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Knowledge Management for Distributed Tracking and the Next-Generation Command and Control

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Abstract

Knowledge Management for Distributed-Tracking (KMDT) is an ongoing research and development project to to improve military-information functions in the battle space, such as command, control, and decision support. It features a scenario that shows how knowledge-management technologies, such as ontologies and intelligent agents can improve battle-space awareness and the decision-making process in command centers with respect to distributed tracking and threat identification of platforms. Cross lines of bearings using heterogeneous sensor data and other information from multiple platforms in the battle space can reduce the uncertainty in platform detection, localization, classification and identification. The paper describes metrics for ontology development and agent performance.

1. Introduction

The goal of KMDT is to explore methods to implement FORCE-net, which is the U.S. Navy's operational construct and architectural framework for naval warfare in the information age [7]. The goal of FORCEnet is to integrate warriors, sensors, command and control, platforms, and weapons into a networked, distributed combat force [7]. KMDT assembles technologies to assess the information content exchanged in the battle space and to develop enhanced awareness. This will enable analysts, operators, and warriors alike to reduce uncertainty in command and control by better organizing and using the data collected from existing sensors.

New approaches to tracking, command and control are explored using knowledge-management technologies such as sensor ontologies [4], intelligent agents [3], ontology-development metrics, and agent-based metrics. During their task execution, intelligent agents can access sensor ontology to obtain information relevant to current sensor-data requirements. Analysis and Monte Carlo simulation can assess information flows in the battle space and the effect of the information on target detection, tracking and the ability of sensors to align to a common frame of reference in time and in space. Not only can multiple homogeneous sensors track individual platforms, but also multiple sensor types can participate in a level-one data fusion task [10] (e.g. detection, localization, classification, and identification) coordinated by intelligent agents, thus reducing uncertainty in command and intelligence centers. According to the program plan, agents retrieve data needed for distributed heterogeneous level-one data fusion using Lines Of Bearing (LOBs). With agent-based metrics, the effectiveness of agents can be assessed as they perform tasks in the simulated environment. Another key component is the integrated sensor ontology and the metrics for its development.

2. Motivation for KMDT

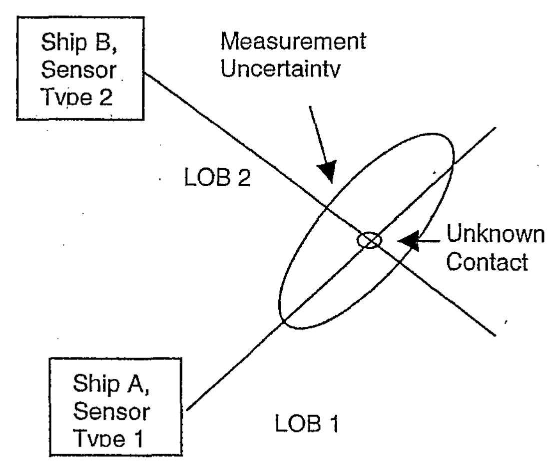

Fig. 1. Platform detection geometry showing lines of bearing from ships A and B detecting an unknown contact with heterogeneous sensor types 1 and 2.

Sensors deployed on a single platform, such as a ship, can provide LOB information on unknown contacts and potential targets in their vicinity (Fig. 1). Cross LOB targeting (i.e. using data from two ships) either is not done or it is limited to homogeneous sensor systems (e.g. all acoustic sensors). Thus, information about multiple LOBs that could localize the position of a target often does not reach a command center in time to support the decision process. Sometimes operators do not know what to do with new data that are not correlated with existing data. Such data fail to reach the threshold of information to support decision confidence.

Commanders and sensor operators often are overloaded with tasks and uncorrelated information. Conversely, they sometimes have difficulty in obtaining the correct information they need to make timely decisions, so decisions are made using uncertain information. Local data are lost because they cannot be correlated with data from remote sensors and observations in a timely manner. Data from remote sensors are either not transmitted efficiently or no payoff is perceived for their propagation. To respond rapidly, the commander may need the data that neither are available locally nor transmitted from remote sensors.

3. Next-Generation Command & Control

This section describes an example scenario to show how the capabilities under development in KMDT will be used in future command-and-control operations. A commander in the Combat Information Center (CIC) on board northbound ship A (Fig. 1) receives a sensor report of a contact detected at a bearing of 045 degrees. The unknown contact cannot be classified or localized with only the information in the report. An operator supporting the commander tasks an intelligent agent to search the network for friendly platforms in the battle space that also have detected the unknown contact. (See, for example [8]).

A calculation is performed in the agent-deployment software to identify the search spaces based on the geometry of ship A and the contact. The agent finds the sensor-ontology web site to correlate the known capabilities of ship B with the kinds of information that could be combined with the sensor of Ship A to classify the unknown contact. The agent searches the web portal for Ship B to find LOB, acoustic data, and the date-time group of the sensor measurements on Ship B with which the contact was detected. The agent discovers that Ship B has detected the contact.

The agent issues an alert to the operator on ship A, that a report from Ship B is available. The information retrieved about the unknown contact enables the operator on Ship A to observe the LOBs and the related data. The operator fuses this information with the original sensor data from ship A and recommends a classification (hostile, friendly or neutral) of the unknown contact to the commander.

4. Background and Method

KMDT is focused on knowledge-management technologies such as sensor ontologies, and intelligent agents to upgrade command and intelligence centers to provide the capabilities described in the above scenario. The modeling-and-simulation effort is conducted to demonstrate the feasibility of the technology. During the simulation, agents access web pages that represent information flowing to and from various platforms available in the battle space, with pages for the data from each sensor on web portals for each friendly platform or sensor station.

The metrics focus on the content of the messages and what they contribute to command-center decisions as opposed to the speed of data flow through the network. These improvements can be demonstrated through the application of heterogeneous sensor data from multiple platforms to distributed tracking of unknown contacts. Modeling and simulation of information flow in the battle space is a relatively inexpensive way to depict both baseline use and more efficient future uses of existing sensors and their data output, without costly field trials.

Distributed localization and tracking can be demonstrated by cross fixing of multiple LOBs obtained from heterogeneous (e.g. acoustic, magnetic) sensor data. Cross LOBs from homogeneous sensor data are used in ship and aircraft navigation to determine position. However, the use of heterogeneous sensor data to determine the position, classification and identity of unknown contacts and potential targets in the battle space has not been utilized effectively.

In the KMDT scenario, sensor data are transmitted in messages available over a network. Multiple sensor ontologies combined in a single format can increase understanding of message content and provide agents reference material for selecting the right platforms from which to retrieve data. Intelligent agents can access the sensor ontology, obtain tasking from command centers, and provide alerts when critical thresholds are crossed. The agents can relieve overloaded operators by retrieving more complete information from existing heterogeneous sources. The availability in the battle space of this additional information is aimed at reducing tracking uncertainty and targeting errors.

Data from sensors include LOB, range, spatial velocity from Doppler radar, acceleration from several position points, pulse repetition rate, peak, frequency, etc. Use of sensor data can be prioritizeds. For example, the order of usage priority could be as follow. 1. Own platform – passive sensors, 2. Own platform – active sensors, 3. Friendly platform – passive sensors, and 4. Friendly platform – active sensors. Similarly, data selected for correlation can be prioritized as follows. First correlate data from similar sensor types (e.g. all acoustic) then consider data from dissimilar sensors (e.g. acoustic, electro-optic) and sources.

5. Metrics for Ontology Development

Ontology metrics can be used in a variety of integration applications. For example, they can be applied to a common ontology reference prior to processing and integration, or they can be applied to schema matching in eXtensible Markup Language (XML) integration [9].

With respect to general statistics, the development of an integrated sensor ontology can be tracked with simple metrics. One metric is the number of initial concepts input into Protégé/OWL. Some other metrics associated with concept acquisition are 1) the number of added ontologies; 2) the total number of concepts in the proposed ontology prior to integration; and 3) the number remaining in the integrated ontology, assuming all non-redundant concepts are retained. Metrics associated with ontology integration are 1) the number of redundant concepts deleted because they were not needed; 2) the number of concepts added to fill gaps that became apparent during the integration process; and 3) the number of remaining concepts in the final integrated ontology. Still another dimension of metrics is to count the number of levels in the ontology hierarchy and the classes or instances residing at each level.

In addition to the metrics described above, a method is needed to characterize, estimate, and eventually measure disjunction in information systems, and particularly in ontology-integration tasks. Class cohesion has been studied in object-oriented systems and metrics have been developed [1], [2]. Ontologies are hierarchical structures similar to structures in object-oriented systems. The cohesion metrics measure cohesion between members of the same class whereas the individual disjunction metric described below tracks the placement of the same concept in related ontologies.

A disjunction metric proposed here specifies the degree of disjunction in ontologies by identifying the level of generality or specificity at which a concept occurs in one ontology, compared to the level of occurrence in another ontology. The disjunction metric is useful in an ontology-integration application when comparing the value added of various ontologies that were developed separately from different sources.

To apply the metric, Dj in equation (1) below, all levels in the hierarchy of concepts in each ontology must be labeled with 1 representing the most specific instances, and higher numbers representing upper-level ontologies.

(1) $Dj\ (O_1(c_i), O_2(c_k) \ldots O_p(c_m)) = (i, k, \ldots m)$

Equation (1) defines the disjunction metric, Dj as a set of levels at which a common concept occurs in a collection of ontologies. In (1), "c" is a concept that occurs at level "i" in ontology 1, which is called "O_1." The same concept, c, occurs in ontology 2, called "O_2," at level "k." Concept "c" also occurs at some arbitrary level "m" in ontology p, called "O_p." The "..." in (1) means that the number of ontologies that can be compared in this manner is not restriction. For example, equation (2) illustrates the disjunction metric in an hypothetical case of two ontologies, 1 and 2. If common concept "c" found at level 3 in ontology 1, were also found at level 5, in ontology 2, one could write the disjunction metric as follows:

(2) $Dj\ (O_1(c_3), O_2(c_5)) = (3, 5)$

Equation (1) is meant to express disjunction for a single concept. However, many concepts are found in any meaningful ontology. To measure and compare the characteristics of various ontologies, an overall disjunction metric is needed to include multiple concepts, not just one. To calculate an overall estimate of disjunction, each index (i, k, ... m) can be averaged separately across a group of concepts that occur in the same ontology. An overall disjunction metric for two ontologies can be calculated using average values of the levels for a collection of "n" concepts:

(3) $< Dj\ (O_1, O_2) > = (\Sigma\, i/n,\ \Sigma\, k/n)$

where the instances of i and k are the values of each pair of levels found for each common concept. To use this metric, the ontology that pertains to each knowledge base (KB) must be sufficiently complete to locate the corresponding levels in the ontologies. Another way to conceptualize the disjunction metric in (2) is to consider that a concept at level 3 of ontology, O_1, is equivalent to a corresponding concept at level 5 of ontology, O_2. The usefulness of disjunction metrics will increase when a more standardized way to organize an ontology is developed. Dj and <Dj> will depend not only on concepts in common but also on the structure of the various ontologies.

For example, consider the calculation of an overall disjunction metric so that "n" in (3) is 3:

(4) $Dj\,(O_1(c_3), O_2(c_5)) = (3, 5)$

(5) $Dj\,(O_1(c_2), O_2(c_4)) = (2, 4)$

(6) $Dj\,(O_1(c_1), O_2(c_3)) = (1, 3)$

(7) $< Dj\,(O_1, O_2) > = ((3+2+1)/3,\ (5+4+3)/3)$

(8) $< Dj\,(O_1, O_2) > = (2, 4)$

An assumption in the above equations is that the each equation addresses a distinct concept. If the overall disjunction metrics are low (e.g. (1,2)) it indicates that the ontologies have common concepts at the same level of granularity, which is important to know for integration purposes. It is also a signal to look for duplicate concepts and delete any redundant information. If the metrics are high, (e.g. 5,7) it implies that: 1) The ontologies proposed for integration may contain concepts that have been overlooked and therefore are missing in the integrated ontology, or 2) The proposed addition to the ontology does not relate to the main topic. Dj will depend on the structure of the various ontologies and therefore can provide at a glance some insight regarding the relative ontology hierarchies. Low numbers for very general concepts, such as 1 or 2, indicate a very flat ontology whereas higher numbers, such as the ones in (4), indicate more levels of specialization/generalization.

6. Intelligent-Agent Performance Metrics

Metrics and statistics can be used to evaluate and document the behavior of agents in simulations. The following metrics can track the activity of the agents:
1. Number of web portals accessed to search for the desired data,
2. Number of relevant data retrieved from each site,
3. Number of successful data retrievals vs. the number of agent deployments on an individual-agent basis,
4. Same statistics as in item 3 above, but summarized to include all agents deployed during a given time period in the simulation.

The following metrics can help analyze agent errors:
1. Number of irrelevant data retrieved from each site,
2. Number of incorrect data retrieved from each site,
3. Number of correct data that the agents could have retrieved but did not (a manual analysis that involves keeping track of all possible alternatives in the simulation and comparing the results to the alternatives.)

The degree of uncertainty in the location of an unknown platform or target depends on many factors, including the correctness of the retrieved sensor data and the angle between the lines of bearing. Thus, agent performance can be monitored by calculating the angle between the lines of bearing for each successful data retrieval that results in a correctly identified cross line of bearing. Equation 10 gives a formula for E, the error that results from the departure from a right angle between two lines of bearing situated at angle, ϕ. This metric can be used to compare data retrievals among the various agents so that the line of bearing with the lowest value of E can be selected in cases where the agents retrieve multiple cross lines of bearing.

(10) $E = 1 - |\sin(\phi)|$

One way to collect the data on agent errors is to save the history of the simulation scenario in a log file for later analysis. Using these metrics, the agent algorithm for platform selection can be tested as well as the correctness of the data retrieved.

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