Information Fusion for Common Operational Understanding

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ABSTRACT

This paper discusses Hybrid Nonmonotonic Reasoning techniques and architectures for information fusion and Common Operational Understanding. We give an example of an application developed for Incident Commanders that uses these techniques along with specialized visualizations to give commanders understanding of their situation as well as course of action suggestions.

1.0 NONMONOTONIC REASONING AND HYBRID ALGORITHMS

1.1 Nonmonotonic Reasoning Techniques

Nonmonotonic Reasoning is a method of mimicking human thought patterns, like neural nets but with one important difference. It accounts for assumptions being made by listing those assumptions inside the rules. A **Nonmonotonic Rule** of inference takes the form $\mathbf{r = a_1, \dots , a_n : b_1, \dots , b_m / \varphi}$ read as "if $a_1, \dots , a_n$ are known to be true and $b_1, \dots , b_m$ are not known to be true then conclude φ."

Using this format, Nonmonotonic reasoning can take advantage of assumptions made during the decision-making process, and even call them to the attention of the user. Nonmonotonic techniques also allow us to reason with conflicting and missing information.

1.2 Hybrid Nonmonotonic Approaches

Each available AI method brings with it certain advantages. Blending two or more approaches has been shown to strengthen the overall method and bring to the table the best abilities of each method. Each technique allows us to assist, analyze, or mimic human reasoning:

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Table 1: Blended Approaches

Approach	Benefits
Probability with nonmonotonic reasoning	This blending returns the probable decision and gives information about why that decision was made, how to encourage that decision and how to counteract a decision in the opposite direction. This method involves attaching statistical values to the elements of nonmonotonic formulas describing the decision.
Neural networks with nonmonotonic reasoning	This method returns a justification along with the answer. Handles conflicting information and greater uncertainty easily. This method is known as “formula augmented networks”, and involves attaching nonmonotonic formulas to the nodes of a traditional neural network.
Custom Algorithms	These approaches can be used layer by layer in the decision making process. Customizing each layer to the least complex method needed may reduce computation time and make the overall tool more efficient.

These techniques advance the ability of computers to “think” and to help the user to think. More advanced Computer Technology has allowed the implementation of all of these techniques to be computationally feasible.

1.3 How Data Becomes Action

To take data and extract from it an understanding of the best actions to take next requires a process of assimilating the data to produce information, situation awareness and finally optimal response. These levels of assimilation relate to the level of decision making that is needed:

- **Data** – Having data in this scenario means having the outputs of various sensors, the observations of various witnesses, blueprints, schematics, etc.
- **Information** – Information in this scenario includes such statements as “Ambulance 324 is on location”, “Event Type is Nuclear”, etc.
- **Knowledge – Manifested as Situation Awareness** – Here, knowledge incorporates the information gained in the last stage with temporal information to create a three-dimensional picture in the mind of the user.
- **Understanding – Manifested as Optimal Response** – Understanding, in this scenario, means knowing what to do next and why.

2.0 THE ADVANCED INCIDENT RESPONSE APPLICATION AND COMMON OPERATIONAL UNDERSTANDING

Given data and information, decision support tools can be designed to assist the progression of a decision. There are many approaches to creating decision support tools, depending on the type of data to be used, and the level of decision to be made.

A simplified application of these techniques was created as an internal research and development project by the Decision Support and Analysis Team at SAIC. This application, called the Advanced Incident Response System (AIR) is intended to aid Incident Commanders during Homeland Security Events. The AIR system takes information input from multiple disparate sources, translates it into a DAML+OIL Schema and runs Nonmonotonic Algorithms on the information in near-real time. This application then provides commanders with a 3D visualization that conveys **understanding** of the situation along with a window that suggests courses of action, justifies those courses of action and gives the commander the ability to control the event with absolute confidence and complete understanding. DAML+OIL was chosen as a convenient and appropriate storage and retrieval structure. The Nonmonotonic Rules make automated decisions about the best courses of action. These actions are then displayed as advice to the commander.

Figure 1: CONOPS and Screen Shot of the AIR System.

The vision behind this project is one of a Common Operational Understanding where various sources of information are collected and brought into central repositories. Various people tie into the repositories through web-based services to use tools designed precisely for their job that allow them to understand what THEY need to understand. Decision support tools can range from near total automation to near total collaboration. To mitigate bandwidth and computability issues, algorithms (seen in red in Figure 2) and filtering (in blue) are distributed across the system. This also makes the system modular and thus able to integrate with existing and developing systems.

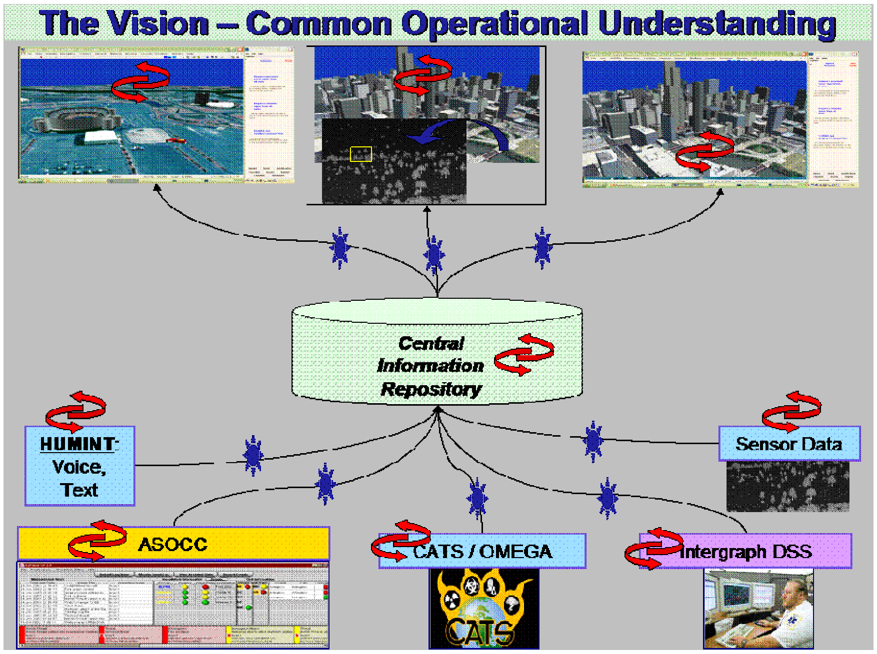

Figure 2: The Common Operational Understanding Concept.

3.0 REFERENCES

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