

# Exploiting Structures of Temporal Causality for Robust Speaker Localization in Reverberant Environments

LISTEN Workshop / Summer School

Christopher Schymura, Peng Guo, Yanir Maymon, Boaz Rafaely, [Dorothea Kolossa](#)

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 Ben-Gurion University  
of the Negev

# Outline

- 1** Introduction
- 2** Time-series modeling
- 3** Building a causal model
- 4** Evaluation
- 5** Outlook

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# Introduction

## Application domain

- Speaker localization in reverberant rooms.
- Applications: Speech enhancement, teleconferencing, smart home, virtual reality, robot audition, ...
- Active field of research.<sup>1 2 3</sup>



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## Localization framework

- Direct-path dominance (DPD) test-based direction-of-arrival (DoA) estimation.<sup>4</sup>
- Clustering of estimated DoAs using a Gaussian mixture model (GMM).<sup>5</sup>
- Speaker DoA determined by selecting the dominant Gaussian component of the GMM.



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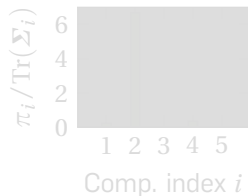
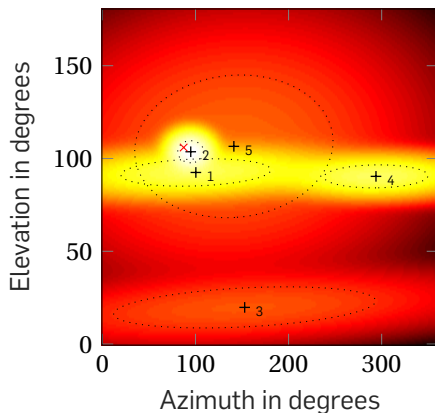
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# GMM-based DoA clustering

Reverberation time:  $T_{60} = 0.5$  s

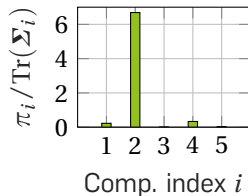
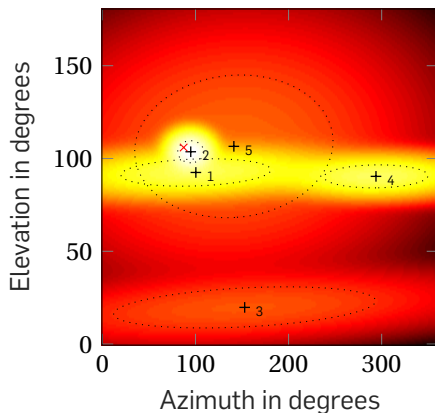
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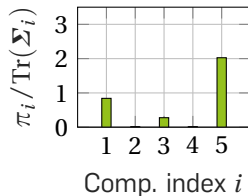
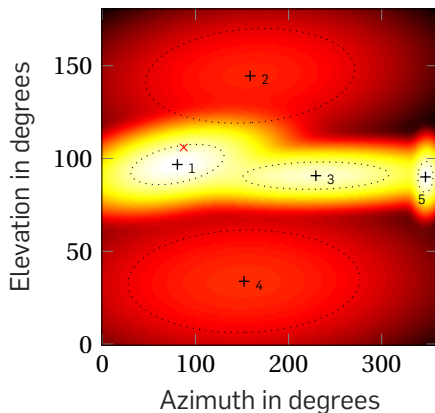
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# GMM-based DoA clustering

Reverberation time:  $T_{60} = 1.0$  s

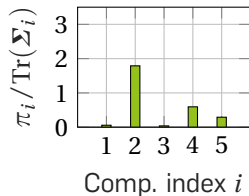
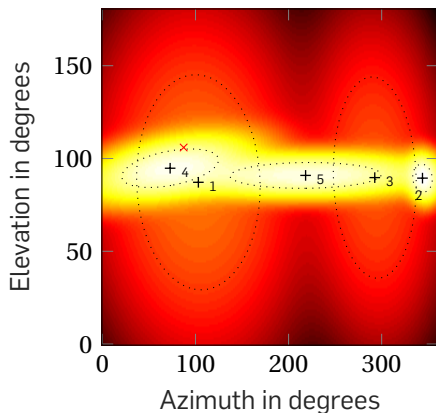
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Reverberation time:  $T_{60} = 2.0$  s

$$\log p(\boldsymbol{\theta} | \{\pi_i, \boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i\}_{i=1}^C)$$

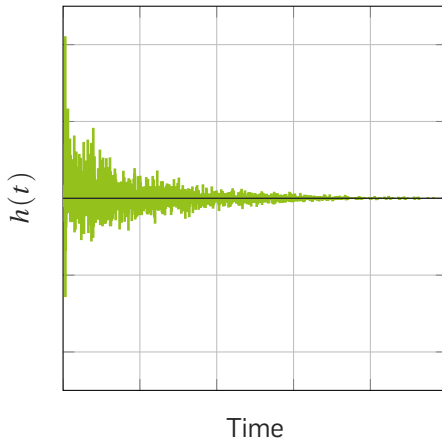


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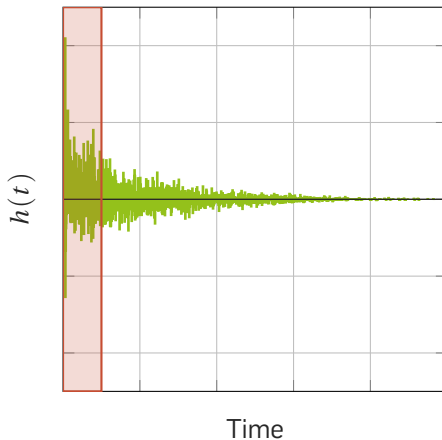
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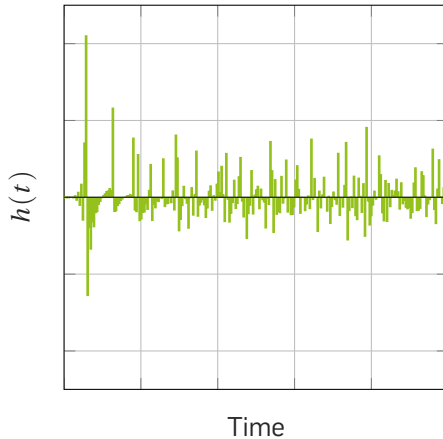
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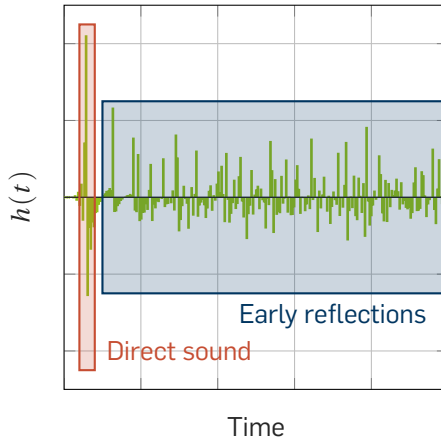
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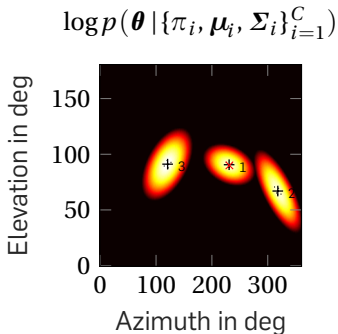
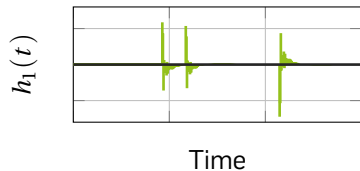
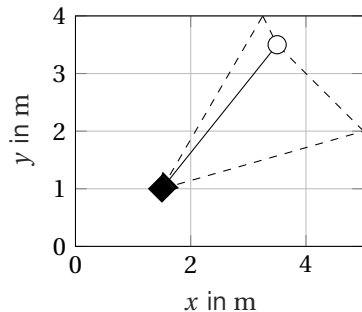
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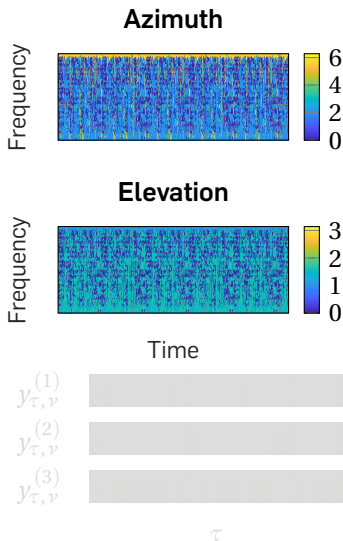
# Temporal structure of RIRs



# Toy example for time-series modeling



# DoA-dependent time-series



1. Generate DoA time-series for each frequency bin:

$$\boldsymbol{\theta}_{\nu} = \left\{ \underbrace{\left[ \phi_{\tau, \nu} \quad \psi_{\tau, \nu} \right]^T}_{\boldsymbol{\theta}_{\tau, \nu}^T} \right\}_{\tau=1}^T$$

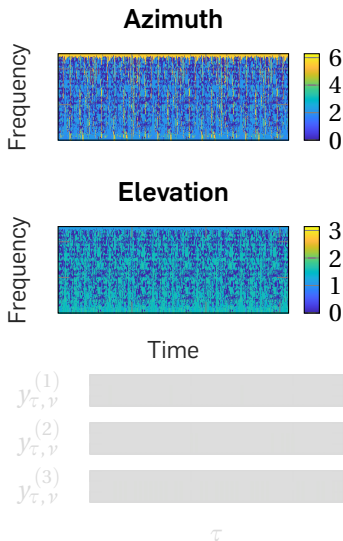
2. Evaluate component-wise Gaussian posteriors:

$$y_{\tau, \nu}^{(i)} = p(\boldsymbol{\theta}_{\tau, \nu} | \boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i)$$

3. Generate time-series from posteriors:

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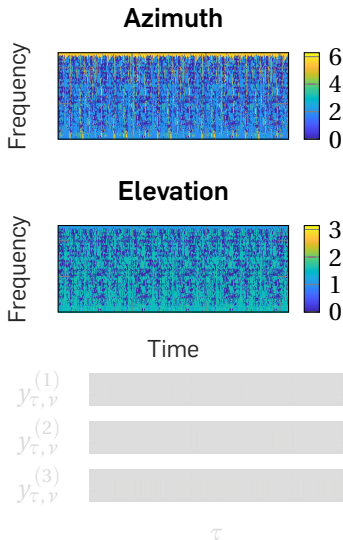
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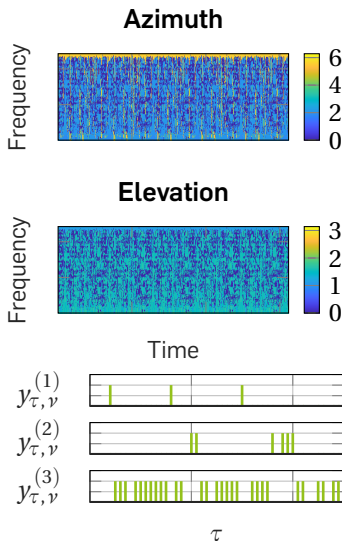
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# Granger causality test

- Statistical hypothesis test to determine whether a time-series is useful to forecast another.
- Initially proposed and widely used in the context of economics<sup>6</sup>.
- Lightweight and computationally efficient framework.
- **Important:** Granger causality does not necessarily imply true causality!

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# Granger causality test: algorithm

1. Given two time-series signals  $\mathbf{x}_\tau$  and  $\mathbf{y}_\tau$ , fit two vector autoregressive (VAR) models

$$\mathbf{x}_\tau = \sum_{\mu=1}^m \mathbf{A}_{xx,\mu} \mathbf{x}_{\tau-\mu} + \sum_{\mu=1}^m \mathbf{A}_{xy,\mu} \mathbf{y}_{\tau-\mu} + \boldsymbol{\epsilon}_{x,\tau}, \quad \boldsymbol{\epsilon}_{x,\tau} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_x)$$

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2. Construct  $F$ -test statistic using the log-likelihood ratio of the residuals

$$\mathcal{F}_{Y \rightarrow X} \equiv \log \left\{ \frac{|\boldsymbol{\Sigma}'_x|}{|\boldsymbol{\Sigma}_x|} \right\}$$

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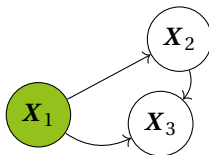
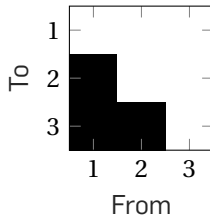
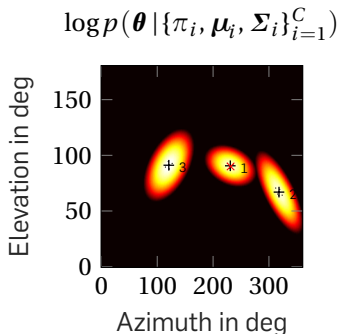
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## Pairwise GCT on toy example data

Constructing the Granger matrix and causal graph:



Root node selection using Tarjan's algorithm.<sup>7</sup>

<sup>7</sup>R. Tarjan (1971): "Depth-first search and linear graph algorithms"

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# Experimental setup

- Simulation study using a single speech source in a reverberant room of size  $8\text{ m} \times 5\text{ m} \times 3\text{ m}$  with varying  $T_{60} \in \{0.5\text{ s}, \dots, 2.5\text{ s}\}$ .
- RIRs for a spherical microphone array with 32 microphones were generated using the image source method.<sup>8</sup>
- Hyperparameter tuning on a dedicated validation set with different speakers, source/array positions and fixed  $T_{60}$ .
- Monte Carlo simulations were conducted with 100 runs for each experimental configuration.
- Localization root mean square error (RMSE) was used as evaluation metric.

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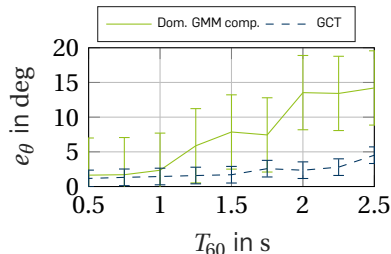
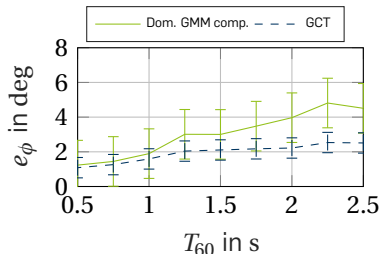
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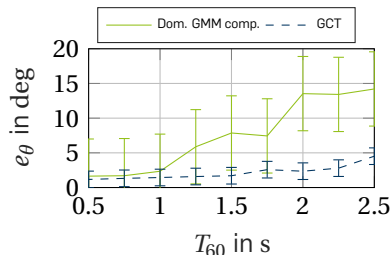
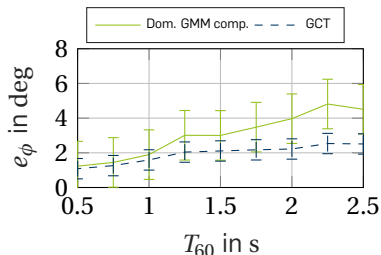
# Results



$T_{60}$ in s	0.50	0.75	1.00	1.25	1.50	1.75	2.00	2.25	2.50
Coincidence rate	0.97	0.93	0.91	0.81	0.79	0.79	0.72	0.65	0.65

Coincidence rate represents the degree to which the same DoA components of the GMM were selected by the proposed method and the baseline.

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# Outlook

Incorporating temporal context yields significant performance improvements. Still, the current study is a proof-of-concept and many important challenges remain to be solved:

- Extensive hyperparameter tuning is required.  
⇒ *Apply machine learning methods to predict hyperparameters?*
- Method is restricted to static acoustic scenarios. Moving arrays and/or sources can not be handled with the current framework.  
⇒ *Extend model to a dynamical system representation?*
- Gaussian assumption of GCT is violated by DoA time-series signals used in this study.  
⇒ *Adapt GCT to non-Gaussian cases?*<sup>9</sup>

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<sup>9</sup>S. Kim, D. Putrino, S. Ghosh, E. N. Brown (2011): "A Granger Causality Measure for Point Process Models of Ensemble Neural Spiking Activity"

# Outlook

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- Extensive hyperparameter tuning is required.  
⇒ *Apply machine learning methods to predict hyperparameters?*
- Method is restricted to static acoustic scenarios. Moving arrays and/or sources can not be handled with the current framework.  
⇒ *Extend model to a dynamical system representation?*
- Gaussian assumption of GCT is violated by DoA time-series signals used in this study.  
⇒ *Adapt GCT to non-Gaussian cases?*<sup>9</sup>

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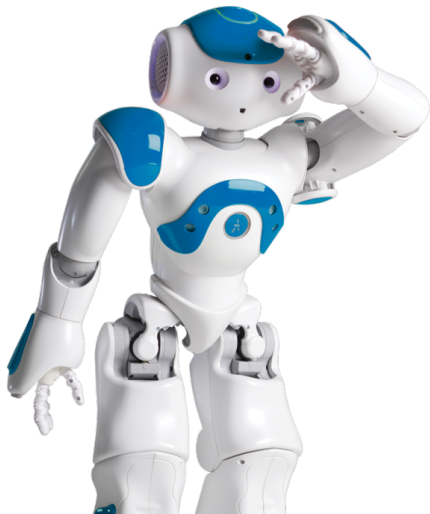
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**Thank you!**