

Site-Specific Safety Map (LIDAR and NFT) Algorithm Description Document

Overview

This data product supports the Safety Map requirement SM.SS.4.17: “SPOC shall develop the software to produce the lidar-based site-specific probability of safety at the resolution of the DTM. The probability shall be a value between 0 (0% safe) and 100 (100% safe) according to the SPOC-SSM ICD (UA-ICD-9.4.4-1014).” and SM.SS.4.26: “SPOC shall develop the software to produce the lidar-based site specific mission safety probability by convolving the safety probability with deliverability at the DTM resolution. The probability of safety shall be a value between 0 (0% mission success) and 100 (100% mission success) according to the SPOC-SSM ICD (UA-ICD-9.4.4-1014).” Here we provide the algorithm description for the generation of the per-facet probability assessment of site-specific safety at the resolution of the site-specific DTM.

Inputs

- Site-specific DTM
- Site-specific Tilt Input Map
- Site-specific Thermal input Map
- Site-specific Thermal Approach Map
- Site-specific Reflectivity Map (LIDAR-Based Map only)
- Site-specific Reflectivity Approach Map (LIDAR-Based Map only)
- Site-specific Plume Map
- Site-specific Gravity Uncertainty Input Map (NFT-based Map only)

Outputs

- Site-specific Safety Probability Map (probabilistic assessment, LIDAR and NFT-based)
 - Per-facet calculation at DTM resolution
- Site-specific Safety Score Map (site ranking algorithm, LIDAR and NFT-based)

Algorithms

Two algorithms for the Site-specific Safety Probability Map will be created, one that uses LIDAR guidance and one that uses NFT guidance. The implementation of both algorithms is based on a Bayesian network where the conditional interdependence between the different user variable parameters are captured in a network and Bayesian theory is systematically applied to compute the final safety probability. Note that the same Bayesian network algorithm can be set up to model conditional independence between each of the inputs, based on the selected algorithm parameters.

In addition, the SPOC should implement the capability to generate two additional Site-specific Safety Score maps (one for LIDAR and one for NFT). These Safety Score maps will use the same Bayesian network methodology as the Safety Probability maps, but will use potentially different parameters and network designs to obtain a preferential ranking of site safety rather than a rigorous estimation of probability. The use of a Safety Score map is still being investigated by the Safety Map team and may be removed at a later date.

Conditional Independence-based Algorithm

This algorithm computes the per-facet probability of safety of the spacecraft according to the following formula, assuming LIDAR guidance.

$$p(\text{Safety} = \text{True}) = p(\text{Tilt} = \text{Safe})p(\text{Roughness} = \text{Safe})p(\text{Thermal} = \text{Safe})p(\text{Reflectivity} = \text{Safe})p(\text{Plume} = \text{Present})$$

This algorithm computes the per-facet probability of safety of the spacecraft according to the following formula, assuming NFT guidance.

$$p(\text{Safety} = \text{True}) = p(\text{Tilt} = \text{Safe})p(\text{Roughness} = \text{Safe})p(\text{Thermal} = \text{Safe})p(\text{Gravity Uncertainty} = \text{Safe})p(\text{Plume} = \text{Present})$$

The algorithm assumes that there is no conditional dependency between input variables as well as with the safety of the spacecraft (no conditional dependency between the state of the spacecraft safety and the state of the input parameters). The probabilities of the input parameters are computed using the procedure identical to the one described in section "Input variable selection and nature of the node".

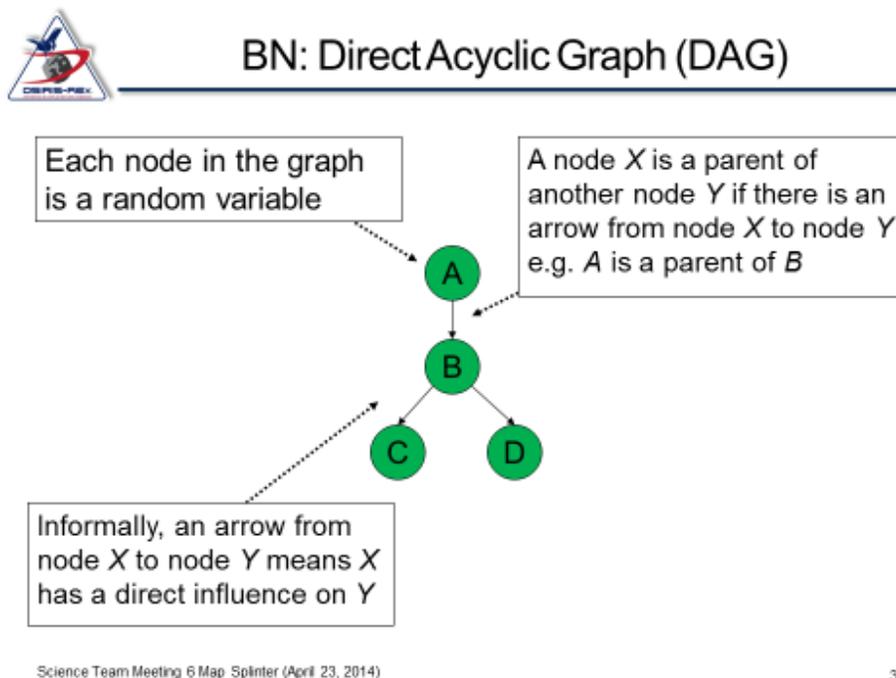


Figure 1. Bayesian Network is represented as a Direct Acyclic Graph

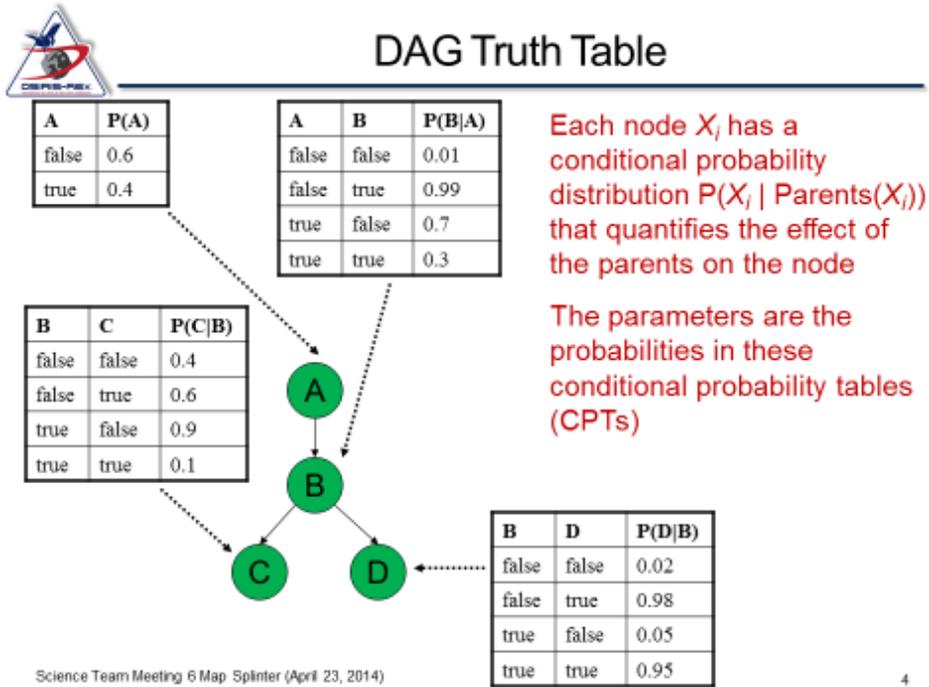


Figure 2. Conditional Probability Tables.

Bayesian Network Algorithm

A Bayesian Network (BN) is a graphical model that efficiently encodes the joint probability distribution for a defined set of variables. A BN for a set of variables $X = \{X_1, \dots, X_n\}$ contains 1) Network structure S encoding the conditional independence assertions about X and 2) a set P of local probability distributions. The network structure S is a Directed Acyclic Graph (DAG) where the Nodes are the one-to-one correspondence with the variables X (Figure 1.). Note that presence of an arc implies conditional dependence whereas lack of an arc denotes conditional independence. Generally, the joint probability distribution can be factorized as product of conditional probability as captured by the DAG structure:

$$P(X_1 = x_1, \dots, X_n = x_n) = \prod_{i=1}^n P(X_i = x_i | \text{Parents}(X_i))$$

Conditional probability is encoded in the Conditional Probability Table (CPT). Each node has a conditional probability distribution that quantifies the effect of the parents on the node. The CPTs capture such probabilities (Figure 2.)



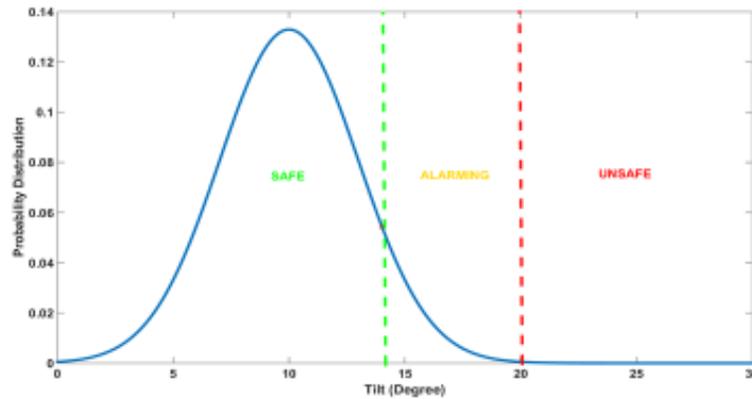
How To Compute Input Probabilities (II)

- Once the limits are established, the probabilities of each state can be computed via numerically integrating the function between two limits (area below the curve within the limits)

$$T_m = 10 \text{ deg}, \sigma = 3 \text{ deg}$$

$$\text{Prob}(\text{Tilt Safe}) = \int_0^{14} \frac{1}{\sigma_T \sqrt{2\pi}} e^{-\frac{(T-T_m)^2}{2\sigma_T^2}} dT = 0.908 \quad \text{Prob}(\text{Tilt Unsafe}) = 0$$

$$\text{Prob}(\text{Tilt Alarm}) = \int_{14}^{20} \frac{1}{\sigma_T \sqrt{2\pi}} e^{-\frac{(T-T_m)^2}{2\sigma_T^2}} dT = 0.098$$



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Figure 3. Example of how to transform the Tilt input and its uncertainty into probabilistic inputs to the BN

Bayesian Network for Site-Specific Safety Assessment

The steps necessary for constructing a Bayesian network to compute the per-facet global safety probability are:

1. Select the input variables and define the nature of the node
2. Define the DAG structure
3. Define the Conditional Probability Tables (CPTs)

Input variable selection and nature of the node

The input variables are defined by the problem and are established to be Tilt, Thermal, Reflectivity and Plumes. Each variable represent an input node in the network and is assumed to be “discrete”, i.e. can take three states, i.e. “safe”, “alarming” and “unsafe”. Each input value per facet (e.g. tilt and its uncertainty) is processed to evaluate the likelihood of being safe, alarming and unsafe for spacecraft safety. The approach is the following: We model the probability distribution of the data as a Gaussian (normal distribution) with parameter as mean and use standard deviation as uncertainty on the value. For example, for a the tilt input given the value T_{ms} and the standard deviation σ_T , we model the pdf as follow:

$$pdf(T) = \frac{1}{\sigma_T \sqrt{2\pi}} e^{-\frac{(T-T_m)^2}{2\sigma_T^2}}$$

Once the limits of safe/alarming/unsafe are established the integral over the limits determine its probability input. Figure 3. Shows an example for the case of Tilt input with value of 10 degrees and uncertainty of 3 degrees (1-sigma).

DAG Definition and CPT structure

The current DAG representing the BN for global safety probability calculation is reported in Figure 4. Sample of CPTs (both deterministic and probabilistic) are reported in Figure 5. Structure of the DAG and the CPTs are subjected to future updates pending improvement of our understanding of the relationship between nodes and the conditional dependencies within the variables of the problem space.

Implementation

The BN is implemented in a commercial software called NETICA (NORSYS Software Corp., version 5.1.5) which is a framework for rapid prototyping of Bayesian networks. The input maps (per facet) are processed using MATLAB script and interfaces with NETICA using the NETICA Java API (version 5.04)

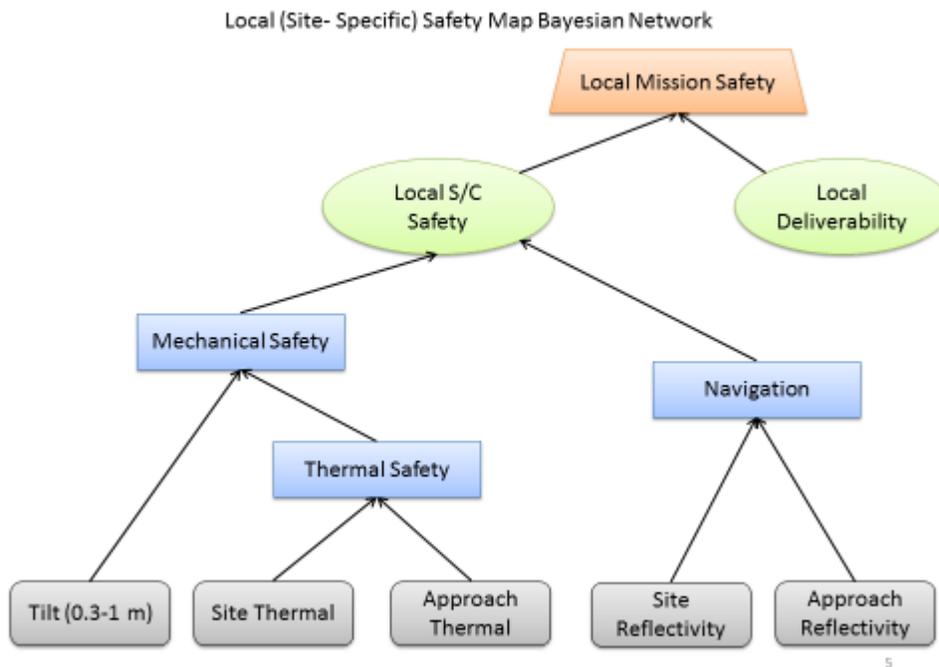


Figure 4. Current Version of the DAG for the Site-specific Safety Map



Truth Tables/ Conditional Probabilities

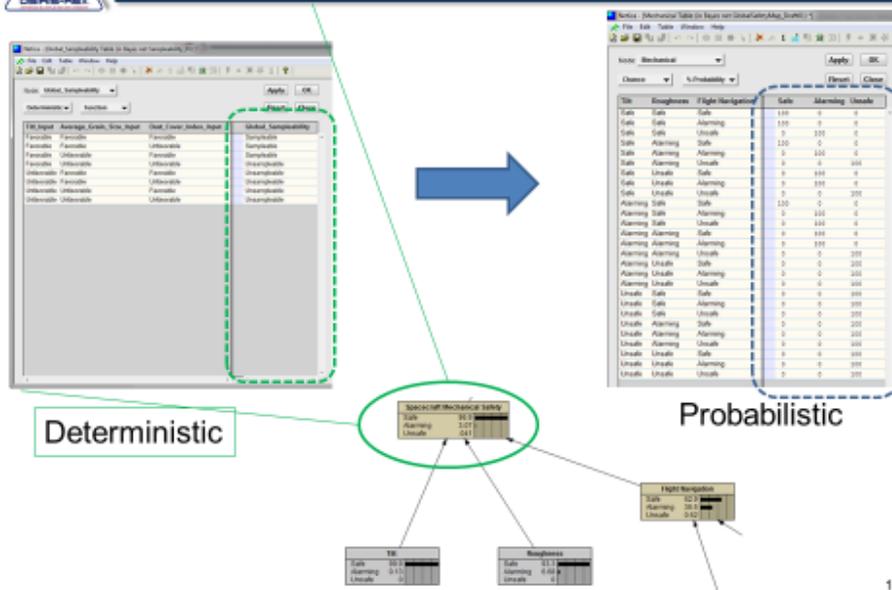


Figure 5. Example of Conditional Probability tables (both deterministic and probabilistic) as implemented in NETICA.