



MicroBayes

https://persyval-lab.org/en/sites/content/microbayes











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Agenda

Context

Project Description

First results

Future work

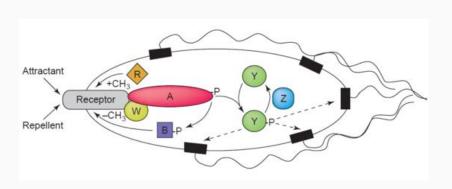




Motivation

- Need for low power computing
- The actual technology reaches some limits
- Need to better understand computation



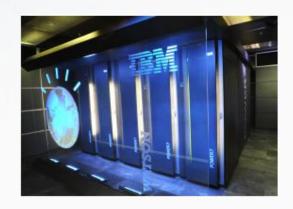






Energy consumption

~ 200 kW ~ 3,9m³





~ 20 W ~ 1,3 L

1 Stereo Camera +

2 lidars





~ 1 kW ~ 0.5 m³





Moore's Law limits







The rebooting computing endeavour

- Quantum computing
- Neuromorphic computing
 - IBM True North
 - HBP SpiNNaker
 - Machine dedicated to Deep Neural Nets, Conv Nets
 - Google Convnet
 - Facebook Big Basin
 - ❖ CEA-leti N2 D2
 - Nvidia....
 - Reservoir computing





Specialized hardware for Bayesian inference

- Vigoda (MIT) -> Lyrics analog device
 - Analog computing
- Jonas Masingka (MIT)
 - Probabilistic programming
 - Sampling machines with fixed point arithmetic's
- Blanche (University of Arizona)
 - Bayesian inference with optical hardware
- Takhur (Sydney University), Friedman (IEF)
 - Magnetic Tunnel Junction





Bambi

 Design of a first generation of stochastic machines dedicated to Bayesian Inference











MicroBayes

 Goal: Design and implementation of stochastic Machines for Low-level Sensor Interpretation with Bayesian inference.

- Started in November 2016
- 1 Phd: Raphael Frisch (Persyval)
- 1 Post-doc for 6 months (Bambi)
- 1 Post-doc for 2 years (Persyval)







Project team





Didier Piau





Emmanuel Mazer Raphael Frisch

Programming



Laurent Girin



Laurent Fesquet



Architecture Hardware





PhD thesis

- Use of dedicated machines for Bayesian inference
- Explore new approaches of sampling strategies
- Applications
 - Sound source localization
 - Sound source separation
- Started 11/2016
- Currently writing a paper for ICRC 2017
- Summer 2017: attending a summer school on Probabilistic Programming in Washington DC

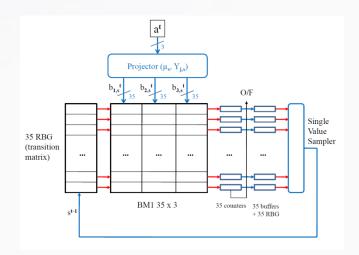


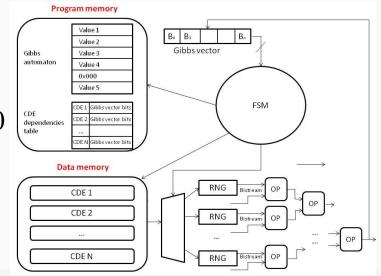


Bayesian machines

- BM1: Parallel sampling
 - Very fast machine
 - Search space $< 2^{12}$

- BM2: Sequential sampling
 - Untractable problems > 2^{100}





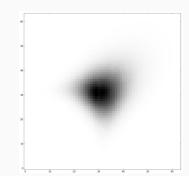




Sampling Machines

- Representing probability distributions
 - With parameters :Normal (μ, σ)
 - With N samples

$$P(x_i y_i) \approx \frac{\sum_{k=1}^{N} \partial_{x_k, y_k = x_i, y_j}}{N}$$

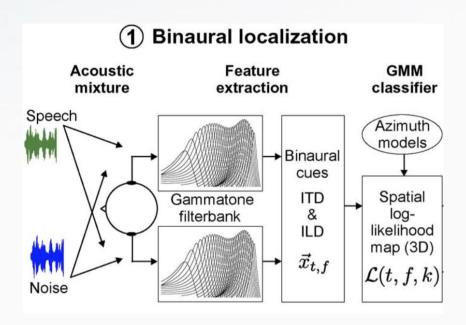


- Stochastic bus: Parallel sampling
- With constraints
 - Maximum entropy distribution :





Sound source localization

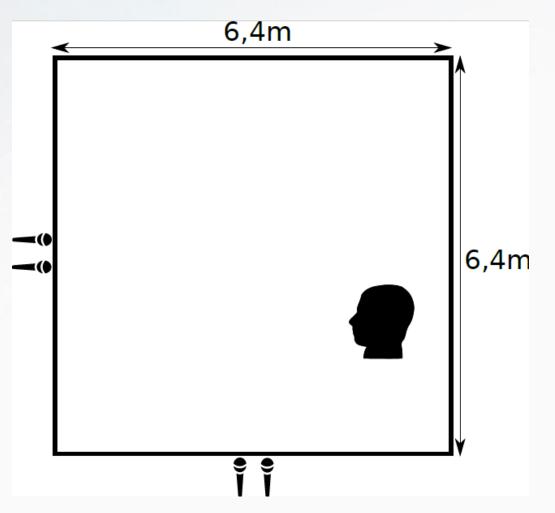


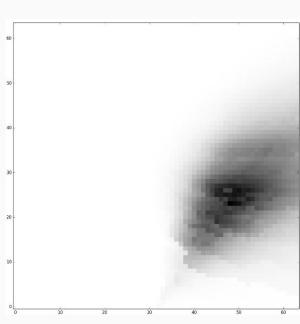
- Use of parallel sampling
 - Bayesian Machine with FPU preprocessing





Principle with source localization









Sound source localization: evidences

- Sensors: pair of microphones
- Assuming the free field model
- Evidence : InterChannel Phase Difference (ICPD)

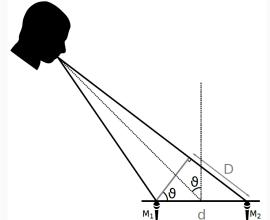
$$R(k) = \frac{Y_2(k,l)}{Y_1(k,l)} \simeq \frac{A_2(k) \cdot S(k,l)}{A_1(k) \cdot S(k,l)} = \frac{A_2(k)}{A_1(k)}$$

$$ICPD(k) = arg(R(k))$$

$$= arg(A_2(k)) - arg(A_2(k))$$

$$= \Delta \Phi(k)$$

$$= \Phi_2(k) - \Phi_1(k)$$







Stochastic bit streams

Probability encoding

Bit stream: 1010011001110100

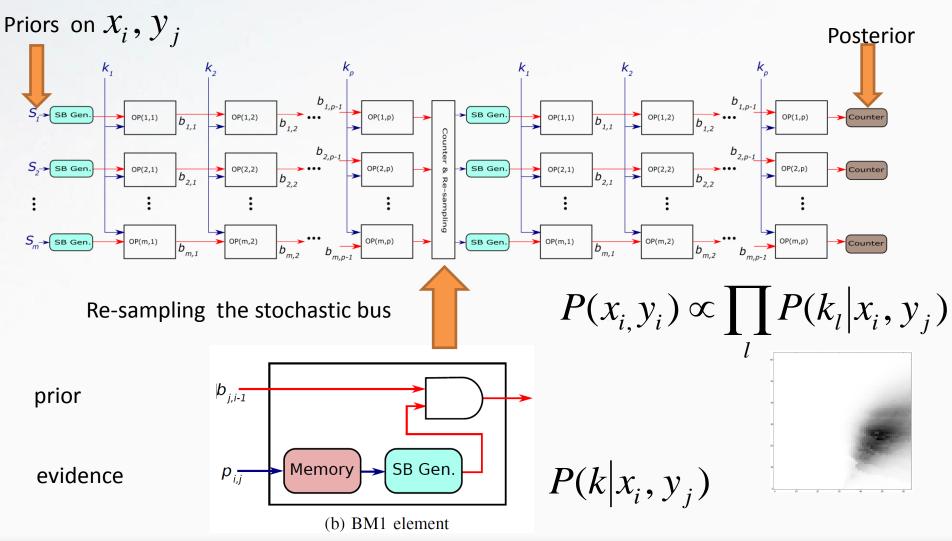
Probability: 0.5

Probability multiplication

$$p1 \cdot p2 = 0.5 \cdot 0.25 = 0.125$$



Principle of a parallel sampling machine







Sound source localization (3)

Workflow

Simulation of sound waves

Feature extraction

Calculation of probability distributions

Simulation of BM1

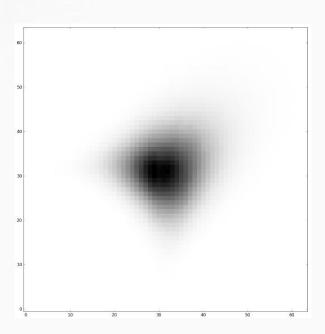
- BM1 Sliced with fast simulator
- Tackling the temporal dilution
 - Re-sampling of the probability distribution after a small subset of sensors

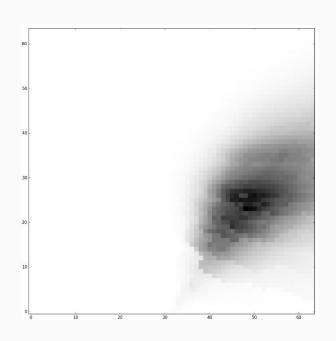




Sound source localization (4) (simulation)

Results after run(100000)



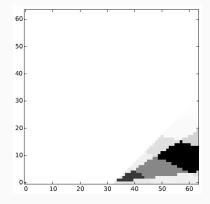






Future work — Source localization

- Move to FPGA
- Remove the time-frequency domain analysis
 - Use of the Fourier transform
 - Currently done on a normal CPU



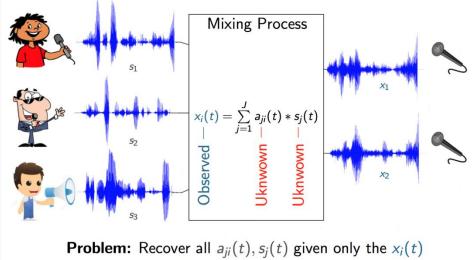
- Compression of probability distributions
- Localize a moving source using a filter





Sound source separation

- Use of sequential sampling
- Design of new algorithms for stochastic inference based on generating sets
- Planned during the second year







Future work – Source separation

- Explore new ways of sampling
 - MCMC
 - Generating sets





Industrial perspective

 Discussion with ProbaYes to launch an ambitious R&D program on stochastic Machines (3 Years -> 6M€)





Conclusion

MicroBayes on track



The future Bayesian valley