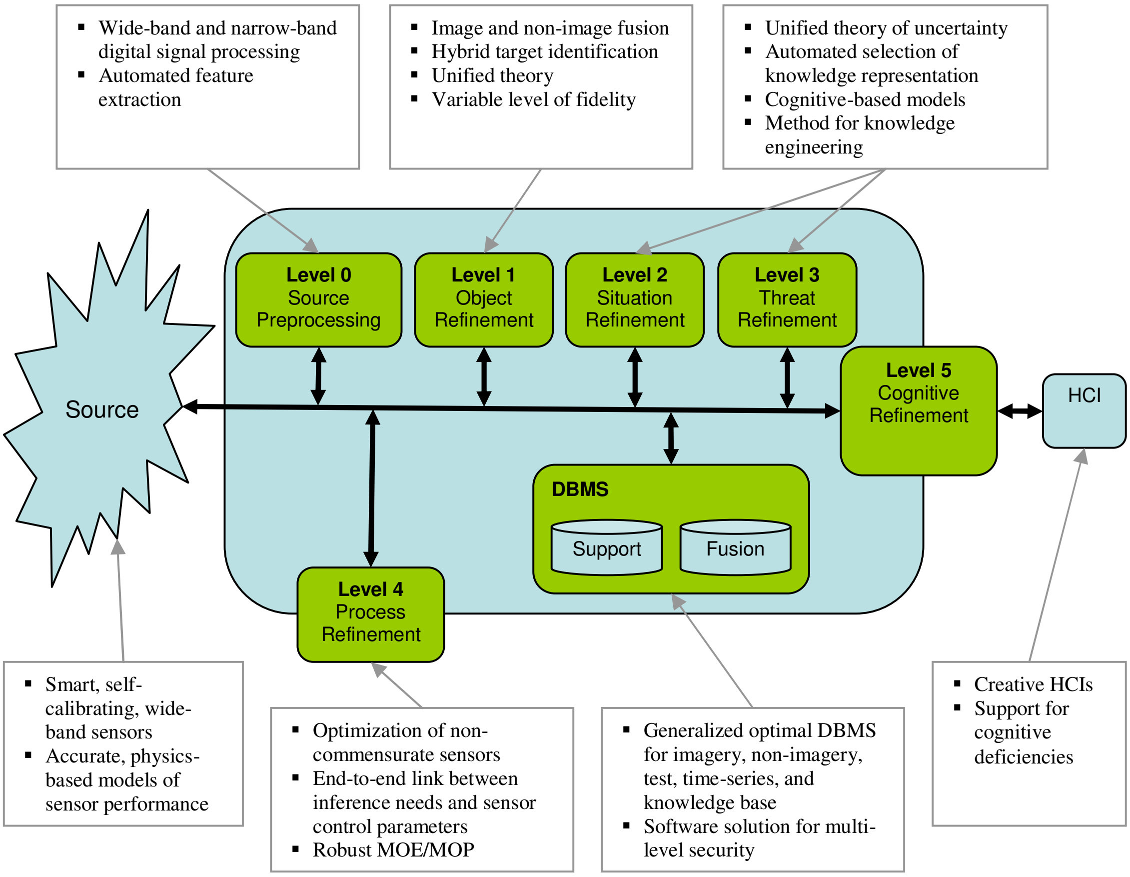

Figure 6 A suggestion of research areas in data fusion according to Hall and Steinberg (2001) (adapted from Hall & Steinberg, 2001).

8 Suggestions for implementation

As discussed in chapter 7 there are a number of areas with the domain of fusion that require more work. The aim our work has been to create a common ground area picture, fusing information from airborne sensors and static data as can be found in geographical databases. We have in this report presented the fusion area, discussed terminology, different functions and algorithms to achieve fusion and work of interest has been presented. It becomes clear that our focus is of high interest in the research community and can be considered to be on the front edge when looking at publication year of the discussed articles. We provide here a quick summary over researchers that point out the interest of fusion in the higher levels of the JDL model, with special focus on situation awareness, and the inclusion of geospatial data in the fusion process.

Overview

Cantwell et al. (2000) suggest a research activity that mainly should focus on the higher levels in the JDL model (Level 2, 3 and 4). They also mention the benefits of using geographical data in order to be able to correlate observations or calculate routes. More researchers (Hall & McMullen, 2004; Hall & Steinberg, Looney, 2001) confer with that more research focus is required on the higher levels.

Ke (1999) states terrain limits ground targets motion patterns and that targets can be classified into on-road and off-road vehicles.

Researchers such as Gustafsson et al. (2002), Gattein et al. (2004), Gong et al. (2004) have been using the road network both in tracking and routing.

Glinton et al. (2004) state that a key prerequisite to higher-level fusion is the use of context, and for ground operations this context is provided by the terrain.

Snell (2002) discusses and motivates the importance of using geographical data in the decision making process of NBD. Especially Snell discusses the IPB process and finding out COAs. Snell further describe the importance of having a GDS on top of the GIS in order to allow more users to interact with the system, using simple “point and click” methods. Waltz (2001) and Choi et al. (2002) are on the same line concerning IPB process.

Yu et al. (2004) and Looney et al. (2002, 2003) both use clustering algorithms to cluster units based on distance measures.

Suggestion

Based on the above comments we are confident that our work will be able to contribute to the fusion area, especially fusing geospatial information with information from airborne sensor network in order to achieve situation awareness. In the second phase of the NFFP3+ project we therefore suggest the following: By using GTSIM as a base for our work we test implementing concepts concerning clustering. The domain that will be used is a military domain (due to the military connection of the NFFP project). As of participation in NBD demonstration at the K3 regiment in Karlsborg, Sweden, we will be using that location in our tests. Further we have available sensor material from UAVs (videos). We will assume that lower level fusion has been performed in that way that objects have been identified. At this stage we will not be working with uncertainty. However, we will be considering this fact in our designs as it is an important factor. In that case, we will be testing the Dempster-Shafer theory based on the motivations in (among others) Yu et al. (2004). Considering the clustering algorithm we will be implementing a dynamic hierarchical agglomerative clustering algorithm. Our choice of an agglomerative algorithm is based on preliminary tests and the human factor, i.e. one of the reasons to choose this algorithm is to allow the end user to interact with it. Therefore it is considered more suitable to start with each observation as a single cluster. The "dynamic" part of the algorithm refers to that the user should be able to change the clustering type, i.e. instead of only relying on distance measures from the geographical database (calculated according to the road network), it will be possible to cluster observations based on, for example, the communication frequency. The user should also be able to control and interact with the online clustering algorithm by controlling the level of detail, both considering the map and the size of the clusters. A simple threat assessment process is even considered, i.e. finding out Commander's Intent and COA. This is considered to be tested by defining a number of point of interest and calculating routes to the nearest enemy cluster(s).

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