Online Inference for Adaptive Diagnosis via Arithmetic Circuit Compilation of Bayesian Networks

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INTRODUCTION AND CONTEXT

- The reliability of embedded systems for autonomous vehicles (like UAVs) is crucial and should be monitored.
- Onboard diagnosis is one solution that can be achieved by means of Bayesian networks [1] [2].
- A hardware implementation of Bayesian inference is proposed in [3] using compilation into an Arithmetic Circuit (AC); it has recently been experimented in Software Health Management of aircrafts or UAVs [4].
- Two kinds of obstacles have to be addressed:
  - ◇ A static analysis of a whole system by means of AC trees can lead to intractable solutions.
  - ◇ An offline static computation cannot capture the dynamic behaviour of a system that can have multiple configurations and applications.
- Our direction :
  - ◇ An adaptive version of the diagnosis computation for different kinds of applications/missions of UAVs based on an incremental generation of the AC structure.
  - ◇ A possible implementation using dynamic reconfiguration of FPGA circuits.

COMPILATION OF A BAYESIAN NETWORK AND INFERENCE COMPUTATION

Each Bayesian network can be represented as a multi-linear function (MLF). The MLF is transformed into an arithmetic circuit (AC) which is used to compute the probabilities by means of a differential approach. The construction of the AC is done offline but probabilities are computed online, as soon as the evidences (indicator values) are given.

Compilation of a Bayesian network into an AC

⇒ Bayesian networks as MLFs

- For each Bayesian network we can define a unique MLF over two types of variables:
  ◇ Evidence indicators (λ_x) ◇ Network parameters ($\theta_{x|u}$)

$$f = \sum_{x} \prod_{xu \sim x} \lambda_x \theta_{x|u} \quad (1)$$

- Example: $f(\overline{b}) = f(\lambda_a{=}1, \lambda_{\overline{a}}{=}1, \lambda_b{=}0, \lambda_{\overline{b}}{=}1) = \theta_a\, \theta_{\overline{b}|a} + \theta_{\overline{a}}\, \theta_{\overline{b}|\overline{a}}$

⇒ Compilation into an AC

- AC by factorisation [5]
- Hierarchical building of an AC

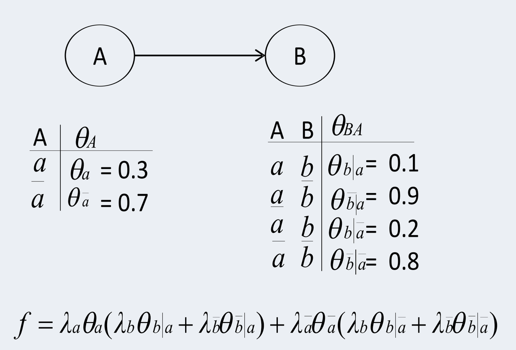

Fig.1.a) A Bayesian network with the factored function

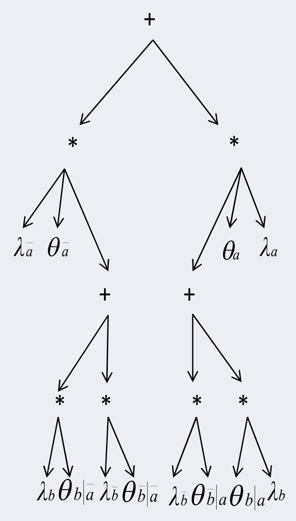

Fig.1.b) The corresponding AC

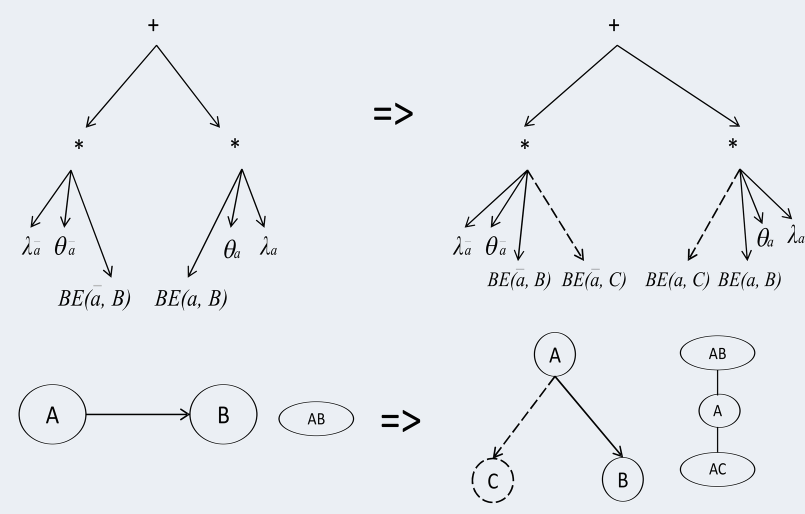

Fig.2 An incremental generation of the AC with Bayesian network structure or jointree

Computing probabilities using an AC

$P(x|e) = \frac{P(x,e)}{P(e)}$. (e: evidences, x: variable)

- Upward-pass: evaluating an arithmetic circuit (computing $P(e) = f(e)$).
- Downward-pass: computing the circuit derivatives (computing $P(x,e) = \frac{\partial f}{\partial \lambda_x}(e)$) .
  ◇ Let v be an arbitrary node in a circuit f:

$$\frac{\partial f}{\partial v} = \sum_{p} \frac{\partial f}{\partial p}\frac{\partial p}{\partial v}$$

◇ Let v' be another child of a parent p (p* multiplication node, p+ addition node).

$$\frac{\partial p*}{\partial v} = \frac{\partial v(\prod_{v'} v')}{\partial v} = \prod_{v'} v' \quad (2) \qquad \frac{\partial p+}{\partial v} = \frac{\partial v + (\sum_{v'} v')}{\partial v} = 1 \quad (3)$$

⇒ The AC approach simplifies the probability computation.

THE ADAPTIVE DIAGNOSIS OF A UAV EMBEDDED SYSTEM THROUGH MISSIONS

Bayesian network corresponding to a task

- Nodes:
  Command (C): representing one demand. (c or $\overline{c}$).
  State (U): indicating the internal state of the system (u or $\overline{u}$).
  Health (H): representing the health of the system (h or $\overline{h}$).
  Sensor (S): indicating the value of the sensor (s or $\overline{s}$).
  Health-Sensor (HS): representing the health of the sensor (hs or $\overline{hs}$).
- Edges:
  U is commanded by C and monitored by H. U is observed by S which is monitored by HS.

Task 1: taking pictures
If the sensor S detects the memory space overflow for the image storage, and a command C is launched, the Health of the system H will be *bad*.

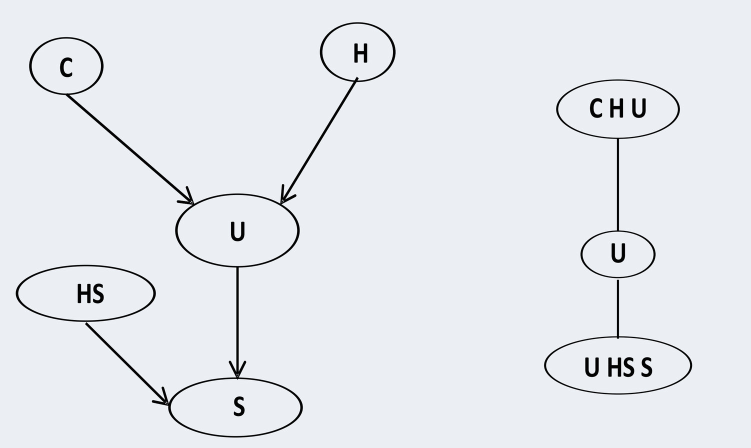

Fig.3 A Bayesian network and the jointree of task 1

⇒ Goal: Compute $P(h|c,s)$
Considering node H as the root node of the AC.
$P(h,c,s) = f(c,s,\lambda_h = 1, \lambda_{\overline{h}} = 0)$

Reconfiguration of an AC for adaptive diagnosis

⇒ We use the AC of task 1 to obtain the complete AC of task 2.

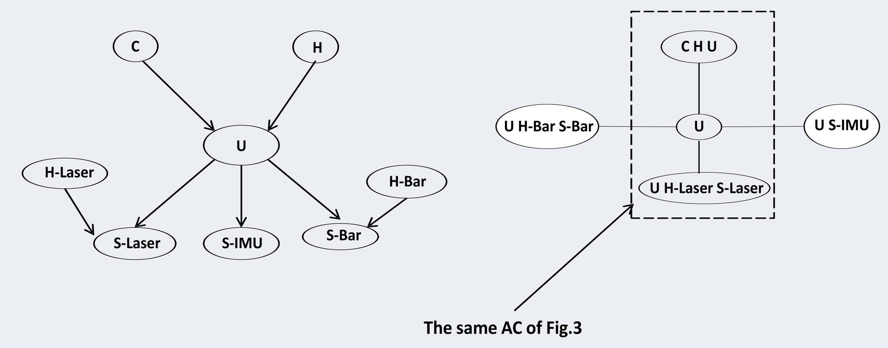

Fig.4 A Bayesian network and the jointree of task 2: computing altitude with 3 sensors (IMU, barometric and laser altimeter)

- For the cluster (U, S-IMU), these steps are as follows:
  1. go to all (*) of U;
  2. add a (+) node for each (*) node and add an arc for BE(u, S-IMU) when the (*) node has λ_u as child and BE($\overline{u}$, S-IMU) when the (*) node has $\lambda_{\overline{u}}$ as child.
- For the cluster (U, H-Bar, S-Bar), these steps are as follows:
  1. go to all (*) of U;
  2. add a (+) node and two (*) nodes for each (*) node of U. For the first (*) node, add an arc for λ_{h-Bar}, θ_{h-Bar} and BE(u h-Bar, S-Bar) when the (*) node has λ_u as child and BE($\overline{u}$ h-Bar, S-Bar) when the (*) node has $\lambda_{\overline{u}}$ as child. For the second (*) node, add an arc for $\lambda_{\overline{h-Bar}}$, $\theta_{\overline{h-Bar}}$ and BE(u $\overline{h-Bar}$, S-Bar) when the (*) node has λ_u as child and BE($\overline{u}$ $\overline{h-Bar}$, S-Bar) when the (*) node has $\lambda_{\overline{u}}$ as child.

CONCLUSION

- We have applied adaptive diagnosis to a number of independent tasks.
- This approach reduces the complexity and provides a gain in space and time.
- For future work:
  - ◇ Apply adaptive diagnosis to tasks with interactions and to a complete system.
  - ◇ Make use of partial/dynamic reconfigurations of Xilinx FPGAs.
  - ◇ Implement an application specific processor as a soft core on an FPGA.

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