Adaptive All-Source Data Fusion System Development

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ABSTRACT

The sensor management is a key element of adaptive all-source data fusion and it must operate so that full advantage is taken of the strengths of each sensor. It is accomplished by (1) coordinating the data collection processes of disparate sensors to support the overall goal (assessment of the environment: displays of tracking kinematics and targets IDs), (2) properly selecting the use of active and passive sensors (emission control), and (3) improving the response time of a sensor by cueing it with information derived from another sensor.

In the adaptive all-source data fusion, the sensor management will play a role as a feedback link connecting the automated situation assessment function and the sensors. We will address how the sensor management can be accomplished and where the sensor management should reside in complex sensor system. There are 3 aspects to the question: (1) architectures, (2) scheduling techniques, and (3) decision-making techniques. The presentation will focus on the development of decision-making techniques (advanced computing techniques) for performing the sensor management. The advanced computing techniques will be based on distinctively different theoretical bases, for example, statistical approach, artificial intelligence (expert system), neural networks, and fuzzy logic. These techniques are discussed in the context of the adaptive all-source data fusion software development.

INTRODUCTION

Sensor management is the study of methods to optimize the measurement process in a target tracking and identification system [6]. Sensor management attempts to achieve overall system optimization by checking target tracking and identification performance relative to certain criteria and generating a feedback control signal to the sensors.

In the adaptive all-source data fusion, the sensor management will play a role as a feedback link connecting the automated situation assessment function and the participating sensors. The feedback is provided to improve the data collection process relative to the following two goals: (1) tactically efficient use of resources, and (2) collection of missing information.

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reside in complex sensor system. There are 3 aspects to this question of how and where:

1. Architecture

This aspect deals with where sensor management fits into the overall sensor, target tracking and identification system. The choices for sensor management location are several: (i) within the sensor itself, (ii) within the tracking system (for multisensor fusion systems), (iii) within fire control system, (iv) within the mission control computer, and (v) distributed among some subset of these.

2. Scheduling Techniques

Sensor management's ultimate role is to task sensors to perform actions. This aspect deals with whether the sensor manager should simply issue commands or build a schedule of activity for each sensor. When building a schedule, how exactly, should the time line is filled with the important task?

3. Decision-Making Techniques

This aspect deals with the process by which the system is to decide which sensor tasks need to be performed. We will consider the following decision-making approaches based on distinctively different theoretical basis: (i) statistical approach, (ii) artificial intelligence (expert system), (iii) neural networks, and (iv) fuzzy logic. The applications of these techniques are dependent on the type of data and information derived from the participating sensors.

As shown in Figure 1, the sensor management system architecture will be partitioned into two parts [6]:

(1) One centrally located macro sensor management subsystem.
(2) Several sensors located micro sensor management subsystems.

In the sections that follow, we will discuss and analyze 4 different computing techniques for achieving adaptive all-source data fusion in the context of this sensor management subsystem architecture [1-7].

TECHNICAL DISCUSSION

The decision about the cooperative reinforcement for sensor fusion and synergism will be made at the central level. Both the micro and macro sensor management subsystems will play a role in emission control: the macro subsystem will decide how to coordinate multiple sensors to minimize active emission requests; and the micro subsystem will attempt to satisfy macro requests without violating a prescribed degree of overtness. The decision making about how sensors will cue each other will be arbitrated at the central level.

Situation assessment will be formed at the central level and, therefore, decisions about how this assessment affects sensor tasking will be done at this level. Similarly, the decisions about how the missing information is collected will be done at the central level.
The operator requests will be carried out via the centrally located macro sensor management subsystem. High level commands will be generated by the macro sensor management subsystem to control the individual participating sensor management subsystems. These subsystems will have a shared access to the central track files (or sensor track files in a single sensor system). The macro management subsystem will need only access the data currently relevant to its decision making. The information will be used to evaluate which tracks need attention and where their location is.

This presentation will focus on the development of algorithms for (1) multi-sensor data fusion, (2) situation assessment, and (3) intelligent decision-making in the macro sensor management subsystem.

The following advanced computing techniques have been considered for developing the algorithms:
(1) Artificial Intelligence (AI)
(2) Neural Networks
(3) Fuzzy Logic

1. Artificial Intelligence

The knowledge-based approach is an artificial intelligence (expert system) approach that may be applied to solve adaptive multisensor fusion problem. The fusion of data from a host of sensors (placed at various locations in order to maintain a master track file, in real-time, for all the targets) is an extremely complex process which requires a high level of expertise to maintain accurate tracking of multiple targets. The intent of the knowledge-based the approach is
to reduce computation time for fusion of sensor data to accurately maintain a master track file, to correctly identify the targets, to provide the battle commanders with timely decisions in a stressful war time situation and to resolve conflicts in making decisions.

We will consider the data fusion expert system as a multi-layered type of expert system. The multi-layered expert system will involve processing of symbolic and numeric information related to the adaptive data fusion environment [5]. The multilayered data fusion expert system will consist of four components: (1) Control System, (2) Knowledge Base, (3) Global Database, and (4) Correlation/Fusion Processor [1, 3].

2. Neural Networks

Neural Networks are not suited for all tasks, but for evaluation and association problems they are the method of choice. Target recognition and classification are of the association type, where a set of inputs is associated with certain outputs. Thus a neural network is a formidable solution to the problem at hand.

Speed is an advantage gained when using neural networks. The processing elements or artificial neurons of neural network are distributed in a parallel fashion. This greatly enhances the computing speed of the networks. Once the network’s structure is built, it is trained with certain training facts. Because of the speed of the resulting trained network, it can be used for predicting outcomes in real-time. This makes it especially appealing to target recognition and classification.

The neural network system is not programmed, they are taught. Therefore, patterns are response rules and are generated internally by correlating inputs and outputs. Learning rules include pattern and response rules, which are generated internally by correlating inputs and outputs. We will select an appropriate learning rule (for example, backpropagation learning rule) and associated network architecture to perform the adaptive all-source data fusion [2, 5].

3. Fuzzy Logic

Both the fuzzy logic and neural networks are model independent. That is, these approaches are applicable when a mathematical model of the process does not complete or it is too complex to be evaluated fast enough for real-time operation. Both the fuzzy logic and neural networks require input and output variables of the process. The input/output variables constitute training sets. Training sets are required to design the fuzzy or neural network systems.

Fuzzy logic is the machinery for dealing with imprecision and uncertainty. System’s variables are described in terms of the fuzzy sets. The crux of any fuzzy model is such that the essential relationships between system's variables are described in term of these fuzzy sets rather than numerical quantities [4, 5, and 7]. We will use fuzzy logic for situation assessment and making intelligent decisions.

CONCLUSION

We will use the simulation programs to evaluate the performance of the adaptive all-source data fusion algorithms, and
use several data sets for testing the performance of the AI, neural network, and fuzzy logic systems.

REFERENCES


