



SECOND ORDER UNCERTAINTY (SOU)

1. Inference with Second Order Uncertainty

Many tracking and target discrimination systems use Bayesian approaches to track objects and determine their identity as a critical part of the system. The Bayesian approaches use models that are characterized by a family of parameters. These parameters can be determined as best estimates from expertise, or as mean values derived from statistical analysis. In either case, current Bayesian approaches do not take into consideration the variability in the expert estimates nor the standard deviation of the statistics. When the correct parameters for the models are different from the selected ones, the outcomes for target tracking and discrimination can significantly change.

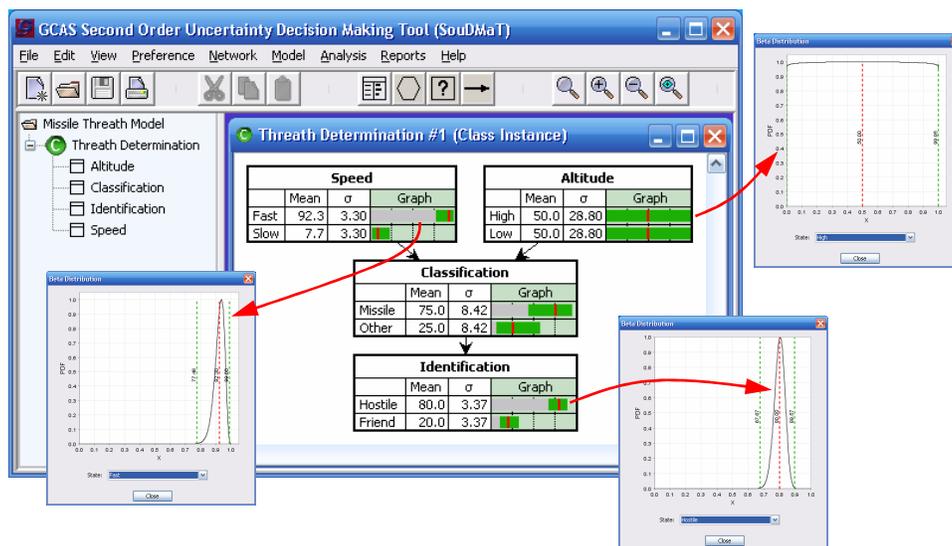


Figure 1: Model with Second Order Uncertainty.

The traditional approach to estimating the variability in the inference output from variability in the model parameter and input data is to perform systematic numerical experiments using sampling techniques. However, this approach is slow and tedious because thousands if not millions of samples are necessary to get the distribution of possible outcomes with real-world models. Even in models with few variables, sampling would require hundreds of different inferences just to obtain probability intervals. Many more samples would be necessary to obtain the distributions, which would require prohibitive execution cost in real-time environments.

GCAS has developed mathematics and software to obtain the distributions in real time, through an on-line technique that takes comparable time and memory as usual Bayesian inference. To achieve this, we express the probability distributions of the model parameters and evidences with their mean values, variances (σ) and covariances. We propagate these quantities in a process that is mathematically exact and similar to usual Bayesian inference. We then interpret the results as Beta distributions for visualization purposes. This translates into a significant improvement in the confidence in the results and in the decisions that can be made with them. Since we are computing probability distributions of probabilities, we call our technique Second Order Uncertainty (SOU), and First Order Uncertainty (FOU) the traditional inference.

Our SOU techniques provide a fundamental advantage over competing approaches. These latter tend to produce intervals that increase towards $[0, 1]$ as inference proceeds along the network. Our technique does not suffer from this problem. This holds in for networks of any size, as a direct consequence of the mathematics adopted.

2. Decision Making under SOU

GCAS has also developed mathematics for *Decision-Making* under SOU, where also utility functions can be expressed as probability distributions. In Decision-Making under SOU, the expected utility of a Course of Action (COA) is a distribution. This results from SOU in the CPT parameters, evidences and utility functions.

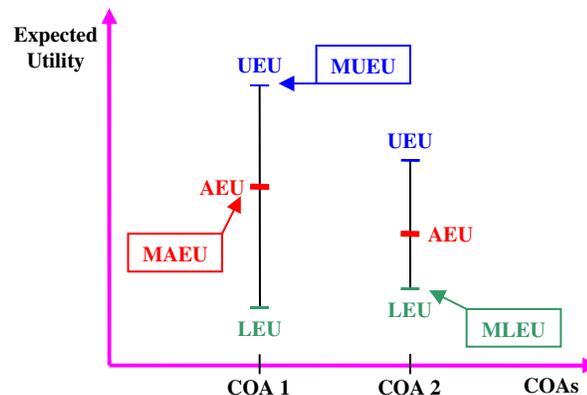


Figure 2: Different Strategies to Select the Best Course of Action under SOU.

The best COA can be determined depending on a number of strategies. Maximizing the smallest expected utility realizes a risk-averse strategy. A risk-prone decision maker will maximize the greatest expected utility. A risk-neutral strategy would maximize the average expected utility. A COA is considered to be robust when it will not change depending on the decision strategy.

3. Backtracking and Sensitivity Analysis

The SOU techniques introduced by GCAS can be used for *Backtracking* and *Sensitivity Analysis*. Suppose that in a variable of interest the probability intervals are too large. Backtracking determines the CPT entries and the evidences that are contributing the most to the result. This information can be used to improve the model and determine the evidence that needs to be refined. Extending this concept, Sensitivity Analysis exploits SOU inference and Backtracking to indicate how much a variable's belief is sensitive to changes in a group of CPT parameters and evidences.

4. SOU Modeling Tool

In addition to SOU techniques, GCAS has developed a tool to create models with SOU, perform inference and present the results. This modeling tool is based on Probabilistic Relational Models (PRMs), where a probabilistic model is expressed as a group of interacting Bayesian Networks (BNs). In PRMs one can represent a BN model using classes, relations between classes, instances of those classes and relations between instances. PRMs can be considered as the probabilistic modeling equivalent to object-oriented programming.

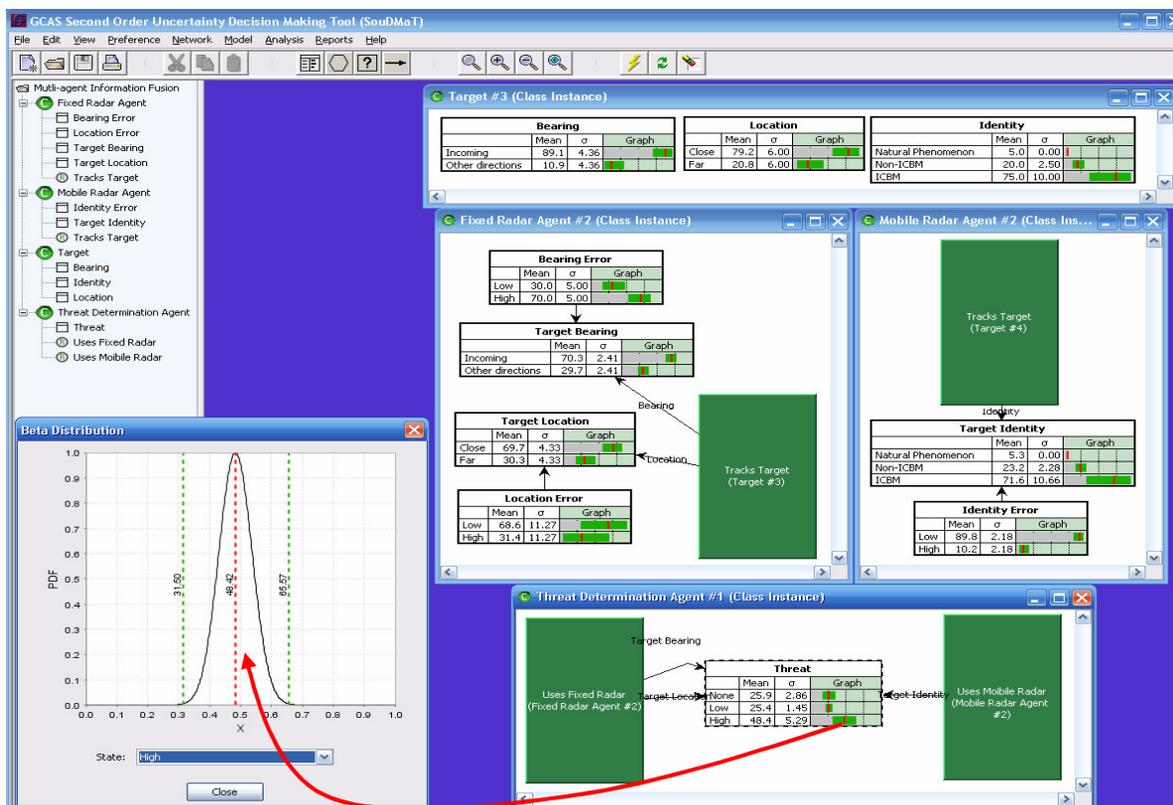


Figure 3: Probabilistic Relational Model with Second Order Uncertainty.

The PRM framework naturally lends to representing multiple interacting agents, which can communicate with more complex schemas than a hierarchical one. PRMs can also express uncertainty over the identity of the interconnected agents, their availability and their respective reliabilities.

5. SOU Application to Multi-Sensor / Multi-Agent Systems

Besides target tracking, SOU and PRM are beneficial to multi-agent sensor systems, where data fusion is distributed across many agents. SOU can be used to estimate, at each agent, the level by which its determinations may be inconsistent with those of the entire sensor network. For example, full consistency may be represented by traditional FOU outcomes. When data are missing or perceived to be unreliable or corrupted, or when data updates have not occurred along a channel for some time, SOU can be used to represent potential deviations of the FOU outcome from the last one that was fully consistent.

When this deviation (or potential inconsistency) level passes a threshold, the agent can decide to ask its neighbors for data update. By exploiting backtracking and sensitivity analysis, the sensor can also decide which data channels may reduce the deviation the most. Therefore SOU can be used to optimize data communication vs. data fusion results quality.