High-level Information Fusion: An Overview

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GEE WAH NG

Data and information fusion (DIF) involves a process of combining data and information from multiple inputs. The purpose is to derive enriched information compared to that obtained from each individual input. DIF techniques were first introduced to the research community in the 1970s. The scope of applications that use DIF techniques for problem-solving has extended tremendously from the military arena at the initial stage to many non-military sectors at present. The Joint Directors of Laboratories data fusion (JDL DF) model is possibly the most widely used model for data fusion. In this functional model, the hierarchical process of data and information fusion comprises two stages, the low-level fusion processes and the high-level fusion processes. After years of intensive research that is mainly focused on low-level information fusion (IF), the focus is currently shifting towards high-level information fusion. Compared to the increasingly mature field of low-level IF, theoretical and practical challenges posed by high-level IF are more difficult to handle. Contributing factors include the lack of: well-defined spatio-temporal constraints on relevant evidence, well-defined ontological constraints on relevant evidence and suitable models for causality. In this survey paper, we first review process models proposed for data and information fusion over the past few decades. Next, we present an overview of existing work on high-level information fusion, based on the fusion levels of the current JDL DF model. Finally, we discuss relevant application areas and topics with potential for further research.

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1. INTRODUCTION

Data and information fusion (DIF) involves a process of combining data from multiple inputs (from one or more sources such as sensors and textual reports).[1] The aim is to obtain information that is better (more useful and meaningful) than that would be derived from each of the sources individually (that is, without fusing). DIF is emerging as an important field of multidisciplinary study [113, 316]. This is due to increase in data and information flow, as well as improvement in communication, computing and sensor technology. The first applications of DIF techniques were in the military arena [177, 179, 455]. The use of DIF techniques for problem-solving has extended to many non-military applications in the commercial and industrial sectors [177, 179, 199, 228].

In general, data and information fusion can provide enhancement to the outcomes of processes for solving various application problems. Some advantages of carrying out DIF include [316]:

- improvement in the accuracy of data, as well as reduction in uncertainty and ambiguity within data, and
- improvement in situation awareness (SAW) and inference that lead to better decision making.

The main objective of this paper is to provide a useful aid to researchers in the field of data and information fusion, through an extensive (albeit non-exhaustive) literature survey. We review existing models for DIF, point to salient publications, and discuss relevant application domains and topics for further research. It is not our intention (and hence, beyond the scope of this paper) to critique or evaluate (a) the research topics presented, or (b) research in the field.

1.1. Structure of the Paper

The remainder of this paper is as follows. In Section 2, we review process models proposed for data and information fusion over the past few decades. Section 3 presents a discussion on the Joint Directors of Laboratories data fusion (JDL DF) model, one of the most widely used models to define the levels of the hierarchical process of data and information fusion. The JDL DF model has been revised and extended several times since it was first proposed. In the current version, the data fusion process comprises five levels, which are categorized into two stages, the low-level fusion processes and the high-level fusion processes. The low-level fusion processes support data pre-processing, target discrimination and target tracking. The high-level fusion processes support

[1] Generally, data entities (for example, raw sensor observations) have limited predefined attributes; information entities have assigned attributes with some logical relationships between them. Here, the terms "data fusion" and "information fusion" are used interchangeably. The term "sensor fusion" refers to the specific case of DIF in which each data/information source is a sensor.

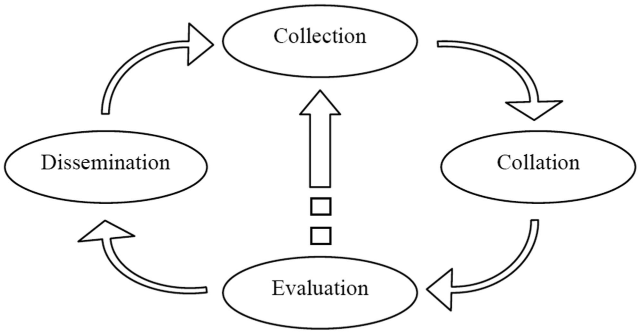

Fig. 1. The Intelligence Cycle [27].

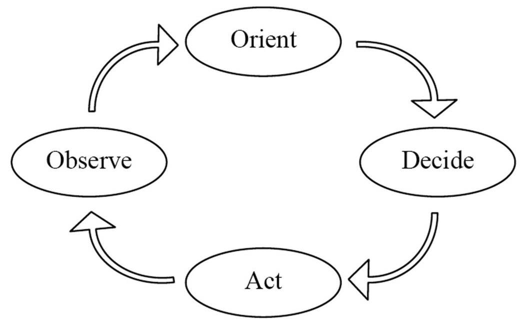

Fig. 2. The OODA Loop [325].

situation assessment, threat (or impact) assessment and process refinement [232]. Section 4 focuses on high-level information fusion, a field that is gaining much interest within the DIF research community in the recent years. An overview of some existing literature pertaining to the higher levels of fusion in the JDL DF model is also provided. Section 5 presents some application areas of high-level information fusion. Section 6 summarizes this work and considers potential topics for further research.

2. REVIEW OF DATA FUSION MODELS

Over the last few decades, many process models have been proposed for DIF [179, 325]. Some of the data fusion models introduced over the years are briefly reviewed in the following subsections. More details on these models are found in the respective sources and the cited references therein.

2.1. Data Fusion Models Introduced in the 1980s

In the 1980s, the Intelligence Cycle [27, 145], the Boyd Control Loop [106, 325, 346] and the Joint Directors of Laboratories data fusion model [59, 176, 280, 416, 422, 423] were developed.

2.1.1. The Intelligence Cycle

In the Intelligence Cycle [27, 145], the intelligence process is described as a cycle applicable for modeling the data fusion process. This model consists of four phases (shown in Fig. 1): *collection* (deployment of assets such as electronic sensors or human derived sources to obtain raw intelligence data, which is usually presented in the form of an intelligence report with a high abstraction level); *collation* (analysis, comparison and correlation of associated intelligence reports); *evaluation* (fusion and analysis of collated intelligence reports) and *dissemination* (distribution of the fused intelligence to users who use the information for decision making).

2.1.2. The Boyd Control Loop

The Boyd Control Loop [106, 325, 346], also known as the Observe, Orient, Decide, and Act (OODA) Loop, was first proposed to model the military command and control (C2) process. It comprises four phases (see Fig. 2): *Observe* (gather information from the environment); *Orient* (gain situation awareness and perform situation/threat assessment based on the information gathered); *Decide* (respond to situation and work out follow-up actions) and *Act* (execute the planned response/action). The emphasis is placed on shortening the cycle to perform the Observe to Act loop, to the extent that the opponent cannot respond in time to carry out countermeasure, thus gaining superiority in the battlespace. This model is well received by military commanders and decision makers.

2.1.3. The JDL Data Fusion Model

The commonly used JDL DF model was proposed for categorizing data fusion related functions. A detailed discussion on this model is given in Section 3.

2.2. Data Fusion Models Introduced in the 1990s

During the 1990s, the Waterfall model [132, 145], the Dasarathy model [110, 111], the Visual Data-Fusion (VDF) model [59, 227], the Omnibus model [27] and the Endsley model [59, 127, 128] were proposed.

2.2.1. The Waterfall Model

The Waterfall model [132, 145] consists of three levels of representation (shown in Fig. 3):

- Level 1 (sensing, signal processing)—proper transformation of raw data is carried out to provide necessary information about the surroundings, via the use of models (based on experimental analysis or on physical laws) of the sensors and where possible, of the measured phenomena;
- Level 2 (feature extraction, pattern processing)—with the aim of minimizing the data content and maximizing the information delivered, feature extraction and fusion are done to produce a list of estimates and their associated probabilities (and beliefs), which provide a symbolic level of inference about the data;
- Level 3 (situation assessment, decision making)—relationships are established between objects and events; based on the repository of information available and the human interaction, possible routes of action are assembled.

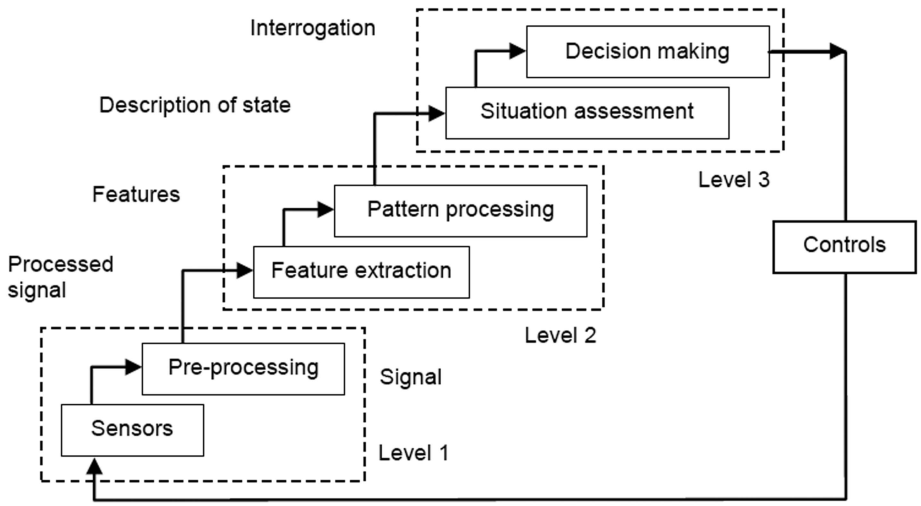

Fig. 3. The Waterfall model [132].

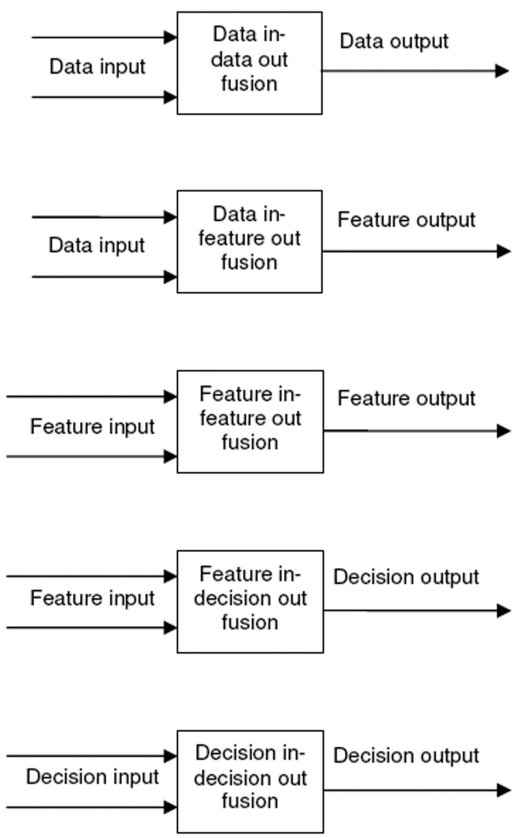

Fig. 4. The Dasarathy model [110].

The focus is on the processing functions at the lower levels. The lack of explicit depiction of the feedback appears to be the major limitation of this model.

2.2.2. The Dasarathy Model

The data fusion process has been commonly identified as a hierarchy with three general levels of abstraction: *data* (more specifically, sensor data), *features* (intermediate-level information) and *decisions* (symbols or belief values). Dasarathy [110, 111] pointed out that fusion may occur both within and across these levels. The Dasarathy model was proposed to expand the preceding hierarchy of fusion into five categories of input-output based fusion (corresponding analogues stated within parentheses): *Data In-Data Out* fusion (data-level fusion); *Data In-Feature Out* fusion (feature selection and feature extraction); *Feature In-Feature Out* fusion (feature-level fusion); *Feature In-Decision Out* fusion (pattern recognition and pattern processing) and *Decision In-Decision Out* fusion (decision-level fusion). This model is based on data fusion functions (illustrated in Fig. 4) instead of tasks and may be incorporated in each of the fusion activities.

2.2.3. The Visual Data-Fusion Model

The Visual Data-Fusion model (see Fig. 5) was proposed by Karakowski [59, 227] as an extension of the JDL DF model, with a human participant added integrally. It has the following advantages [59]:

- maximization of relevant information with minimal display of information;
- ability to provide increasingly sophisticated problem queries, in addition to tailor information fusion (IF) system capabilities for use by all skill levels of users;
- problem-driven system that relates to user's needs directly, through response to his personal perception of the problem situation.

The following premises are embodied in the VDF model [59]:

- the human is a central participant in information fusion, a creative problem-solving process;
- information derived from the fusion process that is visualized by the human is primarily used to help him gain fuller perception, as well as possible approaches towards solving the problem;
- imagery is used as the perceptual transport for user visualization, in order to minimize the amount of information required by the human to solve the problem.

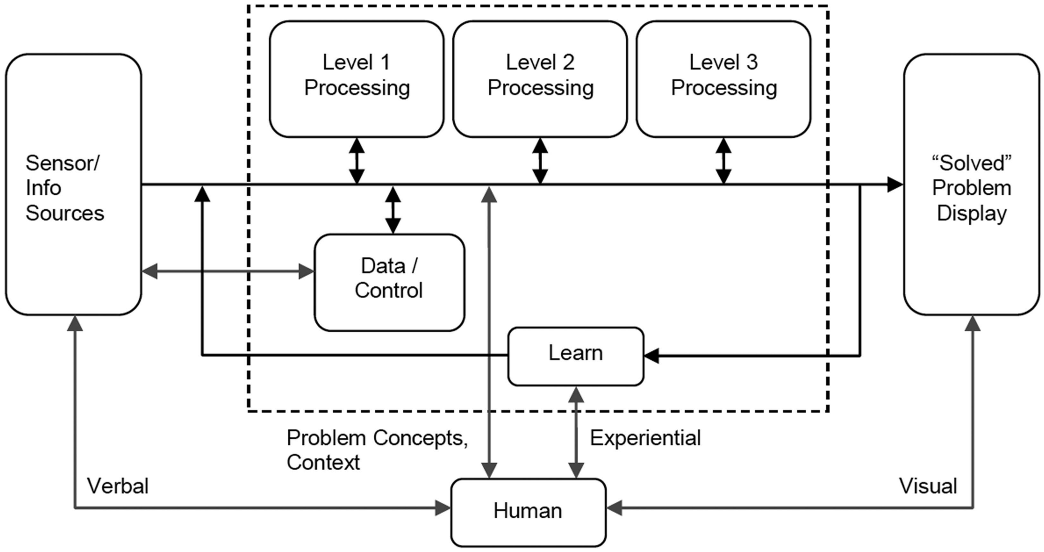

Fig. 5. The Visual Data-Fusion model [59].

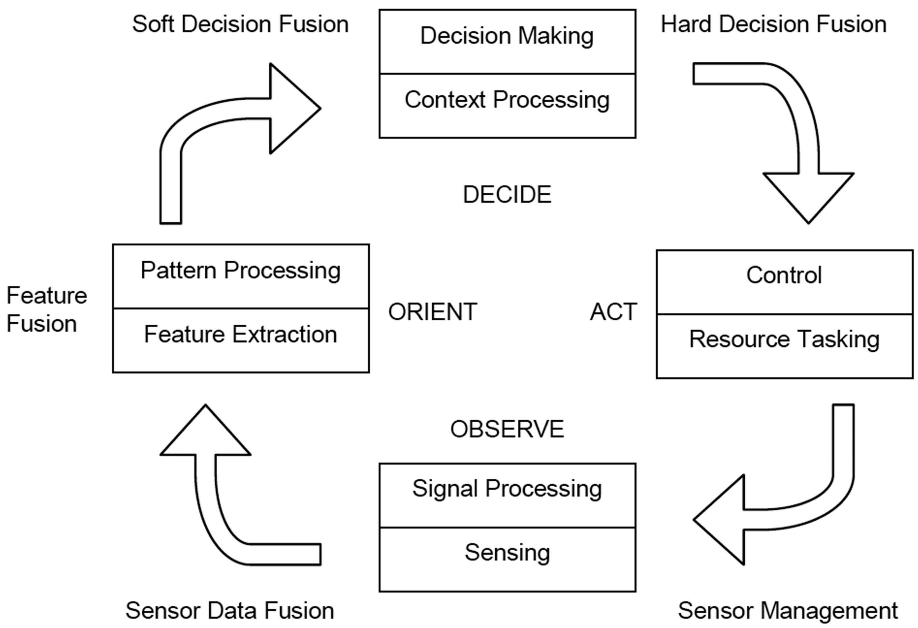

Fig. 6. The Omnibus model [179].

Basic VDF models are used as building-block elements for visual situation awareness and distributed VDF processes. More details on these research topics can be found in [59].

2.2.4. The Omnibus Model

The Omnibus model was proposed by Bedworth and O'Brien [27] as a unification of the Intelligence Cycle, the JDL DF model, the OODA Loop, the Dasarathy model and the Waterfall model. Properties of this model include: explicit feedback; acknowledgement of the *loop within loop* concept; retention of the general structure of the OODA Loop; incorporation of the fidelity of representation expressed by the Waterfall model into each of its four main modules and explicit indication of points in the processes where fusion may take place. Figure 6 presents the layout of this model.

2.2.5. The Endsley Model

The Endsley model [59, 127, 128] (shown in Fig. 7) is widely used to model situation awareness (see Section 4.2.1). It is a cognitive model and uses a general definition of situation awareness that is applicable across many domains: "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." The three hierarchical phases of the definition

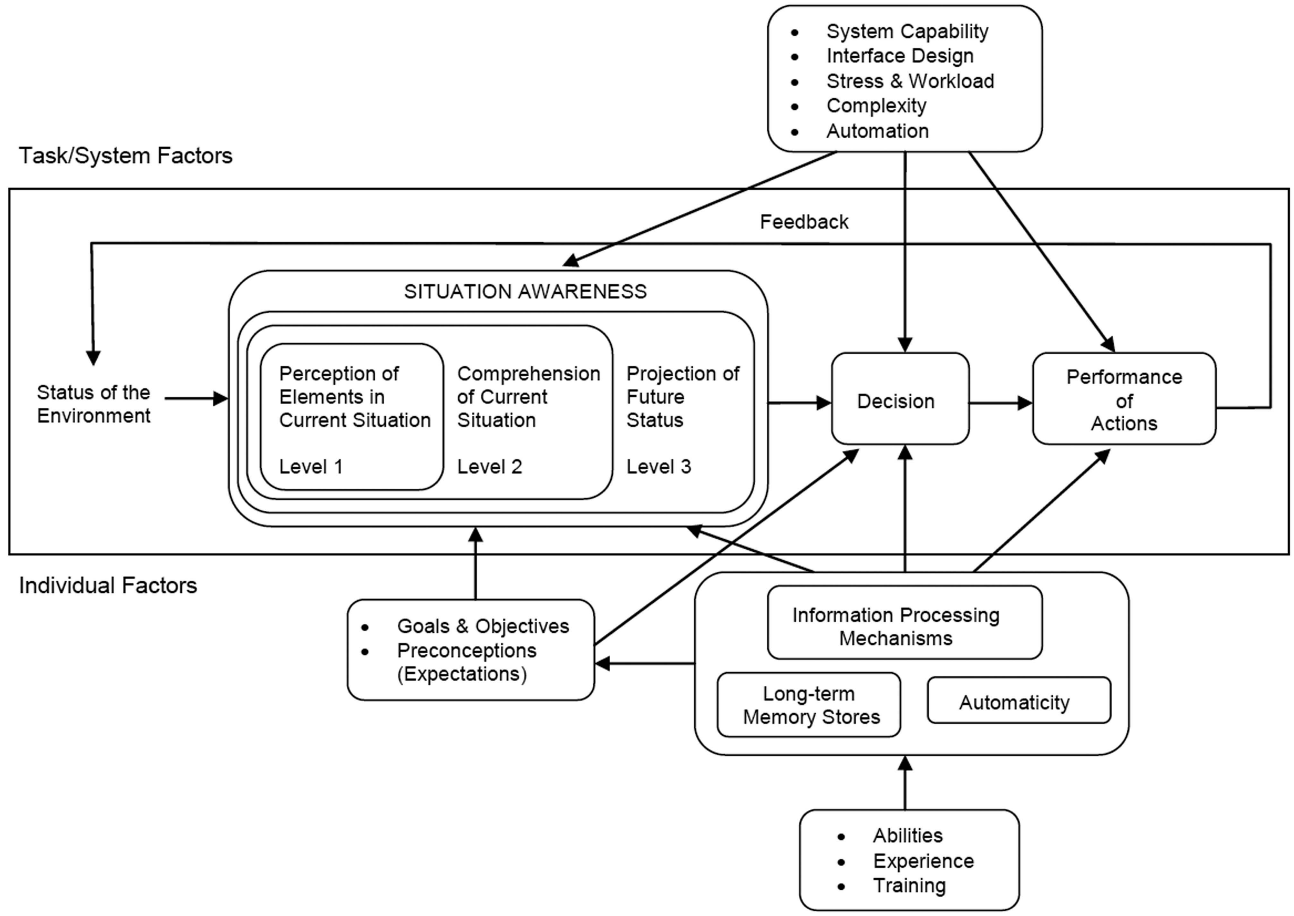

Fig. 7. Endsley's SAW model [127, 128].

are [127, 128]:

- Level 1 SAW (*Perception* of the elements in the environment)—perceive status, attributes and dynamics of relevant elements in the environment;
- Level 2 SAW (*Comprehension* of the current situation)—based on a synthesis of disjoint Level 1 elements, includes perceiving and attending to information, as well as integrating multiple pieces of information and a determination of their relevance to the operator goals;
- Level 3 SAW (*Projection* of future status)—ability to forecast/anticipate future situation events and dynamics, which is achieved through knowledge of status and dynamics of the elements and comprehension of the situation (both Levels 1 and 2 SAW), allows for timely decision making.

2.3. Data Fusion Models Introduced in the 2000s

The following data fusion models have been proposed in the 2000s:

- the Object-Centered information fusion model [236],
- the Extended OODA model [399],
- the Transformation of Requirements for the Information Process (TRIP) model [179, 272],
- the Unified data fusion (λJDL) model [59, 257],
- the Dynamic OODA Loop [65],
- the JDL-User model [48].

2.3.1. The Object-Centered Information Fusion Model

Kokar, et al. [236] introduced a fusion process reference model based on object-oriented design principles. The proposed model addressed essential issues on the design of data fusion systems with a top-down approach. Formal methods were adopted for model analysis at the design stage. They also discussed the need to develop psychological theories related to human-computer interaction (HCI). Research in this area was required for facilitating the proper integration of human and computer objects by fusion system designs based on the proposed object-oriented model.

2.3.2. The Extended OODA Model

Shahbazian, et al. [399] proposed the Extended OODA model which enables multiple concurrent and potentially interacting data fusion processes. This model can be applied to obtain a high-level functional decomposition of a system that uses data fusion for decision making. Each high-level function is examined in terms of the OODA decision loop and can be further decomposed and evaluated with respect to each OODA phase.

The Extended OODA model (see Fig. 8) has some properties that are consistent with those of several pre-

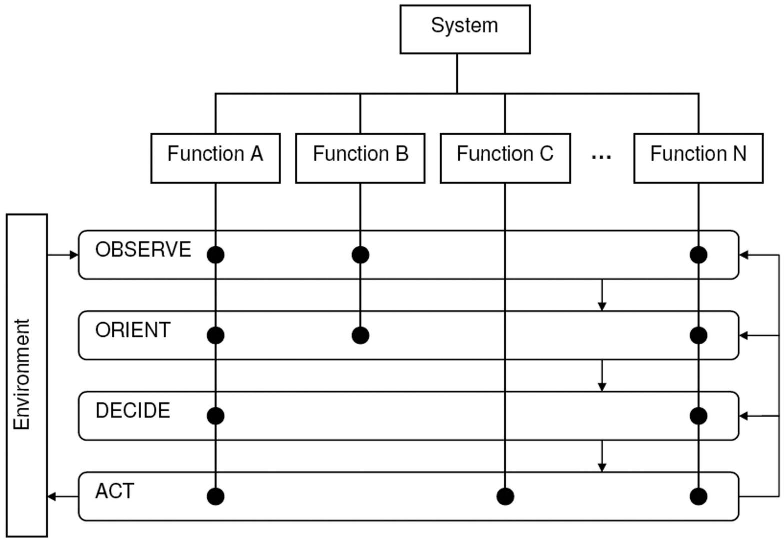

Fig. 8. The Extended OODA model [399].

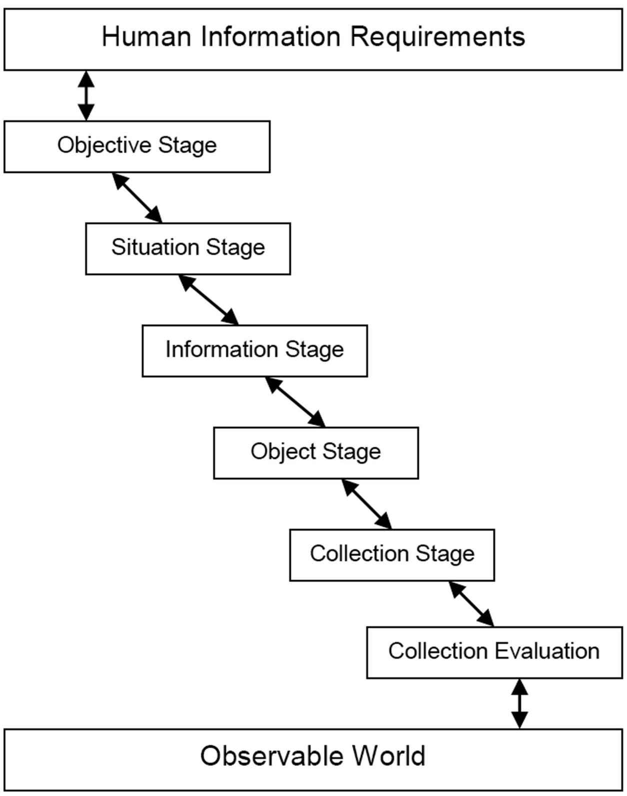

Fig. 9. The TRIP model [179].

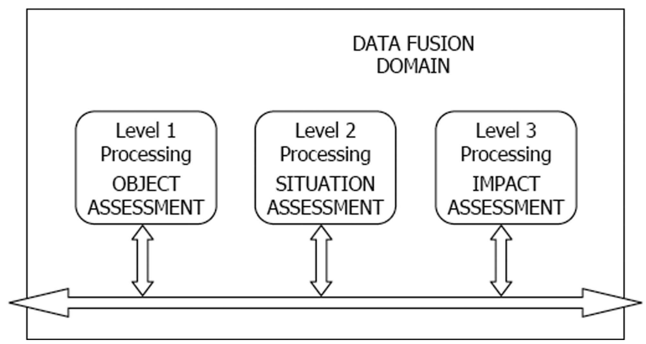

Fig. 10. The λJDL model [257].

ceding models (stated within parentheses): closes the loop between the decision making and its surroundings (OODA Loop); has increasing level of abstraction for information processing in each level (JDL DF model) and provides the *loop within loop* capability (Omnibus model).

2.3.3. The TRIP Model

The TRIP model [179, 272] (depicted in Fig. 9) was developed with the purpose of understanding a tactical commander's transformation of information needs to task assignment of sensor resources. The developers stated the following goals that they aimed to accomplish with this model [179]:

- describe the process for developing collection tasks from information requirements;
- understand relationships between collection management and the situation estimation process;
- understand where the *human in the loop* is required;
- understand the internal and external drivers for the intelligence, surveillance, and reconnaissance process.

Identification of processing functions and the detailed information interfaces between them was attempted. A link between human information requirements and data collection was provided by this model.

2.3.4. The Unified Data Fusion (λJDL) Model

The λJDL model [59, 257] (also known as the deconstructed JDL DF model), a revision of the JDL DF model (the version proposed in [423]), used the following definitions for its fusion levels (see Fig. 10):

- Level 1 (identification of objects from their properties)—*object fusion*: process of utilizing one or more data sources over time to assemble a representation of objects of interest in an environment;

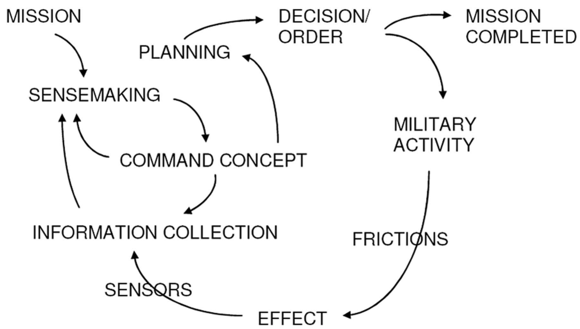

Fig. 11. The Dynamic OODA Loop [65].

object assessment: stored representation of objects obtained through object fusion;
- Level 2 (identification of relations between these objects)—*situation fusion*: process of utilizing one or more data sources over time to assemble a representation of relations of interest between objects of interest in an environment;
  situation assessment: stored representation of relations between objects obtained through situation fusion;
- Level 3 (identification of the effects of these relationships between these objects)—*impact fusion*: process of utilizing one or more data sources over time to assemble a representation of effects of situations in an environment, relative to user intentions;
  impact assessment: stored representation of effects of situations obtained through impact fusion.

The model was proposed for the development of a data fusion system for fusing three distinct types of processes that involved both humans and machines:

- psychological processes (human-related),
- technological processes (machine-related),
- integration processes (interaction between the psychological and technological processes).

The model could be applied to different aspects of the data fusion problem, depending on the different interpretations of the model components (object, situation, impact) obtained from the different combinations of the above processes.

2.3.5. The Dynamic OODA Loop

There exist criticisms that the OODA Loop fails to capture the dynamic nature of decision making in the military command and control process, as it has a limited focus on faster decisions [65]. The Dynamic OODA Loop (shown in Fig. 11) was proposed as a generic model of military command and control, based on concepts from the OODA Loop and cybernetic models of C2.

This model provides the identification of functions essential for effective C2. The problem of handling delays in C2, a form of dynamic decision making, is also dealt with. The required functions are: *sensemaking* (understanding of the current mission/situation in terms of what can be done); *command concept* (commander's overall concept of the operation); *planning* (translation of the command concept into decisions/orders); *information collection* (guided by the command concept) and *decision* (commitment to a course of action (COA)).

Other modifications of the OODA Loop include the M-OODA Loop [370] and the C-OODA Loop [66].

2.3.6. The JDL-User Model

Discussion on the JDL-User model, which was proposed to extend the JDL DF model to support a *human-in-the-loop* decision process, is deferred to Section 4.4.

3. THE JDL DATA FUSION MODEL

The original JDL DF model (shown in Fig. 12) was created by the JDL Data Fusion Group of the United States Department of Defense [176]. It is a functional model developed with the aim of facilitating communication, comprehension, coordination and cooperation among diverse data fusion communities to identify and solve problems to which data fusion can be applied.

The first revision of the initial JDL DF model was proposed by Steinberg, et al. [423]. They broadened the definitions of fusion concepts and functions beyond the original focus on military and intelligence problems, as well as described the need for an approach to the standardization of an engineering design methodology for fusion processes. They also proposed to refine definitions for the fusion "levels" characterized in the original JDL DF model as follows [423]:

- Level 0 (Sub-Object Data Assessment)—estimation and prediction of observable states of signals or features;
- Level 1 (Object Assessment)—estimation and prediction of entity states based on data association, as well as continuous and discrete state estimation;
- Level 2 (Situation Assessment)—estimation and prediction of relationships among entities;
- Level 3 (Impact Assessment)—estimation and prediction of effects of entities' actions on goals/missions;
- Level 4 (Process Refinement)—an element of Resource Management that encompasses adaptivity in the data collection and fusion processes to support mission objectives.

Figure 13 shows this revised version of the JDL DF model, which included the introduction of a "Level 0" to the original model. The five fusion levels were categorized into the low-level fusion process (Levels 0 and 1) and the high-level fusion process (Levels 2 to 4) [232, 316].

Other recent revisions/variants of the JDL DF model include the State Transition Data Fusion (STDF) model [258–260], the ProFusion2 (PF2) model [347] and the Ground C4-ISR Assessment Model (GCAM) [306].

3.1. Proposed Extension/Revision

The JDL DF model accounts for automatic machine processing, but not for human processing. To address

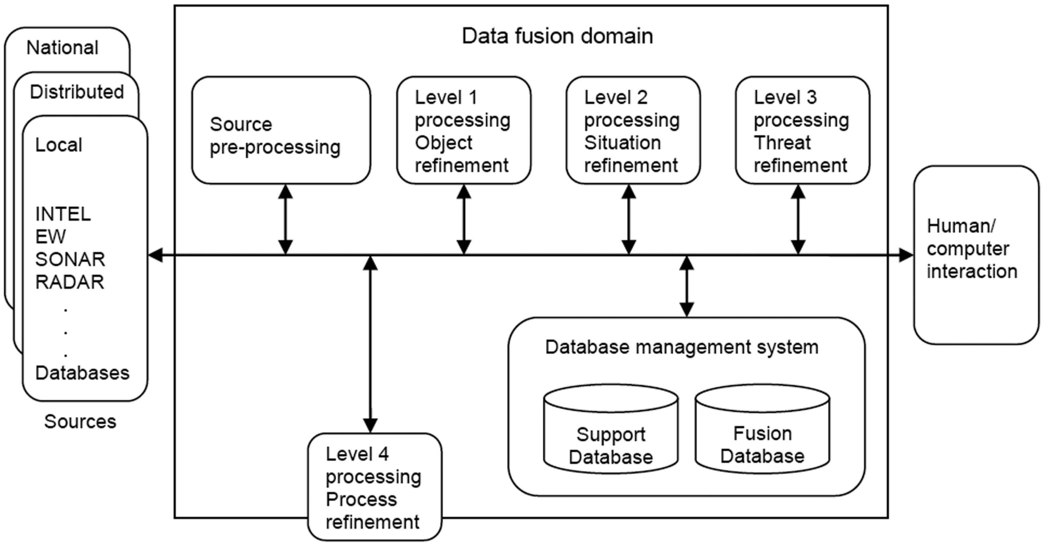

Fig. 12. JDL DF model [176].

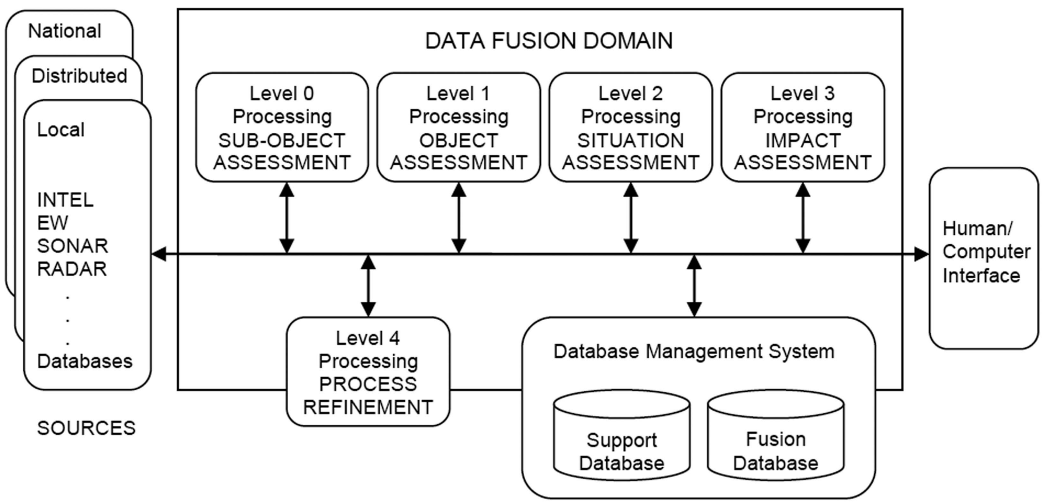

Fig. 13. Revised JDL DF model [423].

issues related to extending the human capabilities within the fusion process, the concept of Level 5 data fusion process was first introduced by Hall, et al. [181] and subsequently, in an independent work by Blasch and Plano [48]. In both works, the authors asserted the need to acknowledge functions necessary for supporting a human-in-the-loop decision process. More details on Level 5 processing are discussed in Section 4.4.

More recently, another revision to the JDL DF model (illustrated in Fig. 14) was suggested by Steinberg and Bowman [422]. The refinement involved a reexamination of the JDL DF level structure. The data fusion levels were extended to a newly introduced set of dual resource management levels (encompassed functions include signal/signature management, individual resource management, coordinated resource management, goal management and system engineering). Based on the entities of interest to information users, revision of the definitions for data fusion functional levels were suggested as follows [280, 416, 422]:

- Level 0 (Signal/Feature Assessment)—estimation and prediction of states of signals or features;
- Level 1 (Entity Assessment)—estimation and prediction of parametric and attributive states of entities;
- Level 2 (Situation Assessment)—estimation and prediction of relational/situational states of entities;
- Level 3 (Impact Assessment)—estimation and prediction of effects of fused entity/situation states on mission objectives;
- Level 4 (Performance/Process Assessment)—estimation and prediction of a system's measures of performance and measures of effectiveness based on given desired system states and/or responses.

In the proposed revision of the JDL DF model [280, 422], the Level 4 (Process Refinement) function [423] was categorized as being within the Resource Management model levels, while the proposed Level 5

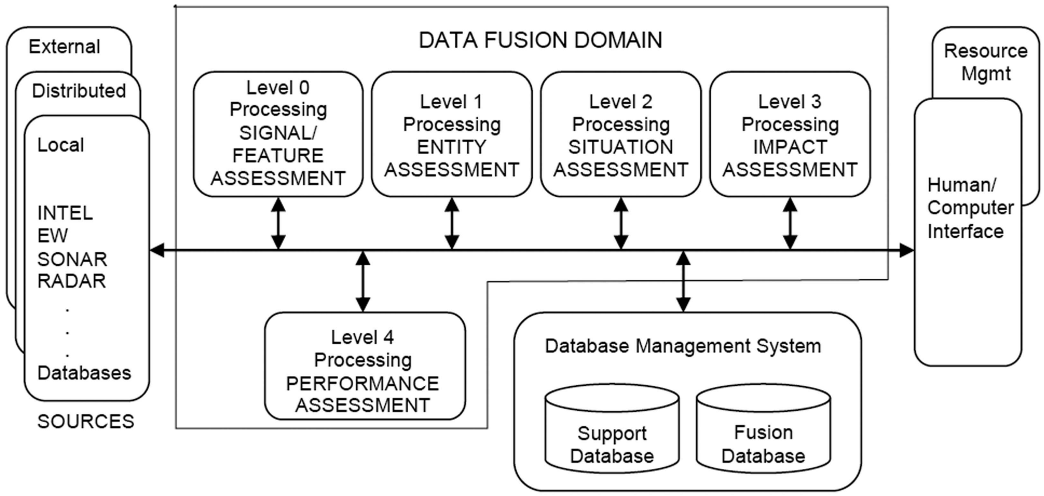

Fig. 14. Proposed revision of the JDL DF model [280].

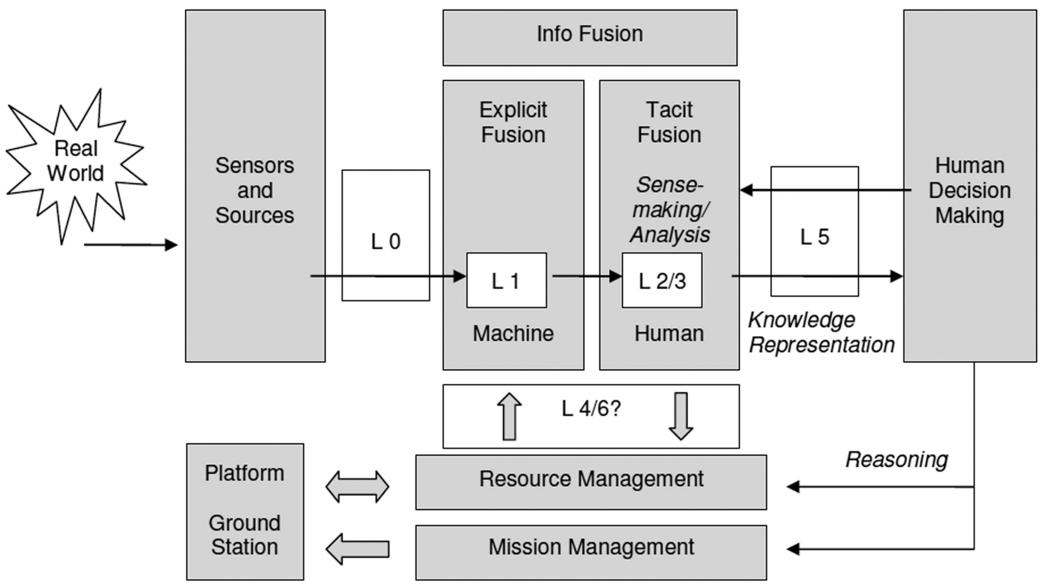

Fig. 15. Proposed DFIG 2004 model [40, 51].

[48, 181, 422] was subsumed as an element of Knowledge Management within Resource Management.

A further upgrade/revision to the JDL DF model (see Fig. 15) was proposed and assessed by the Data Fusion Information Group (DFIG) [40, 51]. The aim was to separate the information fusion and management functions. A detailed explanation on the model can be found in [41]. The definitions for this model, based on the version of the JDL DF model proposed in [423], were:

- Level 0 (Data Assessment)—estimation and prediction of observable states of signals or features;
- Level 1 (Object Assessment)—estimation and prediction of entity states based on data association, as well as continuous and discrete state estimation;
- Level 2 (Situation Assessment)—estimation and prediction of relationships among entities;
- Level 3 (Impact Assessment)—estimation and prediction of effects of entities' actions on goals/missions;
- Level 4 (Process Refinement)—an element of Resource Management that encompasses adaptivity in the data collection and fusion processes to support mission objectives;
- Level 5 (User Refinement)—an element of Knowledge Management that encompasses adaptivity in the determination of user query and access to information, as well as adaptivity in the retrieval and display of data, to support cognitive decision making and actions;
- Level 6 (Mission Management)—an element of Platform Management that encompasses adaptivity in the determination of spatial-temporal asset control, as well as route planning and goal determination to support team decision making and actions.

4. RESEARCH IN HIGH-LEVEL DATA AND INFORMATION FUSION

4.1. Shift of Research Focus from Low-level Fusion towards High-Level Fusion

After many years of intensive research, low-level fusion has become a relatively mature field [409]. The research focus is currently shifting towards fusion at higher levels. The significant amount of interest in high-level information fusion is evident from the related research activities that have been carried out in the recent years.

North Atlantic Treaty Organization Research and Technology Organisation Information Systems Technology Panel held a symposium on "Military Data and Information Fusion" in October 2003 [327] and a specialists' meeting on "Information Fusion for Command Support" in November 2005 [328] to discuss high-level fusion research and technology in the military domain. Panel discussion sessions have been dedicated to address high-level fusion research issues at the International Conference on Information Fusion (FUSION):

- 2004—Challenges in Higher Level Fusion: Unsolved, Difficult, and Misunderstood Problems/Approaches in Levels 2–4 Fusion Research [223];
- 2005—Issues and Challenges of Knowledge Representation and Reasoning Methods in Situation Assessment (Level 2 Fusion) [46];
- 2006—Issues and Challenges in Resource Management and Its Interaction with Level 2/3 Fusion with Applications to Real-World Problems [45];
- 2007—Results from Levels 2/3 Fusion Implementations: Issues, Challenges, Retrospectives and Perspectives for the Future [222];
  Agent Based Information Fusion [109];
- 2008—High-level Information Fusion: Challenges to the Academic Community [241];
- 2009—Issues and Challenges in Higher Level Fusion: Threat/Impact Assessment [221];
  Directions for Higher-Level Fusion Research: Needs and Capabilities [445];
  A Coalition Approach to Higher-Level Fusion [261];
- 2010—Issues and Challenges in Higher Level Fusion: Threat/Impact Assessment and Intent Modelling [379];
  High Level Information Fusion Developments, Issues and Grand Challenges [47];
- 2011—Social, Cultural, and Cognitive Aspects of Situation Management: Issues and Challenges [378];
- 2012—Multi-Level Fusion: Issues in Bridging the Gap between High and Low Level Fusion [233];
  Uncertainty Evaluation: Current Status and Major Challenges [98];
  Issues of Uncertainty Analysis in High-Level Information Fusion [43].

High-level information fusion topics have been gaining considerable presence among the technical sessions at the recent FUSION conferences (see Fig. 16). For example, at the 13th International Conference on Information Fusion held in July 2010, technical sessions on Advances in High-level Information Fusion Design were conducted to discuss research advances and developments in the area of high-level fusion. Areas of interest included modeling, representations, systems design and evaluation [53, 101, 155, 300, 301, 338, 368, 373, 447, 448].

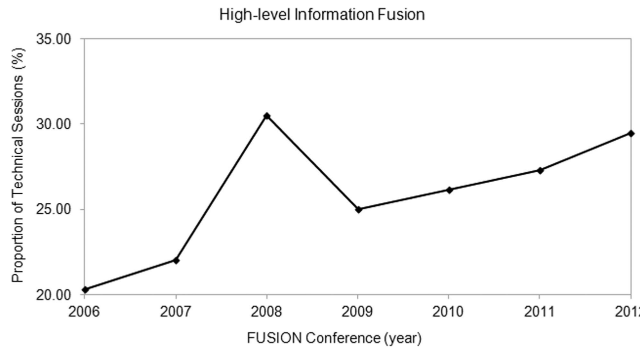

Fig. 16. Technical sessions on high-level IF topics at FUSION conferences.

The journal Information Fusion published a special issue on high-level information fusion and situation awareness [237, 240, 260, 276, 304, 344, 437, 472]. Das [106] authored a book with focus on fusion at Levels 2 and 3. Steinberg [421] provided a detailed study on principles and techniques related to situation and impact/threat assessment.

4.2. Situation and Impact Assessment

4.2.1. Situation Assessment

Level 2 fusion, also known as *Situation Assessment* (SA), is concerned with the determination and interpretation of relationships among objects and of estimation or prediction of situations; that is, of structures in the world. The objectives at this level include the derivation of high-level inference and the identification of meaningful events and activities [316, 421]. *Situation Awareness* (SAW) involves the identification and monitoring of various relationships among Level 1 physical and abstract entities, as well as various relations among them. Situation assessment is regarded as the process of achieving, acquiring or maintaining situation awareness [377]. Models for automated situation assessment tools include the JDL DF model (see Section 3) and the Endsley's Situation Awareness model [127, 128] (see Section 2.2.5).

General issues and challenges in situation assessment and situation awareness have been addressed by different researchers with various perspectives and approaches [46].

- Gorodetsky, et al. [162] did an analysis of formal frameworks proposed for specification of the situation models. Their focus was on approaches and algorithms for on-line update of situation assessment, on the generic architecture of the situation assessment systems.

- Jones, et al. [217] described the use of fuzzy cognitive maps in the development of a data fusion model to support situation awareness and human cognition, based on the Goal-Directed Task Analysis methodology.
- Kadar [220] addressed issues in situation assessment and associated Knowledge Representation and Reasoning models, with focus on a human perceptual reasoning-based model framework.
- Kokar [234, 235] identified and discussed problems pertaining to automatic situation assessment/awareness. Approaches for solving these identified problems were proposed and compared.
- A detailed discussion on developing a conceptual framework for situation assessment and awareness was given by Salerno [376]. He also addressed issues and perspectives on high-level information fusion processing.
- Salerno, et al. [377] explored various techniques believed to be necessary for providing situation awareness. They also investigated how those techniques could be bound together to form an overall system architecture, as well as how various sources of information contributed to the problem of maintaining constant awareness of the environment one was in.
- Qureshi and Urlings [356] proposed an operator assistant with a flexible concept of automation, with the objective of enhancing situation awareness.
- Settembre, et al. [398] designed a multi-agent architecture for situation assessment. The system utilized Web Ontology Language-based reasoning for high-level situation classification and analysis, and provided distributed assessment via the solution of disagreements that might exist among different agent conclusions. Experimental results from a real maritime surveillance scenario showed that the proposed approach had the capability to achieve performance similar to that of a centralized architecture. In addition, the method preserved the independency of decision makers and significantly reduced the amount of communication required.
- Smart, et al. [405] investigated knowledge-based approaches to improving situation awareness in humanitarian operational deployment. A tool for intelligent information fusion, Technical Demonstrator System, was developed for the situation awareness enhancement task. A functional overview of the system with respect to several capability areas was presented.
- Steinberg [420] described an adaptive evidence-accrual inference method for selecting context variables based on their usefulness in the refinement of explicit variables in problems of interest; the probability of obtaining these variables with predetermined amount of accuracy, given candidate system actions such as data collection, mining or processing; as well as the cost of the aforementioned actions.

4.2.2. Impact Assessment

Level 3 fusion, known as *Threat Assessment* in the original JDL DF model, was redefined as *Impact Assessment* to accommodate expansion in the concept of Level 3 fusion [421, 423]. Impact Assessment deals with the determination of the effect of current situational states on user objectives. It involves the prediction of the intent (alternative courses of action) for entities, as well as the estimation of the degree or severity with which impending (possibly adversarial) events may occur.

Broadly speaking, Level 3 fusion involves the estimation of contingent (for example, possible future) states and of their cost/benefit impacts [421]. As such Level 3 fusion can be perceived as a subset of Level 2 fusion, due to the broad definition for the latter [423]. Assignment at Level 3 is usually inferred from Level 2 associations, although processing at the fusion levels need not be performed in order [280]. In addition, given corresponding inputs, any one level can be processed on its own. Table I displays some methods that are applied to different problems on situation and impact assessment [79, 106, 421].

4.3. Process Refinement

Level 4 fusion is known as *Process Refinement* in the early versions of the JDL DF model [423]. The process involves resource management to improve the results obtained at the lower levels of data fusion [316]. In the recent proposed revision of the JDL DF model [280], the data fusion levels were extended to their dual resource management levels. In addition, a new Level 4 of data fusion and its corresponding dual Level 4 of resource management were introduced. A redefinition Level 4 (*Performance Assessment* (PA), also known as *Performance Evaluation* (PE)) was proposed with the existing Level 4 (Process Refinement) function [423] categorized as being within the resource management model levels. Based on a given desired set of system states and/or responses, the Level 4 data fusion functions combined information to estimate a system's measures of performances and measures of effectiveness. It was proposed that the purpose of the existing JDL DF levels would be preserved by these new data fusion and resource management levels.

This section gives some instances of research work that discuss PA/PE methodologies for data fusion processes, as well as issues on data/information fusion and resource management (subjects of management include signals/signatures, individual resources, coordinated resources, goals/mission objectives, system engineering and operational configuration) [45].

4.3.1. Performance Assessment/Evaluation Methodologies

A literature analysis of twenty-four journal articles and twenty-eight conference papers on the topic of performance evaluation was carried out by van Laere [450].

TABLE I
Situation and Impact Assessment: Issues and Approaches

Application Domain	Approach/Technique	Reference
Data association/correlation	Ontology	[239, 242, 243, 292–294]
	Mathematics-based metrics	[428–430]
Semantic Knowledge	Ontology	[173, 266, 330]
Tactical defense	Kohonen's self-organizing maps	[7]
—Air defense	Neural networks	[8, 195]
—Asymmetric warfare	Ontology	[17, 100, 238, 293–297, 374]
—C4ISR	Hidden Markov models and time series	[21]
—Enemy courses of action	Bayesian inference/network/theory	[26, 107, 108, 141, 195, 251, 262, 285, 285, 331, 335, 336]
—Ground battlespace	Evidential theory/networks	[32, 33, 203, 392]
—Information warfare	Fuzzy logic/Fuzzy set theory	[34, 80, 139, 140, 195, 217, 285, 321, 343, 355, 382]
—Interoperability	Support measures/functionalities	[37, 129, 142, 160, 349, 374]
—Maintenance of consistency in intelligence database	Knowledge-based approaches	[57, 93, 195]
—Maritime surveillance	Contextual information, target behavior extraction/classification	[62, 63, 149, 334, 420]
—NBD/NCW	Axiomatic approach	[102]
—Threat analysis	Genetic algorithms	[157, 158, 195]
—Threat stabilization	Self-organizing peer-to-peer SAW system	[194]
—Video/visual surveillance	Real-time automated rule-based system	[200]
	Modified probabilistic neural network	[208]
	Situation, ontology, estimation theory	[216, 417, 418]
	Uncertainty propagation for dynamical systems	[245, 440]
	Asset profiling	[262]
	Team SAW measurement techniques	[263, 380, 402]
	Statistical density estimation	[267]
	Cognitive system engineering	[341]
	Information theory	[343]
	Multiple attribute decision making	[355]
	Graph-based tools	[384, 385, 425]
	Multi-agent system	[398]
	Centralised intelligence fusion	[414]

The objective was to identify the extent to which information fusion researchers were aware of the problematic nature of performance evaluation in practice, as well as problems and related known solutions. He proposed there was a need to define and study a set of comprehensive performance measures which were adaptable to domain or situation context and changing circumstances over time. He also asserted the need for incorporation of optimality checks.

Table II shows some approaches to performance assessment/evaluation for data fusion systems in various application domains.

4.3.2. Data Fusion/Information Fusion and Resource Management

Blackman and Popoli [37, Chap. 15] discussed principles and techniques for sensor management (SM). The main issues of interest were: the necessity to include sensor management in the design of a modern sensor tracking system, the understanding of the aspects of sensor operation that required management and the figures of merit (metrics for the overall performance of an entire sensor tracking system) to be optimized by that management, as well as the approaches to accomplish sensor management.

Ng and Ng [318] studied the roles of sensor management, the motivation to use SM and presented a framework for a generic SM. Ng [316, Chap. 9] discussed classification and roles of SM and carried out simulation studies to demonstrate roles of SM as a controller.

Multi-sensor management deals with the control of environment perception activities by the management or coordination of multiple sensor resource usage. It is an emerging research area and has become increasingly important in the research and development of modern multi-sensor systems for both military and civilian applications. Xiong and Svensson [464] provided a review of multi-sensor management in relation to multi-sensor information fusion. The work done included description of the role of multi-sensor management in the larger context, generalization of main problems from existing application needs and discussion on problem solving methodologies. In addition, many useful related works were cited.

A stochastic dynamic programming based approach to solving sensor resource management problems was described by Washburn, et al. [457]. The sensor resource management problem was formulated as a stochastic scheduling problem and approximate solutions based on the Gittins index rule were developed.

TABLE II
Performance Assessment/Evaluation for Data Fusion Systems

Application Domain	Approach/Technique	Reference
General	Formal definition of validation (references a standard fusion device)	[248]
	Local evaluation measures for image interpretation	[256]
	Measures of input scenario complexity and output quality	[322, 439]
	Rule-based expert system	[337]
	Data association, metrics estimation, Statistical DOE, ANOVA	[382]
Multi-source fusion	Bayesian inference	[76]
	Distributed fusion track-to-truth association, distributed fusion track-to-track association	[117, 381]
	Correlation effect, best linear unbiased estimation criteria	[19, 473]
Target tracking	Measures for assessing track detection performance, accuracy, quality and data association	[52, 95, 161, 273, 307, 393, 427, 471]
—Automatic target recognition	Track-centric metrics	[71]
—Classification, estimation and filtering	Information theoretic measures	[87]
	Context metrics that characterize problem difficulty	[148]
—Decentralized estimation	Optimal subpattern assignment-based metrics	[171, 314, 367, 395]
—Moving target identification	Multi-channel signal subspace methodology	[224]
—Multiple target tracking	Optimization-based hierarchical PE system, Statistical DOE, ANOVA	[283, 360]
	Error bounds	[400, 413]

High-level information is playing an increasingly important role in research on sensor management. There is concern about the appropriateness in using the term *Sensor Management* to encompass the functions on the information level. In view of the necessity of using intelligent agents to perceive the environment to take suitable actions, Johansson and Xiong [214] proposed a generic concept of *Perception Management*, without having to be particular about concrete sensor device details. The concept referred to controlling the data acquisition process from the external world to enhance the perception outcomes. Two different possible interrelations between sensor management and perception management were considered and discussed: either sensor management is encompassed in perception management or sensor management is separate from and independent of perception management.

Bradley [61] gave a discussion on sensor tasking capability pertaining to a resource allocation manager which integrated command, control and communications functions within various types of sensor platforms and had significant contributions to multi-platform interoperability and situation awareness operations. He gave an overview of the fusion architecture and tracking system in which a resource allocation manager was integrated. Performance analysis on the resource allocation manager was done based on measured and modeled data.

Table III provides a summary of some problems and techniques for data fusion/information fusion and resource management.

4.4. Cognitive Refinement

Information representation and human-computer interaction are important for most data fusion systems. For example, it has been noted that the efficacy of the HCI had a significant influence on the overall performance and effectiveness of a data fusion system [455]. On the other hand, the Object-Centered information fusion model [236] (see Section 2.3.1) took into consideration the role of a human for decision making.

The concept of Level 5 (*Cognitive Refinement*) processing in the original JDL DF model was introduced by Hall, et al. [181] to account for functions associated with human-computer interaction explicitly. It involved the development of functions to support a human user in a collaborative human-computer environment. The categories of functions associated with Level 5 processing included [179]: HCI utilities, dialogue and transaction management and cognitive aids. Figure 17 shows the resultant augmented JDL DF model proposed. More discussion on various issues of cognitive refinement and human-computer interaction can be found in [179, Chap. 9].

In an independent work, Blasch and Plano [48] introduced Level 5 (*User* (or *Human*) *Refinement*, an element of Knowledge Management) with the purpose of supporting cognitive workload, trust, attention and situation awareness. In addition, the JDL-User model (shown in Fig. 18) was proposed to extend the JDL DF model [423] via the incorporation of the suggested Level 5. Further issues related to User Refinement were explored in [40–42, 49–51, 54].

More related research has been done recently. Hall, et al. [180] discussed the development of a set of tools to support *whole-brain* information analysis (combines visually-oriented analysis of images with language-based analysis of text and related information). Nilsson and Ziemke [326] suggested adopting a distributed cog-

TABLE III
Data/Information Fusion and Resource Management: Problems and Techniques

Application Domain	Approach/Technique	Reference
Multi-source fusion	Market-based architecture	[16]
	Probabilistic sensor placement algorithm coverage optimization	[122]
	Shannon's entropy-based probabilistic fusion of multiple information sources	[135]
	Sensor subset selection	[151]
	Distributed Bayesian inference and reinforcement learning	[165]
	Sensor scheduling (distributed greedy/myopic algorithms, feedback control theory)	[201, 465]
	Mathematical and statistical analysis	[387]
	Unified sensor performance modeling	[451]
	Hierarchically networked agent architecture	[479]
Tactical defense	Genetic algorithm	[68]
—C4ISR	Intelligent multi-agent based sensor resource management structure	[88]
—Maritime operations	Bayesian belief networks	[159]
—Military mission planning	Fuzzy logic	[159, 305]
—NBD/NCW	Stochastic dynamic programming	[213]
	Distributed fusion on multiple platforms	[271]
	Random sets and equivalence classes of multi-target paths	[291]
	Object classification/detection	[391, 452]
	Simulation-based tool and mixed-initiative interaction	[434]
Target tracking	Sensor selection	[55, 357, 359]
—Attack-avoidance	Bayesian technique-based approach	[81, 193, 362]
—Ground target tracking and classification	Hierarchical dynamic optimal control methods	[92]
	Algebraic framework	[104]
—Multi function radar tracking	Fuzzy logic, neural network system	[244]
—Multiple target tracking	Combine invariance, robustness and self-refusal	[250]
—Target detection	Reinforcement learning	[252]
	Machine learning (active sensing)	[253]
	Game theory (linear quadratic, geometric feature-aided)	[268, 269]
	Optimization-based dynamic algorithm (utilizes Markov models, decision trees)	[348]
	Clustering techniques	[390]
	Mathematical programming-based sensor allocation and management	[443]
	Geometric factors, information and measures of merit	[469, 470]
	Quadratic programming (numerical solver for constrained minimization problem)	[480]

nition perspective to complement existing approaches to understanding and modeling information fusion.

4.5. An Area with Increasing Interest: Hard and Soft Data/Information Fusion

In a decision making task, accurate information is essential for the decision makers concerned to make precise assessment of the situation and possible impact, and subsequently, appropriate and timely decisions. The derivation of relevant information generally involves a fusion process that combines and integrates data/information from multiple sources. Data/information can be classified into two categories, namely, "hard" and "soft."

"Hard information" refers to information from traditional physical sources such as radar and acoustic sensors. Such information usually includes kinematic data on the entities of interest. "Soft information" refers to information from human-based sources such as conversations, documents, newspapers and internet web sites. Such information can include possible location and identity information, as well as activities, intent and relationships among the entities of interest.

Hard and soft data generally contain complementary information, so it is necessary for data and information fusion practitioners to develop automated tools for effective fusion of these data. The disparate characteristics of hard and soft data result in many technical challenges for hard/soft data fusion. For example, hard data is usually structured and can be modeled mathematically. On the other hand, soft data is generally unstructured and inconsistent, and hence difficult to study with a mathematical model.

The DIF community recognizes the importance of hard and soft data/information fusion, and has increasing interest in this research area [99, 229, 282, 466, 467]. In the past few years, technical sessions have been held at the International Conference on Information Fusion to discuss research and development issues related to hard and soft data/information fusion:

- 2008—Hard/Soft Information Fusion [172, 178, 218, 351, 462];
  Challenges of and Methods for Information Fusion of Soft Data [10, 14, 36, 137, 174, 277, 309, 383, 411, 424];

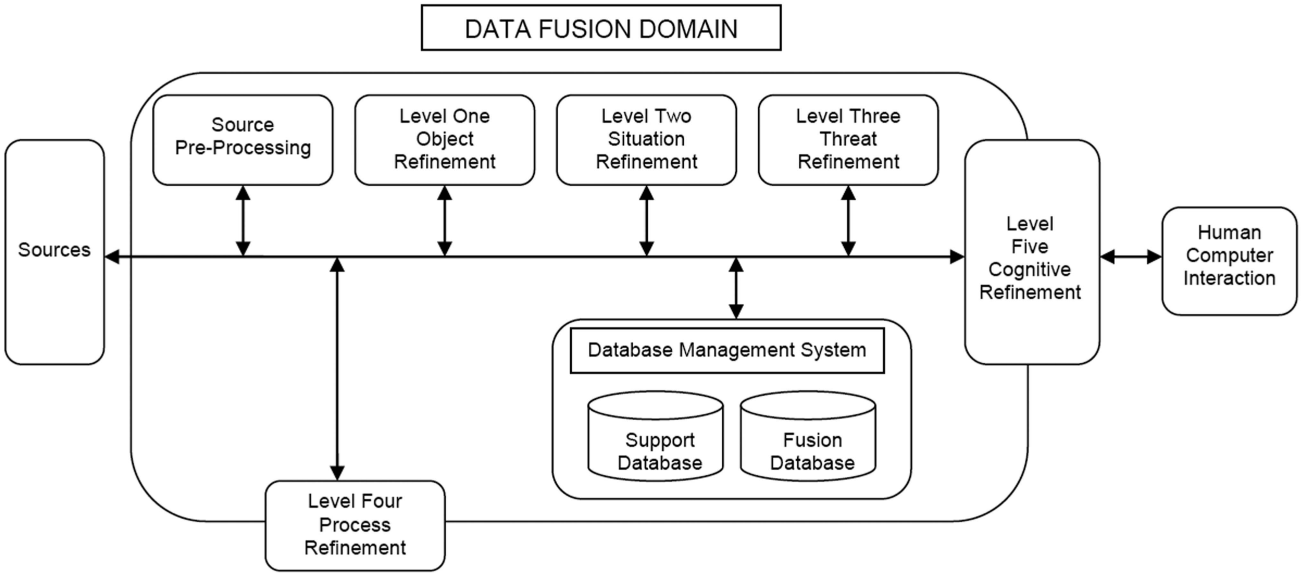

Fig. 17. Augmented JDL DF model [179].

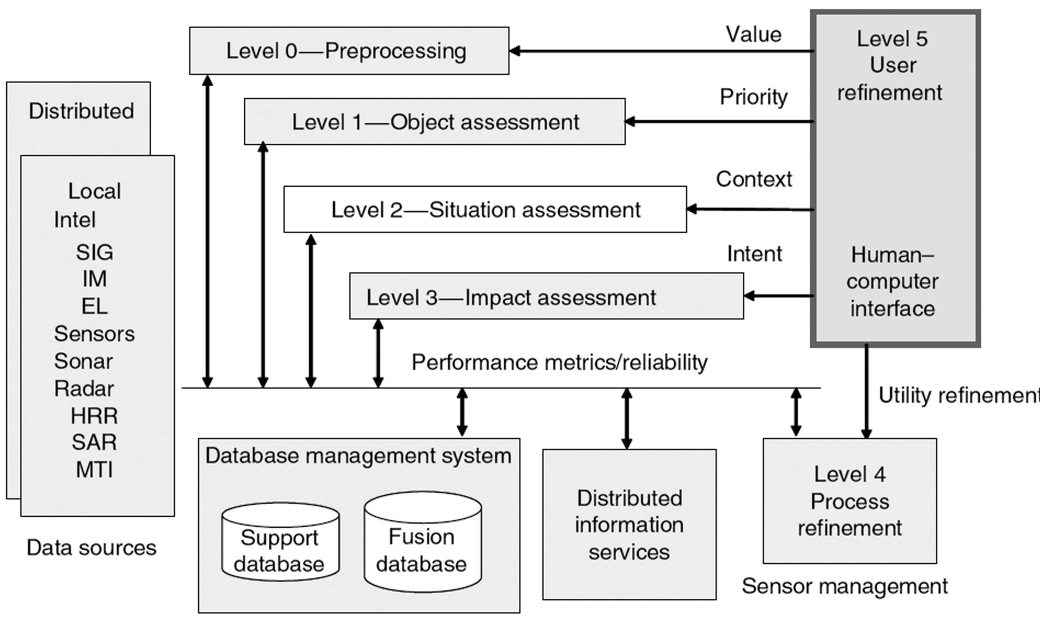

Fig. 18. JDL-User model [48].

- 2009—Fusion of Hard and Soft Information for Asymmetric, Urban Operations [156, 219, 339, 350, 352];
- 2010—Multidisciplinary Research in Hard and Soft Information Fusion [44, 168, 175, 187, 282];
- 2011—Human-based Sensing: From Passive Searching to Active Participation [186, 225, 302, 303, 353]; Hard/Soft Information Fusion: New Data Sets and Innovative Architectures [2, 20, 164, 169, 209];
- 2012—Hard/Soft Fusion [1, 89, 120, 121, 170, 183, 184, 313, 366, 404, 406, 407, 461, 463].

Many applications involve the extraction of information through processing and/or fusing huge quantities of data from multiple sources. Topics for exploration in the relatively immature research area of hard and soft data/information fusion can therefore be expected to continue to increase and evolve.

5. APPLICATIONS

Since the introduction of data and information fusion techniques to the research community in the 1970s, the scope of application areas for DIF has widened significantly. Some of the applications that involve high-level DIF (situation/impact assessment, resource management, and so on) are discussed in the following subsections. Table IV shows a summary of the techniques applied to the problems discussed.

5.1. Strategic/Tactical Defense

Data and information fusion was first used in military defense research related problems. After several

TABLE IV
Problems and Techniques in Various Application Areas that Involve High-Level DIF

Application Domain	Approach/Technique	Reference
Strategic/tactical defense		
—Biosurveillance	Information retrieval and dynamic Bayesian networks	[205]
—Drug interdiction	Multiple platform distributed fusion	[94, 270]
—Homeland security	Analytic network process	[478]
—Maritime surveillance	Hybrid fusion (interaction with data fusion processes at different information levels)	[145]
—NBD C4ISR	Dempster-Shafer clustering and template matching, particle filtering and finite set statistics	[4]
—Undersea warfare	Network-centric theatre undersea warfare architecture	[5]
Computer/information security		
—Dishonest behavior detection	Probabilistic, scalable distributed approach	[96]
	Integration of rule-based filtering, Dempster-Shafer theory and Bayesian learning	[340]
—Intrusion detection	Logic-based data model	[308]
	Fuzzy set theory	[286]
	Adaptive non-stationary autoregressive model	[454]
	Probabilistic inference	[436]
—Threat evaluation	Multiple behavior information fusion based on Markov models and Dempster-Shafer evidential reasoning	[90]
	Modeling and simulation, and risk analysis/assessment	[324]
Post-disaster management		
—Casualty mitigation operations	Cognitive work analysis, ontological analysis	[369]
—Data fusion visualization	Integrated graphical user interface framework	[290]
—Decision making	Bayesian networks, Dempster-Shafer theory, fuzzy logic, neural networks	[279]
—Dynamic situation assessment	Ontology meta-model	[274]
Engine/machinery fault diagnosis	Hybrid system parameter estimation and change detection	[22, 23]
	Dempster-Shafer evidence theory-based multi-source IF	[24, 133, 134]
Biomedical Applications		
—Data exploration/analysis	Multidimensional analysis, self-organizing map clustering algorithm	[146]
	Fuzzy logic, multiple classifier network, decision level data fusion	[477]
—Medical/clinical diagnosis	Dempster-Shafer framework	[311]
	Fuzzy logic	[130, 226]
—Patient monitoring	Dynamic Bayesian network	[29]
Environment		
—Ecological evaluation of urban biotopes	Spatial and statistical analyses of airborne hyperspectral data	[188]
—Fire detection	Formal theory of perception	[397]
	Dempster-Shafer theory	[476]
—Irrigation system management	Genetic algorithm, agrohydrological model	[85]
—Land monitoring and projection	Dempster-Shafer theory of evidence	[202]
—Soil moisture estimation	Support vector machines, relevance vector machines	[230]
Industrial applications		
—Agricultural product quality control	Bayesian inference	[371]
	Neural network training	[289]
—Decision support in manufacturing	Modeling, resource simulation and databases	[118, 119]
—Dislocation detection in construction materials	Belief function theory	[361]
—Information system deployment	Document object model for data fusion and aggregation	[354]
—System monitoring	Hierarchical, multi-layered fusion architecture	[154]
—Unmanned vehicle guidance	Information-oriented perception management	[333]

decades of development, DIF techniques are now being developed and applied in diverse non-military research areas as well. Nevertheless, military defense research remains a very prominent application area for DIF [58, 70, 131, 166, 212, 433]. Here, some research works from various defense applications are summarized.

Liggins, II, et al. [94, 270] developed distributed architectures to support relevant fusion technologies such as multi-source fusion and sensor resource management. The technologies were applied to problems in defense and drug interdiction.

Gad and Farooq [145] discussed various data fusion architectures for maritime surveillance and developed a system that interacted with the data fusion processes at different information levels. This proposed data fusion architecture was shown to perform well when employed to support the maritime surveillance for a typical maritime tactical scenario.

Aldinger and Kao [5] discussed the challenges faced in undersea warfare and some research work done on developing data fusion technology and other techniques to enhance the capabilities of the undersea warfare community.

Ahlberg, et al. [4] developed a concept demonstrator, the Information Fusion Demonstrator 2003 (IFD03), to demonstrate information fusion methodology expected to be suitable for a future network-based defense command, control, communications, computers, intelligence, surveillance and reconnaissance (C4ISR) system. The focus of IFD03 was on real-time intelligence processing in a tactical level ground warfare scenario. The architecture, methodology and user interface of the software system were described. The system was applied to a concrete scenario and related fusion results were discussed.

Introne, et al. [205] developed a novel application that employed a two-level fusion architecture to address the problem of biosurveillance.[2] Feasibility of the approach was demonstrated via simulated outbreak events on a simulation platform.

Zhang, et al. [478] applied a strictly quantitative analysis-based analytic network process to model elicitation in large-scale nation-building simulation models. The proposed approach could be used to study the significance of different kinds of factors and the interdependencies among them. This approach could circumvent the problem of possibly conflicting human expertise, which was encountered by many traditional expert knowledge-based analytic network process methods. Numerical results demonstrated that the proposed methodology could provide good approximate solutions to the nation-building simulation problems. The amount of computational time required for nation-building model analysis was also significantly less than that required for multiple replications of traditional discrete-event simulations.

5.2. Computer/Information Security

In the present age, where the use of information technology is ubiquitous, computer and information security issues are of great importance to both system administrators and general users. Information system issues such as intrusion detection in distributed communication and computer networks are receiving increasing amount of attention. Dasarathy [115] presented a general overview on research work done on intrusion detection.

[2]Biosurveillance: detection of attacks with unknown bioagents, also known as *syndromic surveillance*.

Stein, et al. [415] presented an outline of emerging concepts that were expected to guide future operations of joint military operations, and also explained the achievement of information superiority via the use of network-centric computing. Experimental tests showed the effect of employing information superiority on the approach to fighting battles.

Browne [67] proposed that new approaches to command, control, communications, computers and intelligence (C4I) defensive architecture be developed to defend against multi-mode attacks, which were enemy strategies using clever combinations of conventional and non-conventional warfare. Criticism was made on some popular existing C4I defense technologies that were considered to be vulnerable against multi-mode attacks. A speculative discussion was presented on new C4I defense technologies and policy issues regarding information superiority that were believed to be inadequately addressed in existing literature.

A model based on multiple behavior information fusion was developed for quantitative evaluation of network security threat by Chen, et al. [90]. The proposed method was used for tests in a real network environment and was shown to be a reasonable and feasible tool for its system administrators.

Nicol [324] gave a discussion on using simulation to evaluate computer security in areas such as impact assessment (determine how security measures affect system and application performance) and emulation (combine real and virtual worlds to study the interaction between malware and systems, and probe for new system weaknesses).

Du, et al. [124] formulated the problem of unsupervised classification for non-uniform attack tracks in cyber domains. The authors discussed three methods from distinct fields for solving this problem. The methods are, namely, "the subsequence matching technique," "Fourier analysis" and "the social network approach." The three approaches were compared with a traditional classification algorithm, K-means clustering algorithm. Based on the preliminary results, the three approaches showed promise in the characterization and the categorization of attack tracks.

The journal Information Fusion has published a special issue on information fusion in computer security [96, 97, 152, 286, 308, 340, 436, 454]. Corona, et al. [97] gave a detailed review of issues concerning the application of information fusion techniques in computer security, with particular focus on intrusion detection in computer networks. They also discussed topics such as data organization and data reconciliation that required further research.

Morin, et al. [308] proposed a first-order logic based data model as a support tool reasoning about alerts triggered by network intrusion detection systems. They demonstrated the practicality of the proposed framework by implementing it in a hypothetical attack scenario. Maggi, et al. [286] utilized a fuzzy set theory-based technique to fuse alerts on anomalies in an intrusion detection system. The proposed method was validated in experiments using two prototypes developed earlier by the authors, namely, a host anomaly detector and a network anomaly detector. Viinikka, et al. [454] suggested an adaptive method to model and filter out intrusion detection alerts related to normal system behavior from sequences of aggregated alerts. The authors used a non-stationary autoregressive model whose parameters were estimated by a Kalman fixed-lag smoother to produce a series of differences between observations and model predictions. Anomaly alerts were signaled upon detection of residuals which exceeded pre-defined thresholds. The effectiveness of the method was demonstrated through experiments on processing huge amounts of aggregated alert sequences from an operational information network.

Sy [436] proposed a probabilistic inference-based analytical intrusion detection framework to integrate alert information obtained from sensors deployed throughout a distributive network-based intrusion detection system. The integrated information was used to assist in the generation of the most probable forensic explanation. An experimental study was conducted to evaluate the feasibility of the proposed method. The suggested method yielded favorable results, when compared to the naïve Bayes reasoning approach. Efficient detection of node replication in a wireless sensor network is required to provide authenticity of data fusion in the network.

Conti, et al. [96] developed the Information Fusion Based Clone Detection Protocol (ICD), a probabilistic, scalable distributed protocol for detection of cloned nodes. The ICD combined two different cryptographic mechanisms, namely, pseudo-random key predeployment and asymmetric cryptography. Simulation results verified the robustness of the ICD for different parameter sets considered. Panigrahi, et al. [340] presented a credit card fraud detection system which made use of a transaction history database and the integration of three approaches, namely, rule-based filtering, Dempster-Shafer (D-S) theory and Bayesian learning. For system performance analysis, stochastic models were used to generate simulated credit card transactions. The proposed fraud detection system was found to yield high accuracy in detecting fraudulent transactions.

5.3. Crisis/Disaster Management

In the event of a natural catastrophe or otherwise, there exists a large quantity of crucial data to be dealt with within a very short period of time immediately after the disaster [299]. It is essential to develop efficient data and information fusion tools for effective situation assessment and impact prediction in dynamic post-disaster scenarios, which in turn would be useful for decision making.

In view of the growing threats posed by potential use of chemical and biological agents in the military battlefield, Llinas, et al. [281] addressed issues and challenges related to the development of technologies for effective combat against these weapons of mass destruction, in both military and civilian applications. Effective execution of battle management functions depends very much on high-quality information input. The authors asserted that it was very likely that the high-quality information demands of Nuclear, Chemical, Biological and Radiological (NCBR) battle management functions could be met by many existing information fusion techniques. In addition, it was possible for transition of advanced information fusion technologies from conventional warfare settings to NCBR-specific mission applications.

Llinas [279] described the overall strategic approach (engineering methodology) to a multi-year research program which addressed issues in information fusion to support crisis centre decision makers dealing with post-event situations. Both natural and man-made disasters were considered, with emphasis placed on post-earthquake and post-chemical attack scenarios respectively. The focus was on fusion capabilities at Levels 2 and 3 (higher-level information fusion). Examples of specific research components and subsequent research plans for the program were also discussed.

Little and Rogova [274] worked on the design of a general methodology for situation assessment to support crisis management. The proposed approach utilized understanding the combination of both formal and domain-specific construction methodologies and also described a general taxonomy of relationships, one which could encapsulate many of the complexities associated with catastrophic events.

A disaster monitoring interface for an earthquake simulation was proposed by Mandiak, et al. [290]. The visualization tool was an integrated graphical user interface framework that enabled a user to easily comprehend the trend of a situation, by providing as much information (obtained via the integration of multidimensional graphic displays) as possible to him.

Rogova, et al. [369] addressed the problem of situation assessment to support casualty mitigation operations in the response phase that immediately followed an earthquake. The proposed methodology was based on the cognitive work analysis and ontological analysis of a specific emergency management domain, developed within the framework of a formal ontology.

5.4. Fault Detection and Identification/Diagnosis

The main issues of concern when applying information fusion to fault diagnosis are the acquisition of reliable information about potential faults by incorporating multiple sensors, as well as the derivation of fused decisions based on data from the multiple sensors. It is necessary to develop fusion mechanisms that minimize conflicts among the sensors, as well as imprecision and uncertainty in the sensor data.

Based on Dempster-Shafer evidence theory, a multi-sensor implementation of an engine diagnostic system was introduced by Basir and Yuan [24]. The formulation of the engine diagnostic problem in the context of the evidence theory was explained. Novel ways were introduced to enhance the effectiveness of mass functions in modeling and in evidence combination. Rational diagnosis decision making rules were proposed and the entropy of evidence was introduced to facilitate information fusion performance evaluation. Experimental results demonstrated the effectiveness of the proposed approach in resolving decision conflicts and in improving the accuracy of fault diagnosis via multi-sensor information fusion.

Fan and Zuo [133] introduced a Dempster-Shafer evidence theory-based method with the capability of increasing accuracy of decision making through multi-source information fusion. In the proposed approach, fuzzy set theory, weight of evidence and conflict resolution were introduced to address the issues of evidence sufficiency, evidence importance, and conflicting evidence in the practical application of D-S evidence theory. Test example results validated feasibility of the proposed method, as well as its improvement over the conventional D-S evidence theory in performing fault diagnosis through fusing multi-source information. In the sequel [134], successful application of the improved D-S evidence theory to machinery fault diagnosis was reported. Experimental results showed that the proposed method could enhance diagnostic accuracy and autonomy, in comparison with conventional diagnostic methods.

Bashi, et al. [22] proposed an algorithm for fault detection in large-scale systems with a large number of almost identical units operating in a shared environment. The fault detection algorithm was developed based on the estimation of a common Gaussian-mixture distribution for unit parameters via the Expectation-Maximization algorithm. The estimated common distribution incorporated and generated information from all units and was utilized for fault detection in each individual unit. The algorithm was applicable in various industrial, chemical or manufacturing processes, as well as sensor networks. In the companion paper [23], the authors described the application of their algorithm to the problem of fault detection in heating ventilation and air conditioning (HVAC) systems. Implementation details were described. Monte Carlo simulations and real data collected from three operational large HVAC systems were used in the evaluation of the performance of the proposed methodology in a realistic situation.

5.5. Biomedical Applications/Informatics

Biomedical applications/informatics generally involve voluminous data from multiple heterogeneous sources. In most circumstances, the amount of useful knowledge that can be acquired from an individual data source is limited. Information derived from multi-source data fusion is often of better quality than that obtained from the available sources separately.

Bellot, et al. [29] proposed a generic approach to fuse data in dynamical systems. A notion of qualified gain was defined to help determine the usefulness of a data fusion process developed. The method was applied to a problem of monitoring kidney disease patients who underwent dialysis at home. All the data sources and relations among them were determined. A dynamic Bayesian network-based model was used to fuse the data in order to provide daily diagnosis on the hydration state of the patients. Efficiency of the proposed approach was reflected by the experimental results obtained.

Ganta, et al. [146] described data exploration and analysis of heterogeneous biomedical informatics data sets using an online data warehouse. Experimental results obtained from applying information fusion techniques to multiple prostate cancer data sets demonstrated the feasibility of the proposed system.

Zhang, et al. [477] presented a new approach to explore the cause of human longevity based on comprehensive medical data. Expert knowledge was applied to a longevity model through artificial intelligence techniques. Firstly, fuzzy logic was used in pre-processing biomedical data. Then multiple classifier network and decision level data fusion were applied to improve the modeling accuracy. Simulation test results showed that the proposed model was able to identify individuals who belong to longevity group with high accuracy.

Muller, et al. [311] developed a modular data fusion system with Dempster-Shafer framework. An architecture of fusion was built from this system by chaining two types of elementary modules. Modules of the first type were used for symbolic interpretation of numerical reports from sensors, while those of the second type were used for the combination of these symbolic data to obtain relevant synthetical information for diagnosis. The data fused were generated by tagged Magnetic Resonance Imaging[3] and Positron Emission Tomography.[4] D-S theory was applied to model the uncertainty of the data and the rules of decision. The fusion architecture was applied to the assessment of left ventricular my-

[3]Magnetic Resonance Imaging (MRI): an imaging technique based on the principles of Nuclear Magnetic Resonance, a spectroscopic technique used by scientists to elucidate chemical structure and molecular dynamics. MRI is used primarily in medical settings to produce high quality images of the inside of the human body.

[4]Positron Emission Tomography (PET): a highly specialized imaging technique that uses short-lived radioactive substances to produce three-dimensional colored images of those substances functioning within the body. These images are called PET scans and the technique is termed PET scanning.

ocardial viability.[5] To obtain geometrical information on the potential lesions, diagnosis results obtained from the data of a patient were displayed on polar maps.

A fuzzy logic-based data fusion system for detection of life threatening patient states in cardiac care units was proposed by Kannathal, et al. [130, 226]. Heterogeneous electrophysiological and haemodynamic data were fused and analyzed. In addition, a parameter named *patient deterioration index* was proposed to evaluate the severity of the cardiac abnormality. Test results obtained showed that the proposed approach could give highly accurate clinical diagnosis in monitoring the patients.

5.6. Environment

Human activities and environmental modifications can influence the ecosystem in multiple ways. The impact can be local, regional or even global. It is necessary to develop efficient systems to monitor and control activities that produce effects on the environment.

Hubert-Moy, et al. [202] applied Dempster-Shafer's theory of evidence to support spatio-temporal monitoring and projections of land use and land cover changes. Data from spatial and temporal sources were fused to obtain spatial prediction of the location of winter bare fields for the following season on a watershed located in an intensive agricultural region. A highly accurate prediction on the presence of bare soils was achieved over the entire area of interest. The spatial distribution of misrepresented fields provided a good indicator for identification of change factors.

Heiden, et al. [188] proposed a methodology to facilitate derivation of quantitative parameters for advanced evaluation of urban biotopes,[6] an essential task in ecological urban planning. The proposed approach involved the analysis of airborne hyperspectral data and automated identification of urban surface cover types based on their material-specific spectral reflectance characteristics. The results were then integrated with vector-based urban biotope mapping, an existing database. Finally, the required quantitative parameters were derived from the resultant database. Spatial and statistical analyses showed that using quantitative parameters to complement the predominately descriptive information contained in urban biotope mapping yielded improved evaluation of urban biotopes.

Two data-driven tools, support vector machines[7] and relevance vector machines,[8] were successfully applied to perform reliable soil moisture estimation by Khalil, et al. [230]. The effectiveness and efficiency of the proposed models in soil moisture prediction were evaluated with the use of weather information. The performance and generalization capabilities of the two machines were also compared. Support vector machines and relevance vector machines could be utilized in industries such as large scale water management to attain high-level inference via information, feature and decision level fusion processes.

In order to improve management of irrigation systems, good quality of spatial and temporal data on evapotranspiration, the combination of soil evaporation and plant transpiration, was essential. However, it was not easy to attain good quality for remote sensing evapotranspiration data. Chemin and Honda [85] reported an investigation on the use of genetic algorithms in assimilating parameters of an agrohydrological[9] model. The aim of the research was to find optimized parameters that would enable the model to obtain simulated evapotranspiration output that converged to observed remote sensing evapotranspiration data. The proposed methodology involved the fusion of observed remote sensing data of high spatial resolution, as well as those of low spatial resolution.

Šeric, et al. [397] presented an advanced communication and networking environment with all applications and services being focused on users. The authors detailed environmental intelligence based on a collection (network) of observers. Observer network theory was derived from the formal theory of perception and formed the basis for the design of their forest fire monitoring system. The proposed system was implemented on a multi agent framework. The efficiency of the forest fire observer was evaluated in test examples, using numerical measures proposed by the authors.

Zervas, et al. [476] proposed a multisensor data fusion based method for fire detection. The authors described the system architecture and the application of Dempster-Shafer evidential theory for inference on the probability of fire in a geographical region monitored using a wireless network of environmental (temperature and humidity) and vision sensors. The feasibility of the proposed approach was verified by simulation test results.

[5] A *ventricle* is a heart chamber which collects blood from an *atrium* (another heart chamber that is smaller than a ventricle) and pumps it out of the heart. A *myocardium* is a muscular tissue of the heart. *Ventricular myocardial viability* is the potential for improvement of dysfunction in a ventricular myocardium after a surgical procedure for the provision of a new, additional, or augmented blood supply.

[6] Urban biotope: an area with uniform environment occupied by a unified urban community.

[7] Support vector machine [453]: a constructive machine learning procedure based on statistical learning theory. It can be used to learn a variety of representations, such as neural nets, splines, and so on.

[8] Relevance vector machine [444]: a machine learning technique based on Bayesian theory that has an identical functional form to the support vector machine.

[9] Agrohydrological: of or to do with *agrohydrology*, a research area that deals with climate, soil, and water and how these natural resources are managed in sustainable plant production.

5.7. Industrial Applications

In the recent years, many industrial applications that utilize high-level fusion techniques for problem-solving have emerged [112]. Some instances of research work from prominent areas are reviewed below.

Qiu [354] presented the development of an effective data link between manufacturing and office planning to facilitate the deployment of an integrated plant-wide information system. The information-centric data fusion framework was proposed to help integrate all levels of data, with the aim of achieving synchronization and timely delivery of necessary information, in the information system. Details on the usefulness and practicality of the proposed model in the realization of a desired plant-wide real time information system were described.

A multi-layered fusion architecture and implementation for classifiers with binary and continuous outputs were described by Goebel and Yan [154]. The fusion scheme was structured into three major components which were partitioned into layers. The classifier outputs were transformed into a single continuous domain through logical tasks performed within the layers. The modular design of the fusion architecture allowed relatively easy addition/removal of modules, as well as the re-use of the core fusion engine for other domains. The proposed fusion framework was applied to a system monitoring environment of industrial equipment. The test results obtained were compared to those achieved by a a baseline approach. An improvement in performance over the latter was shown.

Roussel, et al. [371] proposed a Bayesian inference-based fusion method to combine the outputs of various sensors. The mathematical theory concerning the Bayesian approach was discussed and the method was applied to the problem of white grapes variety classification. The classification results verified the effectiveness of the proposed method in grape variety discrimination, an important task for manufacturers in the wine industry who need to determine accurately the origins and/or varieties of the grapes used for production.

Majidi and Moshiri [289] presented a computer vision system for classification of fruits. Estimation of the volume of a fruit was carried out by training a neural network with simple features of profile images of the fruit. Inspection of fruit surface defects was based on fusion of side images of the whole area of the fruit. A set of basic color parameters of the fruit surface was then extracted and the fruit was classified via high level fusion of these visual features. Test results showed that the proposed method had acceptable performance in regard to the execution time required.

Ong and Ibañez-Guzmán [333] reviewed multi-sensor management for sensor fusion with respect to the guidance of unmanned vehicles. An information-oriented concept of perception management was introduced for multi-sensor systems. An outline of the concept of a design framework for sensor perception system was also given.

De Vin, et al. [118, 119] reported how information fusion research could benefit manufacturing applications. One particular area of interest was virtual manufacturing. An information fusion framework involving modeling and simulation was proposed for decision support in manufacturing. Relevant fused information regarding the past, present and future of the manufacturing system were extracted for future use. Interaction of the information fusion process with active databases (capable of propagating abnormal conditions or events to decision level), sensors and the simulation model was described. In [118], they also discussed some analogies between manufacturing and defense tasks, as well as aspects in which the manufacturing sector could benefit from defense research.

Razavi, et al. [361] developed a belief function-based data fusion algorithm for detecting dislocations (changes between discrete sequential locations) of materials on a construction site. The authors focused on the detection of dislocations in a noisy information environment. Each piece of material to be monitored had a Radio Frequency Identification tag attached to it. The technical feasibility and the cost-effectiveness of the proposed method were demonstrated by the implementation results in a construction field experiment.

6. SUMMARY AND FURTHER RESEARCH

In this survey paper, we review some process models that have been developed for data and information fusion. We also present an overview of research publications related to high-level information fusion, which is gaining interest in the recent years after much research focus has been placed on low-level information fusion. We also discuss relevant application areas that involve high-level data and information fusion.

Active research and development on high-level fusion is ongoing among the DIF community. There are many important topics and techniques that have not been covered in this paper. Some examples are belief networks, situation logic, network analysis, graph theory, social network analysis, scene and situation characterization and multi-resolution inferencing. Future research areas of interest include the following examples.

- Comparative assessment of different functional and process models for data/information fusion;
- Critical or comparative evaluation of high-level fusion techniques in applicability to various application problems: functionality, uncertainty, complexity, data and state diversity and dynamics, knowledge representation, knowledge extraction and discovery, context exploitation, situation characterization and prediction, and so on.

TABLE V
Topics for Further Exploration

Topic	Reference
Adversarial intent inference	[12, 25, 28, 38, 86, 136, 139, 140, 143, 147, 153, 198, 210, 247, 249, 284, 298, 317, 319–321, 344, 363, 365, 372, 388, 394, 401, 419, 432, 437, 438, 472]
Biologically-inspired and biomedical applications/informatics	[18, 75, 114, 144, 167, 179, 332, 375, 446]
Electronic and physical anomaly/intrusion detection	[56, 69, 78, 103, 115, 163, 182, 206, 207, 231, 264, 287, 310, 365, 396, 426, 441, 442, 449, 456, 472, 474]
Human cognition related research (cognitive fusion, HCI, etc.)	[30, 39, 116, 179, 181, 326, 412]
Image analysis/processing	[74, 185, 342, 458]
Information warfare	[84, 126, 246, 254, 468]
Interoperability of joint and coalition military forces	[123, 335, 336, 345, 462]
Network-centric warfare/operations and network-based defense	[150, 335, 336, 372, 435, 468]
Ontology-based approaches to high-level information fusion	[35, 44, 60, 72, 77, 82, 83, 105, 204, 237, 265, 275–277, 299, 304, 315, 316, 329, 364, 408, 410, 475]
Resource allocation/management	[3, 6, 11, 13, 15, 31, 45, 64, 73, 75, 91, 125, 138, 189–192, 196, 197, 211, 215, 255, 288, 312, 316, 358, 386, 389, 403, 431, 437, 459, 460]

The variety of application areas which apply DIF techniques has increased tremendously since they were first applied in defense research in the 1970s. The scope of applications is still expanding fast, both in the military arena and civilian sectors (including commercial and industrial applications). Table V provides some examples of high-level fusion concepts and contexts with much potential for exploration.

With rapid advancement in various technologies and accessibility to vast data and information sources, complex information fusion problems are very likely to arise in many applications that involve far more concepts and contexts than the few listed above. It is becoming increasingly necessary to explore the possibility of expanding the base of diverse disciplines (including theories and techniques) upon which existing tools have been built. A lot more research is needed and can be done to develop novel useful tools (including theories, algorithms and architectures) for solving high-level information fusion problems.[10] In addition, efficiency and effectiveness in this multidisciplinary field of research are likely to be enhanced if collaborative relationships can be established/strengthened among the various research groups [9, 278].

APPENDIX

Table VI: List of acronyms.

[10]The following paper surveys various topics and challenges in high-level information fusion: E. P. Blasch, D. A. Lambert, P. Valin, M. M. Kokar, J. Llinas, S. Das, C. Chong, and E. Shahbazian, High level information fusion (HLIF): Survey of models, issues, and grand challenges, *IEEE Aerospace and Electronic Systems Magazine*, **27**, 9 (2012), 4–20.

TABLE VI
List of Acronyms

Acronym	Definition
ANOVA	Analysis of variance
ATR	Automatic target recognition
C2	Command and control
C4I	Command, control, communications, computers and intelligence
C4ISR	Command, control, communications, computers, intelligence, surveillance and reconnaissance
COA	Course of action
DF	Data fusion
DFIG	Data Fusion Information Group
DIF	Data and information fusion
D-S	Dempster-Shafer
DOE	Design of experiments
EW	Early warning
HCI	Human-computer interaction
HRR	High range resolution
IF	Information fusion
INTEL	Intelligence
JDL	Joint Directors of Laboratories
NBD	Network-based defense
NCBR	Nuclear, chemical, biological and radiological
NCW	Network-centric warfare
OODA	Observe, orient, decide, and act
OSPA	Optimal subpattern assignment
PA	Performance assessment
PE	Performance evaluation
RADAR	Radio detecting and ranging
SA	Situation assessment
SAW	Situation awareness
SM	Sensor management
SONAR	Sound navigation and ranging
TRIP	Transformation of Requirements for the Information Process
VDF	Visual Data-Fusion

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