An Introduction to Multisensor Data Fusion

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Invited Paper

Multisensor data fusion is an emerging technology applied to Department of Defense (DoD) areas such as automated target recognition, battlefield surveillance, and guidance and control of autonomous vehicles, and to non-DoD applications such as monitoring of complex machinery, medical diagnosis, and smart buildings. Techniques for multisensor data fusion are drawn from a wide range of areas including artificial intelligence, pattern recognition, statistical estimation, and other areas. This paper provides a tutorial on data fusion, introducing data fusion applications, process models, and identification of applicable techniques. Comments are made on the state-of-the-art in data fusion.

I. Introduction

In recent years, multisensor data fusion has received significant attention for both military and nonmilitary applications. Data fusion techniques combine data from multiple sensors, and related information from associated databases, to achieve improved accuracies and more specific inferences than could be achieved by the use of a single sensor alone [1]–[4]. The concept of multisensor data fusion is hardly new. Humans and animals have evolved the capability to use multiple senses to improve their ability to survive. For example, it may not be possible to assess the quality of an edible substance based solely on the sense of vision or touch, but evaluation of edibility may be achieved using a combination of sight, touch, smell, and taste. Similarly, while one is unable to see around comers or through vegetation, the sense of hearing can provide advanced warning of impending dangers. Thus multisensory data fusion is naturally performed by animals and humans to achieve more accurate assessment of the surrounding environment and identification of threats, thereby improving their chances of survival.

While the concept of data fusion is not new, the emergence of new sensors, advanced processing techniques, and improved processing hardware make real-time fusion of data increasingly possible [5], [6]. Just as the advent of symbolic processing computers (viz., the SYMBOLIC's computer and the Lambda machine) in the early 1970's provided an impetus to artificial intelligence [119], recent advances in computing and sensing have provided the ability to emulate, in hardware and software, the natural data fusion capabilities of humans and animals. Currently, data fusion systems are used extensively for target tracking, automated identification of targets, and limited automated reasoning applications. Spurred by significant expenditures by the Department of Defense (DoD), data fusion technology has rapidly advanced from a loose collection of related techniques, to an emerging true engineering discipline with standardized terminology (see Fig. 1), collections of robust mathematical techniques [2]–[4], and established system design principles. Software in the area of data fusion applications is becoming avavailable in the commercial marketplace [16].

Applications for multisensor data fusion are widespread. Military applications include: automated target recognition (e.g., for smart weapons), guidance for autonomous vehicles, remote sensing, battlefield surveillance, and automated threat recognition systems, such as identification-friend-foe-neutral (IFFN) systems [14]. Nonmilitary applications include monitoring of manufacturing processes, condition-based maintenance of complex machinery, robotics [129], and medical applications. Techniques to combine or fuse data are drawn from a diverse set of more traditional disciplines including: digital signal processing, statistical estimation, control theory, artificial intelligence, and classic numerical methods [16], [12], [54]. Historically, data fusion methods were developed primarily for military applications. However, in recent years these methods have been applied to civilian applications, and there has been bidirectional technology transfer [5]. Various annual conferences provide a forum for discussing data fusion applications and techniques [7]–[10].

In principle, fusion of multisensor data provides significant advantages over single source data. In addition to the statistical advantage gained by combining same-source data (e.g., obtaining an improved estimate of a physical phenomena via redundant observations), the use of multiple types of sensors may increase the accuracy with which a quantity can be observed and characterized. In the accompanying

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FUSION	The integration of information from multiple sources to produce specific and comprehensive unified data about an entity.
ALIGNMENT (Level 1)	Processing of sensor measurements to achieve a common time base and a common spatial reference.
ASSOCIATION (Level 1)	A process by which the closeness of sensor measurements is completed.
CORRELATION (Level 1)	A decision-making process which employs an association technique as a basis for allocating sensor measurements to the fixed or tracked location of an entity.
CORRELATOR-TRACKER (Level 1)	A process which generally employs both correlation and fusion component processes to transform sensor measurements into updated states and covariance for entity tracks.
CLASSIFICATION (Level 1)	A process by which some level of identity of an entity is established, either as a member of a class, a type within a class, or a specific unit within a type.
SITUATION ASSESSMENT (Level 2)	A process by which the distributions of fixed and tracked entities are associated with environmental, doctrinal, and performance data.
THREAT ASSESSMENT (Level 3)	A structured multi-perspective assessment of the distributions of fixed and tracked entities which result in estimates of (e.g.): • expected courses of action; • enemy lethality; • unit compositions and deployment; • functional networks (e.g., supply, comms); and • environmental effects.

Fig. 1. Table of terminology and definitions.

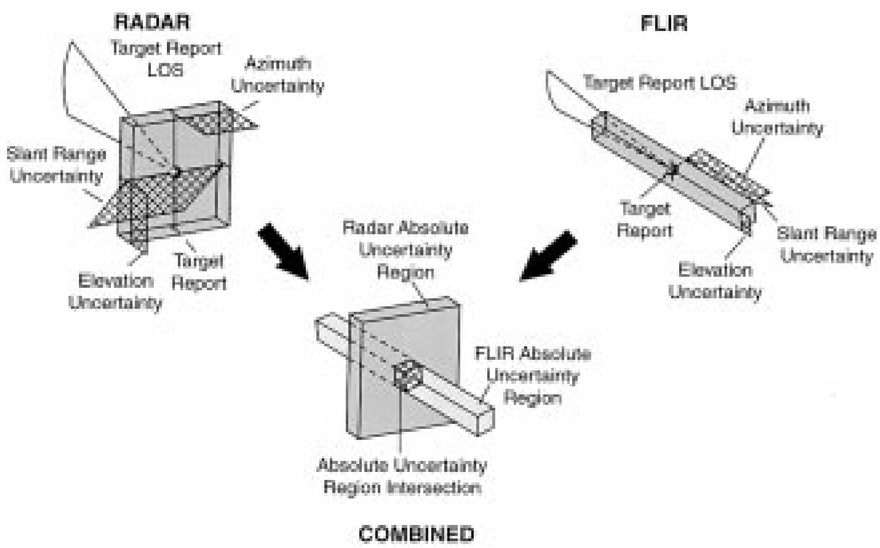

Fig. 2. FLIR and radar sensor data correlation.

Fig. 2 [2], a simple example is provided of a moving object, such as an aircraft, observed by both a pulsed radar and an infrared imaging sensor. The radar provides the ability to accurately determine the aircraft's range, but has a limited ability to determine the angular direction of the aircraft. By contrast, the infrared imaging sensor can accurately determine the aircraft's angular direction, but is unable to measure range. If these two observations are correctly associated (as shown in the central part of the figure), then the combination of the two sensors data provides an improved determination of location than could be obtained by either of the two independent sensors. This results in a reduced error region as shown in the fused or combined location estimate. A similar effect may be obtained in determining the identity of an object based on observations of an object's attributes. For example, there is evidence that bats identify their prey by a combination of factors that include size, texture (based on acoustic signature), and kinematic behavior.

The most fundamental characterization of data fusion involves a hierarchical transformation between observed energy or parameters (provided by multiple sources as

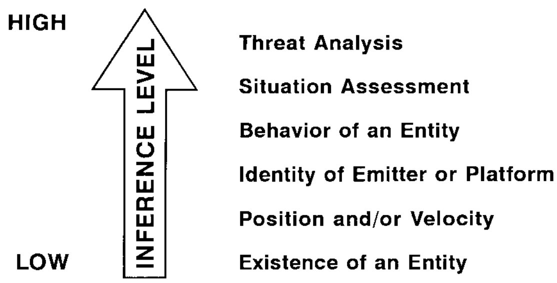

Fig. 3. Inference hierarchy.

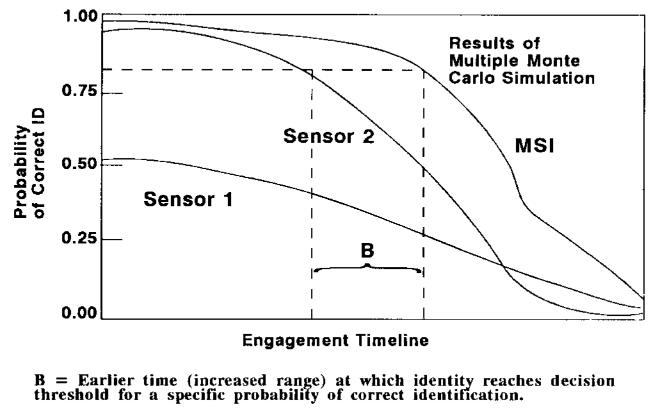

Fig. 4. Example of Monte Carlo evaluation of data fusion benefits.

input) and a decision or inference (produced by fusion estimation and/or inference processes) regarding the location, characteristics, and identity of an entity, and an interpretation of the observed entity in the context of a surrounding environment and relationships to other entities (see Fig. 3). The definition of what constitutes an entity depends upon the specific application under consideration (e.g., an enemy aircraft for a tactical air-defense application, or the location and characteristics of a tumor in a medical diagnosis application). The transformation between observed energy or parameters and a decision or inference proceeds from an observed signal to progressively more abstract concepts. In a target tracking application, for example, multisensor energy, converted to observations of angular direction, range, and range-rate may be converted in turn into an estimate of the target's position and velocity (using observations from one or more sensors). Similarly, observations of the target's attributes, such as radar cross section, infrared spectra, and visual image, may be used to classify the target, and allow a feature-based classifier to declare an assignment of a label specifying target identity (e.g., F-16 aircraft). Finally, understanding the motion of the target and its relative motion with respect to the observer, may allow a determination of the intent of the target (e.g., threat, no-threat, etc.).

The determination of the target's position and velocity from a noisy time-series of measurements constitute a classical statistical estimation problem [68], [62], [63]. Modern techniques involve the use of sequential estimation techniques such as the Kalman filter or its variants. To establish target identity, a transformation must be made between observed target attributes and a labeled identity. Methods for identity estimation involve pattern recognition techniques based on clustering algorithms, neural networks, or decision-based methods such as Bayesian inference [107], Dempster–Shafer's method [111], [130], [110], or weighted decision techniques [3]. Finally, the interpretation of the target's intent entails automated reasoning using implicit and explicit information, via knowledge-based methods such as rule-based reasoning systems [116]–[118].

Observational data may be combined, or fused, at a variety of levels from the raw data (or observation) level to a state vector level, or at the decision level. Raw sensor data can be directly combined if the sensor data are commensurate (i.e., if the sensors are measuring the same physical phenomena such as two visual image sensors or two acoustic sensors). Techniques for raw data fusion typically involve classic detection and estimation methods. Conversely, if the sensor data are noncommensurate, then the data must be fused at a feature/state vector level or decision level.

Feature-level fusion involves the extraction of representative features from sensor data. An example of feature extraction is the use of characteristics of a human's face to represent a picture of the human. This technique is used by cartoonists or political satirists to evoke recognition of famous figures. There is evidence that humans utilize a feature-based cognitive function to recognize objects. In feature-level fusion, features are extracted from multiple sensor observations, and combined into a single concatenated feature vector which is input to pattern recognition approaches based on neural networks, clustering algorithms, or template methods.

Finally, decision level fusion involves fusion of sensor information, after each sensor has made a preliminary determination of an entity's location, attributes, and identity. Examples of decision level fusion methods include weighted decision methods (voting techniques), classical inference, Bayesian inference, and Dempster–Shafer's method.

Qualitative advantages of data fusion for DoD systems have been cited by numerous authors. Waltz [1], for example, cites the following benefits for tactical military systems; robust operational performance, extended spatial coverage, extended temporal coverage, increased confidence (i.e., of target location and identity), reduced ambiguity, improved target detection, enhanced spatial resolution, improved system reliability, and increased dimensionality. Waltz performed Monte Carlo numerical studies to show the quantitative utility of data fusion for improved noncooperative target recognition (see Fig. 4), leading to advantages in tactical air-to-air engagements.

Despite these qualitative notions and quantitative calculations of improved system operation by using multiple sensors and fusion processes, actual implementation of effective data fusion systems is far from simple. In practice, fusion of sensor data may actually produce worse results than could be obtained by tasking the most appropriate sensor in a sensor suite. This is caused by the attempt

Specific Applications	Inferences Sought by DF Process	Primary Observable Data	Surveillance Volume	Sensor Platforms
Ocean Surveillance	• Detection, tracking, identification of targets/events	• EM signal • Acoustic signals • Nuclear related • Derived observations (wake)	• Hundreds of nautical miles • Air/surface/sub-surface	• Ships • Aircraft • Submarines • Ground-based • Ocean-based
Air-to-Air and Surface-to-Air Defense	• Detection, tracking, identification of aircraft	• EM radiation	• Hundreds of miles (strategic) • Miles (tactical)	• Ground-based • Aircraft • Ships
Battlefield Intelligence, Surveillance, and Target Acquisition	• Detection and identification of potential ground target	• EM radiation	• Tens to hundreds of miles about a battlefield	• Ground-based • Aircraft
Strategic Warning and Defense	• Detection of indications of impending strategic actions • Detection/tracking of ballistic missiles and warheads	• EM radiation • Nuclear related	• Global	• Satellites • Aircraft • Ground-based

Fig. 5. DoD applications sumary.

to combine accurate (i.e., good data) with inaccurate or biased data, especially if the uncertainties or variances of the data are unknown. Quantitative evaluation of the effectiveness of data fusion system must, in most cases, be performed by Monte Carlo simulations or covariance error analysis techniques [3], [46], [47]. Fundamental issues to be addressed in building a data fusion system for a particular application include:

1) what algorithms or techniques are appropriate and optimal for a particular application;
2) what architecture should be used (i.e., where in the processing flow should data be fused);
3) how should the individual sensor data be processed to extract the maximum amount of information;
4) what accuracy can realistically be achieved by a data fusion process;
5) how can the fusion process be optimized in a dynamic sense;
6) how does the data collection environment (i.e., signal propagation, target characteristics, etc.) affect the processing;
7) under what conditions does multisensor data fusion improve system operation?

This paper provides a brief overview of multisensor data fusion technology and its applications. An introduction to data fusion techniques is provided along with a discussion of some fundamental issues. Some projections for the future of data fusion are provided along with an assessment of the state-of-the-art and state-of-practice.

II. Military Applications of Data Fusion

Two broad communities have focused on data fusion for specific applications: DoD and non-DoD. We will address each of these in turn, and provide examples of applications.

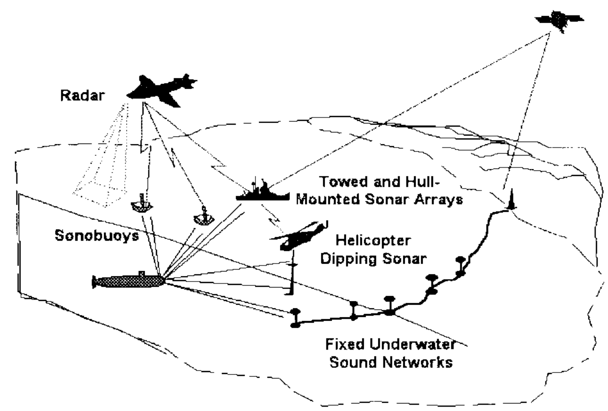

Fig. 6. An example of multisensor ocean surveillance.

The DoD community focuses on problems involving the location, characterization, and identification of dynamic entities such as emitters, platforms, weapons, and military units. These dynamic data are often termed an Order-of-Battle database or Order-of-Battle display (if superimposed on a map display). Beyond achieving an Order-of-Battle database, DoD users seek higher level inferences about the enemy situation (i.e., the relationships among entities, their relationships with the environment, higher level enemy entity organizations, etc.). Examples of DoD related applications include ocean surveillance, air-to-air defense, battlefield intelligence, surveillance, and target acquisition, and strategic warning and defense (see Fig. 5). Each of these military applications involves a particular focus, sensor suite, desired set of inferences, and a particular set of challenges.

Ocean surveillance systems are designed to detect, track, and identify ocean-based targets and events. Examples

Specific Applications	Inferences Sought by DF Process	Primary Observable Data	Surveillance Volume	Sensor Platforms
Condition-Based Maintenance	• Detection, characterization of system faults • Recommendations for maintenance corrective actions	• EM signal • Acoustic signals • Magnetic • Temperature • X-rays • Vibration	• Microscopic inspection to hundreds of feet	• Ships • Aircraft • Ground-based (e.g., factory)
Robotics	• Location, identification of obstacles, and objects to be manipulated	• TV • Acoustic signals • EM signals • X-rays	• Microscopic to tens of feet about the robot	• Robot body
Medical Diagnostics	• Location, identification of tumors, abnormalities, and disease	• X-rays • NMR • Temperature • IR • Visual inspection • Chemical/biological data	• Human body volume	• Laboratory
Environmental Monitoring	• Identification, location of natural phenomena (earthquakes, weather)	• SAR • Seismic • EM radiation • Core samples • Chemical/biological data	• Hundreds of miles • Miles (site monitoring)	• Satellites • Aircraft • Ground-based • Underground samples

Fig. 7. Overview of non-DoD application.

include antisubmarine warfare systems to support Navy tactical fleet operations (Fig. 6), and automated systems to guide autonomous vehicles. Sensor suites may include radar, sonar, electronic intelligence (ELINT), observation of communications traffic (COMINT), infrared, and synthetic aperture radar (SAR) observations [100]. The surveillance area for ocean surveillance may encompass hundreds of nautical square miles, and a focus on air, surface, and subsurface targets. Multiple surveillance platforms may also be involved with numerous targets tracked. Challenges to ocean surveillance involve the large surveillance volume, the combination of targets and sensors, and the complex signal propagation environment—especially for underwater sonar sensing. An example of an ocean surveillance system is shown in Fig. 6.

Air-to-air and surface-to-air defense systems have been developed by the military to detect, track, and identify aircraft and anti-aircraft weapons and sensors. These defense systems use sensors such as radar, passive electronic support measures (ESM), infrared, identification-friend-foe (IFF) sensors, electro-optic image sensors, and visual (human) sightings. These systems support counter-air, order-of-battle aggregation, assignment of aircraft to raids, target prioritization, route planning, and other activities. Challenges to these data fusion systems include enemy countermeasures, the need for rapid decision making, and potentially large combinations of target-sensor pairings. A special challenge for IFF systems is the need to confidently and noncooperatively identify enemy aircraft. The proliferation of weapon systems throughout the world, and the subsequent lack of relationship between the nationality of weapon origin and combatants who use the weaponry, causes increased IFF challenges.

Another application, Battlefield Intelligence, Surveillance, and Target Acquisitions systems attempt to detect and identify potential ground targets. Examples include the location of land mines and automatic target recognition of high value targets. Sensors include airborne surveillance via Moving Target Indicator (MTI) radar, synthetic aperture radar, passive electronic support measures, photo reconnaissance, ground-based acoustic sensors, remotely piloted vehicles, electro-optic sensors, and infrared sensors. Key inferences sought are information to support battlefield situation assessment and threat assessment, and course-of-action estimation.

A detailed discussion of DoD data fusion applications can be found in the collected annual *Proceedings of the Data Fusion Systems Conference* [7], *Proceedings of the National Symposium on Sensor Fusion* [9], and various strategic documents [15].

III. Nonmilitary Applications of Data Fusion

A second broad community which addresses data fusion problems is the academic/commercial/industrial community. This diverse group addresses problems such as the implementation of robotics, automated control of industrial manufacturing systems, development of smart buildings, and medical applications (see Fig. 7), among other evolving applications. As with the military applications, each of these applications has particular challenges, sensor suites, and implementation environments.

Remote sensing systems have been developed to identify and locate entities and objects. Examples include systems to monitor agricultural resources (e.g., the productivity and health of crops), to locate natural resources, and to monitor weather and natural disasters. These systems rely primarily

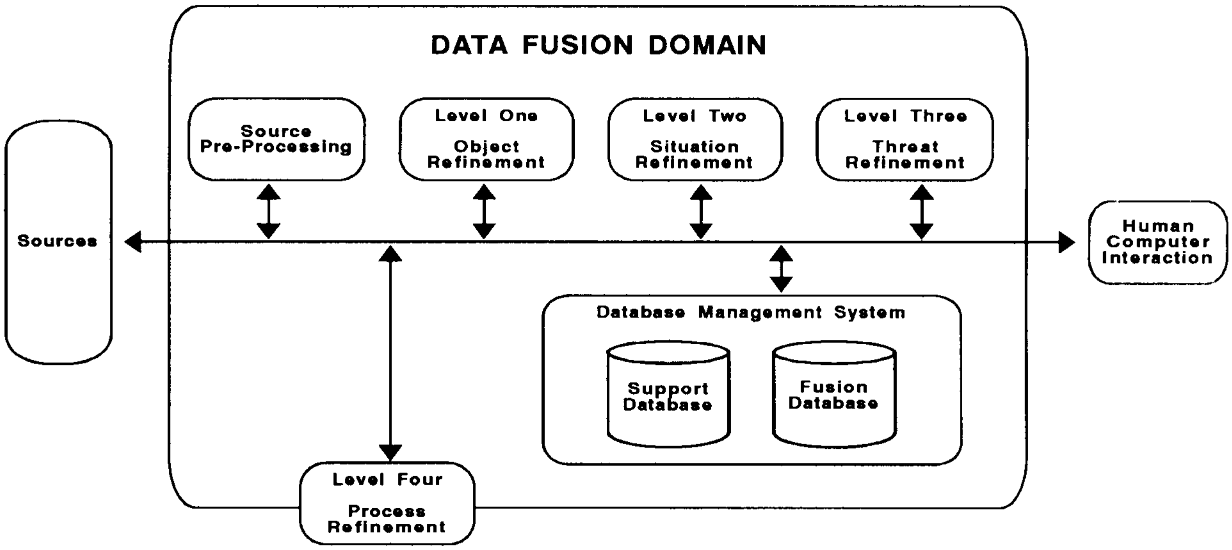

Fig. 8. Top level data fusion process model.

on image systems using multispectral sensors. Such processing systems are dominated by automatic and multispectral image processing. The multispectral imagery employed includes the Landsat satellite system, the SPOT system, or others. A frequently used technique for multisensor image fusion involves adaptive neural networks. Multi-image data are processed on a pixel-by-pixel basis and input to a neural network to automatically classify the contents of the image. False colors are usually associated with types of crops, vegetation, or classes of objects. The resulting false color synthetic image is readily interpreted by human analysts. A key challenge in multi-image data fusion is interimage co-registration. This problem requires the alignment of two or more photos so that the images are overlaid in such a way that corresponding picture elements (pixels) on each picture represent the same location on earth (each pixel represents the same direction from an observer's point of view). This co-registration problem is exacerbated by the fact that image sensors are nonlinear, and perform a complex transformation between observed three-dimensional (3-D) space, and a two-dimensional (2-D) image plane [86]. A second application area which spans both military and nonmilitary users is the monitoring of complex mechanical equipment such as turbomachinery, helicopter gear-trains, or industrial manufacturing equipment. For a drivetrain application, for example, available sensor data may include accelerometers, temperature gauges, oil debris monitors, acoustic sensors, and even infrared measurements. An on-line condition monitoring system would seek to combine these observations in order to identify precursors to failure, such as abnormal wear of gears, shaft misalignment, or bearing failure. It is anticipated that the use of such condition-based monitoring would reduce costs for maintenance, improve safety, and improve reliability [126]. Such systems are beginning to be developed for helicopters and other high cost systems. Special difficulties for data fusion involve noncommensurate sensors and challenging signal propagation and noise environments.

A final example of a data fusion system for nonmilitary applications is the area of medical diagnosis. Currently, increasingly sophisticated sensors are being developed for medical applications. Sensors such as nuclear magnetic resonance (NMR) devices, acoustic imaging devices, and medical tests, individually provide improvements in medical diagnostic capability. The ability to fuse these data together promises to improve the diagnostic capability, and reduce false diagnoses. A clear challenge here is the signal propagation environment, and difficulties in obtaining training data for adaptive techniques such as neural networks.

Military and nonmilitary communities are beginning to share information to create real technology transfer across application domains. For example, the first International Conference on Multi-Sensor Fusion and Integration for Intelligent Systems was sponsored by the IEEE and held in Las Vegas, NV, on 2–5 October 1994 [10]. Also, annual (on-going) SPIE conferences focus on non-DoD applications [8].

IV. A Data Fusion Process Model

One of the historical barriers to technology transfer in data fusion has been the lack of a unifying terminology, which crosses application-specific boundaries. Even within military applications, related but different applications such as IFF systems, battlefield surveillance, and automatic target recognition, have used different definitions for fundamental terms such as correlation and data fusion. In order to improve communications among military researchers and system developers, the Joint Directors of Laboratories (JDL) Data Fusion Working Group, established in 1986, began an effort to codify the terminology related to data fusion. The result of that effort was the creation of a process model for data fusion, and a Data Fusion Lexicon [12], [11]. The top level of the JDL data fusion process model is shown in Fig. 8. The JDL process model is a functionally oriented model of data fusion and is intended to be very general and useful across multiple application areas. While the boundaries of the data fusion process are fuzzy and case-by-case dependent, generally speaking the input boundary is usually at the post-detection, extracted parameter level of signal processing. The output of the data fusion process is (ideally) a minimally ambiguous identification and characterization (viz., location and attributes) of individual entities, as well as a higher level interpretation of those entities in the context of the application environment.

The JDL Data Fusion Process model is a conceptual model which identifies the processes, functions, categories of techniques, and specific techniques applicable to data fusion. The model is a two-layer hierarchy. At the top level, shown in Fig. 8, the data fusion process is conceptualized by; sources of information, human computer interaction, source preprocessing, Level 1 processing, Level 2 processing, Level 3 processing, and Level 4 processing. Each of these is summarized below and summarized in Fig. 9.

- *Sources of Information.* The left side of Fig. 8 indicates that a number of sources of information may be available as input including: 1) local sensors associated with a data fusion system (e.g., sensors physically associated with the data fusion system or organic sensors physically integrated with a data fusion system platform), 2) distributed sensors linked electronically to a fusion system, and 3) other data such as reference information, geographical information, etc.
- *Human Computer Interaction (HCI).* The right side of Fig. 8 shows the human computer interaction (HCI) function for fusion systems. HCI allows human input such as commands, information requests, human assessments of inferences, reports from human operators, etc. In addition, HCI is the mechanism by which a fusion system communicates results via alerts, displays, dynamic overlays of positional and identity information on geographical displays. In general, HCI incorporates not only multimedia methods for human interaction (graphics, sound, tactile interface, etc.), but also methods to assist humans in direction of attention, and overcoming human cognitive limitations (e.g., difficulty in processing negative information).
- *Source Preprocessing (Process Assignment).* An initial process allocates data to appropriate processes and performs data pre-screening. Source preprocessing reduces the data fusion system load by allocating data to appropriate processes (e.g., locational and attribute data to Level 1 object refinement, alerts to Level 3 processing, etc.). Source preprocessing also forces the data fusion process to concentrate on the data most pertinent to the current situation. Extensive signal processing and detection theory may be required [41], [42]. A special case of source preprocessing is the synthesis of multiple component sensory array data to estimate the location and velocity of a target.
- *Level 1 Processing (Object Refinement).* This process combines locational, parametric, and identity information to achieve refined representations of individual objects (e.g., emitters, platforms, weapons, or geographically constrained military units). Level 1 processing performs four key functions: 1) transforms sensor data into a consistent set of units and coordinates, 2) refines and extends in time estimates of an object's position, kinematics, or attributes, 3) assigns data to objects to allow the application of statistical estimation techniques, and 4) refines the estimation of an object's identity or classification.
- *Level 2 Processing (Situation Refinement).* Level 2 processing develops a description of current relationships among objects and events in the context of their environment. Distributions of individual objects (defined by Level 1 processing) are examined to aggregate them into operationally meaningful combat units and weapon systems. In addition, situation refinement focuses on relational information (i.e., physical proximity, communications, causal, temporal, and other relations) to determine the meaning of a collection of entities. This analysis is performed in the context of environmental information about terrain, surrounding media, hydrology, weather, and other factors. Situation refinement addresses the interpretation of data, analogous to how a human might interpret the meaning of sensor data. Both formal and heuristic techniques are used to examine, in a conditional sense, the meaning of Level 1 processing results.
- *Level 3 Processing (Threat Refinement).* Level 3 processing projects the current situation into the future to draw inferences about enemy threats, friendly and enemy vulnerabilities, and opportunities for operations. Threat assessment is especially difficult because it deals not only with computing possible engagement outcomes, but also assessing an enemy's intent based on knowledge about enemy doctrine, level of training, political environment, and the current situation. The overall focus is on intent, lethality, and opportunity. Level 3 processing develops alternate hypotheses about an enemy's strategies and the effect of uncertain knowledge about enemy units, tactics, and the environment. Game theoretic techniques are applicable for Level 3 processing.
- *Level 4 Processing (Process Refinement).* Level 4 processing may be considered a *meta-process*, i.e., a process concerned about other processes. Level 4 processing performs four key functions: 1) monitors the data fusion process performance to provide information about real-time control and long-term performance, 2) identifies what information is needed to improve the multilevel fusion product (inferences, positions, identities, etc.), 3) determines the source specific requirements to collect relevant information (i.e., which sensor type, which specific sensor, which database), and 4) allocates and directs the sources to achieve mission goals. This latter function may be outside the domain of specific data fusion functions. Hence, Level 4 processing is shown as partially inside and partially outside the data fusion process.
- *Data Management.* The most extensive support function required to support data fusion processing is

SOURCES	The sources provide information at a variety of levels ranging from sensor data to *a priori* information from databases to human input.
PROCESS ASSIGNMENT	Source preprocessing enables the data fusion process to concentrate on the data most pertinent to the current situation as well as reducing the data fusion processing load. This is accomplished via data pre-screening and allocating data to appropriate processes.
OBJECT REFINEMENT (Level 1)	Level 1 processing combines locational, parametric, and identity information to achieve representatives of individual objects. Four key functions are: • transform data to a consistent reference frame and units; • estimate or predict object position, kinematics, or attributes; • assign data to objects to permit statistical estimation; and • refine estimates of the objects identity or classification.
SITUATION REFINEMENT (Level 2)	Level 2 processing attempts to develop a contextual description of the relationship between objects and observed events. This processing determines the meaning of a collection of entities and incorporates environmental information, *a priori* knowledge, and observations.
THREAT REFINEMENT (Level 3)	Level 3 processing projects the current situation into the future to draw inferences about enemy threats, friendly and enemy vulnerabilities, and opportunities for operations. Threat refinement is especially difficult because it deals not only with computing possible engagement outcomes, but also assessing an enemy's intent based on knowledge about enemy doctrine, level of training, political environment, and the current situation.
PROCESS REFINEMENT (Level 4)	Level 4 processing is a *meta-process*, i.e., a process concerned about other processes. The three key Level 4 functions are: • monitor the real-time and long-term data fusion performance; • identify information required to improve the multi-level data fusion product; and • allocate and direct sensor and sources to achieve mission goals.
DATABASE MANAGEMENT SYSTEM	Database management is the most extensive ancillary function required to support data fusion due to the variety and amount of managed data, as well as the need for data retrieval, storage, archiving, compression, relational queries, and data protection.
HUMAN-COMPUTER INTERACTION	In addition to providing a mechanism for human input and communication of data fusion results to operators and users, the human-computer interfaction (HCI) includes methods of directing human attention as well as augmenting cognition, e.g., overcoming the human difficulty in processing negative information.

Fig. 9. JDL process model components.

database management. This collection of functions provides access to, and management of, data fusion databases, including data retrieval, storage, archiving, compression, relational queries, and data protection. Database management for data fusion systems is particularly difficult because of the large and varied data managed (i.e., images, signal data, vectors, textural data) and the data rates both for ingestion of incoming sensor data, as well as the need for rapid retrieval.

A summary of the JDL data fusion process components are shown in Fig. 9. Each of these components can be hierarchically broken down into subprocesses. The first level decomposition and associated applicable problem solving techniques as shown in Fig. 10. For example, Level 1 processing is subdivided into four types of functions: data alignment, data/object correlation, object positional, kinematic, and attribute estimation, and finally, object identity estimation. The object positional, kinematic, and attribute estimation function is further subdivided into system models, defined optimization criteria, optimization approaches, and basic processing approach. At this lowest level in the hierarchy (shown in the third column of Fig. 10), specific methods such as Kalman filters, alpha-beta filters, multiple hypothesis trackers, etc. are identified to perform each function.

The JDL model described here is generic, and is intended merely as a basis for common understanding and discussion. The separation of processes into Levels 1–4 is an artificial partition. Implementation of real data fusion systems integrates and interleaves these functions into an overall processing flow. The data fusion process model is augmented by a hierarchical taxonomy which identifies categories of techniques and algorithms for performing the identified functions. In addition, an associated lexicon has been developed to provide a consistent definition of data fusion terminology [11]. The JDL model, while originally developed for military applications, is clearly applicable to nonmilitary applications. For example, in condition-based monitoring, the concept of Level 3 threat refinement can be associated with the identification of potential system me-

JDL Process	Processing Function	Techniques
Level 1: Object Refinement	Data alignment	• Coordinate transforms • Units adjustments
	Data/object correlation	• Gating techniques [52] • Multiple hypothesis association probabilistic data association [63],[64] • Nearest neighbor
	Position/kinematic and attribute estimation	• Sequential estimation [19], [73], [75] - Kalman filter - αβ filter - Multiple hypothesis [79] • Batch estimation [69], [70], [71] • Maximum likelihood [80] • Hybrid methods [76], [77], [78]
	Object identity estimation	• Physical models • Feature-based techniques - Neural networks - Cluster algorithms [56], [57] - Pattern recognition [87], [88], [89] • Syntactic models
Level 2: Situation Refinement	Object aggregation Event/activity interpretation Contextual interpretation	• Knowledge-based systems (KBS) - Rule-based expert systems - Fuzzy logic [60] - Frame-based (KBS) • Logical templating [114], [115] • Neural networks [96], [97], [98], [99] - Blackboard systems
Level 3: Threat Refinement	Aggregate force estimation Intent prediction Multi-perspective assessment	• Neural networks - Blackboard systems [122] • Fast-time engagement models
Level 4: Process Refinement	Performance evaluation	• Measure of evaluation [2] • Measures of performance [2] • Utility theory [59]
	Process control	• Multi-objective optimization [59] - Linear programming - Goal programming
	Source requirement determination	• Sensor models
	Mission management	• Knowledge-based systems

Fig. 10. Examples of data fusion algorithms and techniques.

chanical faults (and their anticipated progression). Thus, the JDL model is useful for nonmilitary applications. Indeed, the JDL model terminology is beginning to experience wide utilization and acceptance throughout the data fusion technical community. It should be noted, however, that there have been a number of extensions to the JDL model as well as discussion about its overall utility. Waltz [86], for example, demonstrated that the JDL model does not adequately address multi-image fusion problems. Waltz described how the JDL model can be extended to include concepts of fusion of image data, especially those involving complex synthetic aperture imagery. Hall and Ogrodnik [127] extended the model further to account for complex meta sensors (e.g., sensors involving multiple components and utilization of wideband processing techniques). Bowman [128] has argued that the JDL model is useful, but does not help in developing an architecture for a real system. Bowman has developed the concept of a hierarchical data fusion tree to partition fusion problems into nodes, each conceptually involving functions such as data association, correlation, and estimation, etc.

V. Architectures for Multisensor Data Fusion

One of the key issues in developing a multisensor data fusion system is the question of where in the data flow to actually combine or fuse the data. We will focus on two situations for Level 1 fusion: 1) fusion of locational information (such as observed range, azimuth, and elevation) to determine the position and velocity of a moving object, and 2) fusion of parametric data (such as radar cross section, infrared spectra, etc.) to determine the identity of an observed object. We will discuss these two cases separately, though in an actual system, fusion of locational and parametric identity information could be performed in an integrated fashion.

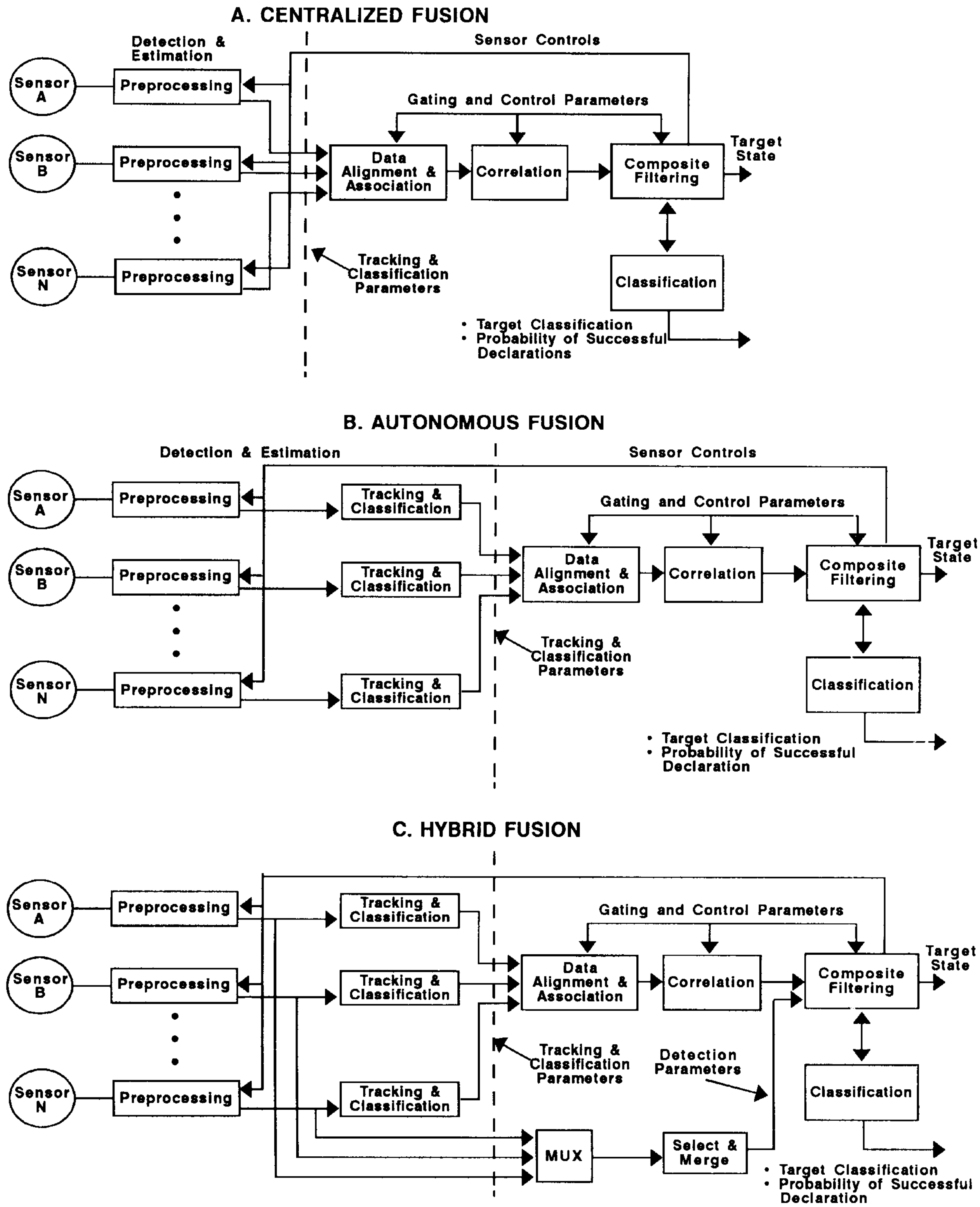

Fig. 11. Generic tracker/correlator architectures.

There are three broad alternatives to fusing locational information to determine the position and velocity of an object: 1) fusion of the raw observational data (so-called data level or report level fusion), 2) fusion of state vectors (in this case, a state vector is an optimum estimate using an individual sensor's measurements of the position and velocity of an observed object), and 3) a hybrid approach which allows fusion of either raw data or state vector data, as desired. These alternative fusion architectures are illustrated in Fig. 11.

The top part of the figure shows fusion of raw observational data. Data from each sensor (or each different sensor type) are aligned to transform the sensor data from sensor-based units and coordinates to convenient coordinates and units for central processing. The data are then associated/correlated to determine which sensor observations belong together. That is, in a multisensor, multitarget environment, it is necessary to determine which observations represent observations of the same physical entity or target. Thus association/correlation determines which observation-to-observation or observation-to-existing target track belong together. This association/correlation problem may be very complicated in dense target tracking environments. Nevertheless, once a determination has been made, then the data are fused, typically using sequential estimation techniques such as Kalman filters. This centralized fusion approach is theoretically the most accurate way to fuse data, assuming that the association and correlation can be performed correctly. However, this approach also requires that the raw data be transmitted (via local communications networks or other mechanism) from the sensors to the central processing facility or computer. For the case of image data, this may require a communications bandwidth which would exceed what is actually available.

The second architecture for locational fusion is distributed (or autonomous) fusion, in which each sensor performs single-source positional estimation, producing a state vector from each sensor. (This is, each sensor provides an estimate of the position and velocity of an object, based only on its own single source data). These estimates of position and velocity (i.e., a state vector estimate) are input to a data fusion process to achieve a joint or fused state vector estimate, based on multiple sensors. It should be noted that the functions of data alignment and association/correlation still need to be performed, but are now performed at the state vector level versus the data level. Distributed fusion architectures reduce the communications required between sensors and the fusion processor (because the sensor data are compressed into a representative state vector). In addition, the association/correlation process is conceptually easier than that performed for data level fusion. However, in general, state vector fusion is not as accurate as data level fusion, because there is an information loss between the sensors and the fusion process. In particular, the original data contains information about the quality of the signal, which is only approximated by the state vector and its associated covariance matrix.

Finally, the third architecture for locational fusion is a hybrid architecture that combines data level fusion and state vector fusion. In this case, during ordinary operations, state vector fusion is performed to reduce computational workload and communications demands. Under specified circumstances (e.g., when more accuracy is required, or in dense tracking environments), data level fusion is performed. Alternatively, based on available sensors, a combination of state vectors and data may be fused. While the hybrid architecture provides the most flexibility, it also requires overhead to monitor the fusion process and select between data and state vector fusion.

Selection from among these types of locational architectures is ultimately a system engineering problem. There is no single optimal architecture for any given data fusion application. Instead, the choice of architecture must balance computing resources, available communication bandwidth, desired accuracy, the capabilities of the sensors, and available funding.

The second type of Level 1 processing considered is identity fusion. Here, we are trying to convert multiple sensor observations of a target's attributes (such as radar cross section, infrared spectral coefficients, etc.) to a joint declaration of target identity. For identity fusion, there are several types of architectures which can be used: 1) data level fusion, 2) feature level fusion, and 3) decision level fusion. These three architectures are illustrated in Fig. 12.

The first architecture [Fig. 12(c)] performs data level fusion. Each sensor observes an object and the raw sensor data are combined. Subsequently, an identity declaration process is performed. This is commonly achieved by extracting a feature vector from the fused data, and a transformation made between the feature vector and a declaration of identity. Methods for this feature-based identity declaration include neural networks, template methods, and pattern recognition methods such as cluster algorithms. In order to fuse the raw data, the original sensor data must be commensurate (i.e., must be observations of the same or similar physical quantities such as visual images) and must be able to be properly associated. Thus, for example, if two image sensors are used, the images must be able to be coaligned on a pixel-by-pixel basis. Analogous to locational fusion, raw data identity fusion provides the most accurate results, assuming proper sensor association and alignment.

The second architecture for identity fusion is feature level fusion. In this case, each sensor provides observational data from which a feature vector is extracted. These features are concatenated together into a single feature vector which in turn is input to an identity declaration technique such as a neural network or cluster algorithm. The output then becomes a joint or fused declaration of target identity based on the combined feature vectors from all of the sensors. The functions of data alignment and association/correlation must still be performed prior to linking the feature vectors from individual sensors into a single larger feature vector.

The third architecture [Fig. 12(b)] is decision level fusion. In this architecture, each sensor performs an identity declaration process based only on its own single-source data. That is, each sensor converts observed target attributes into a preliminary declaration of target identity. Again, this may be performed using a feature extraction/identity declaration approach involving neural networks or other feature-based pattern recognition techniques. The identity declarations provided by the individual sensors are combined using decision level fusion techniques such as classical inference, Bayesian inference, weighted decision methods, or Dempster–Shafer's method, among others. As with the other architectures, data association and correlation are still required to insure that the data to be fused refer to the same physical entity or target.

The selection among these architectures for a particular application is also a system engineering problem which depends upon issues such as the available communications bandwidth, characteristics of the sensors, computational resources available, and other issues. There is no one

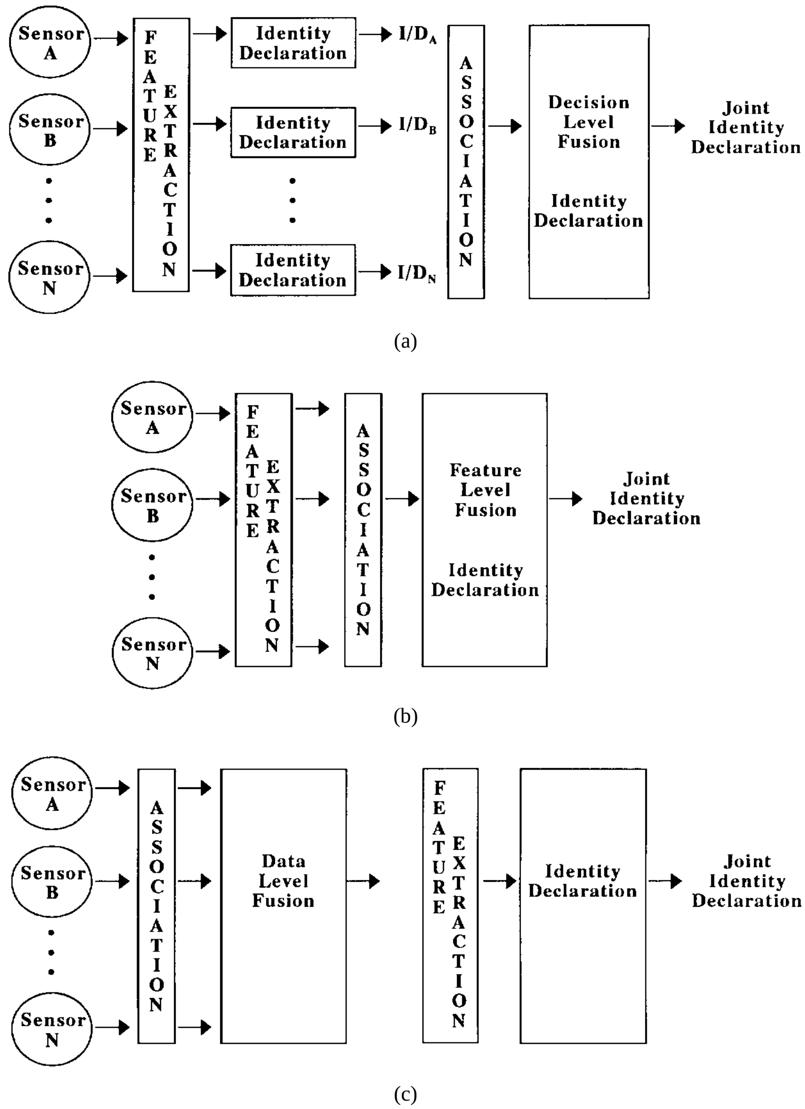

Fig. 12. Alternate architectures for multisensor identity fusion.

universal architecture which is applicable to all situations or applications. The architectures shown here provide a range of possible implementations.

A. Knowledge-Based Methods for Data Fusion

Interpretation of fused data for situation assessment or threat assessment requires automated reasoning techniques drawn from the field of artificial intelligence. In particular, knowledge-based systems (KBS) or expert systems have been developed to interpret the results of Level 1 processing systems, analyzing issues such as the context in which the data are observed, the relationship among observed entitles, hierarchical groupings of targets or objects, and predictions of future actions of targets or entities. Such reasoning is normally performed by humans, but may be approximated by automated reasoning techniques. The reader is referred to the artificial intelligence literature for more details. A frequently-applied approach for data fusion involves the use of so-called blackboard KBS [122]. These systems partition the problem into related subproblems and use interacting reasoning techniques to solve the component problems, with an evolving solution obtained by combining the results for each subproblem. This is analogous to how human experts might gather around a blackboard and solve a problem (hence the name of the KBS architecture). An example of a blackboard architecture is shown in Fig. 13.

Regardless of the specific KBS technique used, three elements are required: 1) one or more knowledge representation schemes, 2) an automated inference/evaluation process, and 3) control schemes. Knowledge representation schemes are techniques for representing facts, logical relationships, procedural knowledge, and uncertainty. Many techniques have been developed for knowledge representation including production rules, frames, semantic networks, scripts, and others. For each of these techniques, uncertainty in the observed data and the logical relationships can be represented using probability, fuzzy set theory, Dempster–Shafer evidential intervals, or other methods. The goal in building an automated reasoning system is to capture the reasoning capability of a human expert by

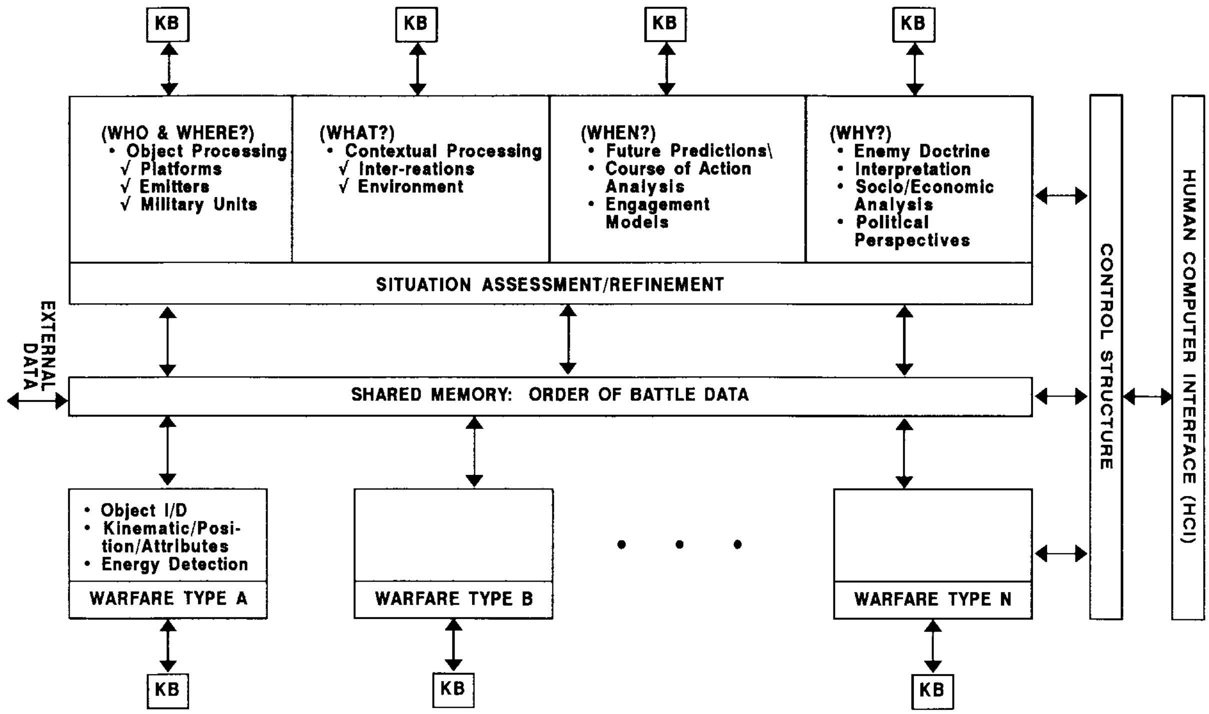

Fig. 13. Notational "blackboard" architectures for higher level fusion processing.

specifying the rules, frames, scripts, etc. which represent the essence of the interpretive task. In contrast to the highly numerical fusion processes at Level 1, the fusion of data and information at these higher levels of inference is largely (but not exclusively) conducted at the symbolic level,. Thus, in general applications can require a mixture of numerical and symbolic processing.

Given a knowledge base, an inference or evaluation process must be developed to utilize the knowledge. There are formal schemes which have been developed based on formal logic, fuzzy logic, probabilistic reasoning, template methods, case-based reasoning, and many other techniques. Each of these automated reasoning schemes has an internally consistent formalism which prescribes how to utilize the knowledge base (i.e., the rules, frames, etc.) to obtain a resulting conclusion or inference.

Finally, automated reasoning requires a control scheme to implement the reasoning process. Techniques include search methods (e.g., search a knowledge base to identify applicable rules), reason maintenance systems, assumption-based and justification-based truth maintenance, hierarchical decomposition, control theory, etc. Each of these schemes involves assumptions and an approach for controlling the evolving reasoning process. Control schemes direct the search through a knowledge base in order to exploit and fuse the multisensor, dynamic data.

The combination of selected knowledge representation scheme(s), inference/evaluation process, and control scheme are used to achieve automated reasoning. Popular techniques are rule-based KBS and more recently fuzzy logic based techniques. There are numerous prototype expert systems for data fusion, and readily available commercial expert system development tools to help the rapid prototyping of such an expert data fusion system. Key issues for developing such a system include the creation of the knowledge base (i.e., actually specifying the rules, frames, scripts, etc. via a knowledge engineering process), and the test and evaluation of such a system. Despite these difficulties, such systems are increasingly being developed for data fusion.

B. Assessment of the State-of-the-Art

The technology of multisensor data fusion is rapidly evolving. There is much concurrent ongoing research to develop new algorithms, improve existing algorithms, and to understand how to assemble these techniques into an overall architecture to address diverse data fusion applications. A brief assessment of the state-of-the-art is provided here and shown in Fig. 14.

The most mature area of data fusion processing is Level 1 processing, using multisensor data to determine the position, velocity, attributes, and identity of individual objects or entities. In particular, determining the position and velocity of an object based on multiple sensor observations is a relatively old problem. Gauss and Legendre developed the method of least square for the particular problem of orbit determination for asteroids [66], [68]. Numerous mathematical techniques exist to perform coordinate transformations, associate observations-to-observations or observations-to-tracks, and to estimate the position and velocity of a target. Multisensor target tracking is dominated by sequential estimation techniques such as the Kalman filter. Challenges in this area involve circumstances in which there is a dense target environment, rapidly maneuvering targets, or complex signal propagation environments (e.g., involving multipath propagation, co-channel interference, or clut-

JDL Process	Process Description	Current Status	Challenges and Limitations
Level 1 Processing	Refines the estimates of an object's position, kinematics, attributes, and identity	• Sensor preprocessing - Standard DSP • Multi-target tracking - MHT - Ad hoc maneuver algorithms - Association metrics • Object identification - Feature-based dominance - Context-free processing - PR via neural nets - Model-based approaches	• Dense target environments • Rapidly maneuvering targets • Complex signal propagation • Co-dependent sensor observations • Background clutter • Contextual ATR • Integration of identity/ kinematic data
Level 2 Processing	Develops a description of current relationships among objects and events in the context of the environment (i.e., situation assessment)	• Numerous prototypes • Dominance by KBS - Blackboard methods - Rule-based representation - Logical templates • KBS experiments - Case-based reasoning - Fuzzy logic - IPB • Non-real-time implementation	• Dominated by proto-types • No experience on scaling to field models • "Excedrin" cognitive models • Difficult KB develop-ment • Perfunctory T&E • Integration of identity/ kinematics data
Level 3 Processing	Projects the current situation into the future and draws interferences about threats, vulnerability, and opportunities	• Same as Level 2 • Limited advisory status • Limited deployment experience • Dominated by ad hoc methods • Doctrine-specific implementations	• Same as Level 2 • Difficulty in quantifying intent • Models require established enemy doctrine • Rapidly evolving situations difficult
Level 4 Processing	A meta-process that monitors data fusion processing to assess performance and refine the process to achieve goals	• Robust systems for single-sensor systems • Operations research formulation • Limited approximate reasoning approaches • Focus on MOP vs MOE	• Incorporation of mission objective/constraints • Environmental context for sensor utilization • Conflicting objectives (e.g., PCD vs accuracy) • Dynamic algorithm selection/modification • Diverse sensors

Fig. 14. Assessment of data fusion technology.

ter). Single target tracking in high signal-to-noise environments, for dynamically well-behaved (i.e., dynamically predictable) targets is straightforward. Current research focuses on solving the correlation and maneuvering target problem for the more complex multisensor multitarget cases. Techniques such as multiple hypothesis tracking (MHT), probabilistic data association methods, random set theory [81], [82], and multiple criteria optimization theory [76] are all being used to resolve these issues. Some researchers are utilizing multiple techniques simultaneously, guided by a knowledge-based system to select the appropriate solution, based on algorithm performance.

A special problem in Level 1 processing is achieving robustness in the automatic identification of targets based on observed characteristics or attributes. At this time, object recognition is dominated by feature-based methods in which a feature vector (i.e., a representation of the sensor data) is mapped into feature space with the hope of identifying the target based on the location of the feature vector relative to *a priori* determined decision boundaries. Popular pattern recognition techniques include neural networks and statistical classifiers. While there are numerous techniques available, the ultimate success of these methods depends upon the ability to select good features. (Good features are those which provide excellent class separability in feature space, while bad features are those which result in greatly overlapping areas in feature space for several classes of targets.) More research is needed in this area to guide the selection of features, and to incorporate explicit knowledge about target classes. (For example, model-based or syntactic methods provide additional information about the makeup of a target and reduce the so-called training requirement necessary for the feature-based approaches. These model-based methods have in fact become the dominant focal point of much of the recent ID fusion algorithm research.) In addition, some limited research is proceeding to incorporate contextual information, such as target mobility with respect to terrain, to assist in target identification. Similar to the position estimation case, fused target ID estimation methods can work well in simpler cases where the target is exposed (i.e., not occluded), but when targets are partially occluded, decoys and countermeasures are used, etc., achieving dependable, automated, fusion-based ID has been elusive.

Level 2 and Level 3 fusion (situation refinement and threat refinement) are currently dominated by knowledge-based methods such as rule-based blackboard systems. These areas are relatively immature with numerous prototypes, but very few robust operational systems. The main challenge in this area is the need to establish a viable knowledge base of rules, frames, scripts, or other methods to represent knowledge that support situation assessment or threat assessment. Unfortunately, there exist only very primitive cognitive models for how humans accomplish these functions. Much research is needed in this area before reliable and large-scale knowledge-based systems can be developed for automated situation assessment and threat assessment. New approaches which appear promising are the use of fuzzy logic, and hybrid architectures which extend the concept of blackboard systems to hierarchical and multitime scale reasoning.

Finally, Level 4 processing, which assesses and improves the performance operation of an on-going data fusion process, has a mixed maturity. For single sensor operations, techniques from operations research and control theory have been applied to develop effective systems, even for complex single sensors such as phased array radars. By contrast, situations that involve multiple sensors, external mission constraints, dynamic observing environments, multiple targets, etc. are more challenging. At this time, it is difficult to model and incorporate mission objectives and constraints to balance optimized performance with limited resources such as computing power, limited communication bandwidth (viz., between the sensors and processors), and other effects. Methods from utility theory are being applied to develop measures of system performance and measures of effectiveness. Knowledge-based systems are being developed for context-based approximate reasoning. A special area which will provide significant improvements is the advent of smart, self-calibrating sensors, which can accurately and dynamically assess their own performance.

A final comment on the discipline of data fusion is that it has suffered from a lack of rigor on test and evaluation of algorithms, and in considerations of transitioning theory to application. The data fusion community needs to exert discipline in insisting on high standards for algorithm development, test and evaluation, creation of standard test cases, and systematic evolution of the technology to meet realistic applications. On a positive note, the introduction of the JDL process model and emerging nonmilitary applications are expected to result in increased cross discipline communication and research. The nonmilitary research in robotics, condition-based maintenance, industrial process control, transportation, and intelligent buildings will produce innovations which will cross fertilize the whole area of data fusion technology.

VI. Summary

The data fusion community is rapidly evolving. Significant investments in DoD applications, rapid evolution of microprocessors, advanced sensors, and new techniques have led to new capabilities to combine data from multiple sensors for improved inferences. Applications of data fusion range from DoD applications such as battlefield surveillance and automatic target recognition for smart weapons to non-DoD applications such as condition-based maintenance and improved medical diagnosis. Implementation of such systems requires an understanding of basic terminology, data fusion processing models, and architectures. This paper is intended to provide an introduction to these areas as a basis for further study and research.

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