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Parallel Particle Filters for Tracking of Voice Glimpses

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Department of Medical Physics and Acoustics,
University of Oldenburg

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Presentation:

I. INTRODUCTION

I. 1. MOTIVATION
I. 2. PSYCHOACOUSTIC STUDY
I. 3. MODELING FRAMEWORK
I. 4. SIMULATION APPROACH

II. METHODS

II. 1. TRAJECTORY GENERATION
II. 2. OBSERVATION GENERATION
II. 3. PARTICLE FILTERING
II. 3. a. Initialization
II. 3. b. State prediction
II. 3. c. Glimpse association
II. 3. d. Weight update
II. 3. e. Current state estimation
II. 3. f. Resampling

III. SIMULATION

III.1. EXPERIMENT DESIGN
III.2. RESULTS
III.3. CONCLUSIONS
III.4. OUTLOOK

1. INTRODUCTION

I. INTRODUCTION

I. 1. MOTIVATION

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I. 1. MOTIVATION

- cocktail party

- challenging acoustic conditions, many competing voices

- but still we are able to follow a desired acoustic object

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- cocktail party

- challenging acoustic conditions, many competing voices

- but still we are able to follow a desired acoustic object

- understand this phenomenon

- we know: pitch, timbre, location help to form streams

- but what if they change in time? can we still follow?

I. INTRODUCTION

I. 2. PSYCHOACOUSTIC STUDY

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Attentive Tracking of Sound Sources

Kevin J.P. Woods[1,2,*] and Josh H. McDermott[1,2]
[1]Department of Brain and Cognitive Sciences, Massachusetts Institute of Technology, Cambridge, MA 02139, USA
[2]Program in Speech and Hearing Bioscience and Technology, Harvard University, Cambridge, MA 02138, USA
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http://dx.doi.org/10.1016/j.cub.2015.07.043

SUMMARY

Auditory scenes often contain concurrent sound sources, but listeners are typically interested in just one of these and must somehow select it for further processing. One challenge is that real-world sounds such as speech vary over time and as a consequence

[1, 13–16], but less is known about the processes underlying attentional selection and their interaction with sound segregation [17–19].

Both segregation and selection could be aided by features of a target source that distinguish it from other sources, such as a unique pitch or location [20–23]. Studies of stream segregation have largely focused on cases such as this [1, 13–16, 24–30],

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- **reduced** cocktail party to two simultaneously active '**singing**' voices (only vowels)

- voices synthesized: **no constant differences** for example in timbre

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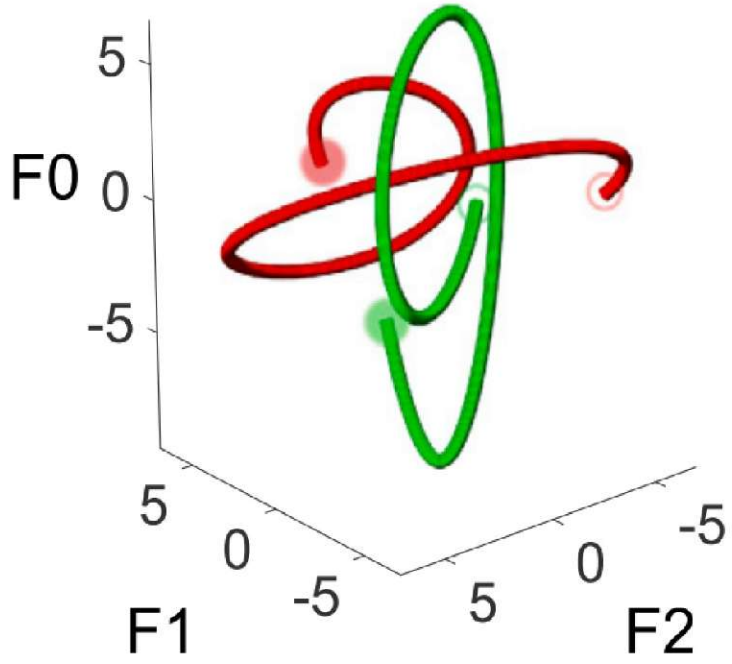
- only thing varied: how parameters(formants) **change in time**

- parameter trajectories might **cross**



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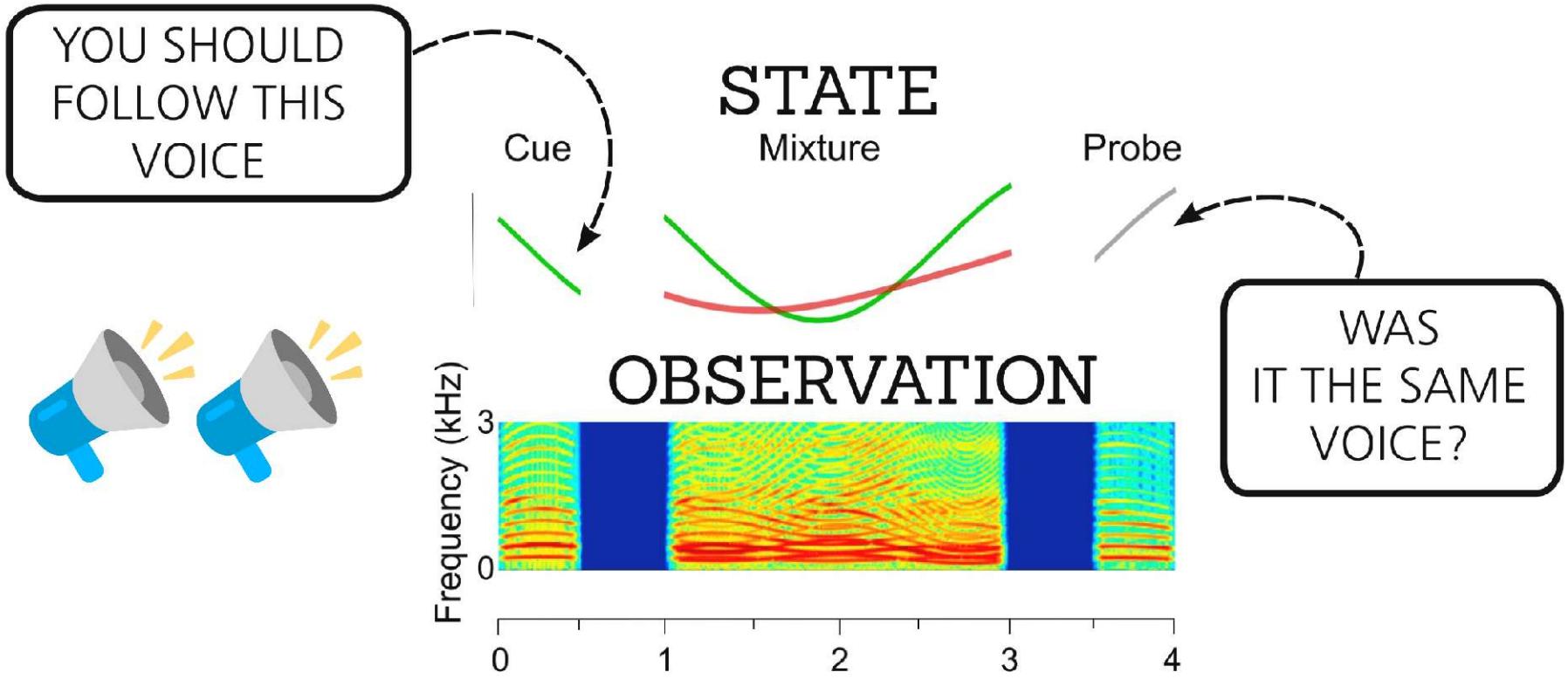

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- **Question**: is it possible to follow one of two voices in the absence of constant dissimilarities between them?

- different conditions (including signals with speech-like **pauses**)

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- **Question**: is it possible to follow one of two voices in the absence of constant dissimilarities between them?

- different conditions (including signals with speech-like **pauses**)

-> Result : **YES**, it is possible to discriminate if the probe belongs to the cued voice

-> **ATTENTIVE TRACKING** - moving locus of attention

I. 3. PSYCHOACOUSTIC STUDY

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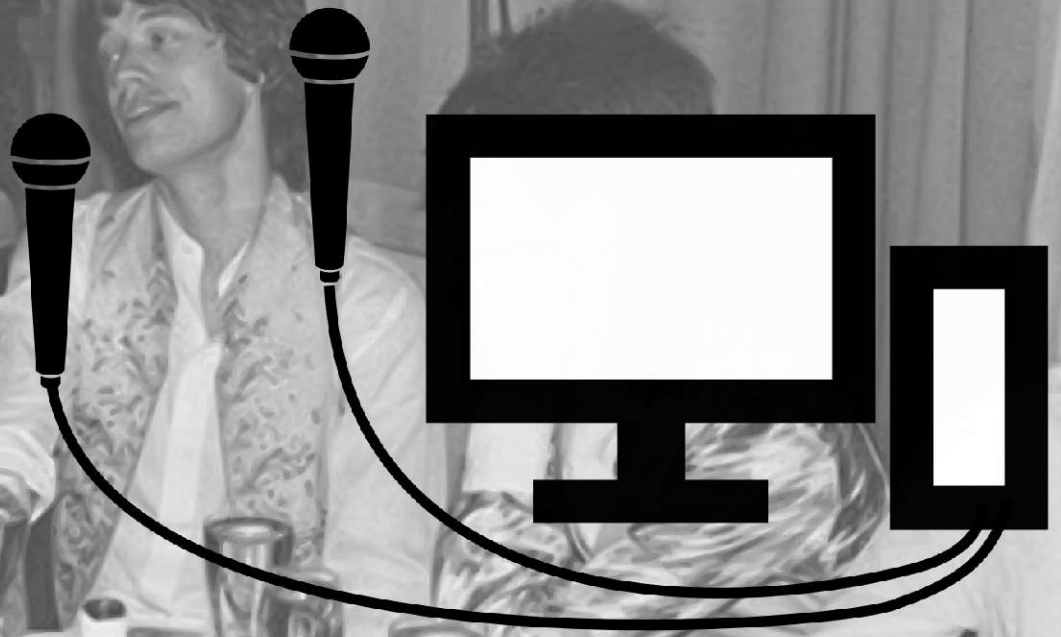
Goal: computational model of attentive tracking task



I. INTRODUCTION

I. 3. MODELING FRAMEWORK

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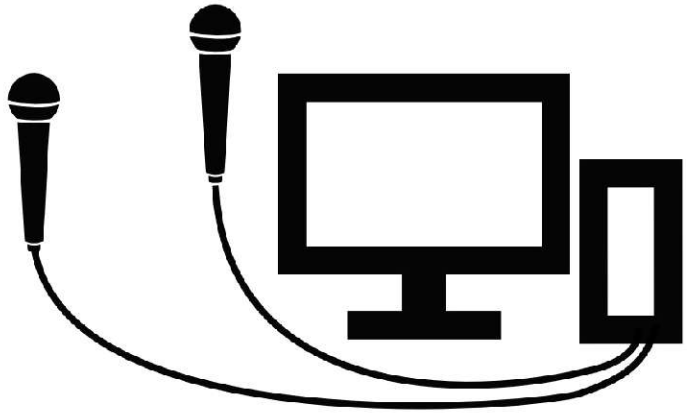
ASA

Phenomenon that we want to model - **Auditory Scene Analysis**

CASA:

Computational procedures simulating this phenomenon - **Computational Auditory Scene Analysis**



I. 3. MODELING FRAMEWORK

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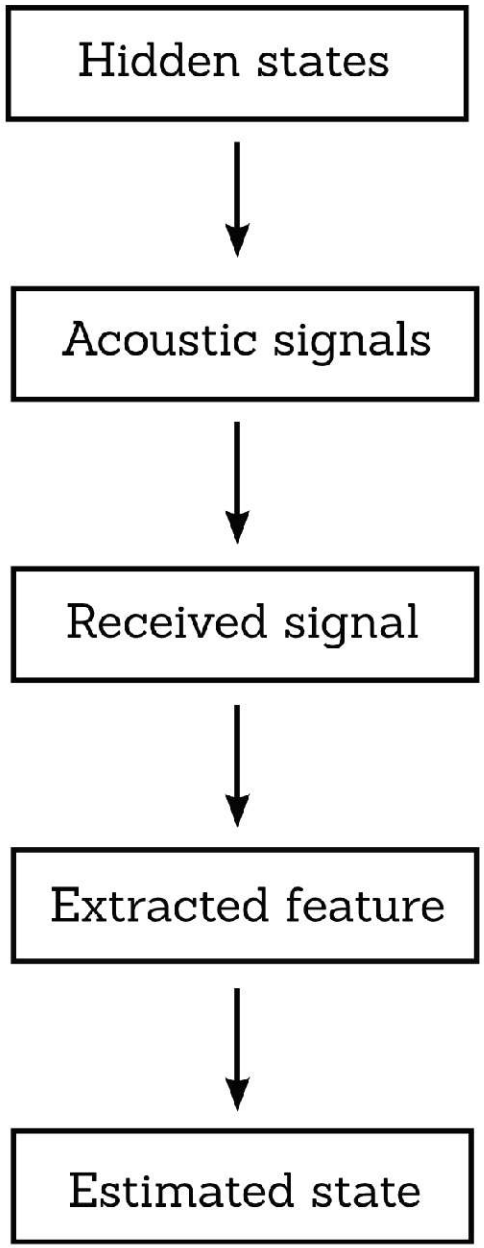
ASA

- What do I want to model?

- Block diagram ->

- General information processing / signal path

- reflected both in CASA and ASA



CASA:

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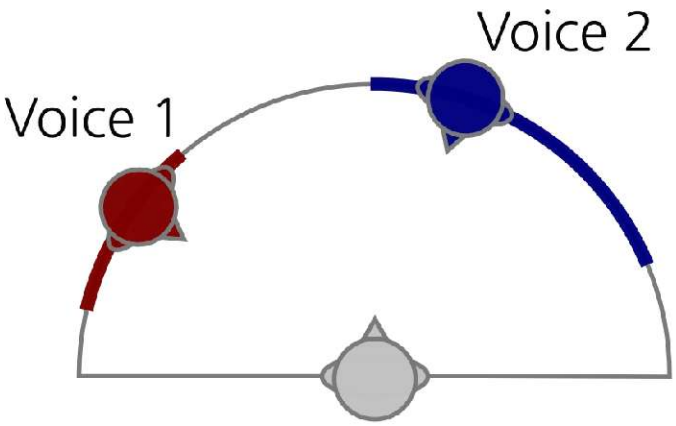
ASA



acoustic environment
two moving sources,
one receiver

REAL STATE OF A SYSTEM:
description of what is realy happening

Hidden states

↓

Acoustic signals

↓

Received signal

↓

Extracted feature

↓

Estimated state

CASA:

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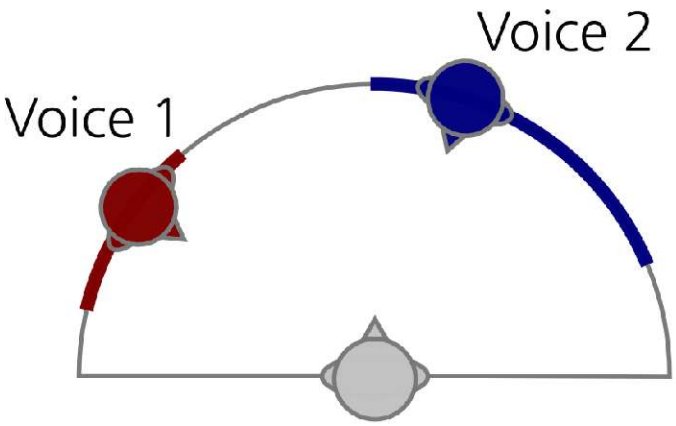
ASA



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description of what is happening in reality

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CASA:

multidimensional state vectors with high level parameters

$$\vec{s}_{1,n} = \begin{pmatrix} F0_{1,n} \\ F1_{1,n} \\ F2_{1,n} \\ \alpha_{1,n} \end{pmatrix}$$ Voice 1

$$\vec{s}_{2,n} = \begin{pmatrix} F0_{2,n} \\ F1_{2,n} \\ F2_{2,n} \\ \alpha_{2,n} \end{pmatrix}$$ Voice 2

GROUND TRUTH STATE

I. 3. MODELING FRAMEWORK

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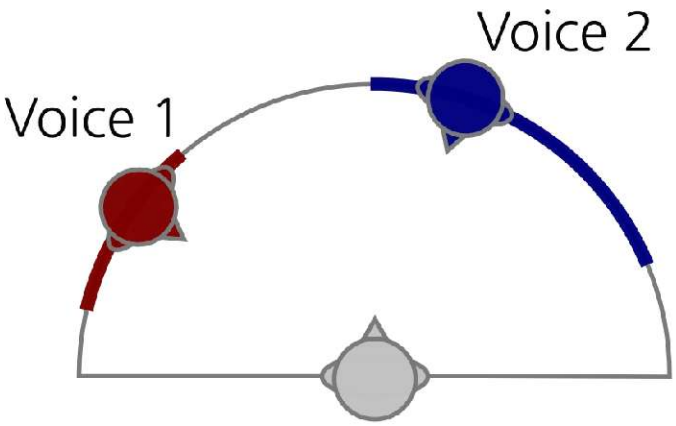

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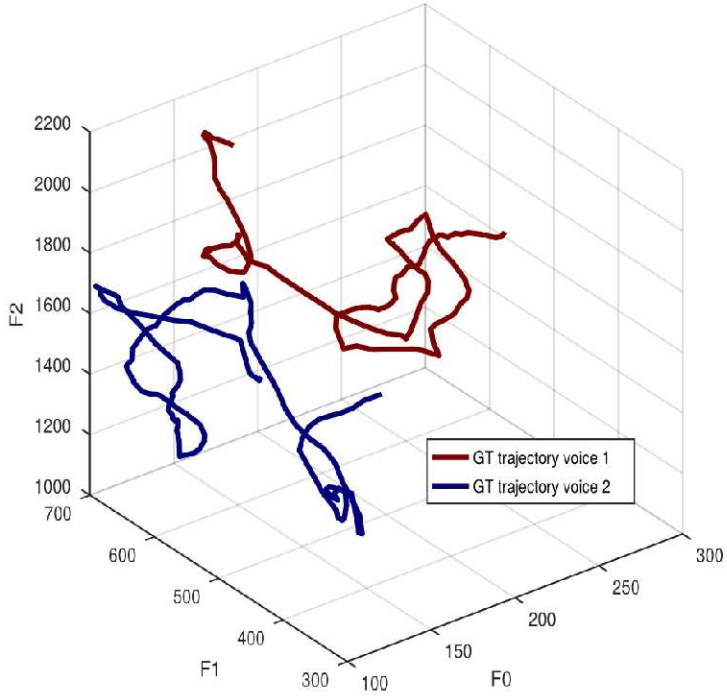
Estimated state

CASA:

state in time :
state trajectories



GROUND TRUTH STATE TRAJECTORY

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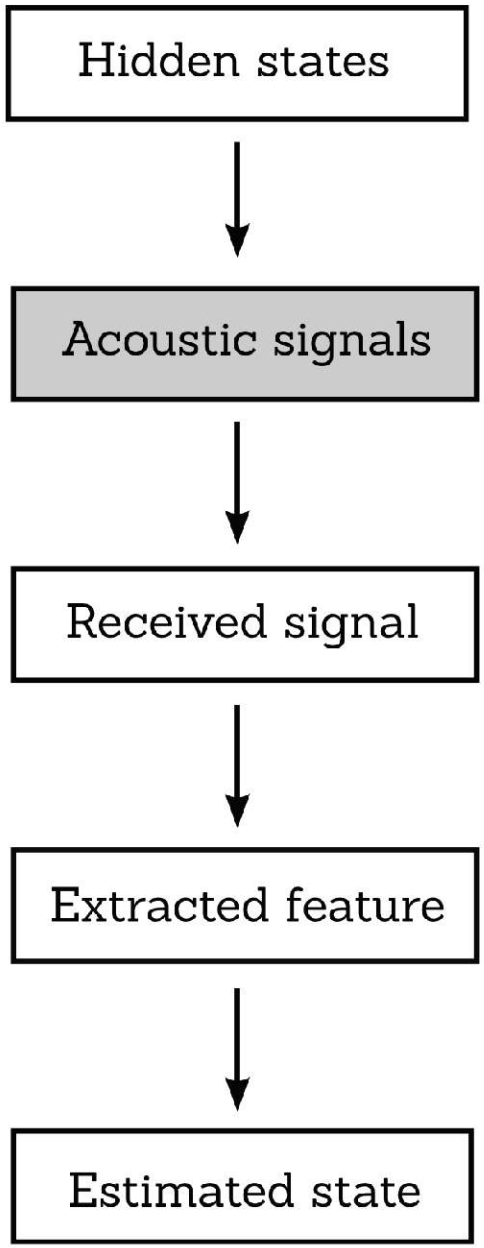

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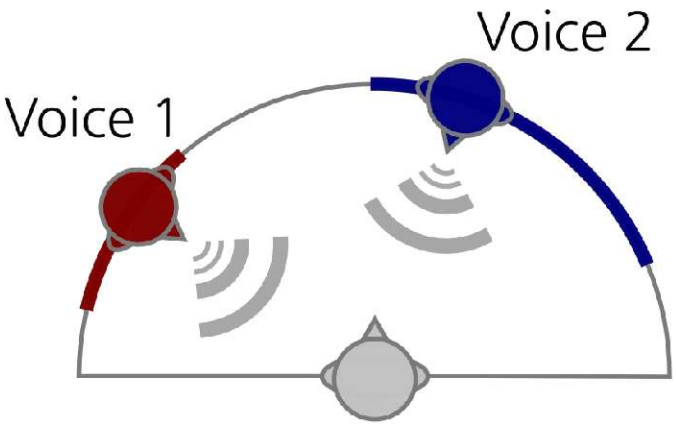

Sources in the acoustic environment generate sound pressure waves

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Received signal

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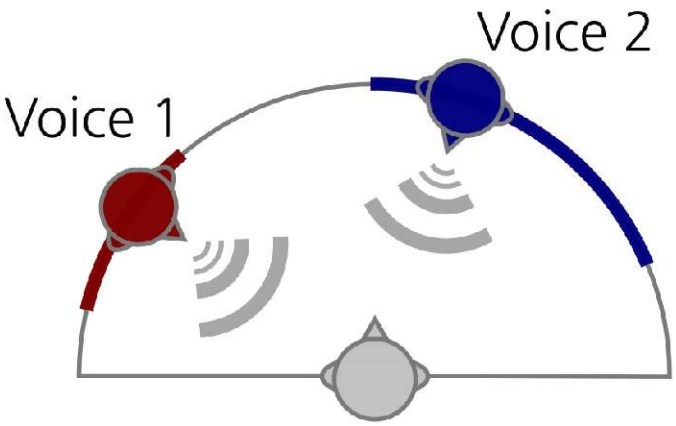

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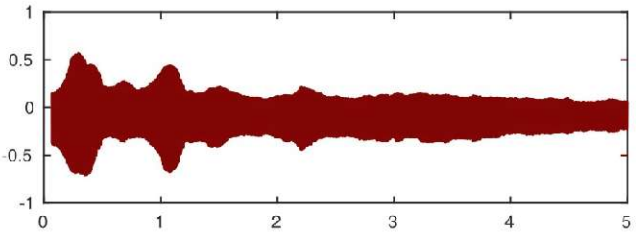
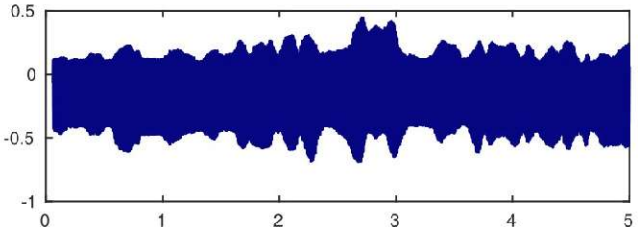


Voice 1



Voice 2

Waveforms of the generated sounds in a digital form

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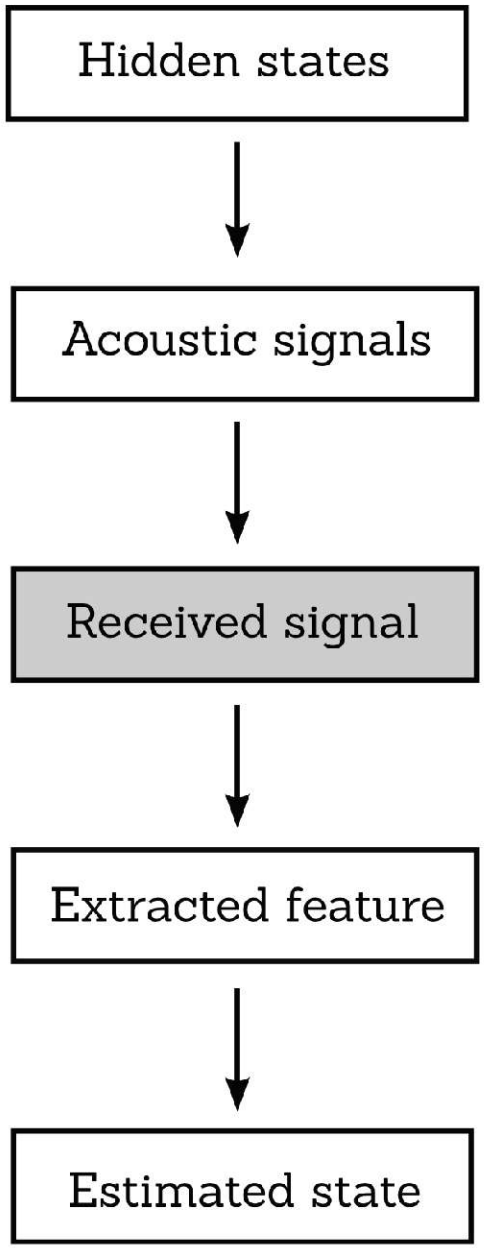

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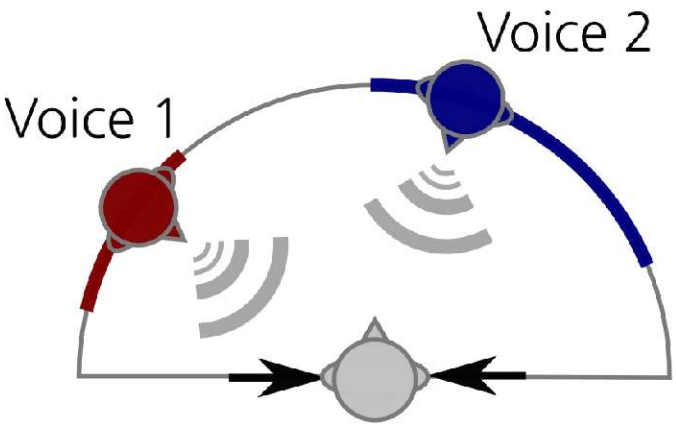

Listener - the interfering **mixture** of two sound waves makes the eardrums vibrate

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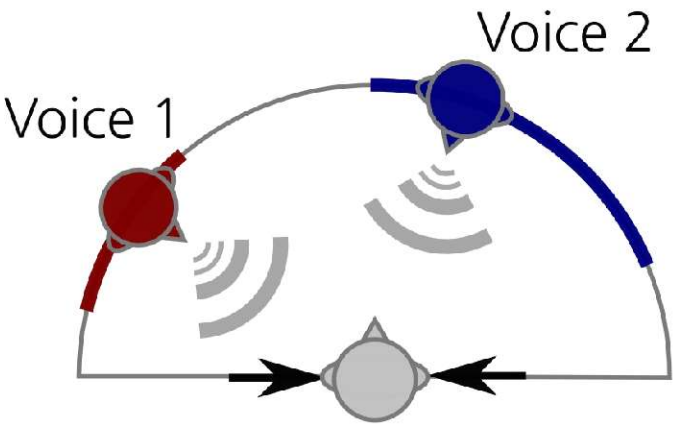

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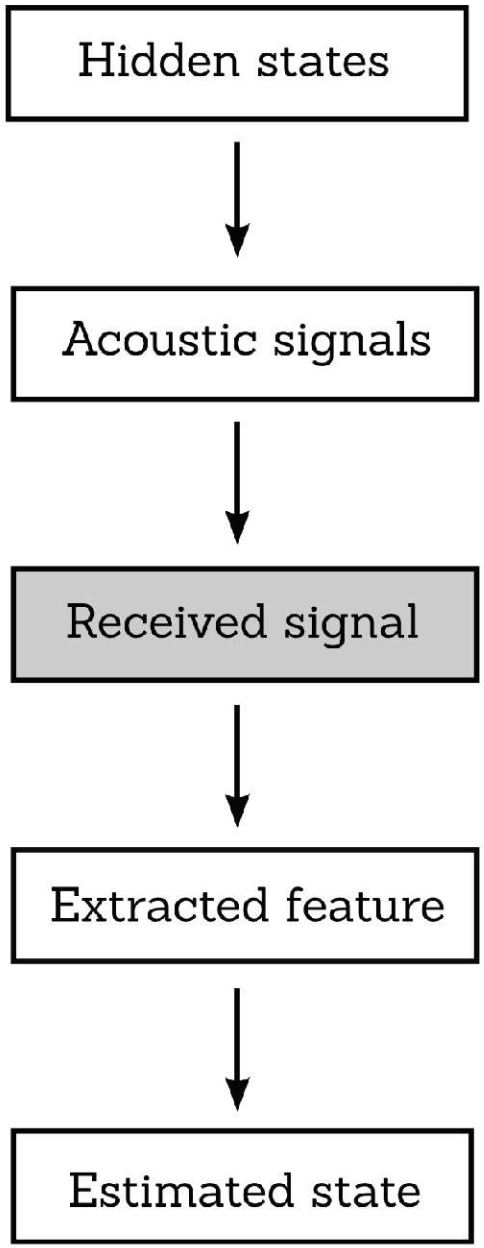

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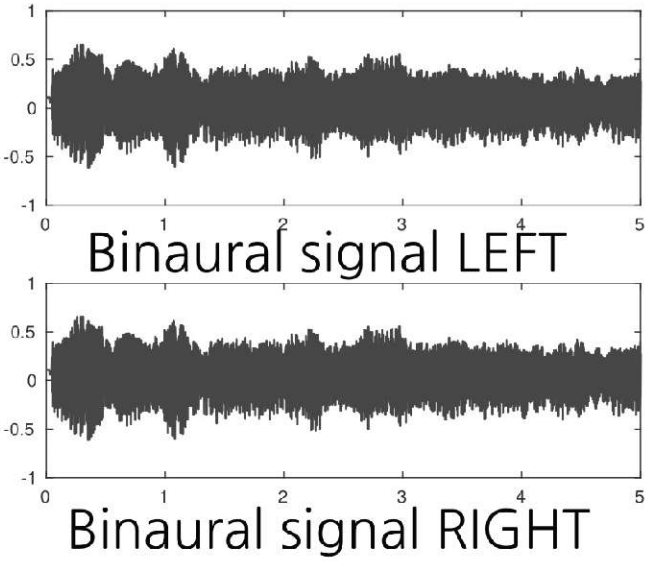

Binaural receiver -> **sum** of both signals **convolved with HRIRs** of left and right ear

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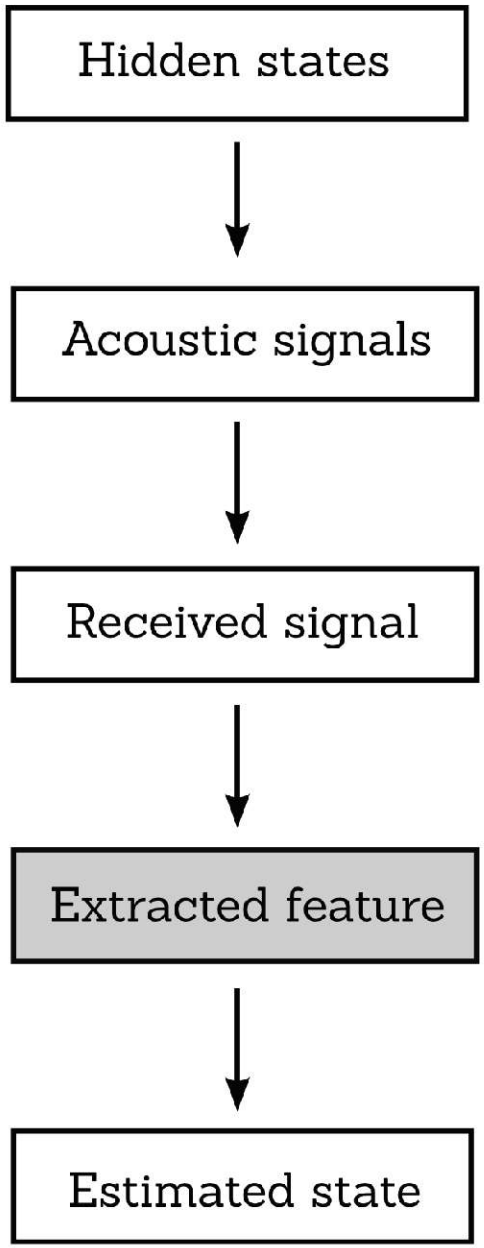
- What's next? Hearing research...

- Focus: modeling of information processing.

- At this stage: data transformation/ compression that results in redundancy reduction

- Called: feature extraction



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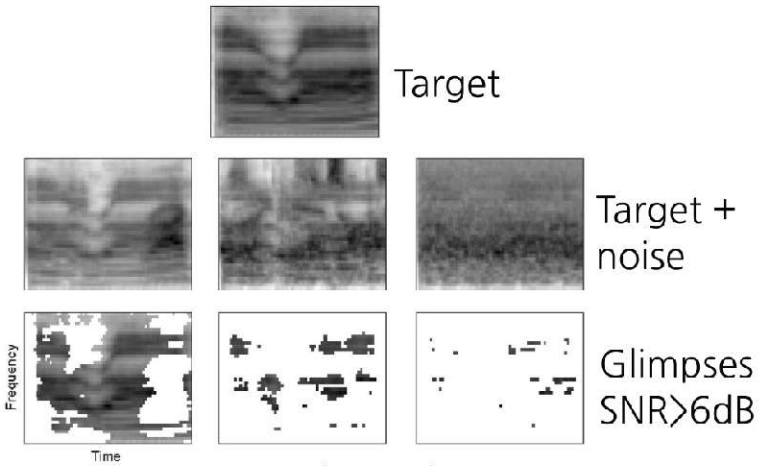
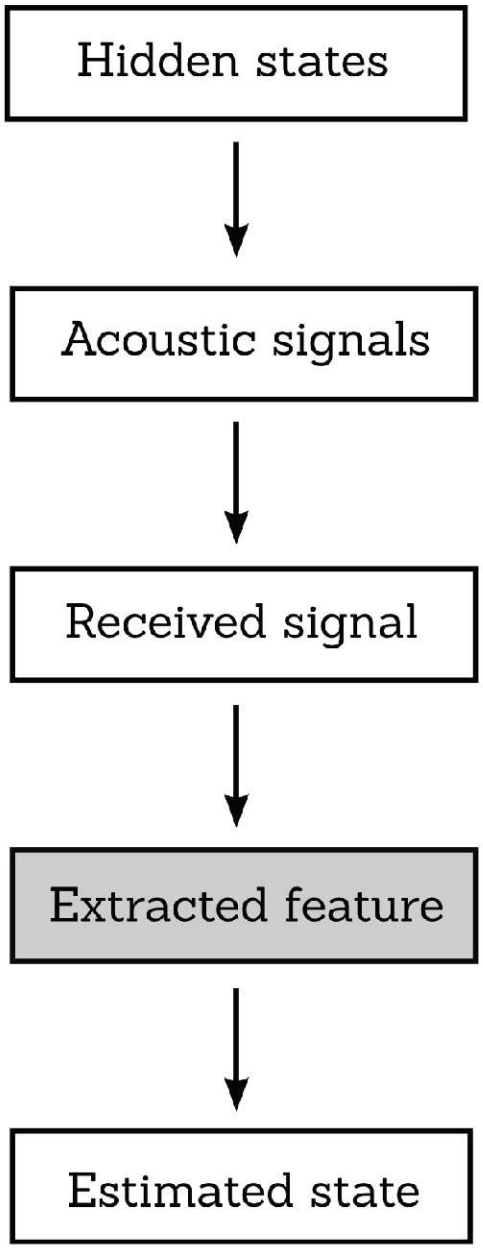
GLIMPSES

- Sparse spectro-temporal pieces of information least affected by the background.

- 'pixels' with high SNR



Cooke (2006)



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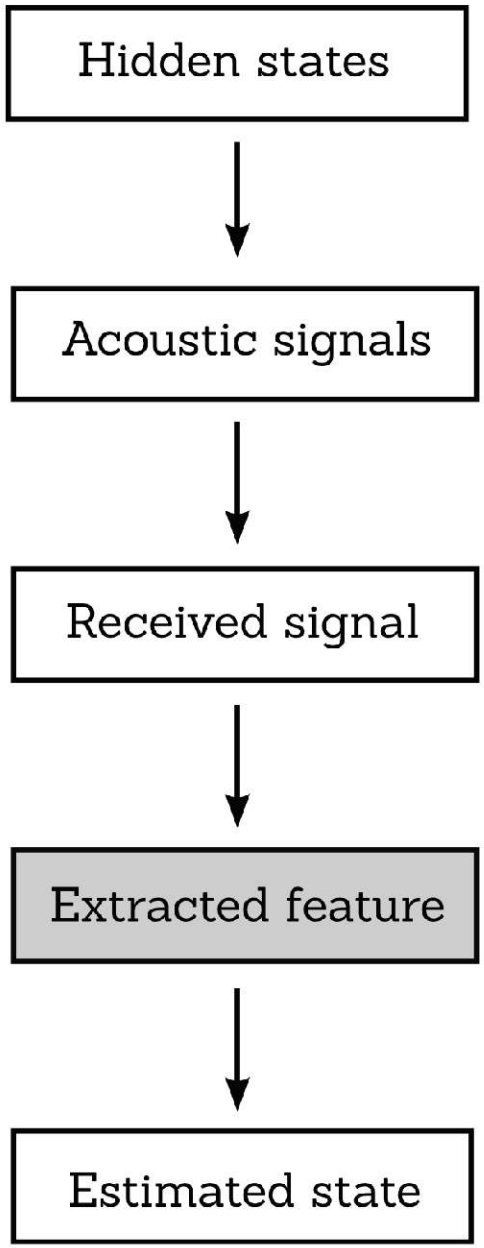
GLIMPSES

- sparse
- salient
- robust
- not a mixture

Studies* show:

Target-related glimpses are important for solving certain tasks in a complex multi-talker scene.

* Cooke (2006)
* Schoenmaker and van den Paar (2016)
* Josupeit et al. (2016)



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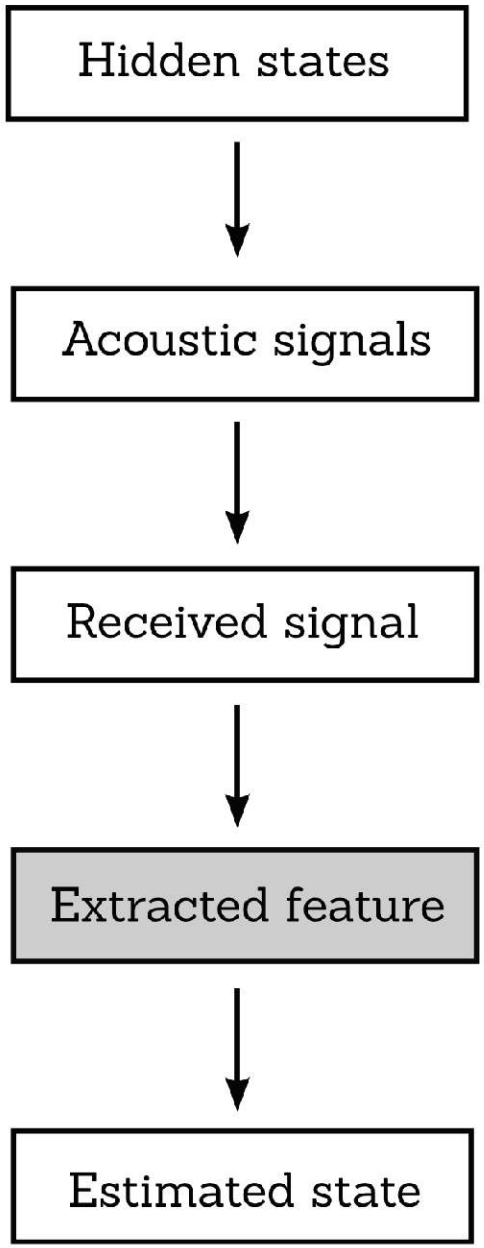

CASA:

Problem: How to find target-related glimpses without having the perfect knowledge about the individual target and masker energies?

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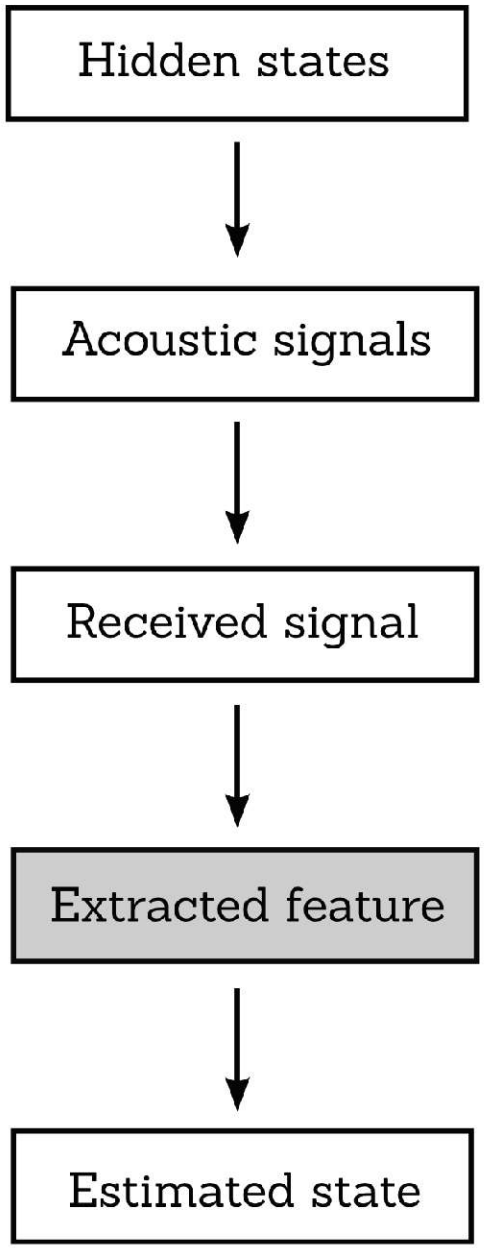

CASA:

PERIODICITY-BASED GLIMPSING FEATURES

Josupeit and Hohmann (2017)

high periodic energy indicates a robust piece of information coming from speech

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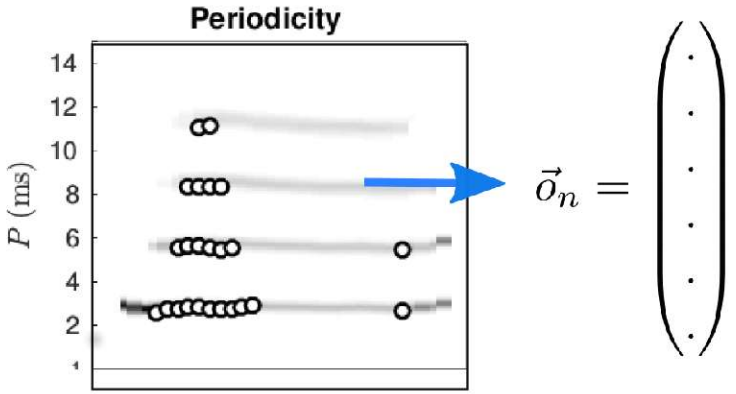
PERIODICITY-BASED GLIMPSING FEATURES

Josupeit and Hohmann (2017)



multidimensional **observation vector**

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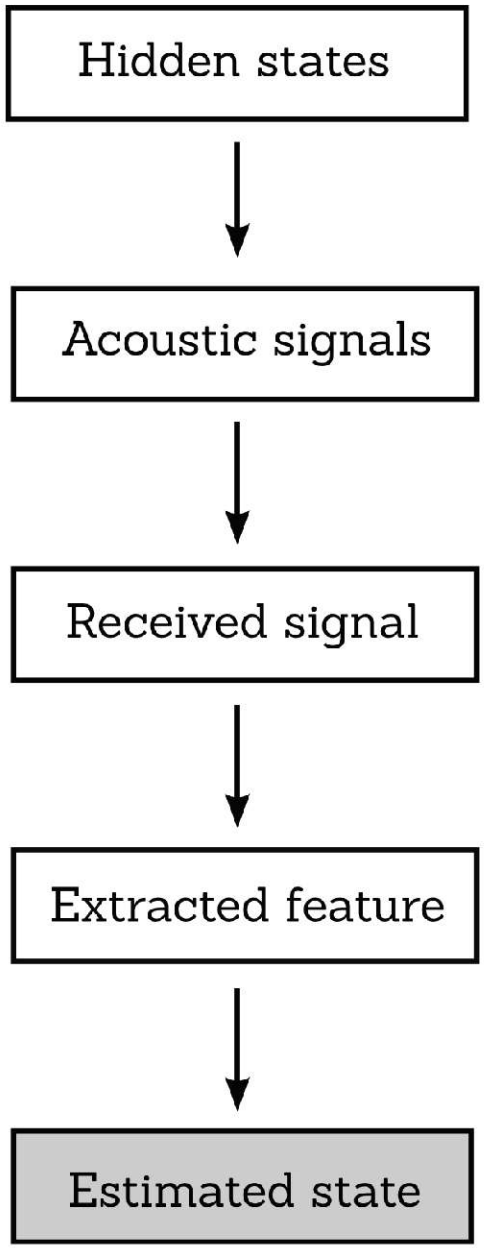

CASA:

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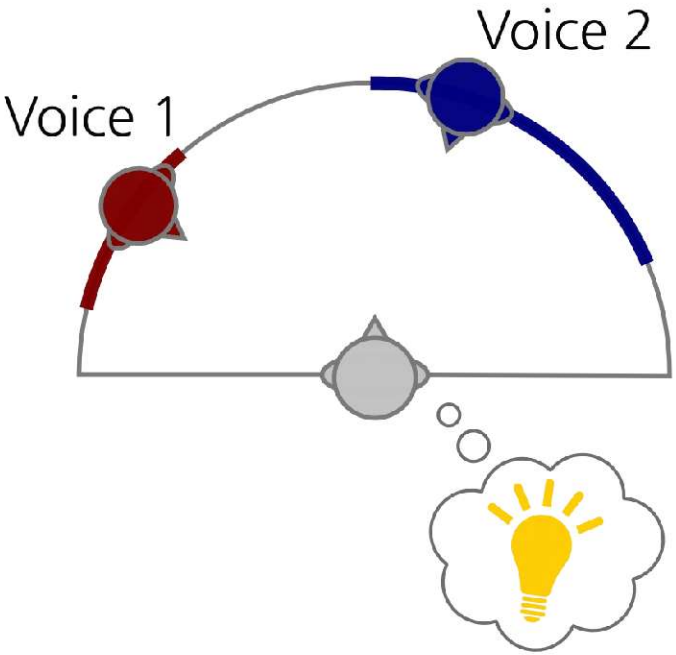
- conclusions about the reality



INFERRED STATE OF A SYSTEM: description of what we think is happening

Hidden states

↓

Acoustic signals

↓

Received signal

↓

Extracted feature

↓

Estimated state

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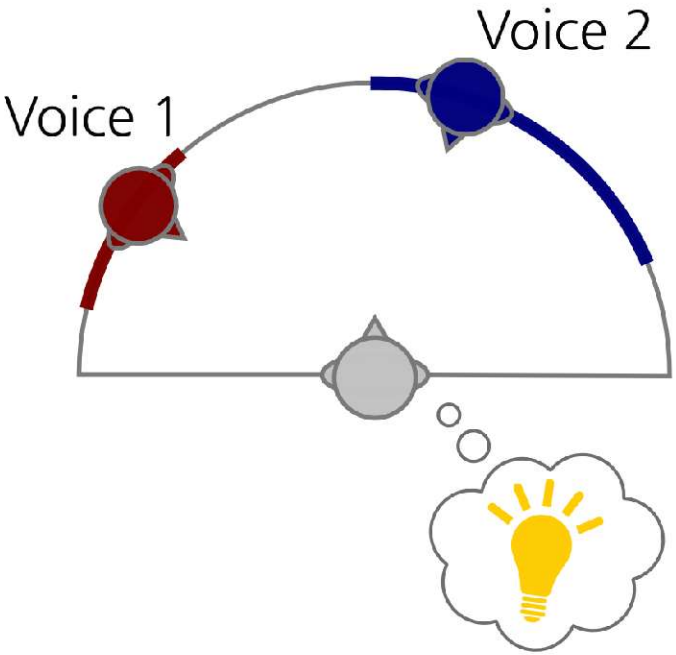

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CASA:

multidimensional state vectors

$$\hat{\vec{s}}_{1,n} = \begin{pmatrix} \hat{F}0_{1,n} \\ \hat{F}1_{1,n} \\ \hat{F}2_{1,n} \\ \hat{\alpha}_{1,n} \end{pmatrix}$$ Voice 1

$$\hat{\vec{s}}_{2,n} = \begin{pmatrix} \hat{F}0_{2,n} \\ \hat{F}1_{2,n} \\ \hat{F}2_{2,n} \\ \hat{\alpha}_{2,n} \end{pmatrix}$$ Voice 2

ESTIMATED STATE

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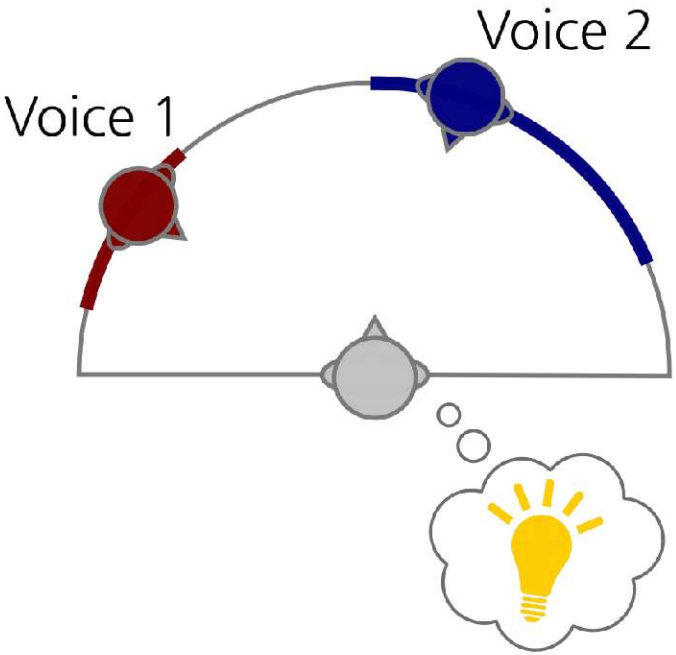
- conclusions about the reality



INFERRED STATE OF A SYSTEM:
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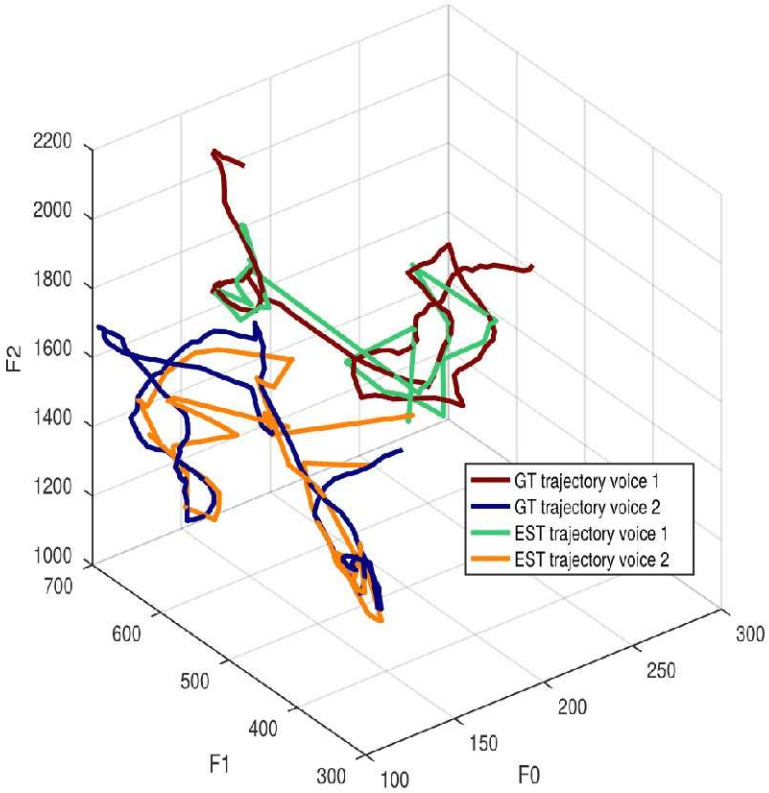
Estimated state

CASA:

state in time :
state trajectories



ESTIMATED STATE TRAJECTORY

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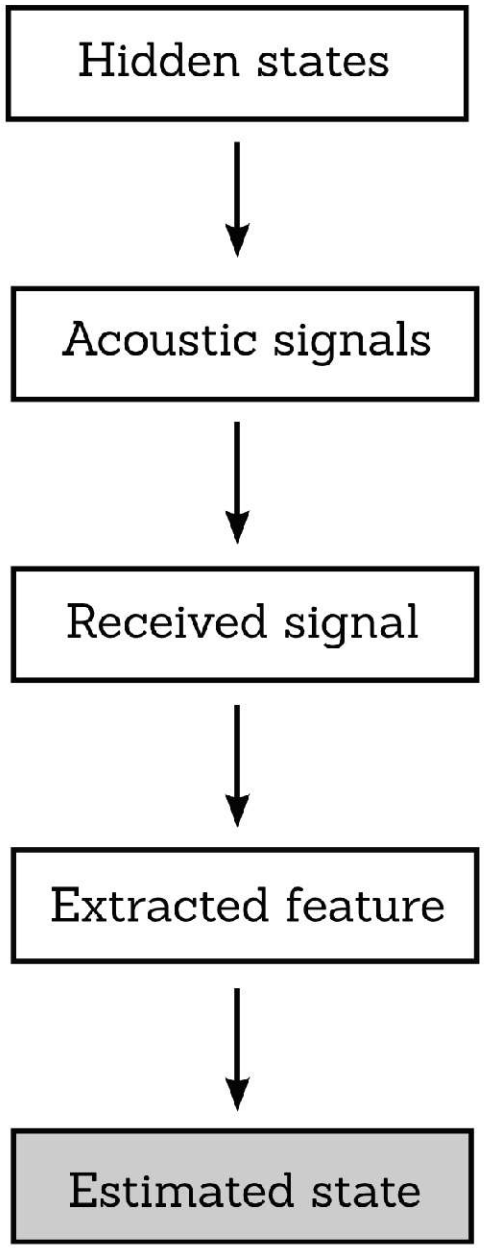
- But how is the state estimation done?

- **Theory**: Inference made by constantly creating and comparing hypotheses about the state of the system with the sensory input.



CASA:

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PREDICTIVE CODING

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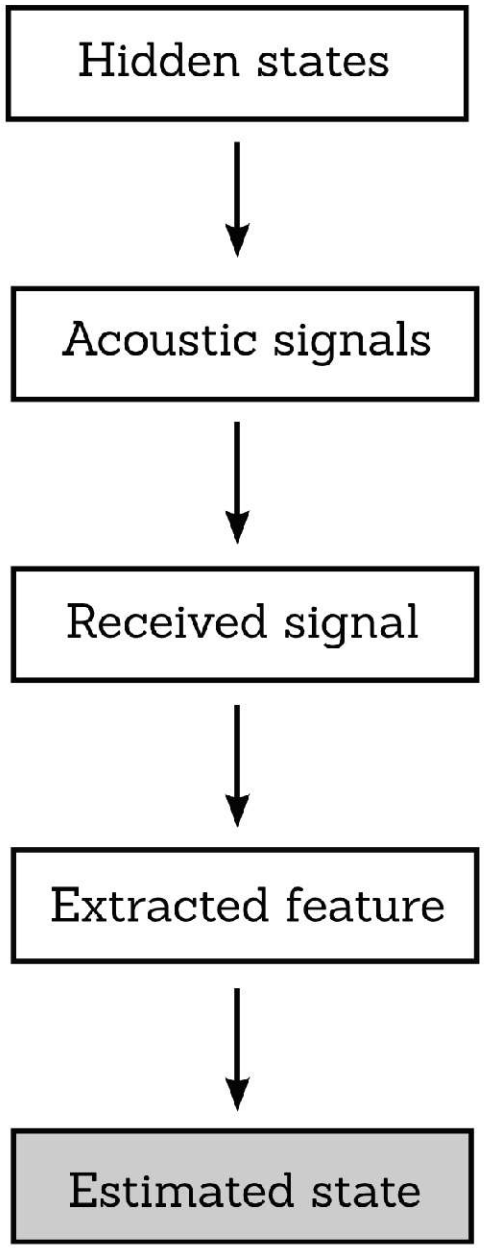

CASA:

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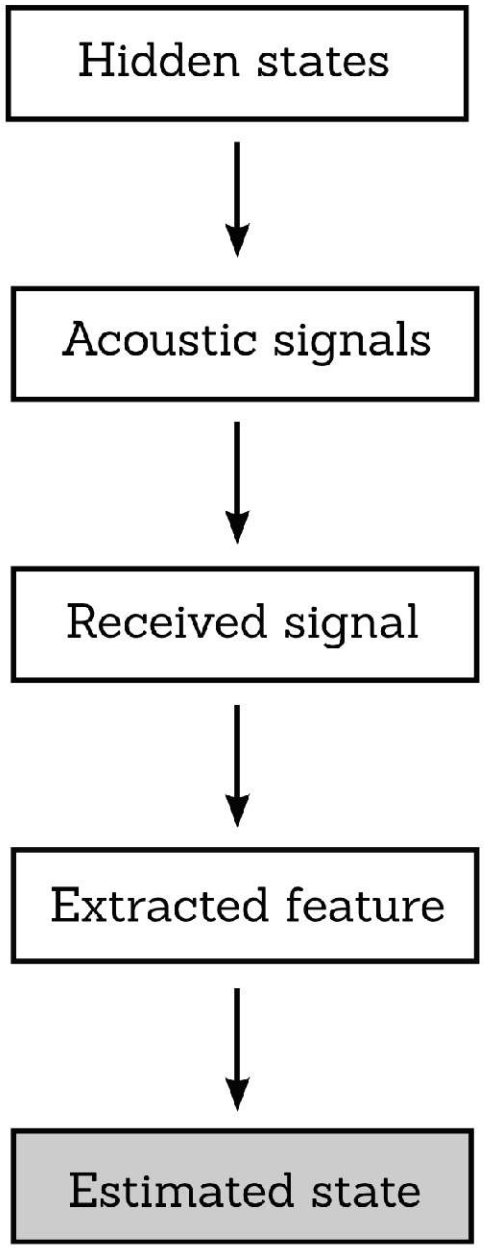

CASA:

Math form of sequential competing hypotheses:

$$p(\vec{s}_n|\vec{o}_{0:n}) = \frac{p(\vec{o}_n|\vec{s}_n)p(\vec{s}_n|\vec{o}_{0:n-1})}{p(\vec{o}_n|\vec{o}_{0:n-1})}$$

SEQUENTIAL BAYESIAN ESTIMATION

- Given a sequence of observations up to now, estimate the **current state distribution**.

- Having this distribution, estimate the **most likeli state** of the system.

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PREDICTIVE CODING

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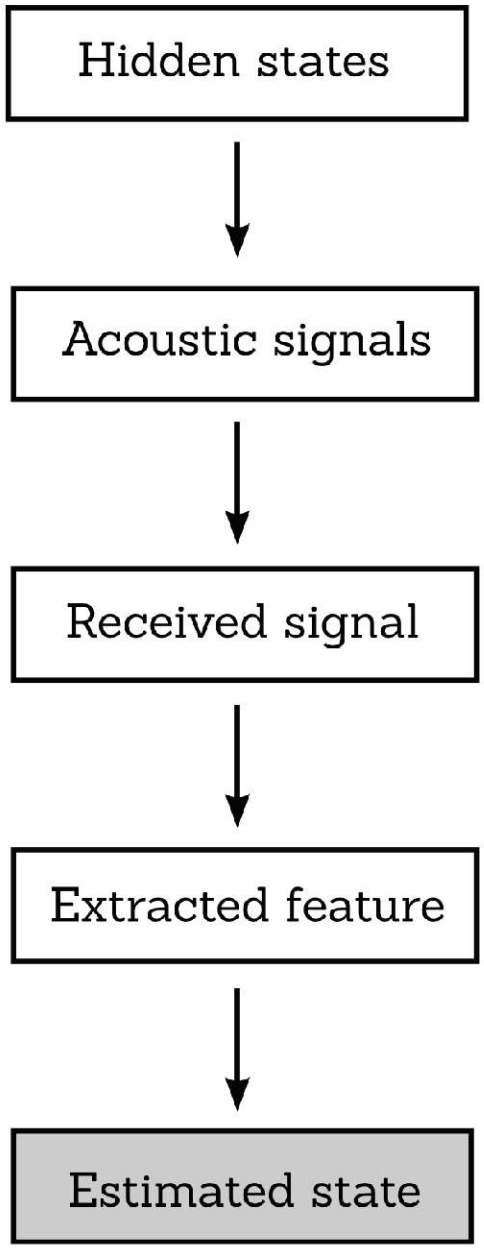

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SEQUENTIAL BAYESIAN ESTIMATION

No analytical solution.
Approximation:

PARTICLE FILTERING

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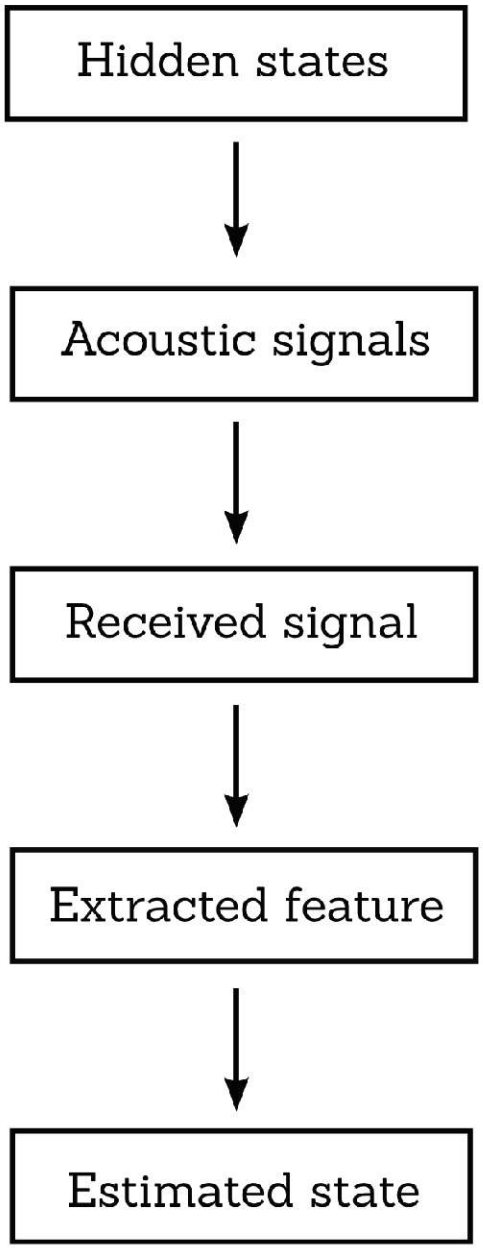
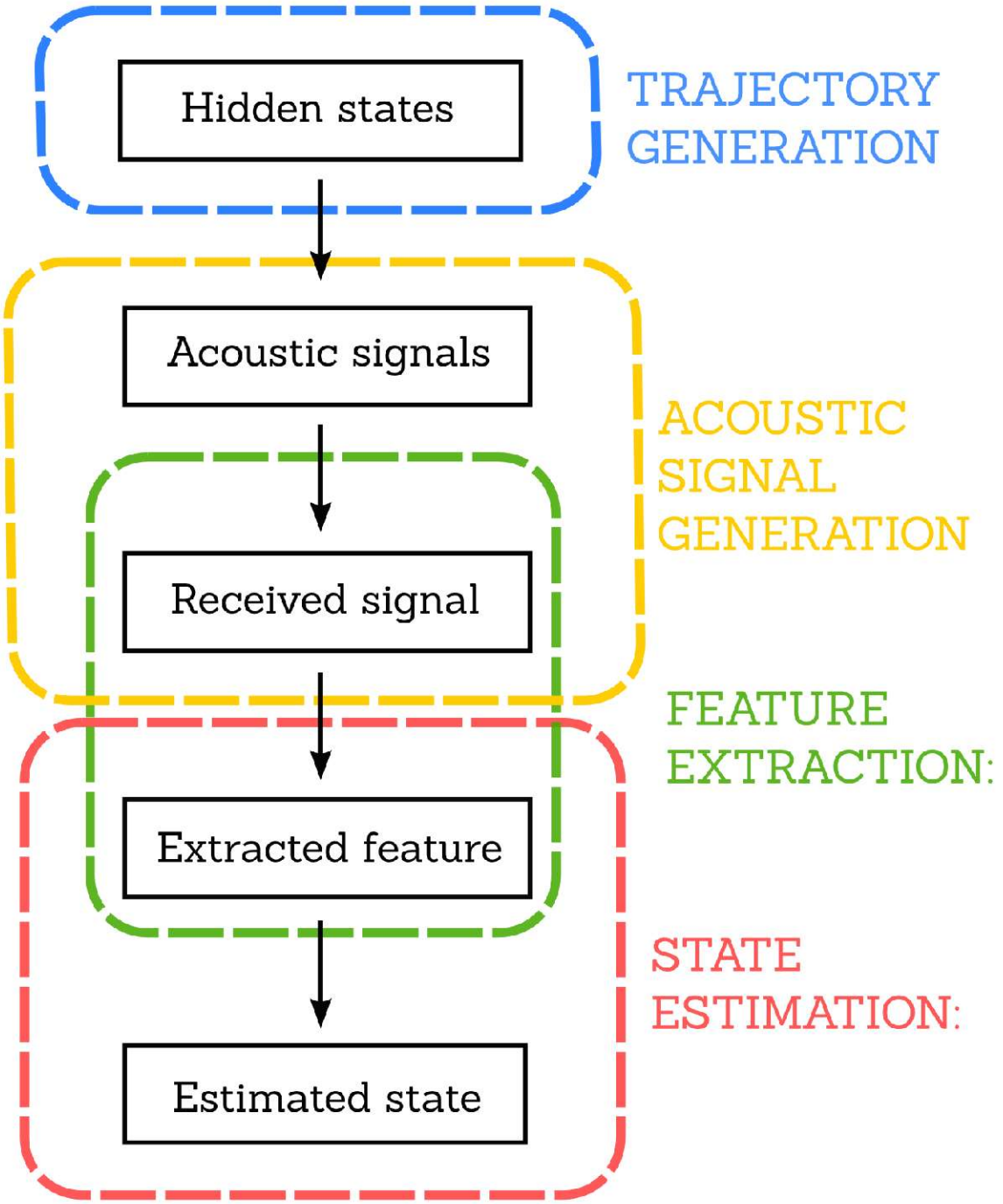


I. 3. MODELING FRAMEWORK

How to approach it?



I. INTRODUCTION

I. 4. SIMULATION APPROACH