Meaning and Processing of Evidence
Technical Note 05-17

This note explains the meaning and use of uncertain evidence as provided to CAT/JCAT for the “Sensor Evidence” paradigm. Sensor Evidence is the paradigm currently implemented in C++ CAT and one of the paradigms implemented in JCAT. This note explains Baysean Inference with respect to this type of evidence, and how such inferences are computed in the software.

Sensor Evidence: By a “sensor” we mean a device whose reliability is parameterized by two rates, its “false alarm rate” (FAR) and its “missed detection rate” (MDR). We limit discussion to binary sensors whose results are equivalent to “target detected / target not detected”. The FAR is the percentage of “target detected” responses in which there were no targets actually present, making the response a false alarm. The MDR is the percentage of “target not detected” responses in which there was actually a target present. One can imagine presenting a sensor with a sequence of targets to determine the MDR and querying the sensor multiple times with no target present to determine the FAR.

Baysean Use of Sensor Evidence: Bayesian reasoning can be used to combine prior beliefs about targets with sensor evidence. Measuring FAR and MDR involve only extreme prior beliefs, 0.0 and 1.0 respectively. In non-measurement, practical situations one generally does not have such extreme beliefs. A model combining intermediate prior target beliefs with sensor evidence is shown in shown in Figure 1.

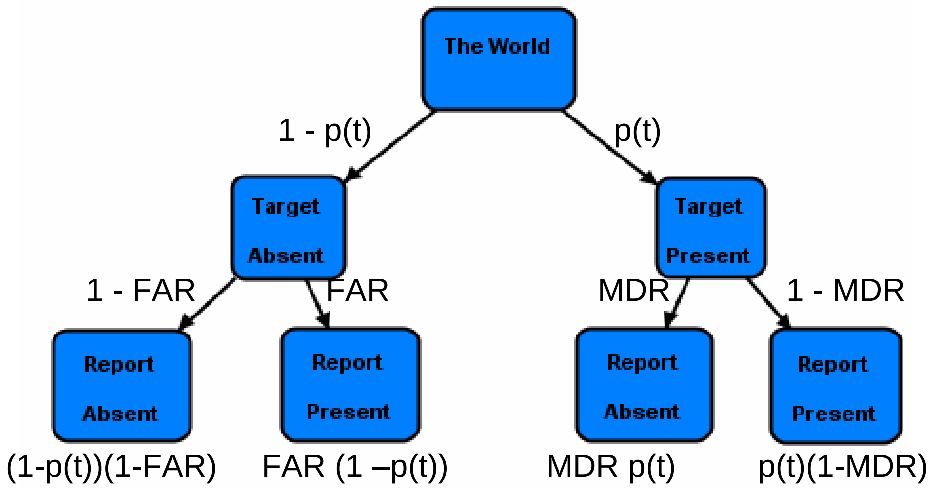

Figure 1: Target/Sensor Interaction

There are four possible states of target/sensor interaction as shown in Table 1.

Target	Report
present	present
present	absent
absent	present
absent	absent

Table 1: Target Sensor States

If the 'world' is such that the probability of a target is p(t), then the prior joint distribution over the four possible states, given the world, is shown at the bottom of Figure 1. When a sensor report of 'present' is received, Bayes Rule prescribes renormalizing over two of the initial four states, the two states in which the sensor reports the target is present. Thus by Bayes rule we can conclude that after the sensor has reported observing a target, the updated, posterior probability, $p'(t)$, is given by

$$p'(t) = \frac{p(t)(1 - MDR))}{FAR(1 - p(t)) + p(t)(1 - MDR)} \tag{1.1}$$

If the sensor reports no target, then

$$p'(t) = \frac{p(t) \cdot MDR}{(1 - FAR)(1 - p(t)) + p(t) \cdot MDR} \tag{1.2}$$

Note that the posterior probability, $p'(t)$, is a function of both the priors beliefs and the sensor parameters. For example if the prior for 'target present' is small, the posterior remains small (unless the FAR is also small).

This formulation assumes that sensor reports are independent of all other events, given the state of the event the sensor is designed to detect.

Using Sensor Evidence while Sampling: In samplers such as those in CAT and JCAT, it is not necessary explicitly to represent the sensor reports as nodes. Using the likelihood ratio approach, it is sufficient to choose <target = present, report = present> with probability $p'(t)$ while updating the likelihood only by $p(t)(1 - MDR)$, and to choose <target = absent, report = present > with probability $(1 - p'(t))$ while updating the likelihood by $(FAR(1 - p(t)))$.

To see the above, first imagine estimating the prior distribution by sampling according to Figure 1, then applying Bayes Rule. Bayes Rule renormalizes so that only the samples in which the sensor has reported the target present are considered. The expectation for the sampling result,

$$\frac{n_{t=present;report=present}}{n_{t=present;report=present}+n_{t=absent;report=present}}$$

is given by equation (1.1). This procedure is, in essence, logic sampling.

The likelihood ratio approach described first is equivalent to the logic sampling approach just described. After *n* samples, the likelihood associated with <target = present, report = present> will, in expectation, be $n\left[p(t)(1-MDR)\right]$ and the likelihood associated with the total sample set will be $n\left[FAR(1-p(t))+p(t)(1-MDR)\right]$. Thus the likelihood ratio computation will also be equivalent to (1.1).

Current C++ CAT Algorithm: The current algorithm in C++ CAT takes a single probability parameter, x, for each node for which there is evidence. Currently when the sensor reports a target present, this parameter is processed as though the evidence is from a sensor such that $x=(1-MDR)$ and $MDR=FAR$. After *n* samples, it accumulates, in expectation, $np(t)x$ likelihood for <target present> and $np(t)x+n(1-p(t))(1-x)$ for the total likelihood entire sample set. Using the likelihood ratio

$$p'(t)=\frac{n\cdot p(t)x}{n(1-x)(1-p(t))+n\cdot p(t)x}=\frac{p(t)x}{(1-x)(1-p(t))+p(t)x}$$

Thus if $x=(1-MDR)$ and $(1-x)=FAR$, we have Equation 1.1. (Note that together these two condition imply that $MDR=FAR$.) If $x=MDR$ and $(1-x)=(1-FAR)$, we have Equation 1.2.

Using Current C++ CAT Algorithm: For evidence from a sensor for which $FAR=MDR=x$, provide the value, *x*, if the sensor reports target present. If the sensor reports no target present, provide the value $(1-x)$.

Next Version Baysean Sensor Evidence: The currently implemented algorithm will be expanded to use two parameters instead of a single parameter. This will allow evidence to be input to the model which includes both the FAR and the MDR and whether or not the sensor reported “present.”