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Contextual Merging of Uncertain Information for Better Informed Plan Selection in BDI Systems

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Abstract—Sensor information (e.g. temperature, voltage, etc.) obtained from heterogeneous sources in SCADA systems may be uncertain and incomplete, while sensors may be unreliable or conflicting. To address these issues we apply Dempster-Shafer (DS) theory to correctly model the information so that it can be merged in a consistent way. Unfortunately, existing merging operators are not suitable for every situation. We adapt a context-dependent strategy from possibility theory where we determine the context for when to merge using Dempster's rule of combination (i.e. for low conflicting information) and then resort to Dubois and Prade's disjunctive rule to merge information which is highly conflicting. We demonstrate the suitability of our approach with a scenario of a smart grid SCADA system modelled using the Belief-Desire-Intention (BDI) multi-agent framework. In particular, we use the notion of epistemic states to model combined uncertain sensor information for better informed selection of predefined plans.

Keywords—Dempster-Shafer theory; information fusion; context-dependent merging; BDI; uncertain beliefs.

I. INTRODUCTION

Supervisory control and data acquisition (SCADA) systems [1] monitor and control plant and equipment through gathering and analysing sensor data. In a power setting, sensors independently gather information about the environment such as temperature, voltage etc. However, this information may be uncertain or incomplete (e.g. due to noisy measurements etc.) while the sensors themselves may be unreliable or conflicting (e.g. due to malfunctions etc.). As such, an important challenge is how to accurately model and merge this information to ensure better informed decision making.

To address these issues, we apply Dempster-Shafer (DS) theory [5] by modelling imperfect sensor information as a mass function. Dempster's rule of combination [5] only allows us to merge mass functions obtained from reliable and independent sources. Thus if a sensor is unreliable, we discount the information and then treat it as fully reliable. The main issue is how to combine conflicting information as existing approaches are not suitable for every situation. We propose an approach to merge mass functions based on a context-dependent strategy from possibility theory [4]. We describe the *context* for when to use Dempster's rule and then resort to an alternative (i.e. Dubois and Prade's disjunctive rule [3]). Specifically, we

identify a partition of a set of mass functions using a conflict measure in DS theory. This ensures we find subsets with a low degree of conflict. Each element in this partition is called a largely partially maximal consistent subset (LPMCS) and identifies a subset to be merged using Dempster's rule. Once each LPMCS has been merged using Dempster's rule, we then resort to Dubois and Prade's rule to merge the highly conflicting information. Furthermore, we use heuristics on the quality and similarity of mass functions to ensure the LPMCSes are based on high quality information.

We then model complex SCADA systems using the Belief-Desire-Intention (BDI) multi-agent framework [2]. Our merging approach ensures the agent can reason about numerous sensors so they are well-informed about the current state of the world during plan selection. Additionally, we describe how we can model combined uncertain sensor information to aid decision making.

II. APPROACH

A. Modelling uncertain sensor information

Dempster-Shafer (DS) theory is capable of dealing with incomplete and uncertain information. The *frame of discernment* $\Omega = \{\omega_1, \dots, \omega_n\}$ is a set of possible hypotheses where one is true at a particular time. A mass function is a mapping $m : 2^\Omega \rightarrow [0, 1]$ that satisfies the conditions $m(\emptyset) = 0$ and $\sum_{A \subseteq \Omega} m(A) = 1$.

In a smart grid SCADA system, sensor information such as temperature and voltage is obtained from heterogeneous sources to represent the current state of the environment. As such, we may have $\Omega = \{normal, \neg normal\}$ to represent *normal* or *not normal* readings. Specifically, information from thermometers will map their value to a hypothesis where, for example, $normal = \{0, \dots, 40\}$ and $\neg normal = \{41, \dots, 80\}$. Once information has been obtained it will be modelled as mass functions. Since sources may be unreliable a discounting factor will be applied to derive mass functions that are treated as fully reliable.

Example 1. Consider two independent sources S_1 and S_2 located within the solar park that are 80% and 50% reliable, respectively. Information has been obtained such that $S_1: [25^\circ\text{C}, 30^\circ\text{C}]$ and $S_2: [50^\circ\text{C}, 55^\circ\text{C}]$. By modelling the (uncertain)

information as mass functions we have $m_1(\{normal\}) = 1$ and $m_2(\{\neg normal\}) = 1$. By applying their corresponding reliability factors we have:

$$m_1^{0.8}(\{normal\}) = 0.8, m_1^{0.8}(\{normal, \neg normal\}) = 0.2,$$

$$m_2^{0.5}(\{\neg normal\}) = 0.5, m_2^{0.5}(\{normal, \neg normal\}) = 0.5.$$

B. Context-dependent information fusion

Existing merging operators are often too restrictive (losing valuable information) or too permissive (resulting in ignorance). To exploit the benefits of different approaches, we propose an approach to merge mass functions based on a context-dependent strategy for merging information in possibility theory. In particular, we describe the *context* for when to use Dempster's rule and then resort to Dubois and Prade's rule. Dempster's *rule of combination* [5] is defined as:

$$(m_i \oplus m_j)(A) = \begin{cases} c \sum_{B \cap C = A} m_i(B)m_j(C), & \text{if } A \neq \emptyset, \\ 0, & \text{otherwise,} \end{cases} \quad (1)$$

with c a normalization constant, given by $c = 1/1-K(m_i, m_j)$ with $K(m_i, m_j) = \sum_{B \cap C = \emptyset} m_i(B)m_j(C)$. The effect of the normalization constant c , with $K(m_i, m_j)$ the degree of conflict between m_i and m_j , is to redistribute the mass value assigned to the empty set. This rule is well suited to merge mass functions with a low level of conflict. Note that, we use the $K(m_i, m_j)$ value to determine the context for using Dempster's rule. Dubois and Prade's *disjunctive consensus rule* [3] is defined as:

$$(m_i \otimes m_j)(A) = \sum_{B \cup C = A} m_i(B)m_j(C) \quad (2)$$

Notably, the disjunctive rule omits normalisation and incorporates all conflict. As such, this rule is suitable to merge mass functions with a high degree of conflict.

Our context-dependent merge identifies the highest quality source using measures for non-specificity and strife. The mass functions are merged with those that are closest (i.e. in agreement) based on a similarity (distance) measure so that we can identify a partition of a set of mass functions using a conflict measure in DS theory. This ensures we find subsets with a low degree of conflict which satisfy the context of merging mass functions using Dempster's rule. As such, an LPMCS is an element in this partition, based on high quality information. Once the set of LPMCSes are created and each LPMCS has been merged using Dempster's rule, we then merge the set of LPMCSes using Dubois and Prade's rule (see Fig. 1). This merging operator is sufficient for information that is highly conflicting and allows us to obtain a result for reasoning.

C. Handling uncertain beliefs in BDI

An epistemic state Φ_i represents an agent's uncertainty over a distinct subset of beliefs, e.g. probabilistic beliefs about an

$$\boxed{m_1 \oplus m_2 \oplus m_3} \otimes \boxed{m_4 \oplus m_5} \otimes \boxed{m_6 \oplus m_7 \oplus m_8}$$

Figure 1. A context-dependent approach using Dempster's rule ($\oplus$) and Dubois and Prade's rule ($\otimes$) on a set of mass functions.

Figure 2. A GUB models the belief of an agent as a set of epistemic states Φ_i , each having its representation.

observation or the world after a context-dependent merge of sensor data. A global uncertain belief set (GUB) is used to reason about all the epistemic states of an agent (see Fig. 2).

After executing our context-dependent merge to obtain a mass function and then transforming it into a probabilistic epistemic state, the agent can determine which state is the most plausible. Based on the combined sensor information (as in Example 1), the solar panel agent believes it is more plausible that the temperature is normal than not normal i.e. $normal > \neg normal$. This means a plan will be selected for a normal state.

Example 2. Considering the solar park setting, the goal of the agent is to select plans to achieve a safe and efficient supply of electrical power to meet consumer demand. This might involve sub-goals such as running the combiner to distribute power when we obtain a normal temperature reading (i.e. P1) or stopping a combiner and generating an alert when the temperature is outside of the normal range (i.e. P2) etc.

P1: $!run_combiner : normal > \neg normal \leftarrow !run_inverter; distribute_power; \dots$

P2: $!run_combiner : \neg normal > normal \leftarrow !generate_alert; !stop_combiner; !run_windfarm; \dots$

III. CONCLUSION

This paper presents a framework to handle uncertain sensor information obtained from heterogeneous sources in a smart grid SCADA system. The proposed approach takes into account the context for when we should use Dempster's rule of combination and when to resort to its alternative i.e. Dubois and Prade's disjunctive rule for a set of independent and reliable mass functions. Using a BDI framework, we model the combined uncertain sensor information using epistemic states for better informed plan selection and decision making.

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