Blackboard Architectures

Two!Ears Summer School on Active Machine Hearing

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Outline

Introduction

What is a blackboard system?

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Characteristics of blackboard systems [Corkill, 1991]:

- Independence of expertise

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- Diversity in problem-solving techniques

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How to put this into a computational framework?

Introduction

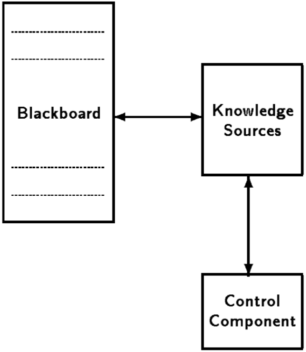

Figure 1: Basic Components of the Blackboard Model

Image taken from [Corkill, 1991]

Introduction

Basic blackboard system components:

- **Knowledge sources**
  - Independent (software) modules, designed to solve specific subtasks
  - Can retrieve and write data from/to the blackboard
  - May include additional knowledge (e.g. prior supervised training)

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  - Arbitrary data representations (e.g. numerical, probabilistic, semantic)

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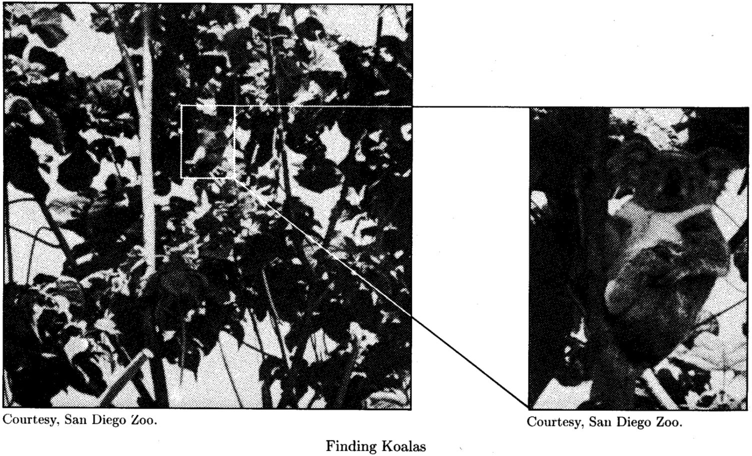
  - Global database, containing input data and partial solutions
  - Arbitrary data representations (e.g. numerical, probabilistic, semantic)
- **Control component ("Scheduler")**
  - Determines order of knowledge source execution
  - Keeps track of blackboard events and pending activations
  - Different task-dependent implementations described in the literature

Introduction

Example from [Nii, 1986]: *Finding Koalas*



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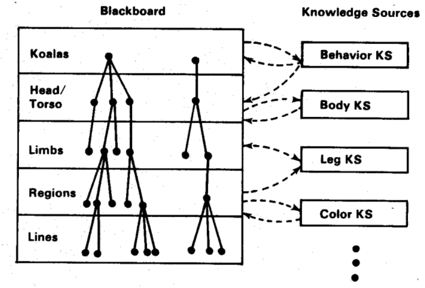

The koalas in the scene are described as a part-of hierarchy. Specialist knowledge modules contribute information about what they "see" to help in the search for koalas.

Koalas: Blackboard Structure and Knowledge Sources

Image taken from [Nii, 1986]

Introduction

Areas where blackboard systems have been applied:

- Speech recognition [Erman et al., 1980]
- Circuit design and layout [Milzner, 1991]
- Process monitoring and control [Cord, 1994]
- Robotics [Tzafestas & Tzafestas, 1991]
- Distributed planning [Han et al., 2014]
- Wireless networks [Reddy et al, 2008]
- ...

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- a scheduler $f: \ \epsilon_i \mapsto \alpha, \quad \epsilon_i \in \mathcal{E}, \ \alpha \in \mathcal{A}$.

Blackboard basics

A **knowledge source** κ_i comprises

- a mapping function $f_i : \mathcal{X}_i \rightarrow \mathcal{Y}_i$, where
  - $\mathcal{X}_i \subseteq \mathcal{Z}$ is the set of possible inputs of knowledge source i and
  - $\mathcal{Y}_i \subseteq \mathcal{Z}$ is the set of possible outputs of knowledge source i,
- a set of internal parameters λ_i (optional) and
- an associated importance weight w_i (optional, system dependent).

$$\xrightarrow{x \in \mathcal{X}_i} \boxed{y = f_i(x,\, \lambda_i)} \xrightarrow{y \in \mathcal{Y}_i}$$

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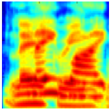
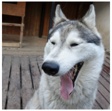




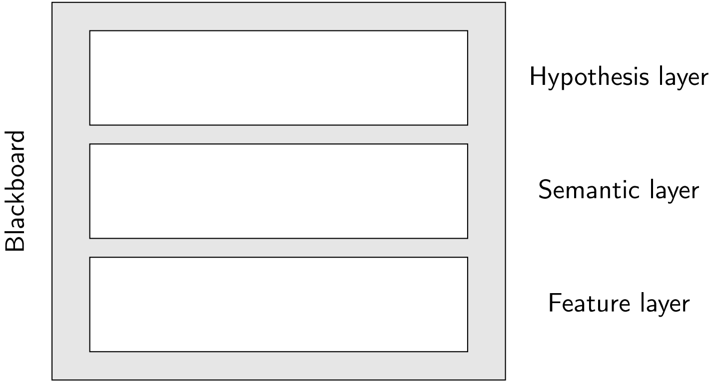
$$\xrightarrow{x \in \mathcal{X}_i} \boxed{y = f_i(x,\, \lambda_i)} \xrightarrow{y \in \mathcal{Y}_i} \quad \texttt{'dog'}$$

Blackboard basics

The **blackboard** serves as "memory" and solution space of the system. The blackboard state is dynamically changing over time:

$$z_{t+1} = h_t(z_t), \quad z_{t+1},\, z_t \in \mathcal{Z}$$

$h_t(z_t)$ represents an action chosen by the scheduler at time instant t.



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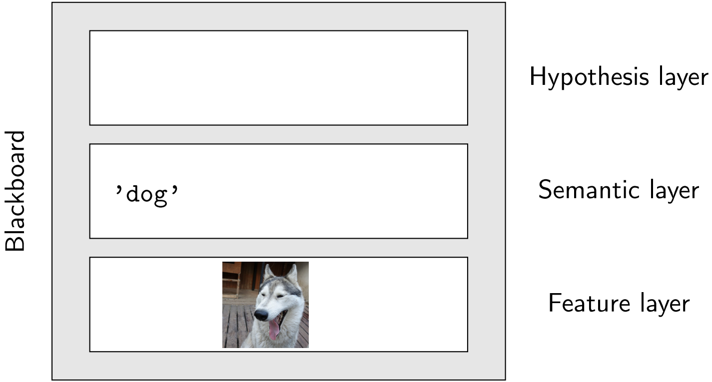

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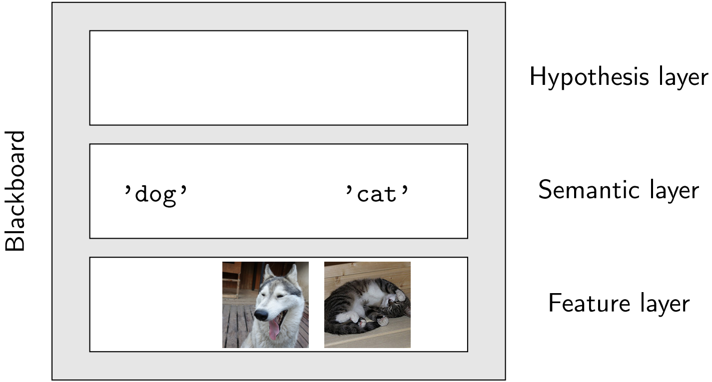

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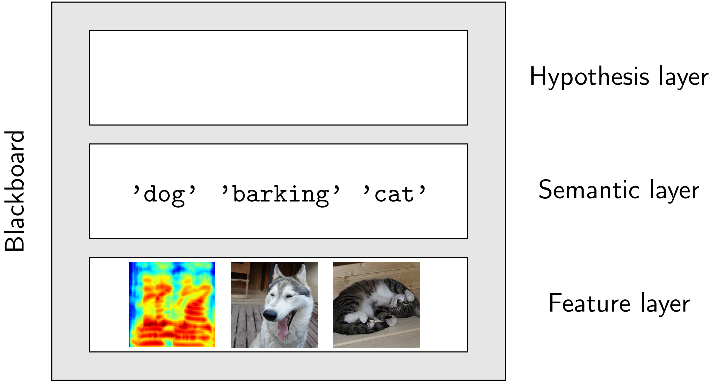

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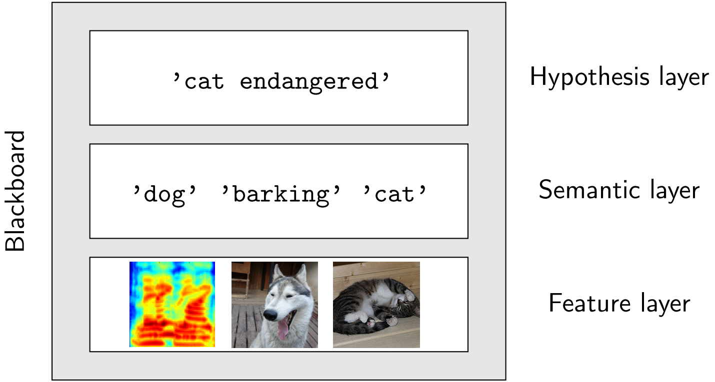

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The **scheduler**

- maintains the order of knowledge source execution based on possible actions listed in the current agenda $a_t \in \mathcal{A}$ and
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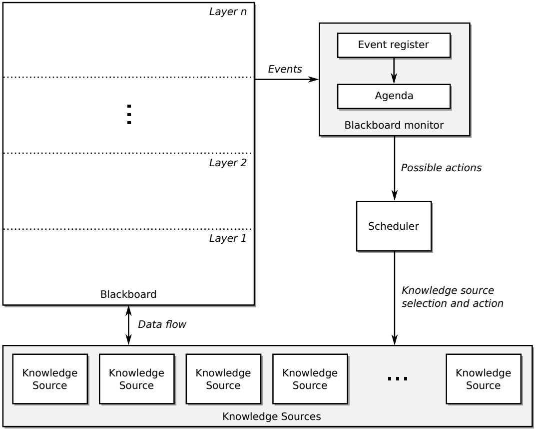
Alternative scheduling approaches exist (e.g. [Sutton et al, 2004]).

Blackboard basics

Blackboard architecture used in Two!Ears:



Online documentation: `http://twoears.aipa.tu-berlin.de/doc/latest/blackboard/`

Blackboard basics

Can blackboard systems be combined with modern statistical learning approaches to solve complex tasks in field of active machine hearing?

Probabilistic graphical models

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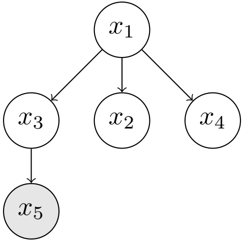

Probabilistic graphical models

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$$
\begin{array}{ccc}
 & x_1 & \\
\swarrow & \downarrow & \searrow \\
x_3 & x_2 & x_4 \\
\downarrow & & \\
x_5 & &
\end{array}
$$

This model encodes the fact that

$$p(x_1, x_2, \ldots, x_5) = p(x_1)p(x_2 \,|\, x_1) \ldots p(x_5 \,|\, x_1, \ldots, x_4)$$

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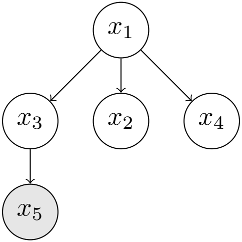

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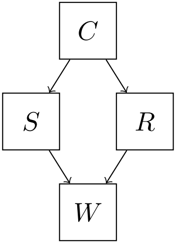
p(x_1, x_2, \ldots, x_5) &= p(x_1)p(x_2 \mid x_1) \ \ldots \ p(x_5 \mid x_1, \ldots, x_4) \\
&= p(x_1)p(x_2 \mid x_1)p(x_3 \mid x_1)p(x_4 \mid x_1)p(x_5 \mid x_3)
\end{aligned}
$$

Probabilistic graphical models

Example from [Pearl, 1988]: *The sprinkler network*

	S
T	0.50
F	0.50

	S	
C	T	F
T	0.10	0.90
F	0.50	0.50



	R	
C	T	F
T	0.80	0.20
F	0.20	0.80

		W	
S	R	T	F
F	F	0.00	1.00
F	T	0.90	0.10
T	F	0.90	0.10
T	T	0.99	0.01

Random variables:

- C: Cloudy
- S: Sprinkler
- R: Rain
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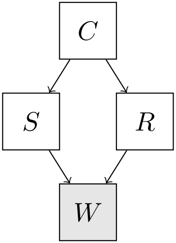

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Using a given graphical model, finding values of queried nodes given observed nodes is termed *inference*.

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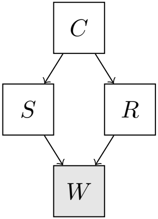
Example from [Pearl, 1988]: *The sprinkler network*

Question:

What is the probability that the sprinkler was on if the grass is wet?



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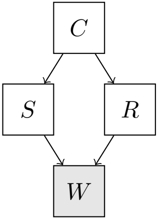

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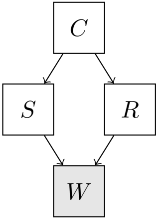
$$= \frac{\sum_{\forall\, c,\, r} P(c,\, S = \mathrm{T},\, r,\, W = \mathrm{T})}{\sum_{\forall\, c,\, r,\, s} P(c,\, s,\, r,\, W = \mathrm{T})}$$



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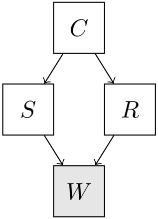

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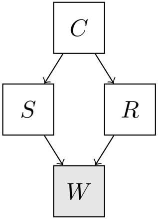
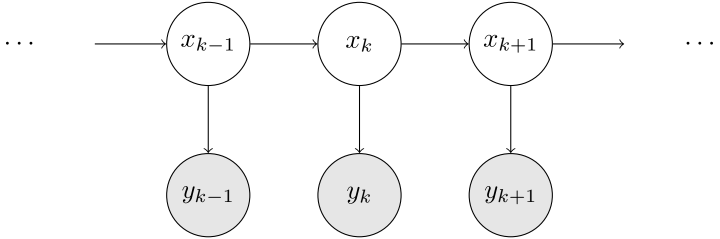
&= \frac{\sum_{\forall\, c,\, r} P(c) P(S = \mathrm{T} \,|\, c) P(r \,|\, c) P(W = \mathrm{T} \,|\, S = \mathrm{T},\, r)}{\sum_{\forall\, c,\, r,\, s} P(c) P(s \,|\, c) P(r \,|\, c) P(W = \mathrm{T} \,|\, s,\, r)} \\
&= \frac{0.2781}{0.6471} \approx 0.43
\end{aligned}
$$



Probabilistic graphical models

In **temporal graphical models** (or **dynamic Bayesian networks**), temporal evolution is described by replicating the network over time. Temporal dependencies are explicitly denoted by introducing additional connections between nodes.



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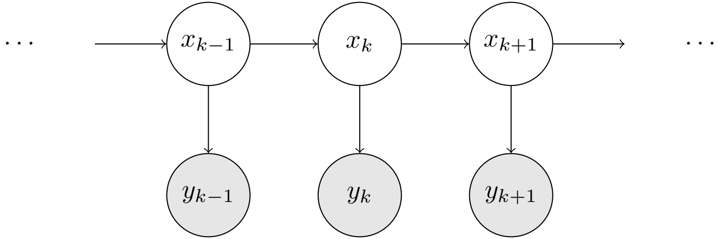

Examples: Hidden Markov models, linear/nonlinear dynamical systems, ...

Probabilistic graphical models

(Problematic) characteristics of graphical models:

- **Local optima**
  - Graphical models of sufficient complexity may allow a number of different interpretations (each locally optimal).
  - This may not be problematic, because it allows to drive the search into certain directions and the exploration of different hypotheses.

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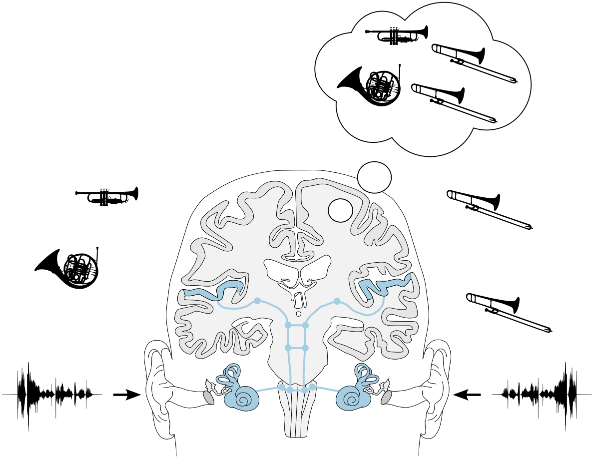
  - This may not be problematic, because it allows to drive the search into certain directions and the exploration of different hypotheses.
- **Computing effort:**
  - Despite algorithmic progress, topologies exist where exact inference is NP-hard. Computational complexity may grow exponentially with the number of nodes in the network.
  - Efficient algorithms for approximate inference in certain network topologies exist. Furthermore, heuristics to provide specific search directions (such as expert rules) may be applied.

Probabilistic graphical models

The role of graphical models in Two!Ears:



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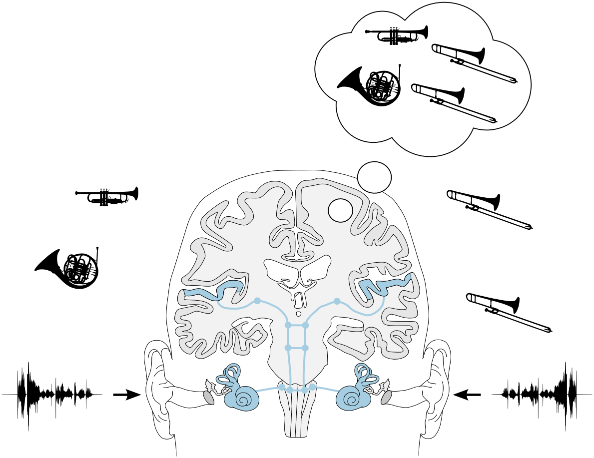

audible state (observations) $\longrightarrow$ hidden state (internal world model)

Applications in Two!Ears

Example from [Schymura et al., 2014]: *Sound source localization*

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    - head rotations can help to reduce these ambiguities [Wallach, 1940]

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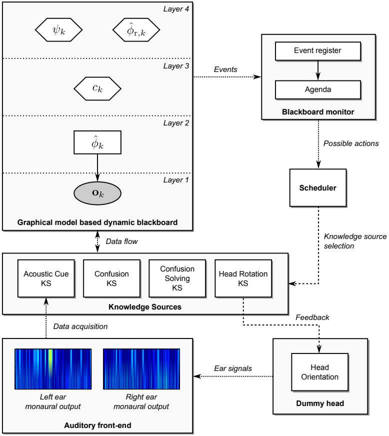

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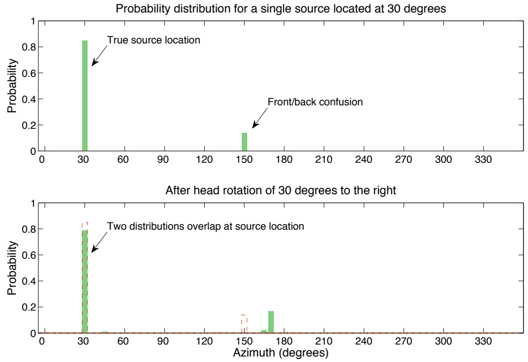
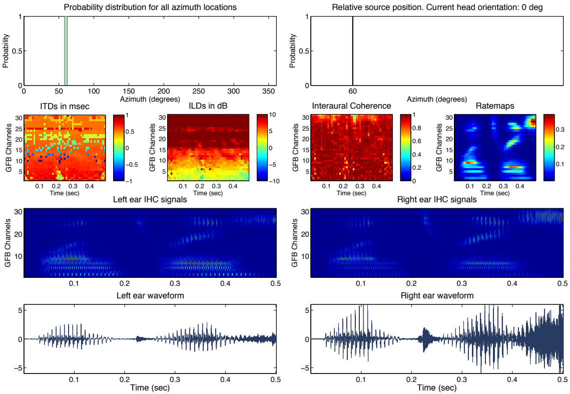
A simple heuristic to solve front-back ambiguities:



Applications in Two!Ears

Example from [Schymura et al., 2014]: *Sound source localization*

Data representation at different blackboard layers:



Applications in Two!Ears

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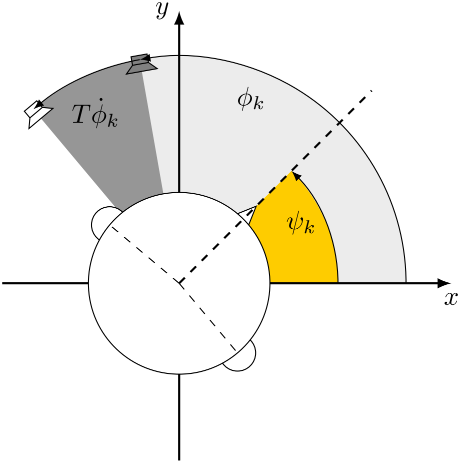
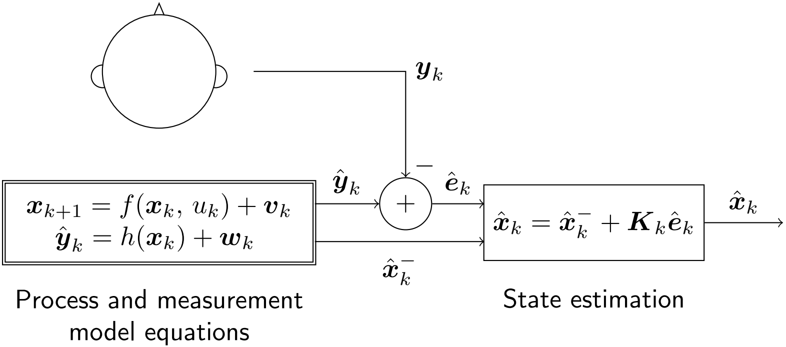
Applications in Two!Ears

Task: Tracking a moving sound source



Applications in Two!Ears

System overview:



Applications in Two!Ears

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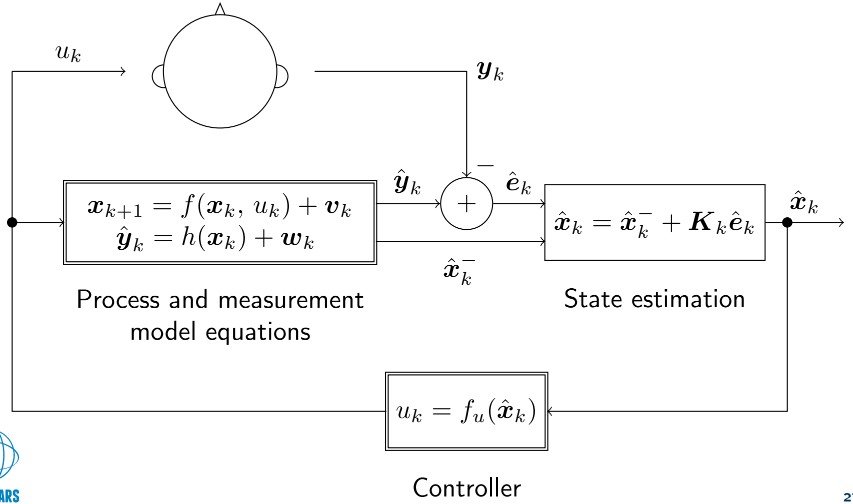
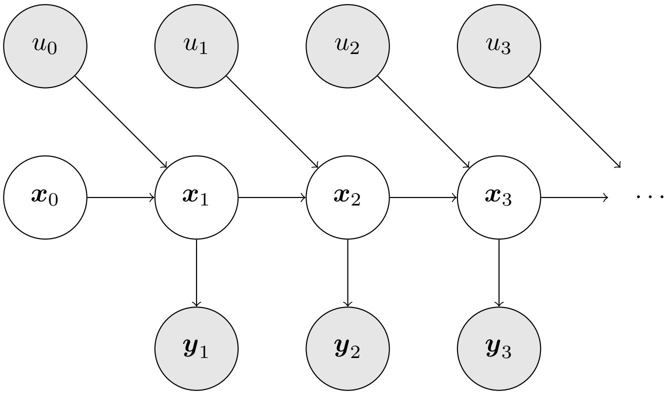


Applications in Two!Ears

State estimation as a temporal graphical model:



Applications in Two!Ears

State space:

$$\boldsymbol{x}_k = \begin{bmatrix} \phi_k & \dot{\phi}_k & \psi_k \end{bmatrix}^T$$

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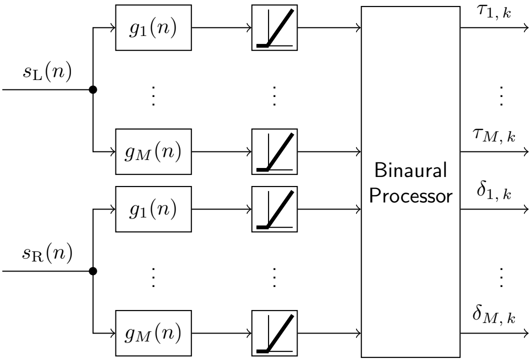
$$v_{\phi,\,k} \sim \mathcal{N}(0,\, \sigma_\phi^2),\ v_{\dot{\phi},\,k} \sim \mathcal{N}(0,\, \sigma_{\dot{\phi}}^2),\ v_{\psi,\,k} \sim \mathcal{N}(0,\, \sigma_\psi^2)$$

$$\mathrm{sat}(x,\, x_{\max}) = \min(|x|,\, x_{\max}) \cdot \mathrm{sgn}(x), \quad u_k \in [-1,\, 1]$$

Applications in Two!Ears

Binaural front-end:



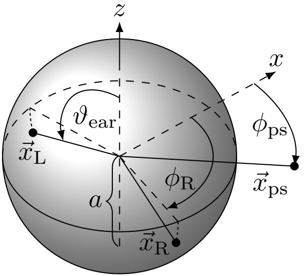
$$\boldsymbol{y}_k = \left[\tau_{1,k}, \cdots, \tau_{M,k}, \delta_{1,k}, \cdots, \delta_{M,k}\right]^T$$

Applications in Two!Ears

Spherical head model [Brungart, 1999], [Algazi et al., 2001]:

$$R_i(\boldsymbol{x}_k, \omega) = \frac{c}{4\pi\omega a^2} \sum_{\nu=0}^{\infty} \frac{h_\nu\left(\frac{\omega}{c}d\right)}{h'_\nu\left(\frac{\omega}{c}a\right)} (2\nu+1)\, L_\nu\Big(\sin(\vartheta_{\text{ear}}) \cos\left(\phi_k - \psi_k - \phi_i\right) \Big)$$

$$i \in \{\text{R, L}\}$$



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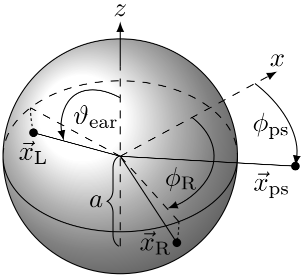


Spherical head parameters [Algazi et al., 2001]:

- Head radius a: $8.5\,\mathrm{cm}$
- Ear's azimuth angle ϕ_i: $93.60°$
- Ear's polar angle ϑ_ear: $110.67°$

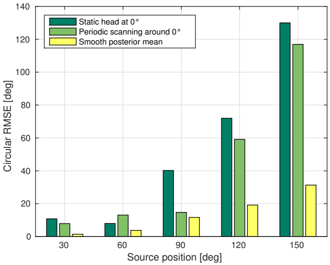
Applications in Two!Ears

Evaluation of three different head rotation strategies:

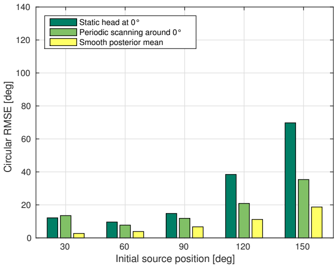
	No head rotation	Periodic sweeping	Smooth posterior mean
f_u	0	$\sin\left(2\pi k \frac{T}{T_\mathrm{p}}\right)$	$\left(\frac{\lvert\phi_k - \psi_k\rvert}{1+\lvert\phi_k - \psi_k\rvert}\right) \operatorname{sgn}\left(\phi_k - \psi_k\right)$
Type	-	feed-forward	feedback

Applications in Two!Ears

Results from [Schymura et al., 2015]: *Sound source localization and tracking*



Static scenario



Dynamic scenario

Evaluation metric:

$$\mathrm{cRMSE} = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\min_{l\in\mathbb{Z}}\left(\hat{\phi}_k - \phi_k + 2\pi l\right)^2}$$

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Thank you for your attention!

Questions?