Sensors Design with Bayesian Network

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1 Problem Description

We need to support the design of an autonomous drone, which will have to follow a trajectory and land on a target.

The presence of obstacles near the target will be encoded on a parameter, called *Difficulty*, which will be taken into consideration when deciding if it is safe enough to continue.

The sensors' ring will be composed of n distance sensors, with a maximum range, called *max sense*, and the drone will have to maintain a safe-zone around itself, called S.

2 Bayesian Network

The Bayesian network used to perform inference is shown in figure 1.

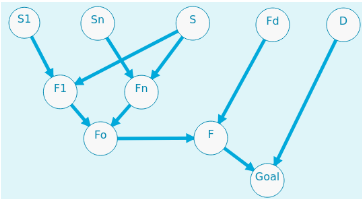

Figure 1: Bayesian Network used.

The network is composed of $n+3$ input nodes: F_d, Default Failure, which works as leak-node, D, which encodes the difficulty of the target, S, for the safe-zone around the drone, and n nodes for the sensors, where S_i is the reading associated to sensor i.

Moreover, there are $n+2$ hidden nodes:

1. $F_i = \lambda e^{-\lambda(S_i - S)}$ if $S_i \geq S$ otherwise $F_i = 1$, with $i \in 1..n$, $\lambda = 2$ and S_i equal to the distance to the closest obstacle in the i-th direction, clipped between 0 and Max Sense
2. F_o noisy-or from the set of node F_i with $i \in 1..n$
3. F, probabilistic node with F_d and F_o as evidence

Lastly, the network has one output node, called *Goal*, which takes in input F and D and is used to determine if, with the given configuration, it is safe to proceed or it is better to stop and compute an alternative plan.

2.1 CPD Tables

Here are reported the tables used by the network.

F_0	$F_0(0)$	$F_0(0)$	$F_0(0)$	$F_0(0)$	$F_0(1)$	$F_0(1)$	$F_0(1)$	$F_0(1)$
F_1	$F_1(0)$	$F_1(0)$	$F_1(1)$	$F_1(1)$	$F_1(0)$	$F_1(0)$	$F_1(1)$	$F_1(1)$
F_2	$F_2(0)$	$F_2(1)$	$F_2(0)$	$F_2(1)$	$F_2(0)$	$F_2(1)$	$F_2(0)$	$F_2(1)$
$F_o(0)$	1.000	0.683	0.683	0.366	0.683	0.366	0.366	0.050
$F_o(1)$	0.000	0.316	0.316	0.633	0.316	0.633	0.633	0.950

Table 1: Example of CPD table for F_o with 3 sensors.

F	F(0)	F(0)	F(1)	F(1)
D	D(0)	D(1)	D(0)	D(1)
G(0)	0.0	0.5	1.0	1.00
G(1)	1.0	0.5	0.0	0.00

Table 2: CPD table for *Goal*

For F_o we have the table 1, while for F and *Goal* the tables are, respectively, 3 and 2.

The tables have been filled up by looking at extreme cases, such as "$F_d \rightarrow F$" or "$F \rightarrow \neg G$" and by using heuristics and noisy-or in the case of Obstacle Failure, F_o, and Goal, G.

2.2 Inference

This network is used to perform sensitivity analysis and explanation, but they could be used also for decision making and to plan evidence gathering.

2.2.1 Sensitivity Analysis & Explanation

Here the objective is to understand which values are more critical when choosing if it is safe enough to continue or if it is better to stop, these results can be used to guide the design of the drone.
In image 2 are reported the results obtained by performing a few trial inferences with random distances and random difficulties.

2.2.2 Evidence Gathering

Lastly, it could be useful to give different priorities to different kind of information, especially when the operations performed to elaborate them are costly.
This BN could be used to guide the decisions of the autonomous drone, by giving it a way to discriminate between tasks and allocate them in a optimal manner.

2.3 Inference Algorithms

In order to perform inference different kind of methods can be used, either exact or approximate; due to the nature and size of the problem, I chose to test only exact algorithms, in particular Belief Propagation and Variable Elimination.
In image 3 is shown a plot of the time required for each method to perform difference inferences.
As can be seen, Belief Propagation performs better then Variable Elimination for this problem, even

F_o	$F_o(0)$	$F_o(0)$	$F_o(1)$	$F_o(1)$
F_d	$F_d(0)$	$F_d(1)$	$F_d(0)$	$F_d(1)$
F(0)	1.00	0.00	0.01	0.00
F(1)	0.00	1.00	0.99	1.00

Table 3: CPD table for F

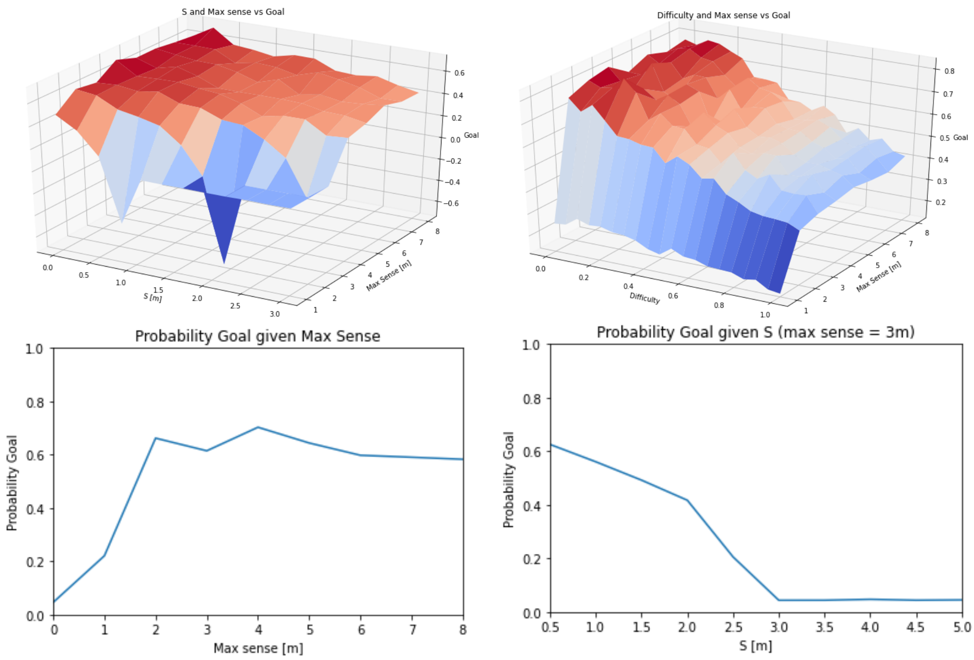

Figure 2: Plots to search for more critical parameters.

though its computation time increases significantly more then that of Variable Elimination in a few cases.

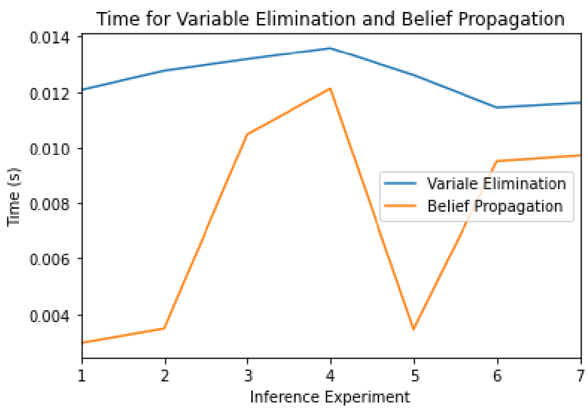

Figure 3: Time taken by Belief Propagation and Variable Propagation for different inferences, in particular: (1) goal as variable and no evidence, (2, 5) goal as variable and difficulty as evidence, (3) goal as variable and obstacle failure as evidence, (4) goal as variable and obstacle failure and difficulty as evidence, (6) failure obstacle as variable and goal as evidence, (7) failure obstacle as variable and goal and difficulty as evidence.