Intelligent Fusion and Asset Management Processor

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Abstract

Owing to continual advances in sensor capabilities, avionics, and inter-service C^4I, the volume of battlefield intelligence data to which the modern-day military intelligence analyst has access is increasing at an exponentital rate. This has created the need for more intelligent systems capable of scanning and extracting the tactically most useful information for presentation to the human analyst. The presence of a more extensive and flexible sensor asset infrastructure also mandates more intelligent and accountable asset deployment and management. Accordingly, we describe an effort to develop for the Air Force Research Laboratory's Information Directorate an ***Intelligent Fusion and Asset Management Processor*** *(**IFAMP**) for enhancing tactical situation awareness and for providing needs-based sensor asset planning and scheduling information to assist the C^2 staff. The IFAMP architecture incorporates three distinct modules: a fuzzy logic-based level one fusion module responsible for low-level event detection, unit/echelon type discrimination, observation-to-track gating and assignment, and track database management; a belief network-based level two situation assessment module responsible for generating probabilistic hypotheses for high-level situational state descriptors; and a fuzzy logic-based level four collection management expert system responsible for mapping informational requirements and current state information into asset resource requests.*

I. INTRODUCTION

The analysis of intelligence data to generate a comprehensive understanding of all tactical elements in the battlespace and of the likely evolution of the battlespace•i.e., to achieve situation awareness•is a major task for Air Force personnel. This task naturally overlaps with and benefits from the deployment and management of the sensor/collection assets themselves. We therefore develop an **Intelligent Fusion and Asset Management Processor** (**IFAMP**) which provides an integrated framework for analysis of data in support of enhanced tactical awareness and needs-based sensor asset planning and scheduling information to assist the C^2 staff. IFAMP's flexibility in generating high-level tactical situation knowledge stems from combining the model-based approximate reasoning capabilities of fuzzy logic [1] and Bayesian belief networks [2][3].

The overall goal of data fusion is to combine data from multiple sources into information that has greater benefit than would have been derived from each of the contributing parts [4]. An obvious analogy exists between data fusion and human cognitive processing, in particular, the way humans process multi-sensory information (i.e., sight, sound, smell, etc.) to make inferences regarding the environment. Therefore IFAMP uses a coordinated application of two artificial intelligence technologies, fuzzy logic (FL) and belief networks (BNs), to the problem of tactical fusion and collection management. Fuzzy logic provides a means of converting low-level imprecise information in non-numerical format into mid-level knowledge units about individual battlespace entities. Belief networks provide a means for constructing and mantaining a hierarchical, probabilistic model linking multiple entities, at various levels, in the context of the overall mission goals, rules of engagement, etc. Evidence gathered incrementally and in real-time first undergoes FL filtering and is then applied to the appropriate node(s) of the BN. This evidence then automatically propagates throughout the BN resulting in revised probability estimates concerning the higher-level tactical situational hypotheses. Our experience from prior research projects ([5][6]) has shown that this approach provides an effective solution to the problem and offers a natural framework for encoding complex tactical knowledge.

II. SYSTEM DESCRIPTION

Figure 1 illustrates how the overall scope of IFAMP falls within the various levels of the data fusion and other key components of Air Force tactical C^4I systems. Data concerning the various entities present in the battlespace, is collected by a variety of sensor assets (JSTARS, AWACS, etc.) and then fused (level one) within IFAMP to generate individual target tracks and to classify and characterize targets. The situation assessment (SA) module of the IFAMP uses this fused track data to generate a probabilistic situational state hypothesis from detected events. This SA information is then forwarded to higher-level threat assessment and decision-aiding modules, currently outside IFAMP's scope. Finally, the SA information is used by IFAMP's collection management module to schedule, prioritize, and communicate intelligence requests.

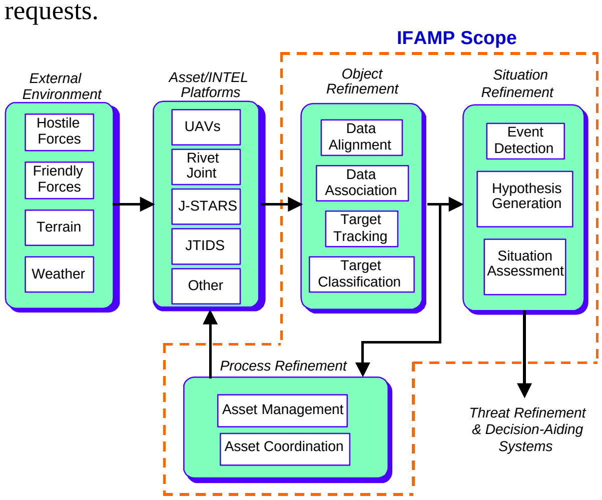

Figure 1: IFAMP Scope

Figure 2 displays IFAMP's overall architecture, incorporating all modules necessary to support management and control of level one fusion processing, multi-scale information processing and situation assessment, and to provide enhanced collection management functionality. The system incorporates three distinct modules: a fuzzy logic-based level one fusion module responsible for low-level event detection, unit/echelon type discrimination, observation-to-track gating and assignment, and track database management; a belief network-based level two situation assessment module responsible for generating probabilistic hypotheses for high-level situational state descriptors; and a fuzzy logic-based level four collection management expert system responsible for mapping informational requirements and current state information into asset resource requests

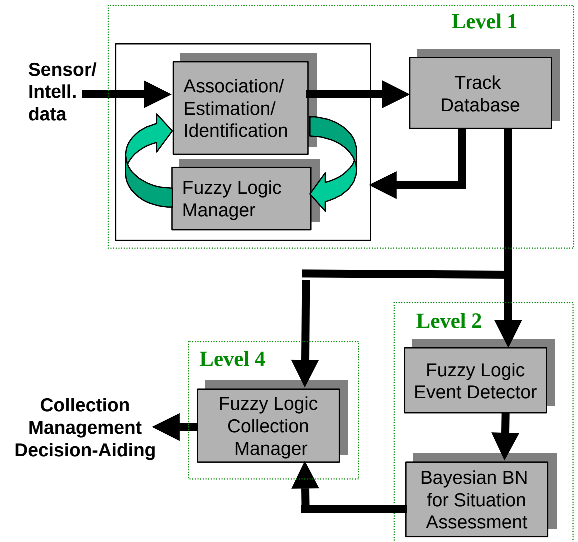

Figure 2: IFAMP System Architecture

At level one, incoming sensor/INTEL data is parsed for descriptions of enemy units detected and associated object data structures are created. A Unit Echelon/Type Discriminator block then analyzes the sensor data and makes hypotheses on echelon and type of the detected unit using enemy order of battle information. If the object is of known type, it is directly fed into the track database. Objects of unknown type are passed to a Gating Algorithm block. Here, the association function of matching new observations to existing tracks is performed based on a spatial distance metric. For observations with no matching tracks, a new track is initiated. For observations satisfying multiple gates, an Assignment block performs track assignment based on spatial considerations and unit type information (if available). A State Estimator block is responsible for updating track positions. The final element of the Level one IFAMP system is the Fuzzy Logic Manager whose functions include the track management functions of initialization, track confirmation, track deletion, and ensuring timeliness and accuracy of all information in the Track Database.

At the heart of level two is a belief network which is a probabilistic model of the battlefield and fighting units. The belief network allows uncertain evidence concerning any of the represented battlefield and unit features to be incorporated so as to consistently update any other contingent features of the model. The network, shown in Figure 3, can be interpreted as representing causal relationships between the variables. For example, a particular enemy mission (*E.Miss*) combined with enemy knowledge about where friendly troops are located

(*F.Loc*) *cause* a rational enemy to choose a specific objective (*E.Obj*) which will maximize its utility. Friendly locations and enemy objectives are represented in terms of Named Areas of Interest (NAIs) which are identified in a prior stage of terrain analysis and intelligence preparation of the battlefield (IPB). An enemy's objective, in turn, causally influences which of many possible courses of action (COAs) it will execute. Finally, specific COAs are associated with specific mobility corridors (MCs) also identified in the terrain analysis/IPB stage. All network variables (nodes) are discrete-valued; the domains appear alongside or above each node. Once the set of variables is chosen and the BN topology established, each directed link is quantified with a conditional probability table (CPT) which encodes the probability distribution of the child variable as a function of its parent variables.

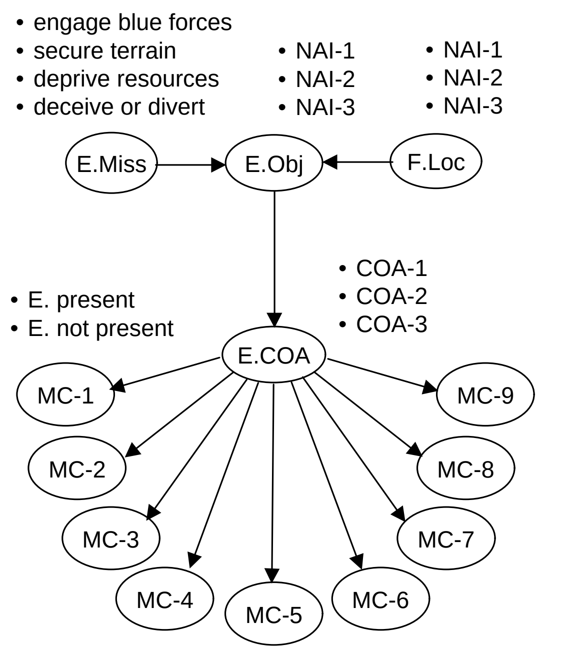

Figure 3: Belief Network for Situation Assessment

At level four, a Fuzzy Logic Collection Manager maps current situation assessment state, and enemy track information, into sensor/INTEL requests. The mapping is performed using repository knowledge of sensor/asset capabilities and enemy tactical doctrine. High-level event notifications and observations relating to asset requests are also relayed to the user. The mapping from situational state and track information to asset request is based on several *appropriateness* metrics, including timeliness, desired classification level, availability, and geographic coverage. Timeliness refers to an asset's turnaround time to meet a given request. Classification level refers to the asset's classification capabilities, i.e., *detection* (find enemy units), *classification* (discriminate enemy units, tanks vs. APCs), and *identification* (T-80 tanks). Availability refers to the period in which the asset is accessible.

III. Performance Demonstration

To assess feasibility and demonstrate our IFAMP approach, we have developed a battlefield scenario covering a 24-hour period in which friendly ground forces, a mechanized infantry brigade, defend against a Soviet-like adversary consisting of a motorized rifle division (MRD). A terrain analysis/IPB stage results in a constrained set of possible enemy objectives, courses of action, and avenues of approach. Friendly intelligence-gathering assets inlcude ground-based reconnaissance units, electronic support measures (ESM) equipment (TRQ-32), reconnaissance aircraft (Mohawk), and the multi-mode radar capabilities of the airborne Joint STARS platform.

The level one fusion simulation consists of: a) a main window (see Figure 4) which displays the evolution of the battle; and b) a track database window that displays the current associations of individual sensor reports to tracks.

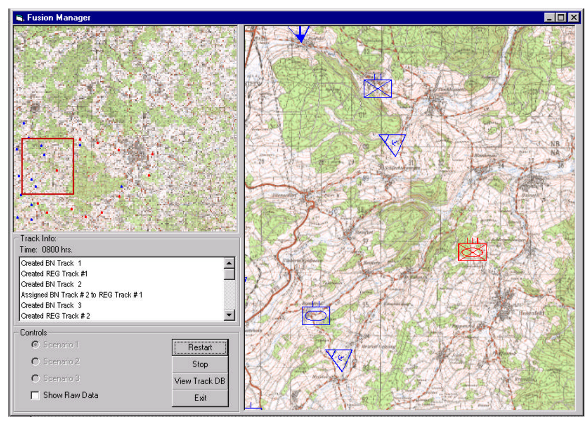

Figure 4: IFAMP Level One Main Screen

We tested three variations of our main scenario. The overall qualitative conclusions derived from these simulations can be summarized by the following [7]: a) fuzzy logic provides a natural human-like reasoning mechanism for handling uncertainty; and b) the IFAMP level one fusion manager was able to discriminate multi-level unit types, perform track generation and maintenance, and aggregate lower echelon units into higher echelons

In our scenario, the fusion manager was able to discriminate battalion and regimental units. Gating and assignment control ensured reasonable track maintenance. Finally, the fusion manager could aggregate lower units into higher echelon units, e.g. battalion units into regiments.

The level two demonstration entailed the sequential posting of sensor/INTEL evidence to the BN model of Figure 3. The results showed that the model was able to maintain correct hypotheses regarding the higher-level (hidden) variables, e.g., enemy objective, for a range of scenarios. These results demonstrate the feasibility of the belief network framework for modeling causal battlefield relationships. A single, integrated model combines variables of differing scales and allows probabilistic inferencing of higher-level, hidden variables, e.g., enemy objective, intent, etc., based on evidence concerning lower-level variables, e.g., enemy unit locations, types, movements, etc. The belief network formalism simultaneously allows a consistent means for combining prior information, e.g., derived from terrain analysis/IPB, weather reports, and enemy doctrine and order of battle information, with evidence gathered in real-time from sensor assets and units deployed in the battlespace.

The level four demonstration tested the fuzzy rulebase for collection management. The system displayed basic capabilities for combining hypothesized unit locations and intents with friendly intelligence requirements and asset capabilities to produce asset requests sufficient to acquire the needed intelligence. The fuzzy expert system rulebase contains over 100 rules and assumes an asset suite consisting of the JSTARS platform, including both moving target indicator (MTI) radar and imaging synthetic aperture radar (SAR), and a generic electronic support measures (ESM) platform. The rulebase uses several fuzzy variables including sensor resolution, timeliness, availability, area coverage, and a user-specified information criticality level.

IV. CONCLUSION

We designed and developed a limited-scope prototype intelligent fusion and asset management system, incorporating three modules: a fuzzy logic-based level one fusion module for low-level fusion management; a belief network-based level two situation assessment module for generating probabilistic hypotheses for high-level situational state descriptors; and a fuzzy logic-based level four collection management system for mapping information requirements and state information into asset requests. Basic system feasibility was shown by exercising the system using variations of the specified tactical battlefield scenario.

V. FUTURE WORK

Future work will focus on: a) augmenting the model with the ability to represent multi-scale enemy disposition and composition information and to identify high-level enemy activities and significant events to assist in overall situation assessment; b) incorporating temporal aspects of battlefield information processing to enhance current situation assessment and predict future enemy evolutions; and c) incorporating select architecture components within fielded C^4I-related information processing systems to enhance overall data fusion, situation assessment, and collection management.

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