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Multisensor Fusion for Decision-based Control Cues

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ABSTRACT

Data acquired from multiple sensors provides a means for defining a knowledge base and a current situation scenario. The data is accepted and integrated as intelligence with the use of signal- and symbol-level fusion to translate the raw data into intelligence information that can be used to baseline the knowledge of a control system.

An application of this technique is applied to a robotic inspection and dismantlement system. This system is used to dismantle materials in a potentially hazardous environment that involves nuclear waste. The objective is to gather information about the environment using a suite of sensors to include range, electro-optical and proximity sensors to develop a current situation scenario and initiate cues to the control system.

By including evidential reasoning in the fusion process, all of the data that is gathered can be used to build the knowledge base where lower belief factors are attributed to things with significant uncertainty. Logical inferences are also incorporated to develop certainty measures and truth values. The results suggest an approach to multisensor fusion for decision-based control using a knowledge base and current situation scenario framework.

Keywords: Information fusion, knowledge base, situation analysis, sensing

1. INTRODUCTION

A defined set of mechanical tasks is required to refine a workspace housed within a potentially hazardous environment. The scenario contains a robotic system and power tools. Basic functions such as position and orientation, location of the workspace in global coordinates, toolrack, and the work area specification are the required functions for navigating through the workspace. The objective of the robotic task is to evaluate the current situation of the workspace and then to proceed with the dismantlement exercise unless the decision cues suggest otherwise[1].

A sensor module that is attachable to a robot manipulator is proposed. The module collects data relative to the surroundings and assimilates it into intelligence. Together, sensing and intelligence combined with control and manipulation, form a system that provides a basis for conducting industrial tasks. Figures 1 and 2 describe the specifications of the assembly that is to be dismantled.

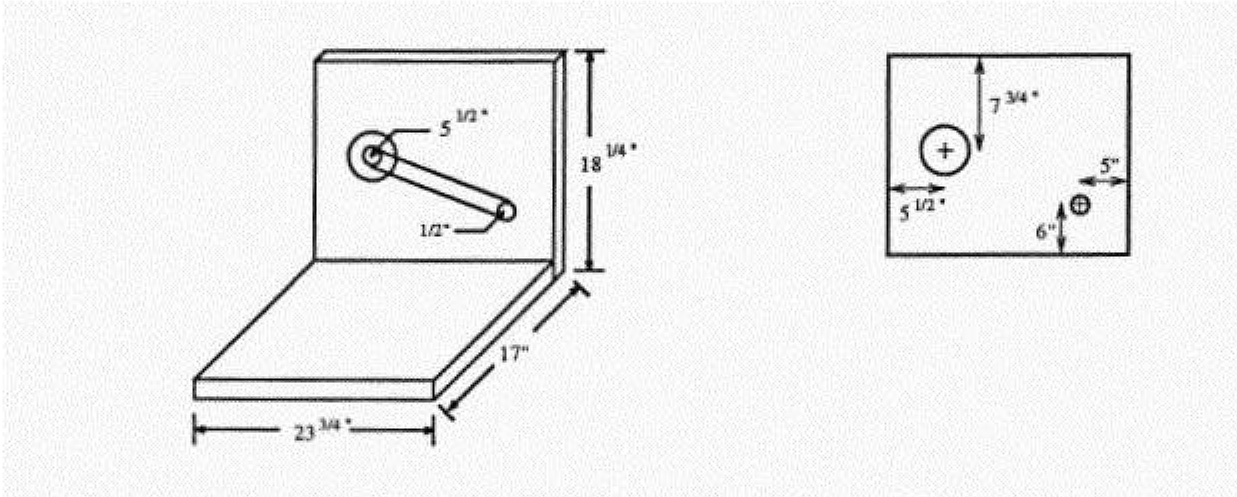

Figure 1. Specifications for the dismantlement activity

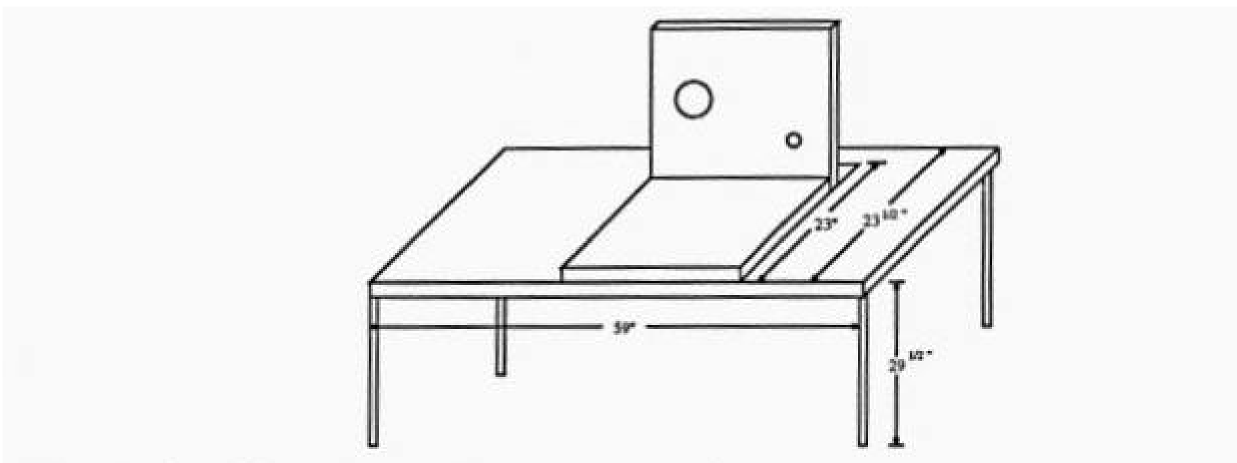

Figure 2. External specifications.

The intent is to suggest an alternative platform from the Robotics Research RRC2107 robot arm [1] due to the impractical constraints of this particular stationary robot arm. In this way, a robot manipulator combined with a mobile base platform allows for ease of mobility from one scenario to the next.

The details described in this paper suggest one method for refining the initial attempt to address the dismantlement problem. Instead of focusing on the data acquisition scenario, the goal is to provide an information fusion framework to bound some of the associated challenges with decision-based control.

2. SENSING

The sensing module is required to be small in size and weight due to the restrictions of the robot arm. The hosted sensors include: CCD camera, laser range finder, and a proximity sensor. The required tasks that are affiliated with the dismantlement activity include:

1. Locating the position and orientation of a tool rack and its workspace
2. Determining the distance measures and orientation of the assembly
3. Acquiring sufficient data from the workspace to maneuver through the workspace
4. Providing navigational information throughout the workspace
5. Performing the industrial dismantlement tasks with the associated power tools

This list is not inclusive, but provides a basic guideline for the expectation of the sensor module. Figure 3 demonstrates the data acquisition results from the B/W CCD camera in a laboratory setting. Application constraints are discussed in the analysis found in Section 4. The discussion of a relational database and real-time data management system are also addressed in the analysis.

The dismantlement activity also requires the use of power tools for pipe cutting and draining. The use of a drill and a saw are facilitated by incorporating these utilities onto the toolrack where the robot arm has the ability to interchange its main function. It is assumed that the power constraints of the tools are addressed by means of battery operation to eliminate the restrictions associated with electrical power cords and entanglement. The toolrack is depicted in Figure 4.

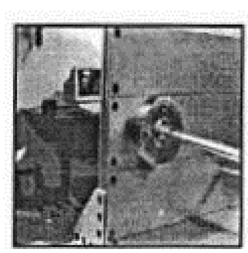

Figure 3. Intensity image from the CCD camera of the laboratory mockup

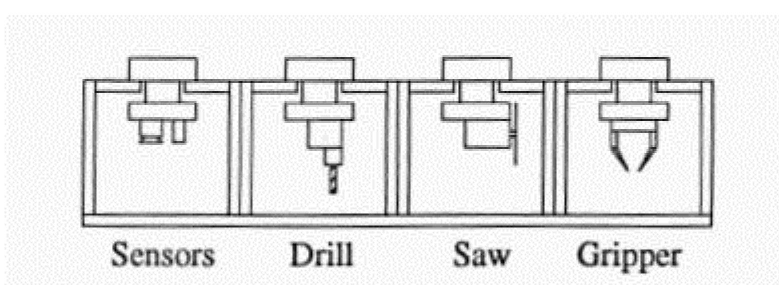

Figure 4. Interchangeable modules from the toolrack for dismantlement

3. FUSION

Better accuracy is a desired benefit that results from using multiple sensors for scene analysis. Fusing the redundant observations usually generates an improved current situation snapshot. Identity estimation requires decision-based methods whereas interpreting a plan of action requires a knowledge base and rule-based reasoning.

Raw data can be combined easily if the redundant sensor information measures the same quantity. For sensors that do not measure homogeneous quantities, fusion at a feature level or decision level is required. Feature level fusion involves the use of feature or state vectors and decision level fusion uses Dempster-Shafer or classical inference methods. The fundamental issues [9] that impact a data fusion system are:

- Techniques and algorithms applied to a problem
- System architecture of the data fusion system
- Sensor information processing
- Achievable accuracy
- Optimization of the fusion process
- Data collection parameters
- Improvement with the initial system intelligence

Joint Directors of Laboratories (JDL) Process

According to Hall [9], the JDL Working Group has defined a conceptual model for data fusion. The model identifies a framework that specifies the major elements of a data fusion system. The elements of the data fusion system model are:

- Information sources: refers to all of the sensors included in a data fusion system
- Human Computer Interface (HCI): provides an interactive mechanism for user feedback and visualization
- Source preprocessing: refers to the signal processing and analysis functions associated with object detection
- Level 1 processing: denotes the conversion of sensor data into a reference frame
- Level 2 processing: describes the current relationship among objects for interpretation within a scene
- Level 3 processing: estimates the future from the current situation with a combative strategy
- Level 4 processing: monitors the fusion process and identifies the sensory information required for inferencing
- Data management: refers to data retrieval, storage, archive, compression, queries, and security

In our case, we shall follow the JDL model as it applies and assume values for the modules that are not germane to our experimental setup.

Object Detection and Identification

There are three kinds of fusion that are associated with object identification[10].

1. Data level fusion
2. Feature level fusion
3. Decision level fusion

Data level fusion deals with each sensor independently according to an identification scheme. Feature level fusion involves extracting feature vector information and creating a single feature vector for identifying an object. Decision level fusion deals with inference techniques such as the Dempster-Shafer method.

Knowledge-Based Data Fusion

To use a knowledge base[10], inference and evaluation are necessary. One implementation of the knowledge base is to automate the reasoning process. Search methods are available to parse the knowledge base and to identify the applicable rules. In order to facilitate this, the following items are necessary: assumptions, an approach to defining the reasoning process and a search scheme. The key issue associated with developing a knowledge-based system (KBS) is rule specification. For situation assessment, the details of Levels 2 and 3 are addressed through knowledge-based methods.

Signal-Level Fusion

Signal-level fusion [3] is most beneficial to real-time applications. The input is in the form of raw signals that provide low-level information. The information typically demonstrates the alignment and synchronization of the sensors. The most significant improvement that is associated with using signal-level fusion is to reduce the variance in expected values. Combining signals by modeling them as random variables (r.v.s) is a common way to define the data mathematically. The fusion process is then modeled as a procedure using r.v. estimation. One example of an application using this type of fusion is signal processing to perform image generation.

Symbol-Level Fusion

Symbol-level fusion represents high-level information where the symbol represents a decision. The symbol represents an input in the form of a decision where the fusion describes both a logical and a statistical inference. The most significant improvement with using symbol-level fusion is the increase in the truth values. This type of fusion can also be considered as decision fusion. Dempster-Shafer evidential reasoning is an extension of the Bayesian approach, where unknown values are defined as ignorance until support information arrives to overturn the opinion of the system. The uncertainty measures define how well the sensory information that has been captured from field sensors to match according to their independent levels. An example of this type of fusion is the construction of probabilities associated with object recognition.

Production Rules

Production rules are used symbolically to associate the attributes of target objects with sensory information to infer intelligence. A production rule-based system lends itself to a modular multisensor fusion configuration[3]. Two methods of inference are identified as: forward chaining inference and backward chaining inference. Forward chaining inference occurs when a conclusion is derived from a premise. Backward chaining inference occurs when a proposition is defined as a future goal. Uncertainty is defined within a system that uses production rules where a certainty factor (CF) is associated with each proposition and rule. The CF quantity measures the amount of belief or disbelief on a scale from

$$-1 \leq CF \geq 1 \tag{1}$$

where *CF = -1 denotes absolute disbelief*
CF = 1 denotes absolute belief
CF = 0 denotes lack of information

4. ANALYSIS

Conceptual Development

For our case, we define the general components of the system as high-level work centers:

- Perception Center
- Decision Center
- Action Center

Employing this approach ensures that the appropriate feedback information is forwarded from the Decision Center and the following actions can then be monitored by the Perception Center. This method is applied to the robotic control operations for dismantling an assembly that resides in a nuclear waste facility. The intent is to provide a transportable robot arm assembly that can be easily moved from one storage facility to another to conduct a consistent dismantlement task. The goal is to conduct scene identification and execute the dismantlement activity based on decision and control cues obtained from the sensor fusion module that is hosted in the Decision Center of the system. Figure 5 describes the system functionality between the work centers.

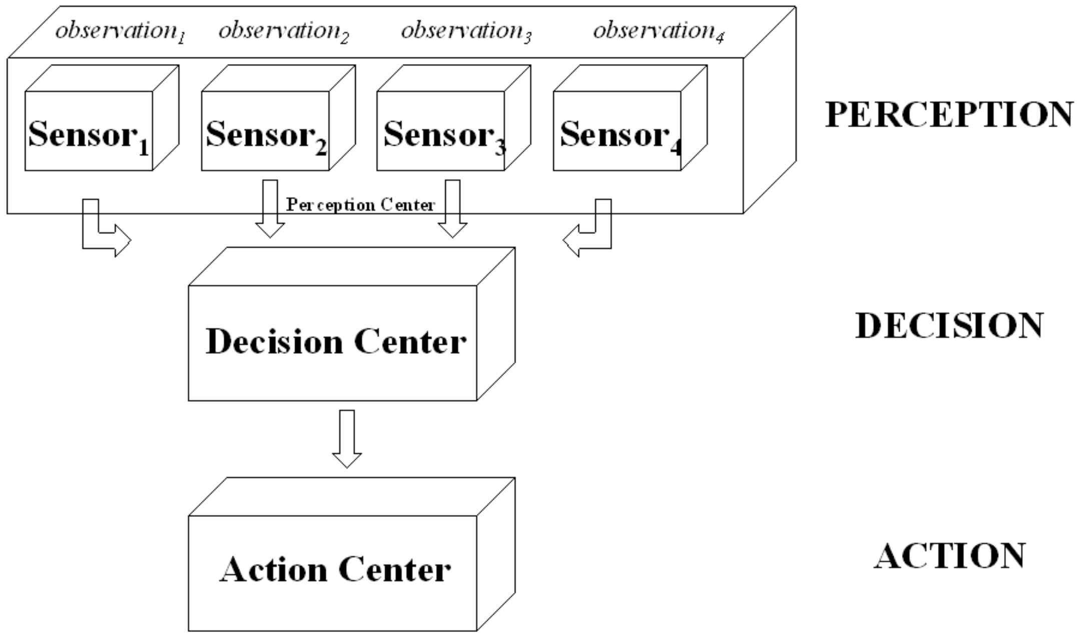

Figure 5. Work Center Configuration

Parallel Decision Fusion

Parallel decision fusion [11] is addressed by Viswanathan *et al.* to compare the differences between the approach of serial and parallel fusion. A major pitfall of the serial approach is the sensitivity to link failures. For this reason, the parallel decision fusion scheme is selected as the method to resolve multisensor fusion issues that face the dismantlement activity. Figure 5 describes the parallel decision fusion configuration with respect to the work centers. This configuration is elemental and can be extended to multiple instantiations to form an Enterprise Decision Center (EDC). In this discussion, we assume that each fundamental entity possesses an observation and influences the system positively or negatively.

Each sensor represents an on-board processor that is attached or controlled by the robotic manipulator. In the parallel decision fusion environment, the current situation scenario is treated as a sensor input with an appropriate weighting factor and likewise for the knowledge base. Figure 6 depicts the fusion framework.

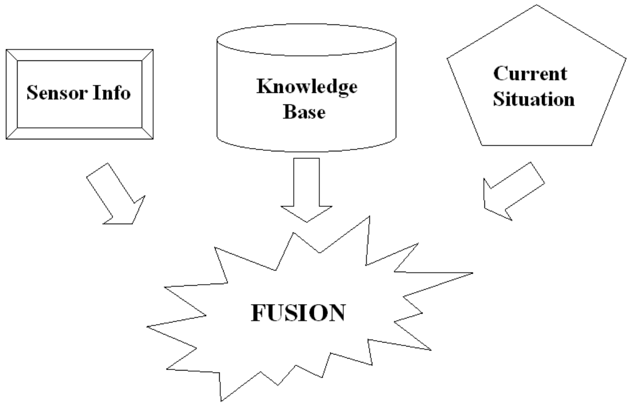

Figure 6. Fusion System Framework

The current situation scenario consists of the following possibilities:

- Control system at rest
- Control system is currently engaged in the dismantlement activity
- Control system is in an unknown state

The knowledge base is defined under the premise of a relational database. The fundamental components of the database include tables that are defined according to:

- Activity: refers to the series of steps to perform a defined task specific to the dismantlement task
- Environment: refers to the parameters associated with the workspace and activity domain
- Intelligence: refers to the information that is gathered from the sensors that is used to update the knowledge base

Each one of the tables is dereferenced according to the corresponding sensor information. That is, the sensor name is the primary key for each of the database tables. The Activity Table is defined according to a specific task and the required manipulation strategy for each dismantlement subtask. The Environment Table is dynamically updated according to the data and the information processed from the on-board sensors. The Intelligence Table is dynamically updated with new information that is ingested from the sensors relative to the environment and the action/reactions from the robotic manipulator.

Assumptions

Several assumptions are required in order to propose a dismantlement solution. They are namely:

1. *A priori* system knowledge forms the baseline of the knowledge base
2. A current situation status is always available
3. The priority information scheme drives the Action Center and remains constant in the following order:

    - Current situation status
    - Sensor status/feedback
    - Knowledge base information for each sensor

Fusion occurs to determine the course of action that the Action Center signals to the control system. The products from the information scheme are: sensor collection details, input to the current situation status, and a historical log of the knowledge base.

The limitations on the number of inputs gathered from the control system are:

- As many as five inputs (includes input from each of the three sensors, the current situation status, and the knowledge base)
- As few as two inputs (no input from any of the sensors, input from the current situation status and the knowledge base)

The formal steps to determine the decision cues include:

1. Determining the current situation scenario
2. Seeking guidance from the knowledge base
3. Engaging in a dismantlement task

We suggest combining the above inputs using the formalisms defined in evidential reasoning [3,12]. The main properties are summarized as follows:

The basic probability assignment is given as:

$$m_i: \{A_j \mid A_j \in 2^{\Theta}\} \rightarrow [0,1] \qquad (2)$$

subject to the conditions: $m_i(\emptyset) = 0$ and $\sum_{A_j \in 2^{\Theta}} m_i(A_j) = 1$

where m_i represents the probability mass associated with an entity
A_j represents a focal element
Θ represents the frame of discernment

The belief function is defined as:

$$bel_i(A) = \sum_{A_j \subseteq A} m_i(A_j) \qquad (3)$$

Dempster's rule of combination is defined as:

$$m_{ij}(A) = \sum_{x \cap y = A} \frac{m_i(x)\, m_j(y)}{1 - \sum_{x \cap y = \emptyset} m_i(x)\, m_j(y)} \qquad (4)$$

Using equations 2, 3, and 4 it is possible to define the probability masses for each event of a system. In so doing, the definition of the presence or non-presence of a signal or an object can be derived from the outcome with the largest mass. An extension to this approach is to deduce the outcome from multiple events using inference and production rules.

5. CONCLUSION

In this paper, we discuss how to address a dismantlement activity using multisensor fusion with a robotic control system. The intent is to suggest an alternative method for resolving multiple sources of information based on evidential reasoning. In particular, a framework including work centers is defined based on the JDL model and an implementation of a relational database for the knowledge base. The formal steps used to determine the control cues are based on a pre-defined hierarchical assumption that the current situation scenario is the initial catalyst.

6. ACKNOWLEDGEMENTS

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