Direction of Arrival Estimation for Wildlife Protection

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Licentiate Seminar

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Opponent: Andreas Jakobsson (LU)
Examiner: Svante Gunnarsson

LINKÖPING UNIVERSITY

WALLENBERG AI, AUTONOMOUS SYSTEMS AND SOFTWARE PROGRAM

Background

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- Decreasing rate between 2010-2014 was 8%.

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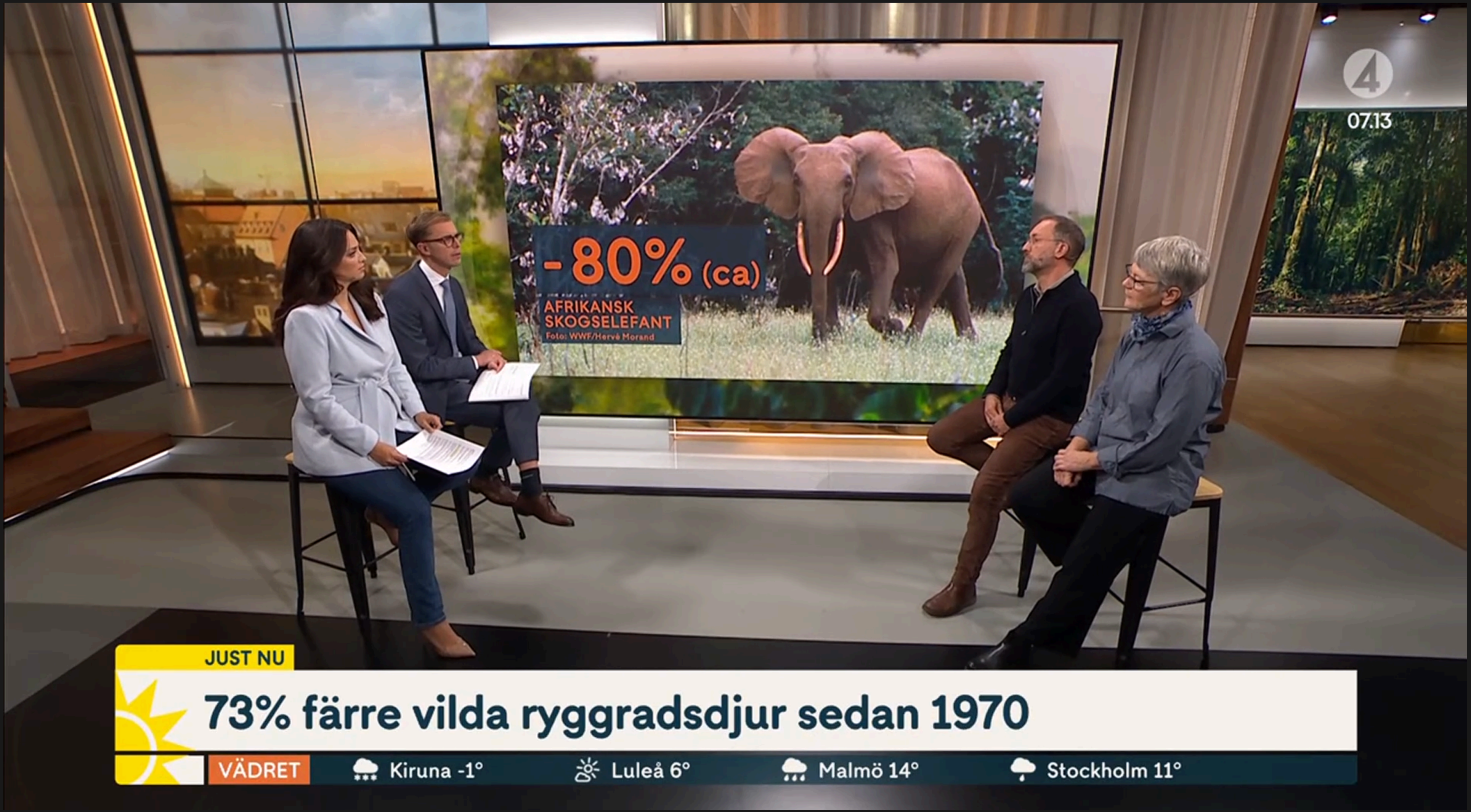

Nyhetsmorgon 10th of October

Example 1 - Elephant tracking

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- A geophone-based system detects seismic waves from elephant footsteps to estimate direction.
- Real-time tracking helps warn residents and guide elephants back to their habitats.

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Example 2 - Acoustic Surveillance for Savanna Protection

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- Microphone arrays estimate the direction of rifle shots to locate poachers.
- Key sounds monitored: elephant trumpets, a woman's scream, and police sirens.
- The system offers a complete overview, enhancing response and conservation efforts.

Outline

1. Problem Formulation

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2. Classical Direction of Arrival

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5. Conclusions & Future Work

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- How can the **directional sensitivity** of the sensors be utilized to estimate the DOA, and how should the directional sensitivity be **modeled**?

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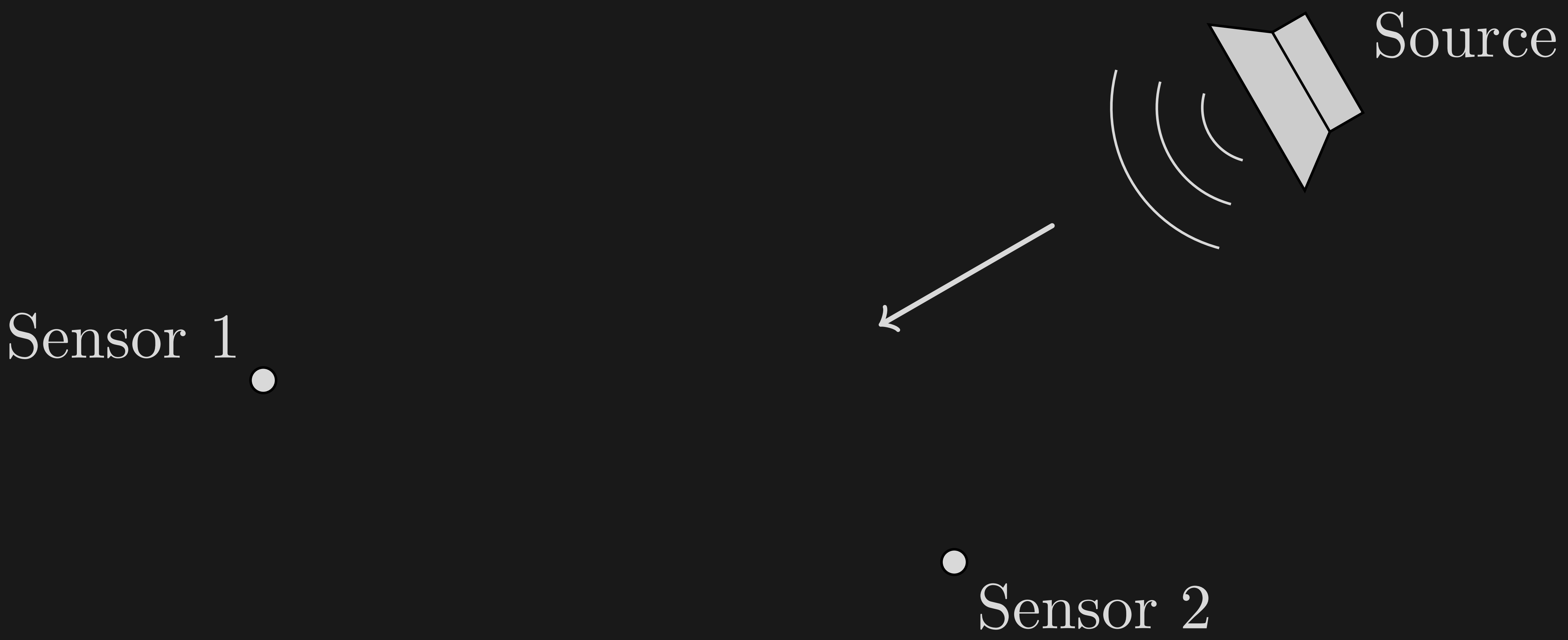
- What are the **theoretical limits** of the directional sensitivity based DOA estimator, and how does the **frequency content** of the signal affect the directional sensitivity?
- How does the directional sensitivity based DOA estimate **compare to state-of-the-art** methods using narrowband and realistic signals?

Classical DOA Estimation



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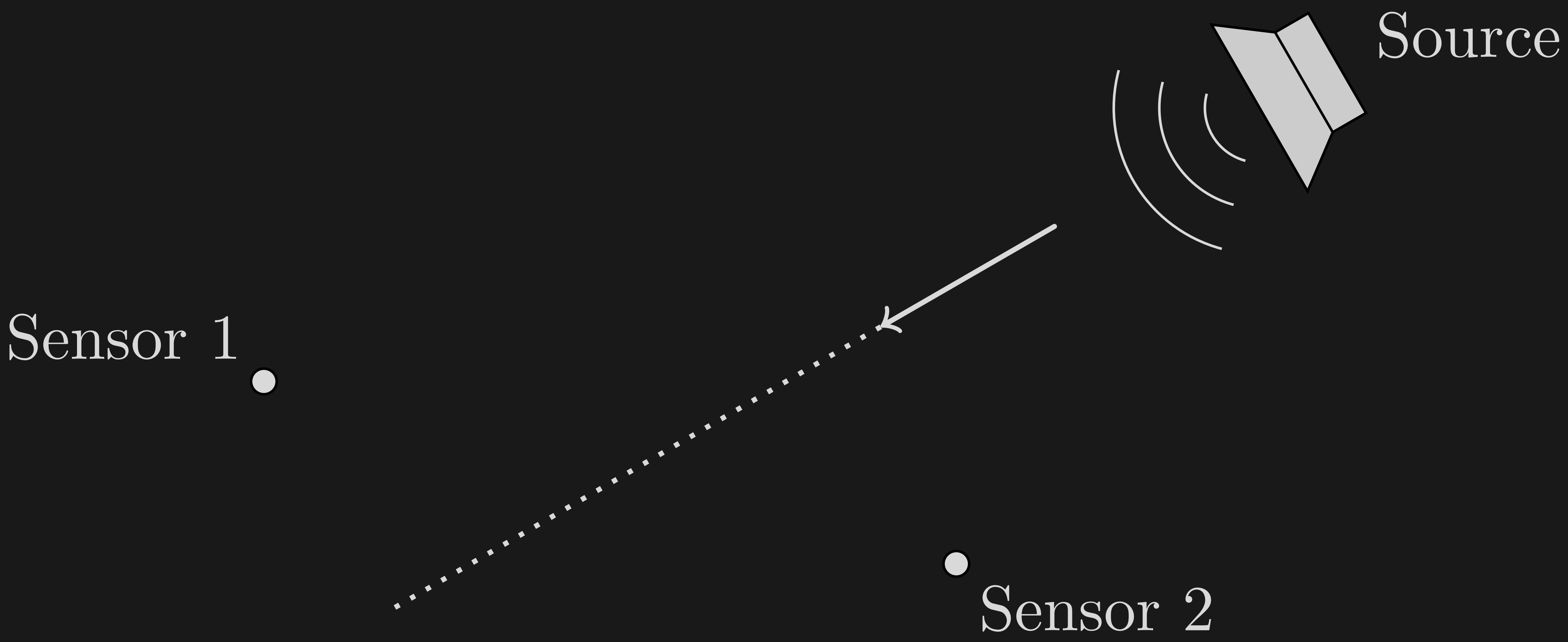

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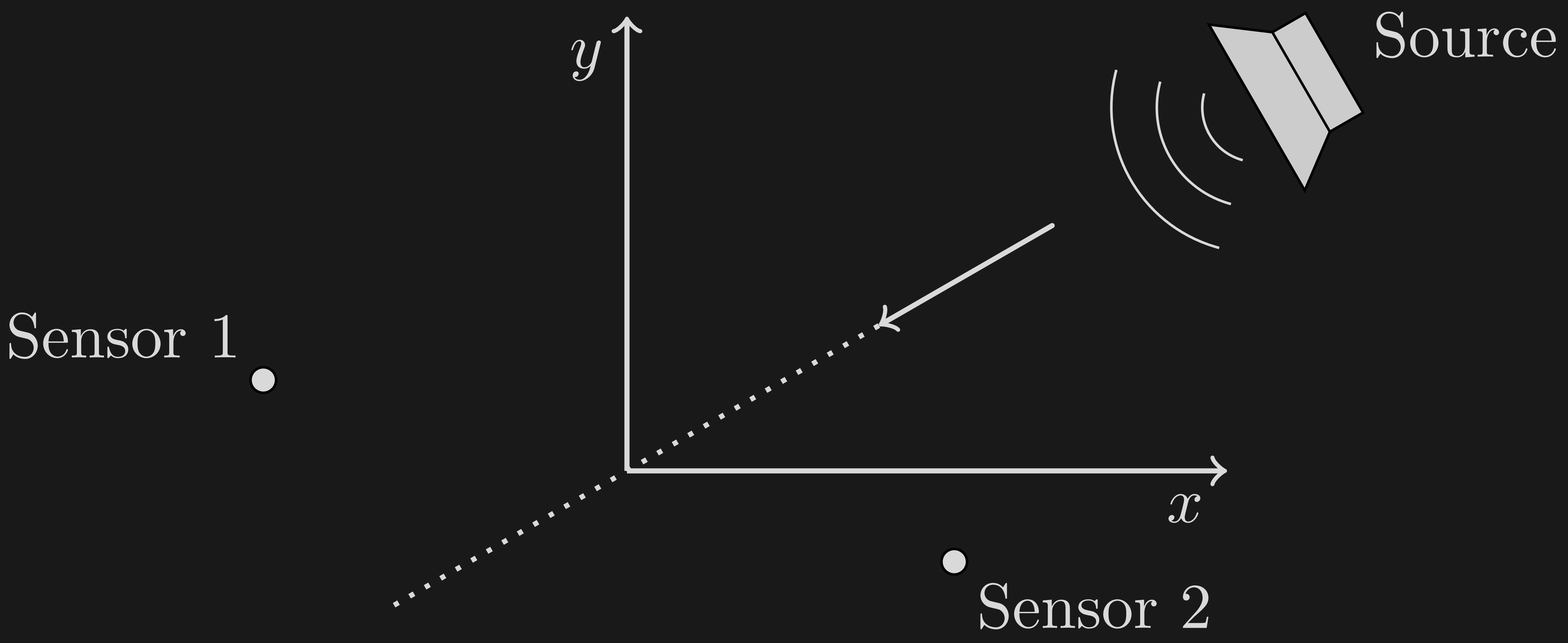

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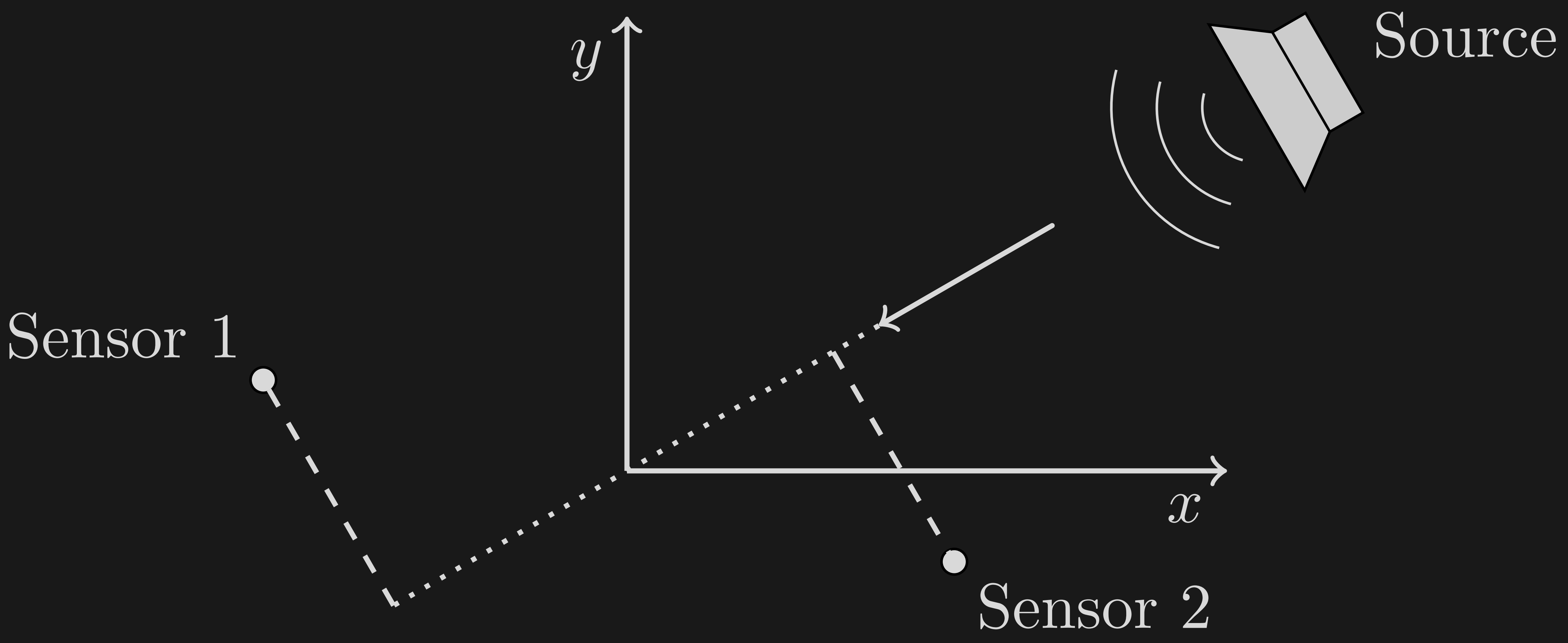

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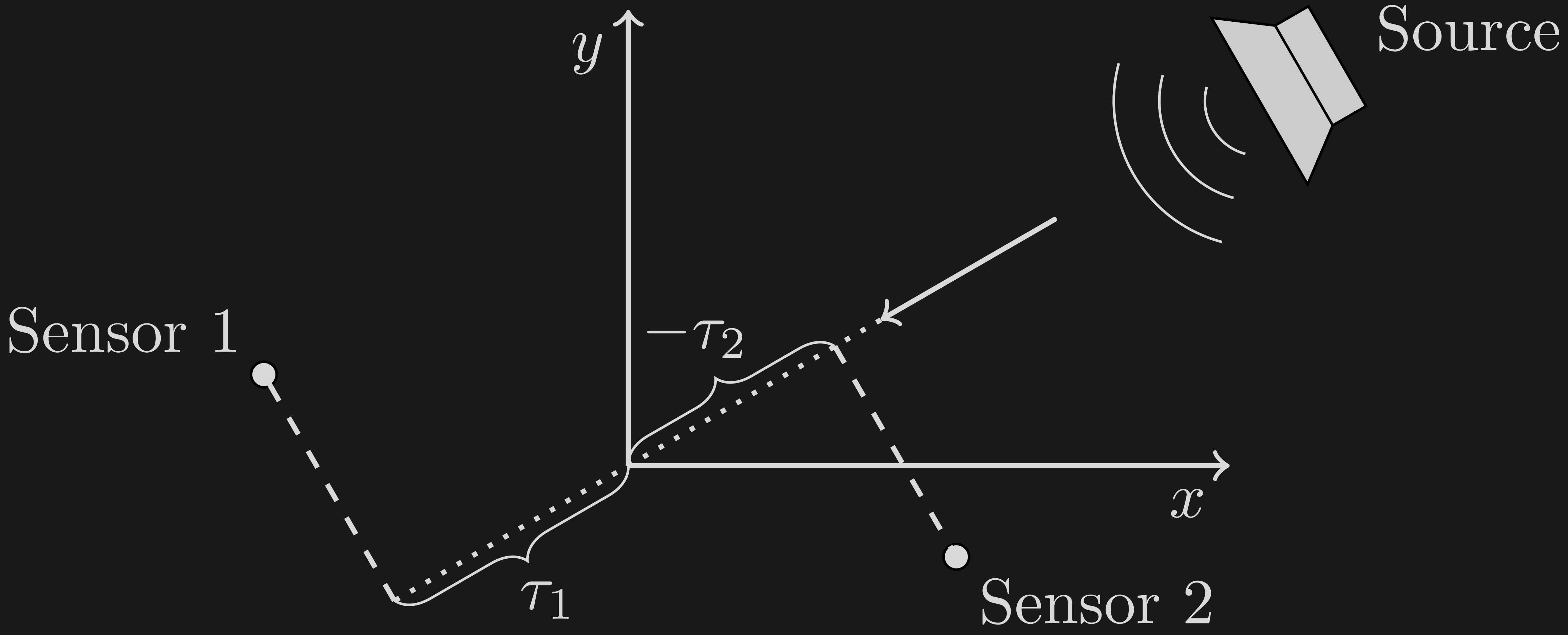

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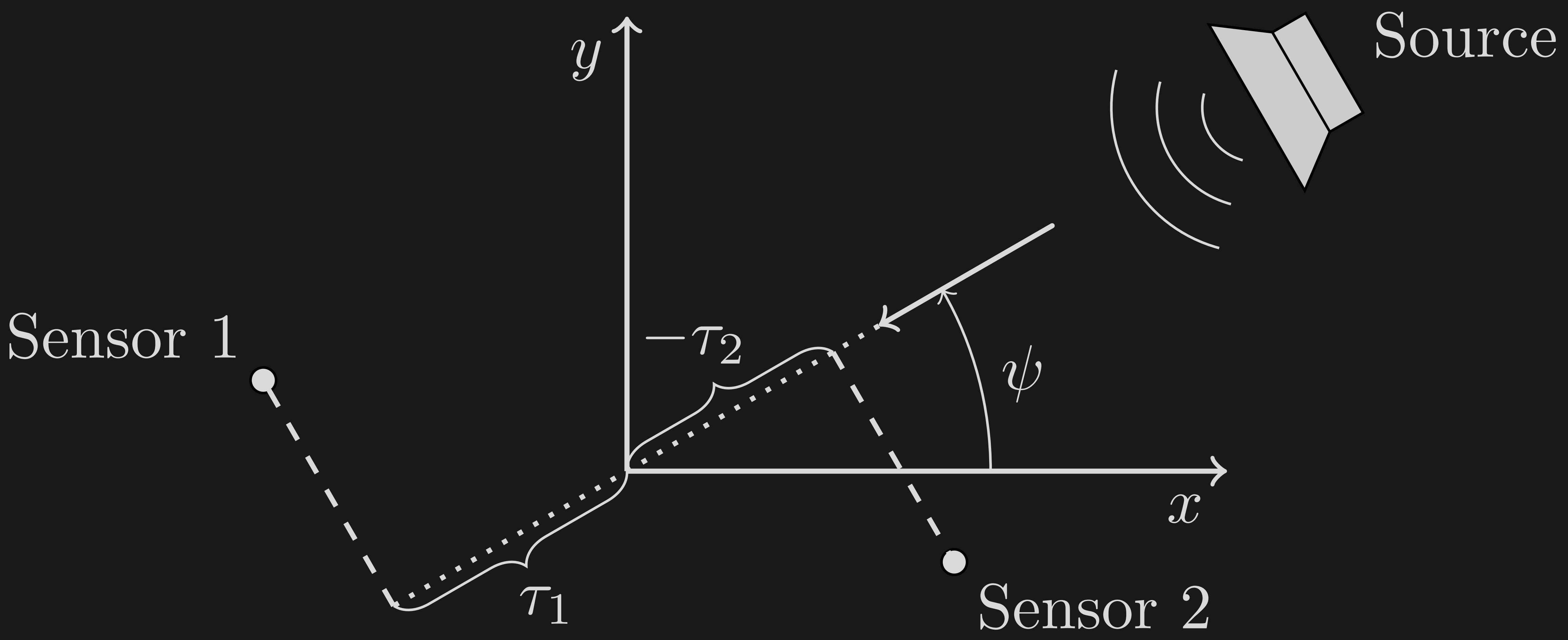

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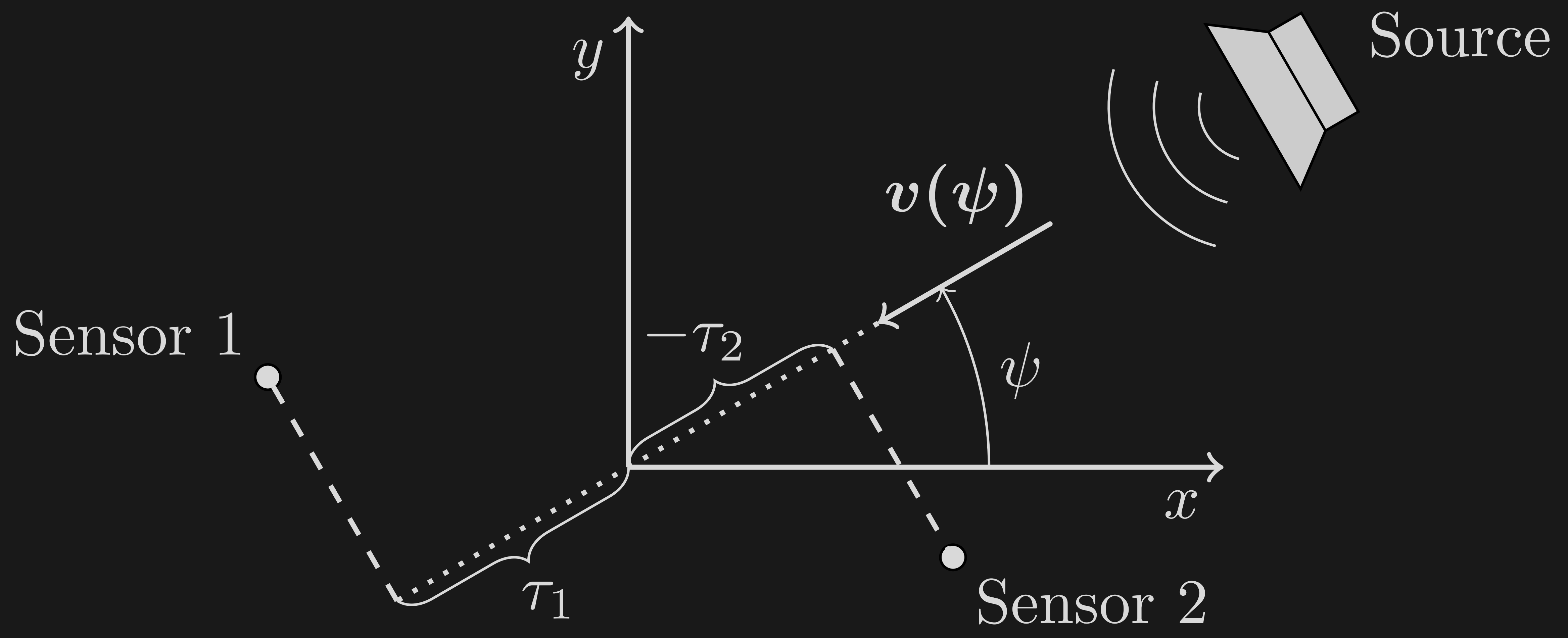

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$\boldsymbol{v}(\psi)$: direction vector

c: speed of sound

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$$\xrightarrow{\mathcal{F}} Y_m(f) = S(f)e^{-j2\pi f \tau_m(\psi)} + E_m$$

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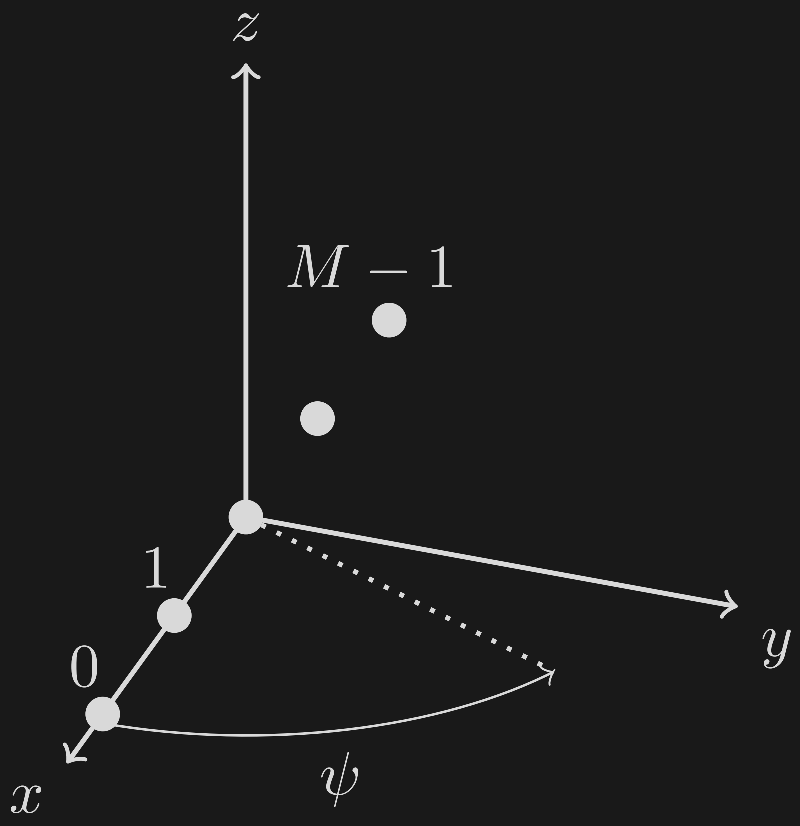
Array Structures



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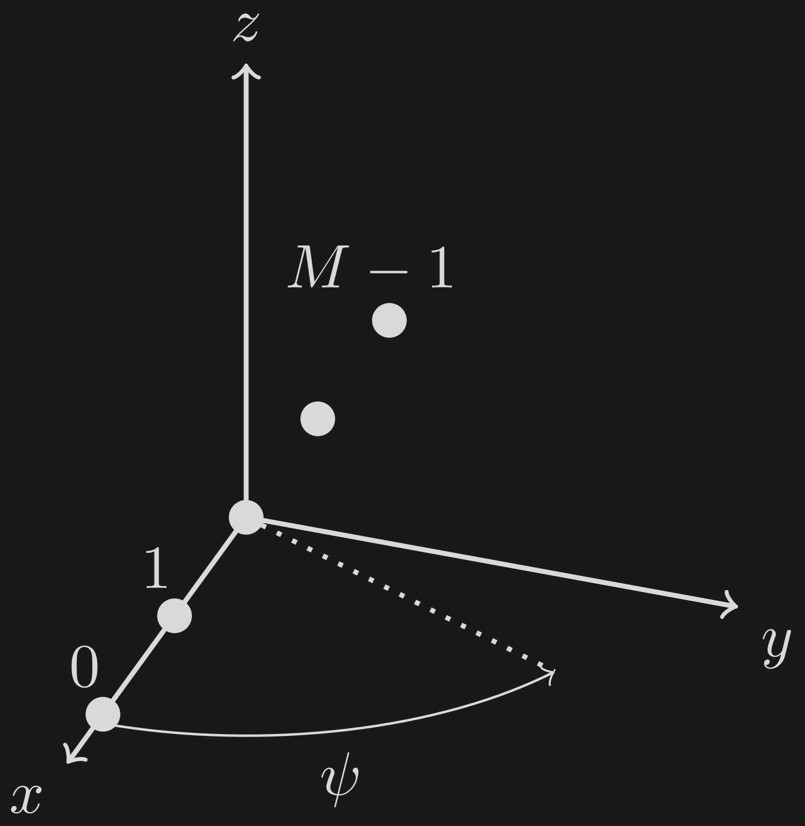

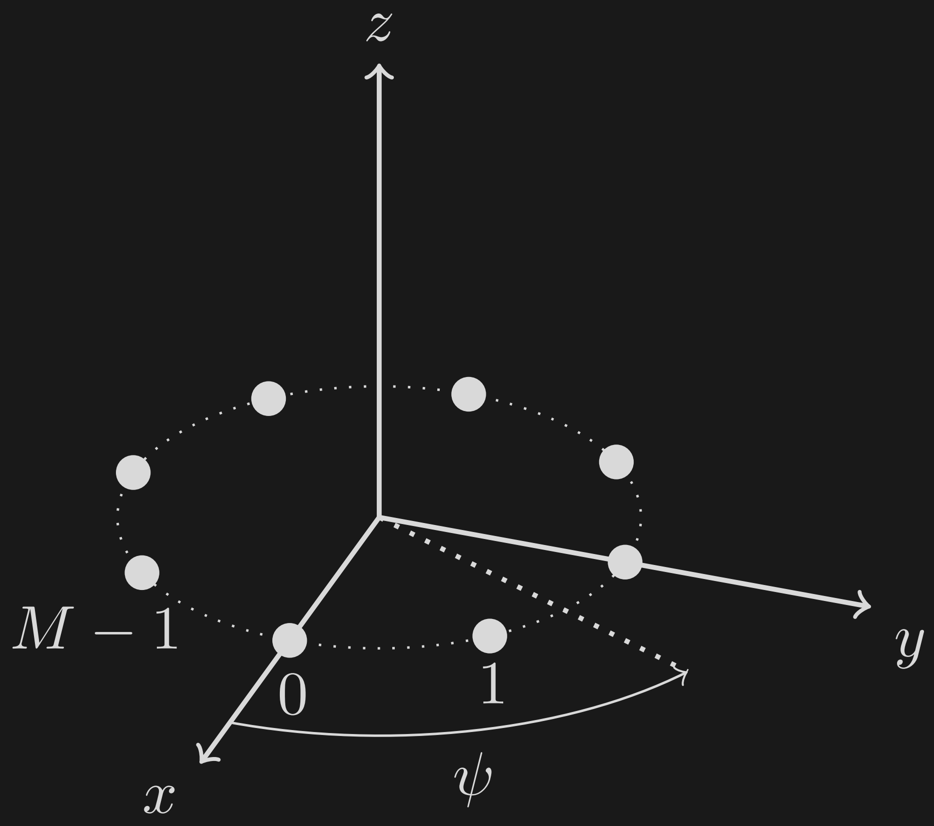

Estimation Metods

- Delay-and-Sum Beamformer
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- Bartlett
- MVDR (Capon)
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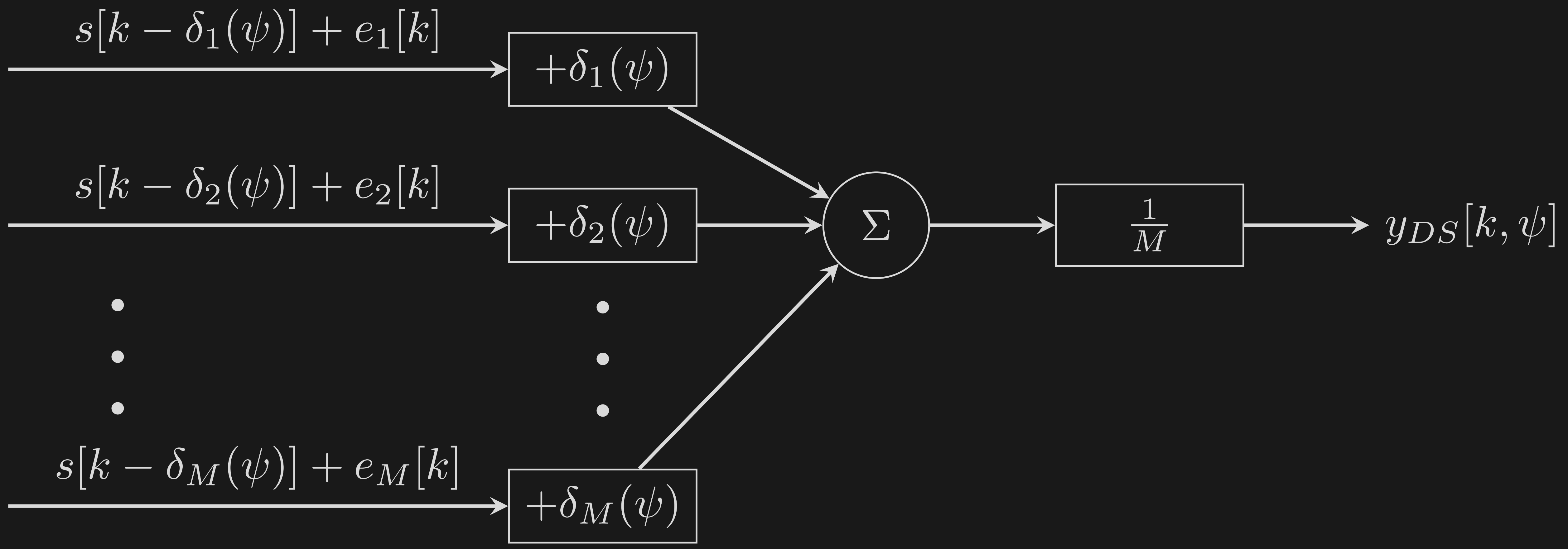

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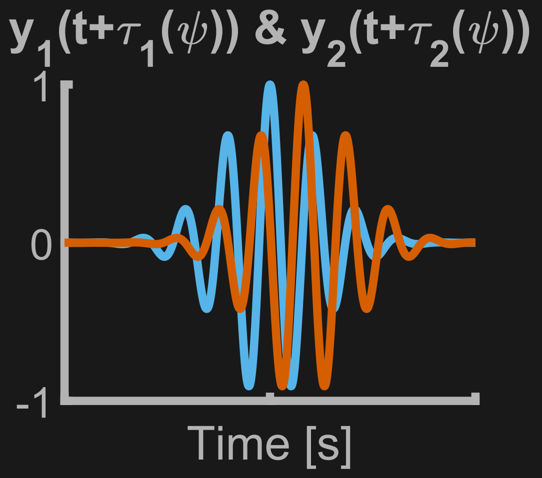

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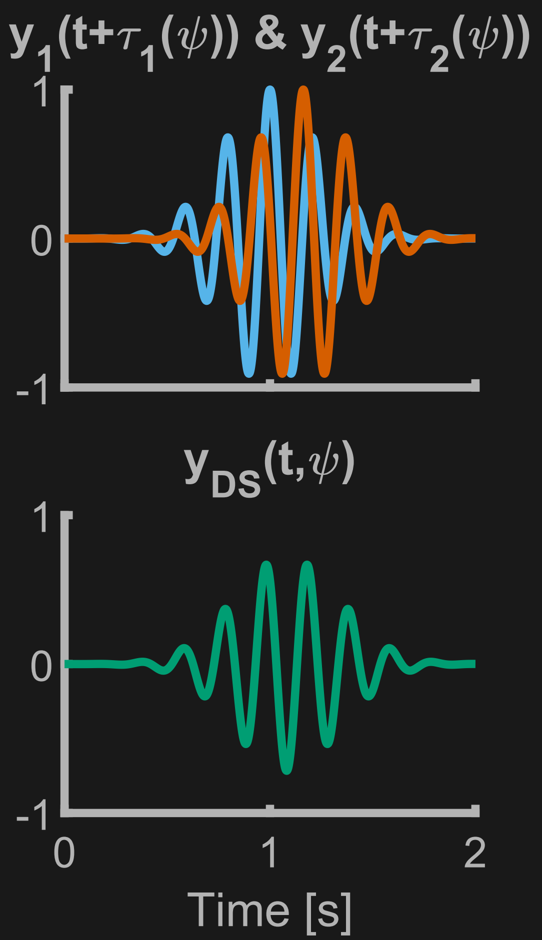
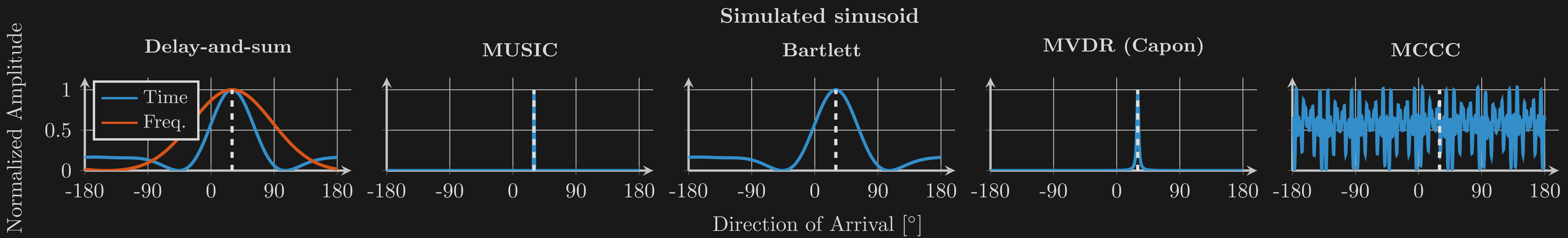


Direction of Arrival Estimation

Method Comparision



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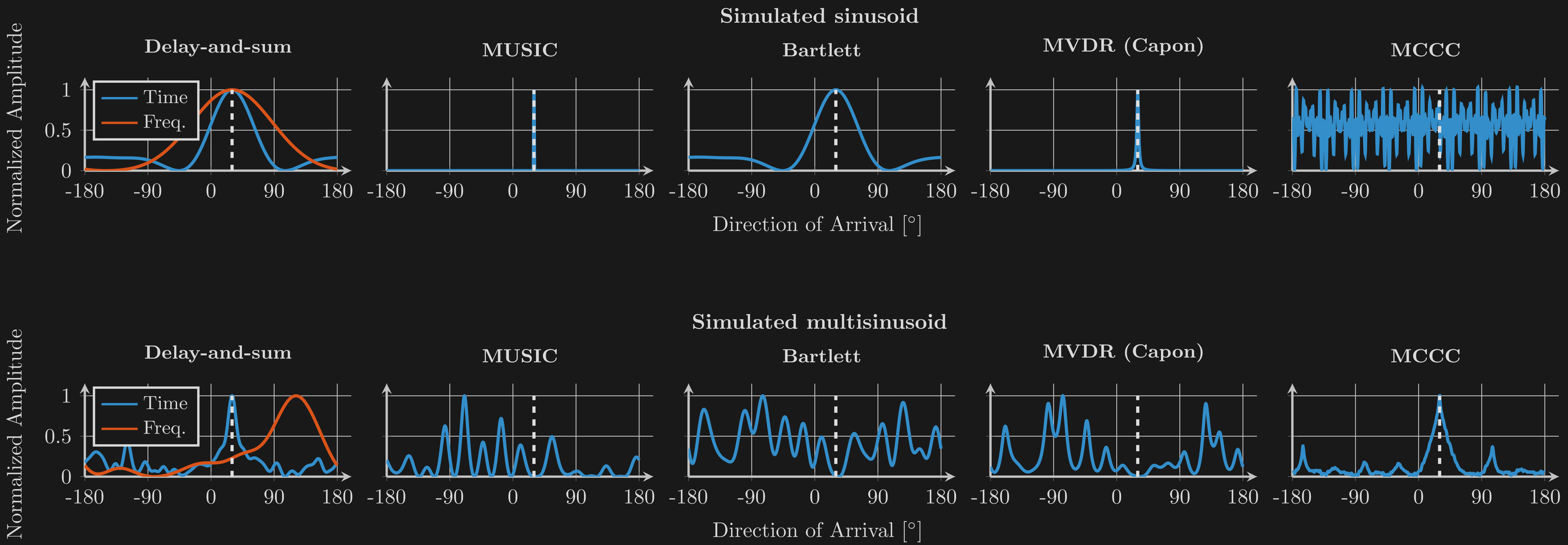
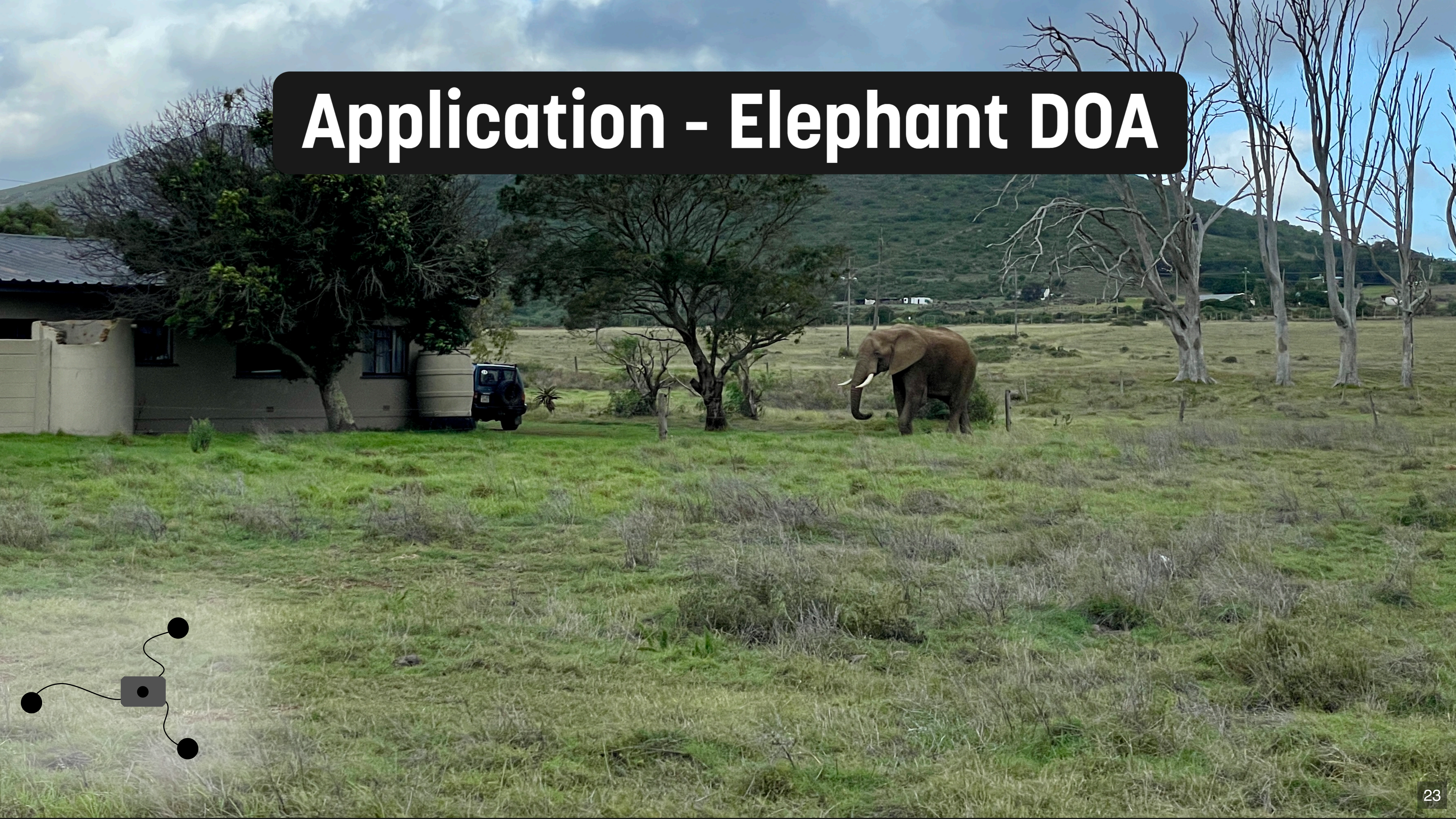


Application - Elephant DOA



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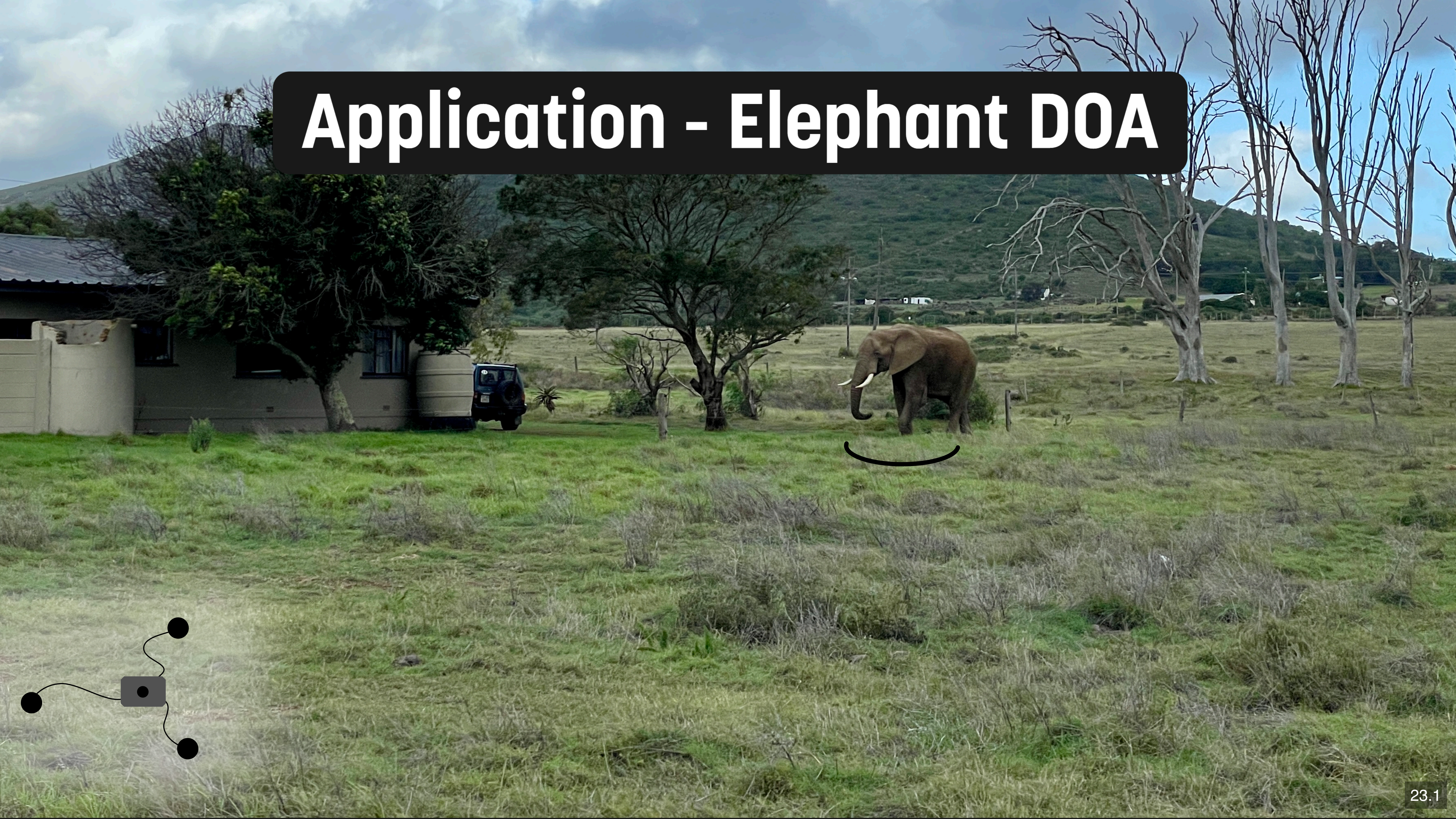
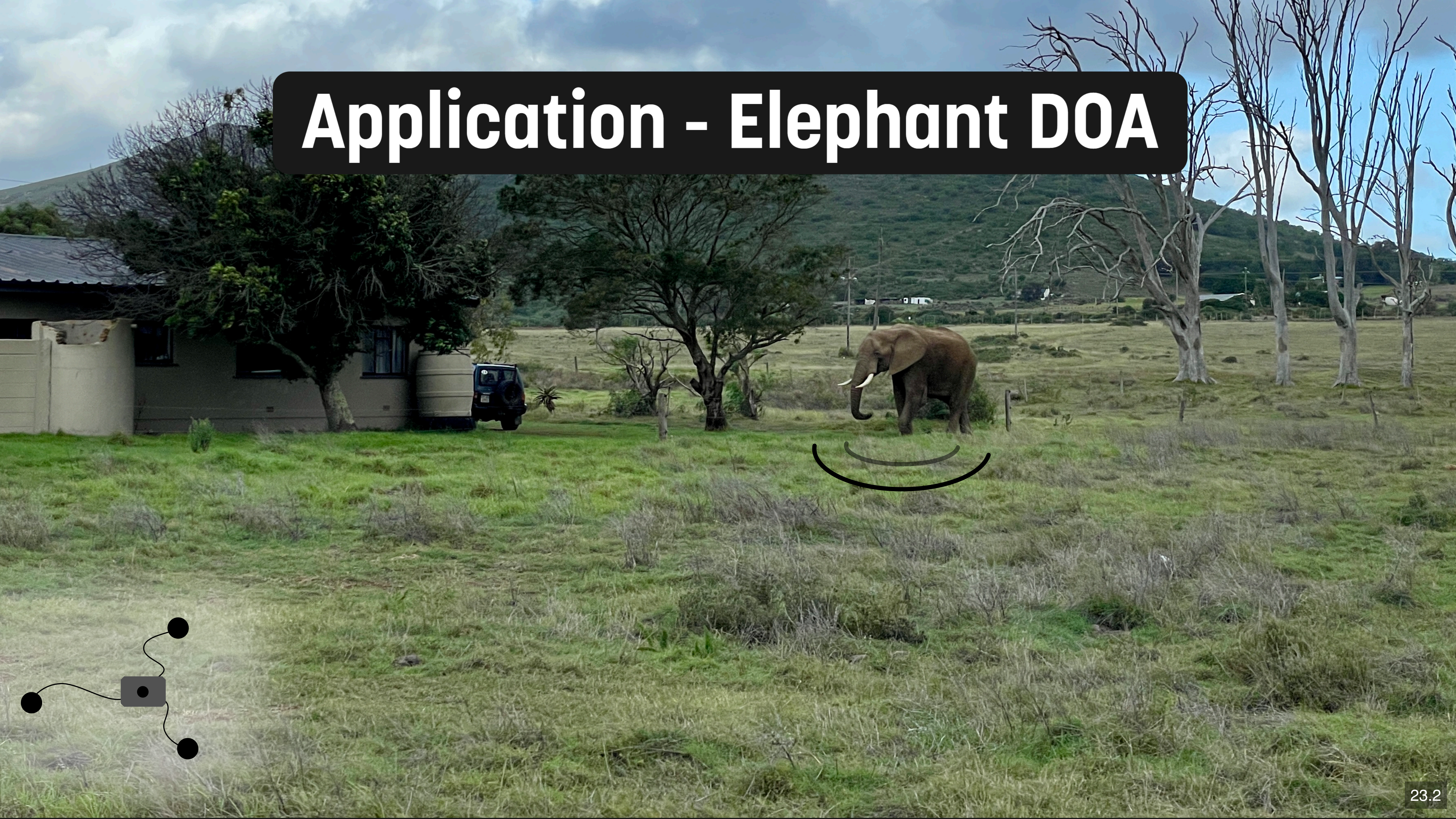
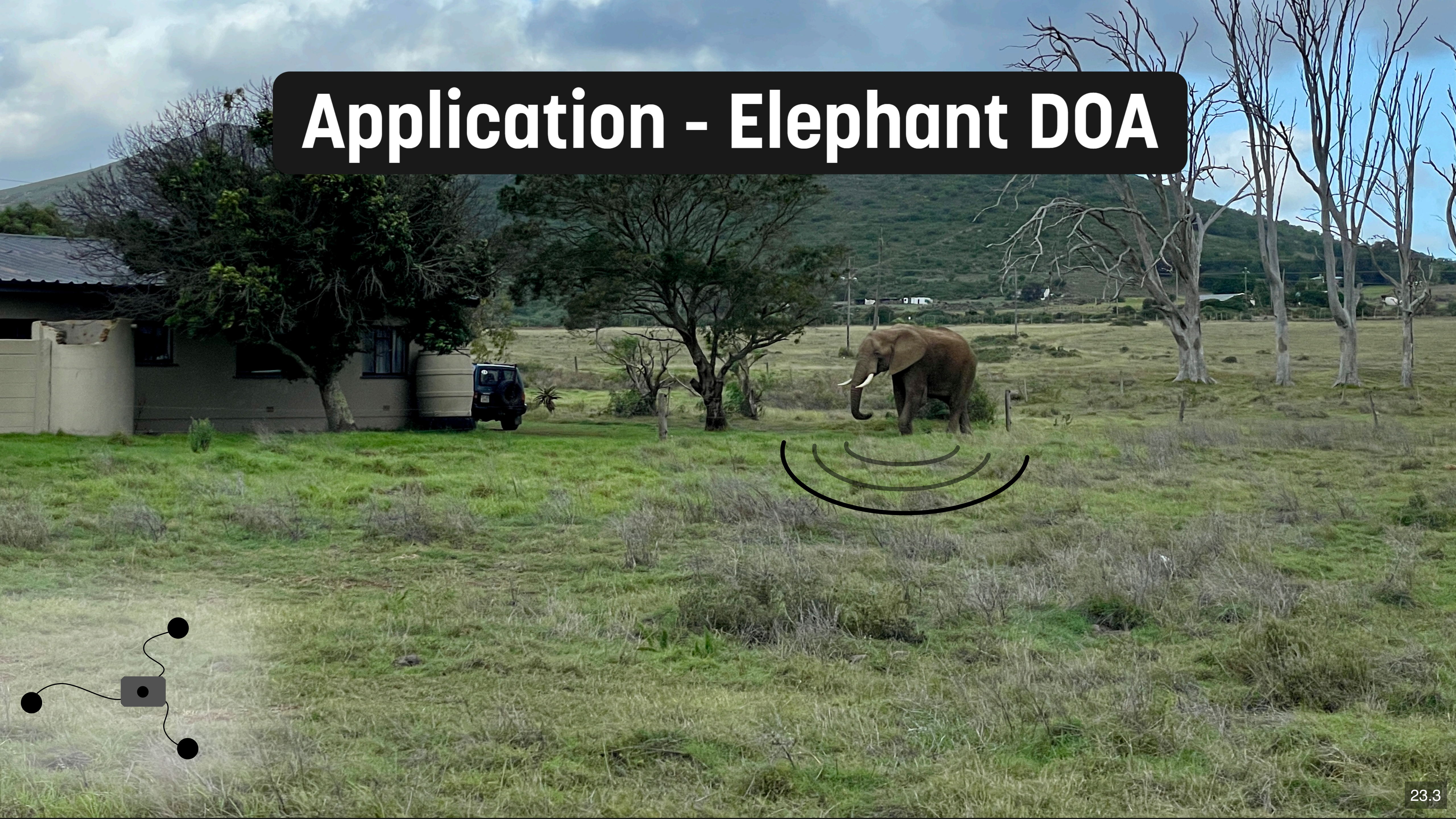
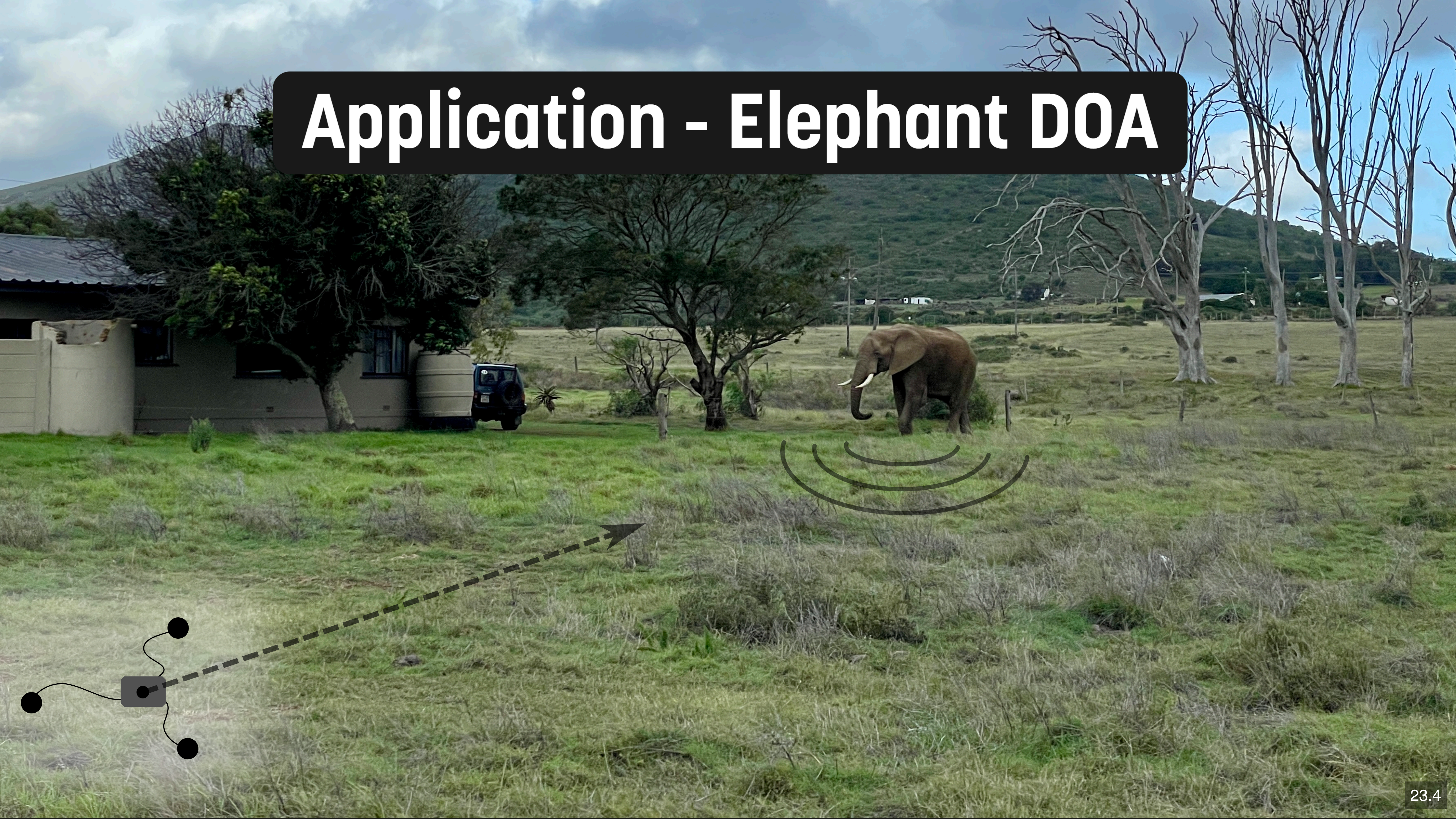



Application - Elephant DOA
23.2


Application - Elephant DOA
23.3

Application - Elephant DOA



Signal Model

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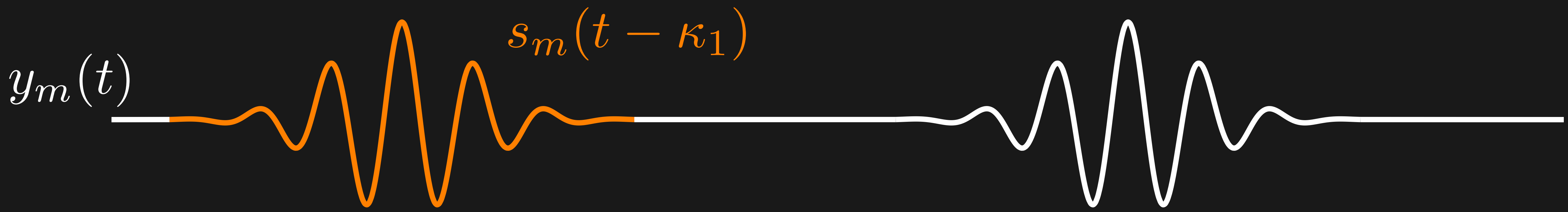

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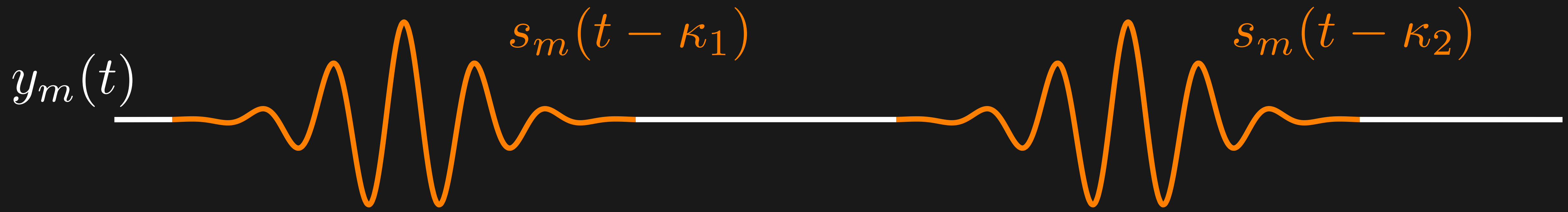

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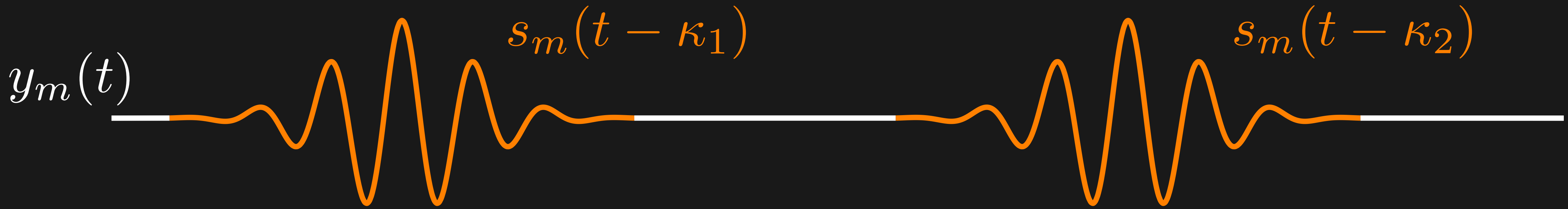

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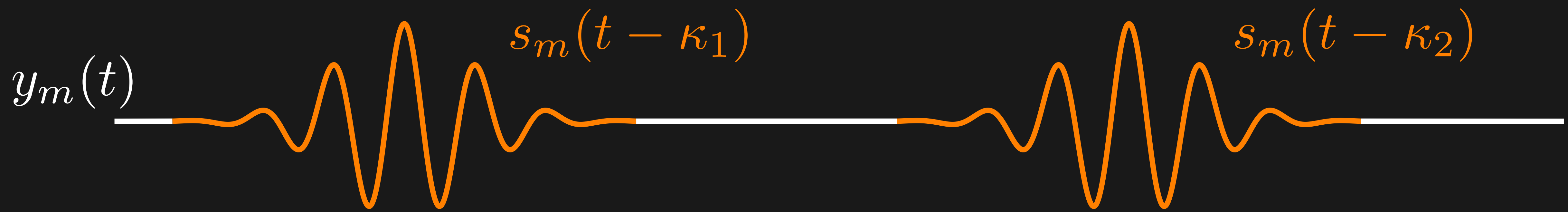


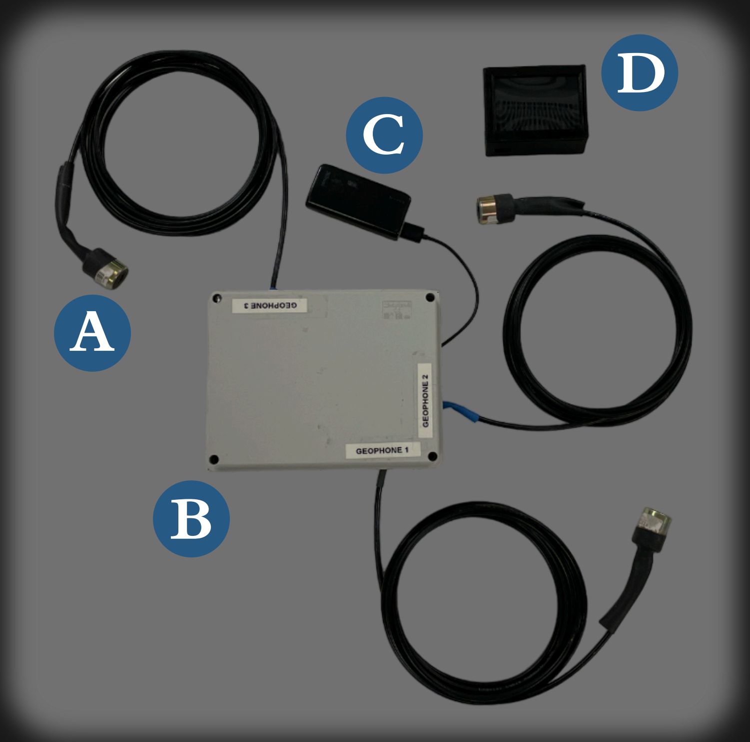
$$y_m(t) = \sum_n s_m\left(t - \kappa_n\right) + e_m(t),$$

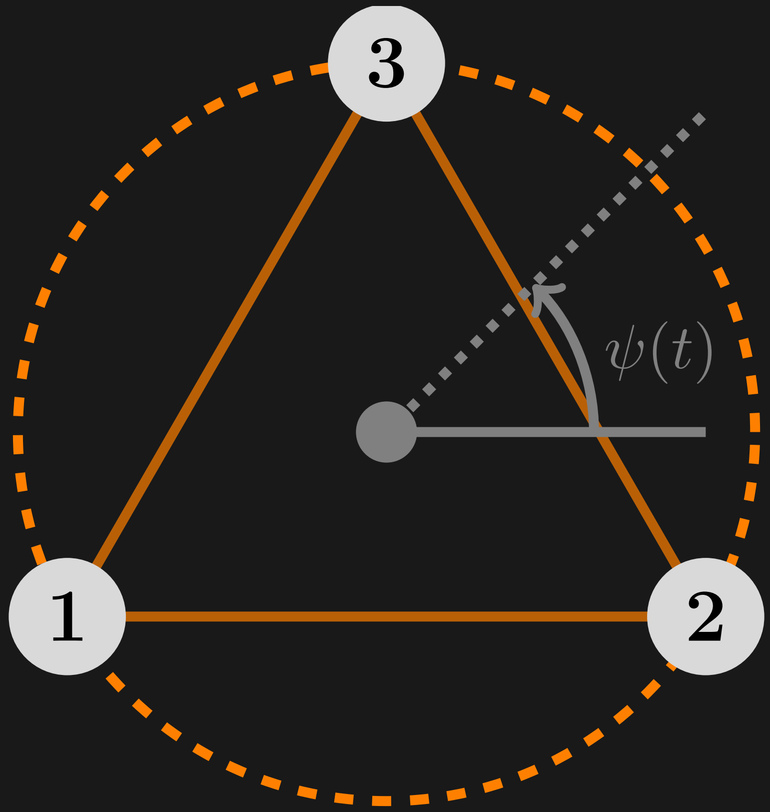
$s_m(t-\kappa_n)$: nth footstep for geophone m

κ_n: time for footstep n

$e_m(t)$: ambient noise

Experimental setup





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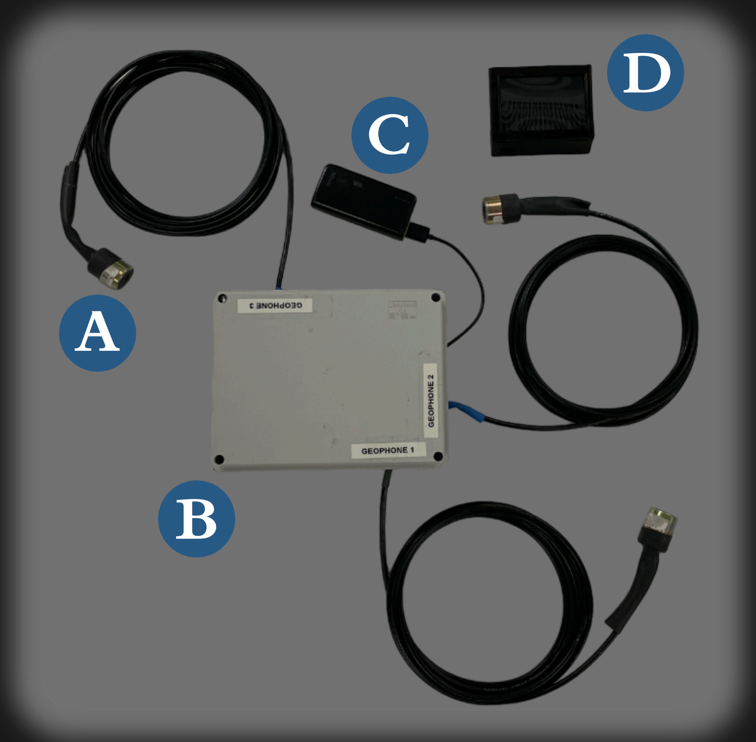
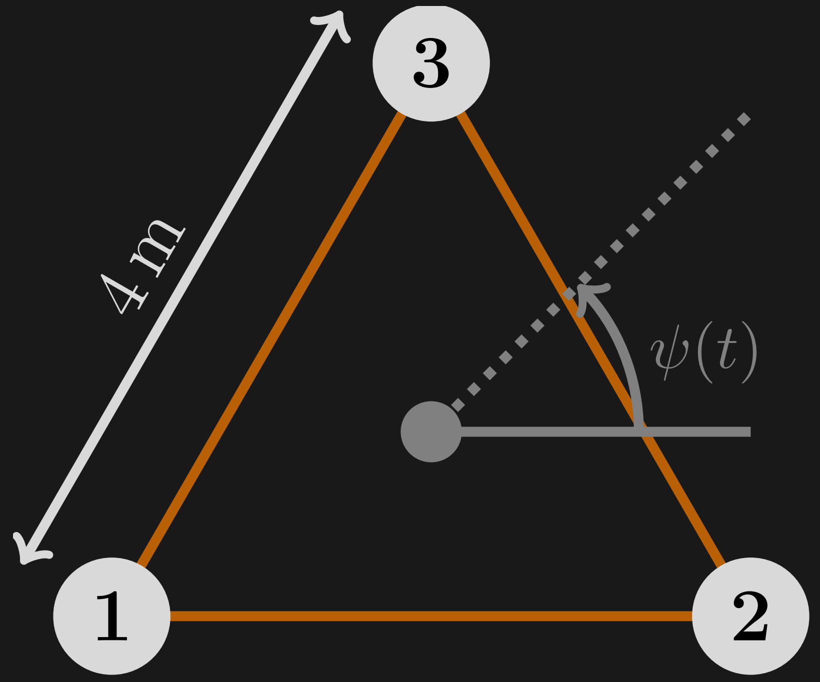
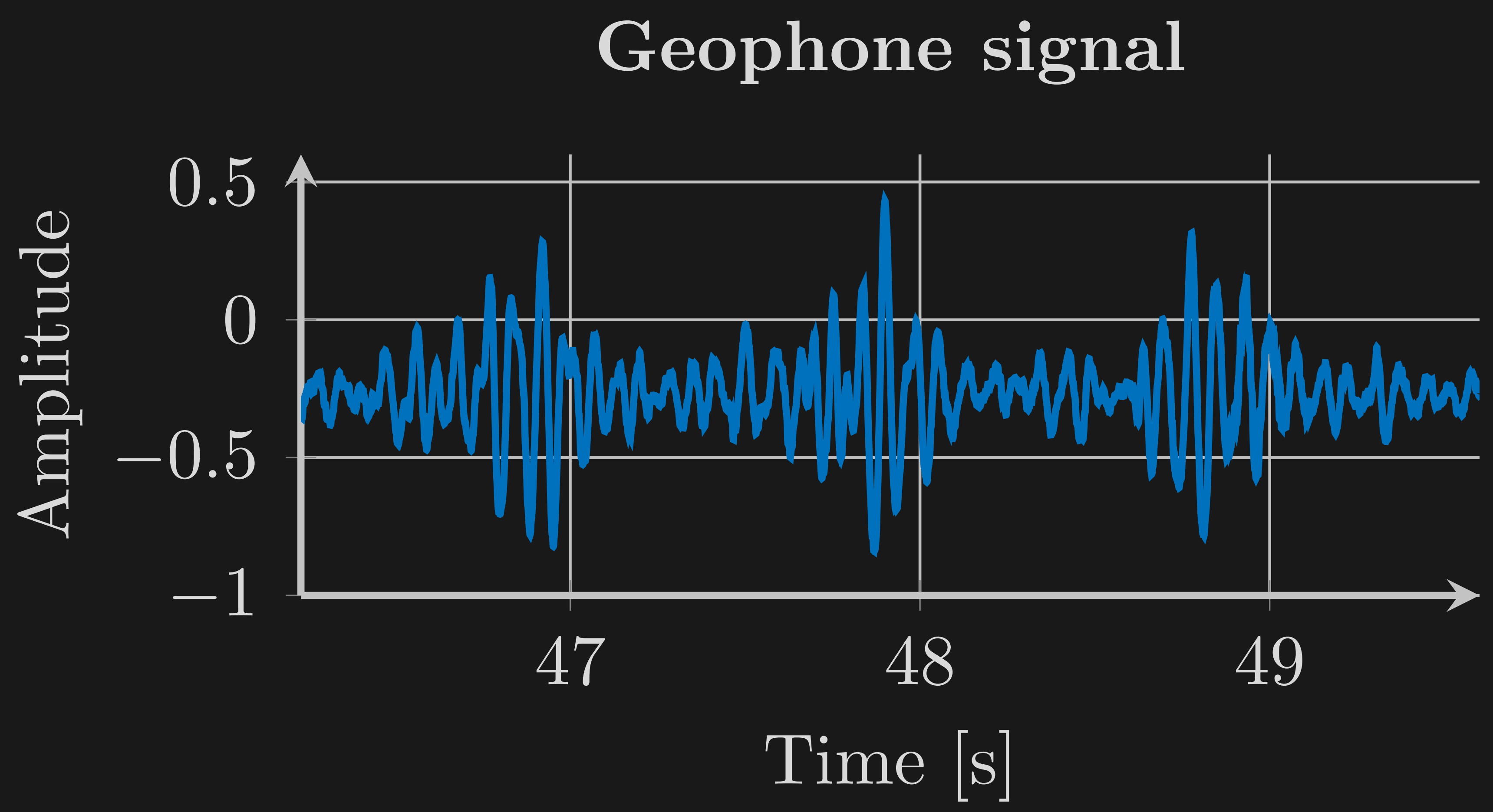
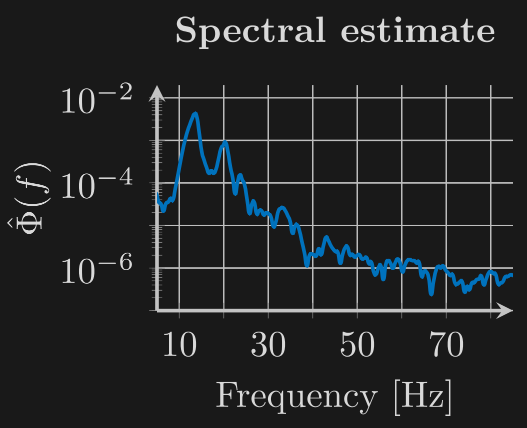




Experimental setup

Signal Characteristics





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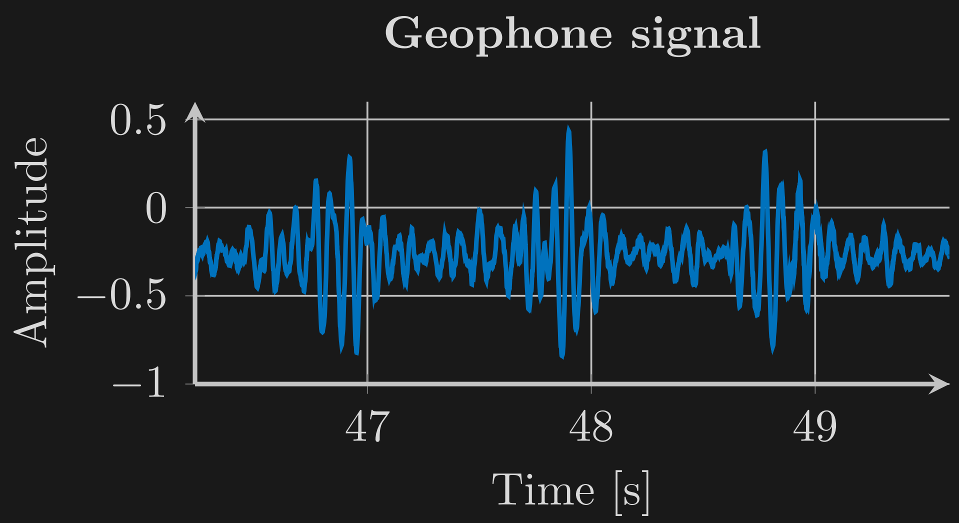

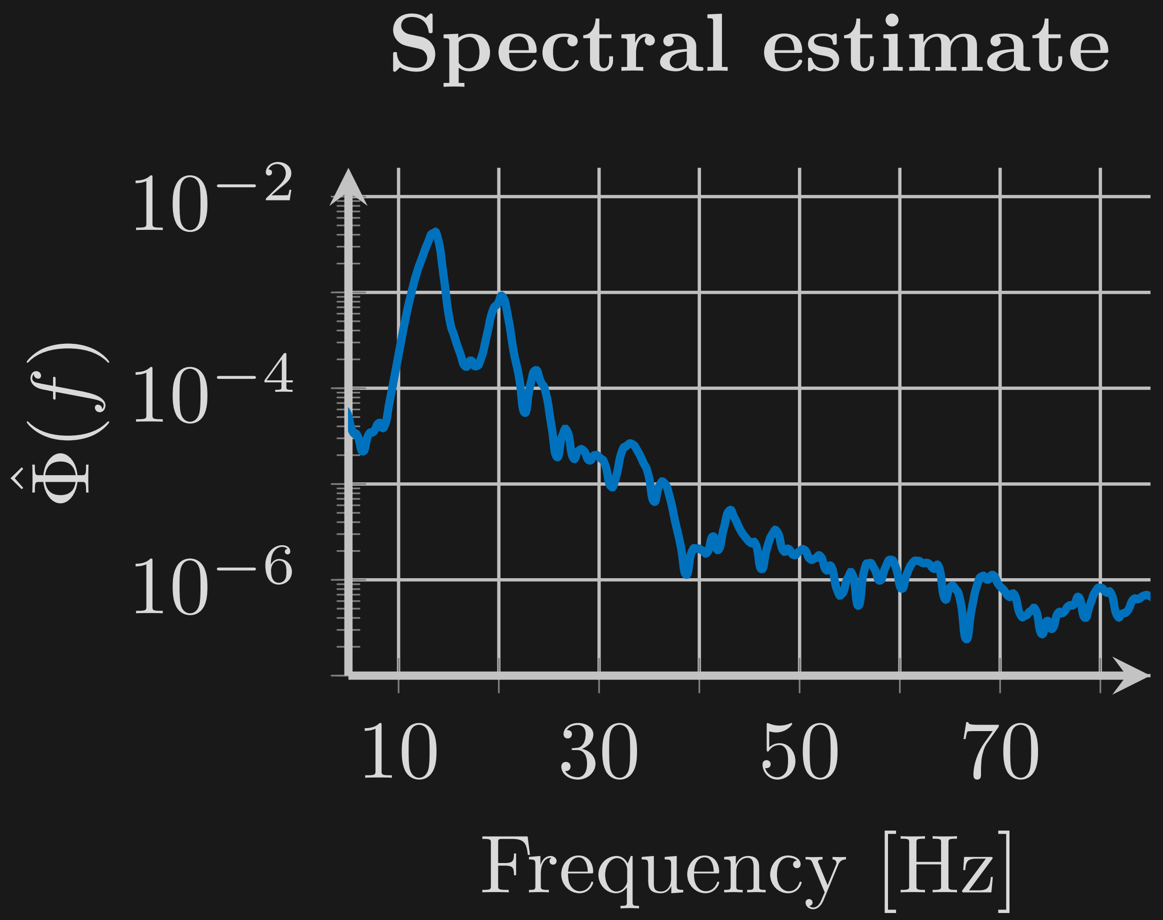

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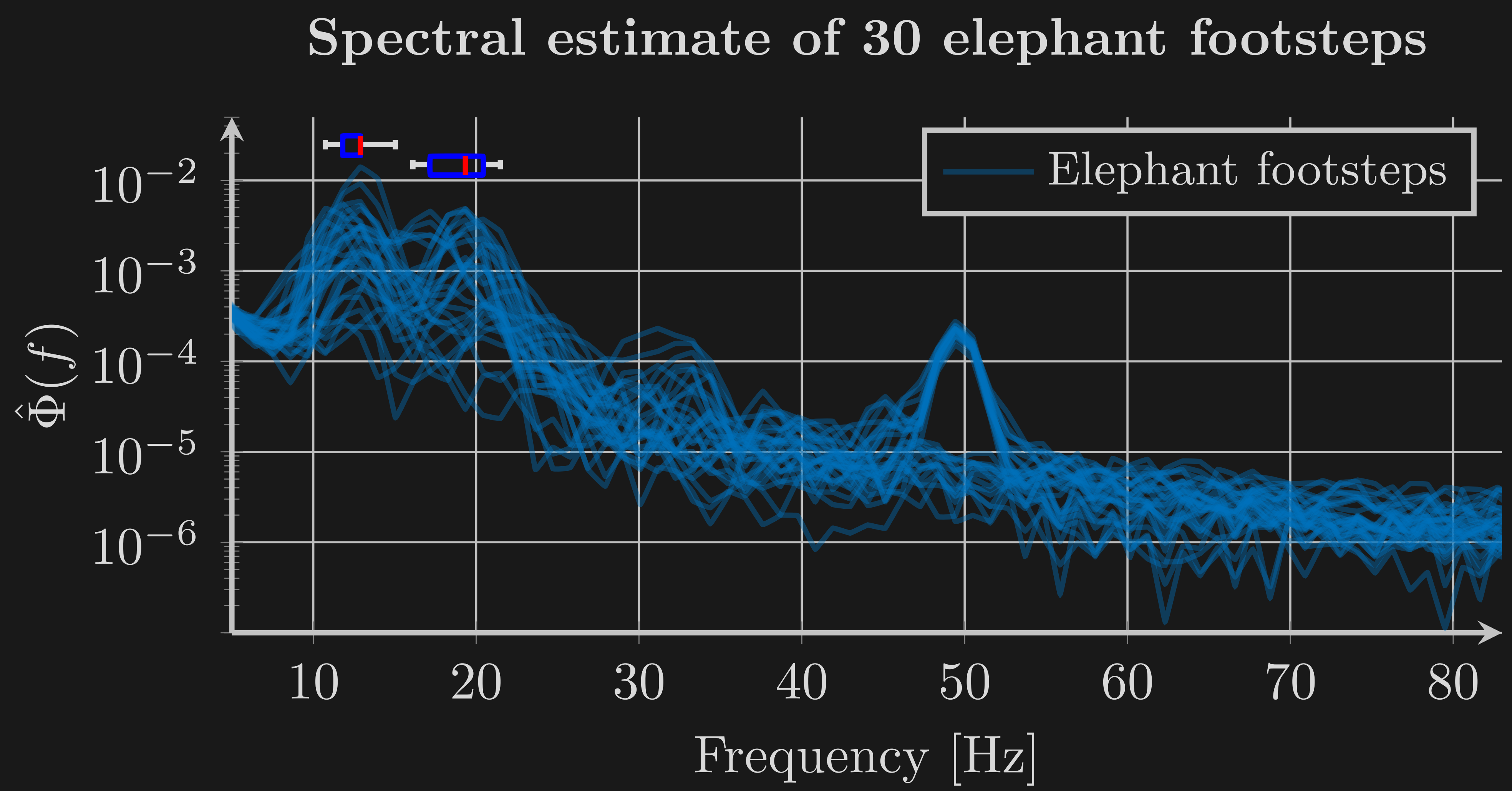
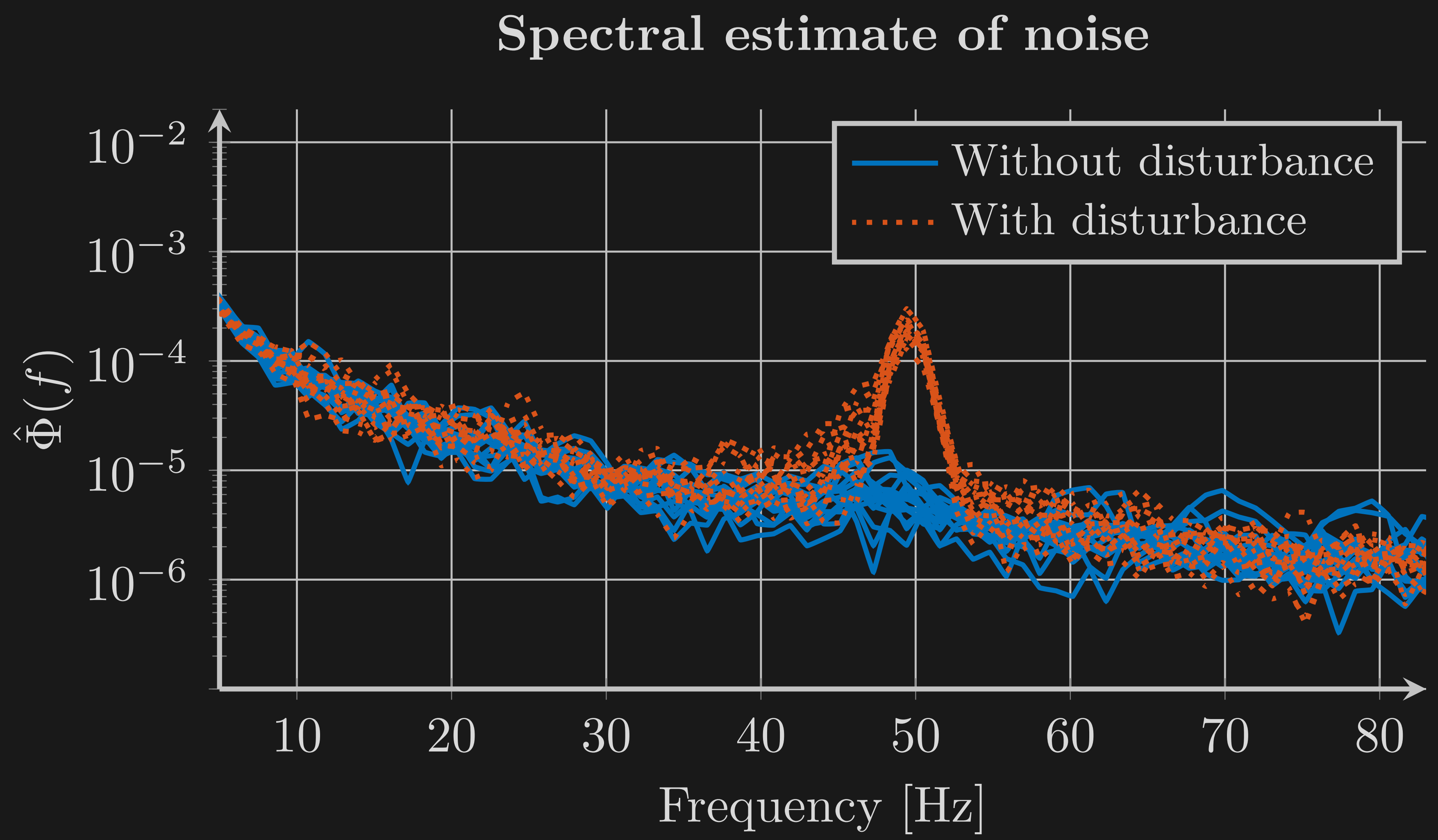
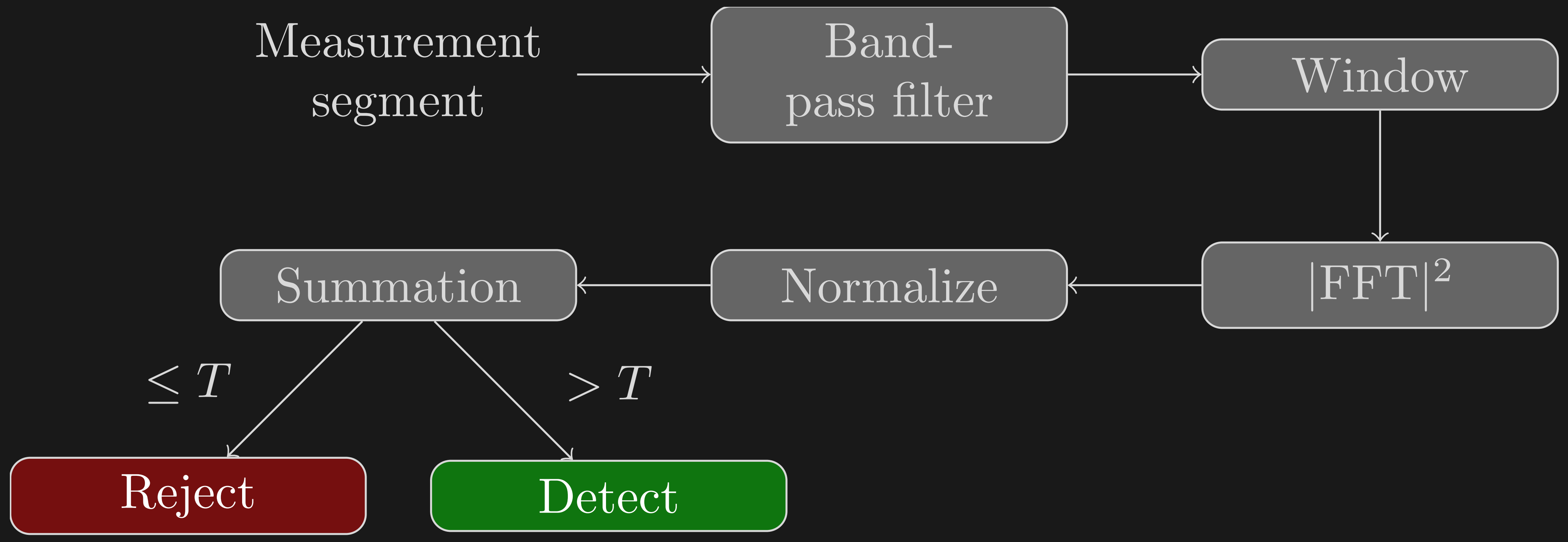


Noise Characteristics



Elephant Footstep Detection



Pre-processing

- Bandpass filter between 4 and 30 Hz
- Hanning Window

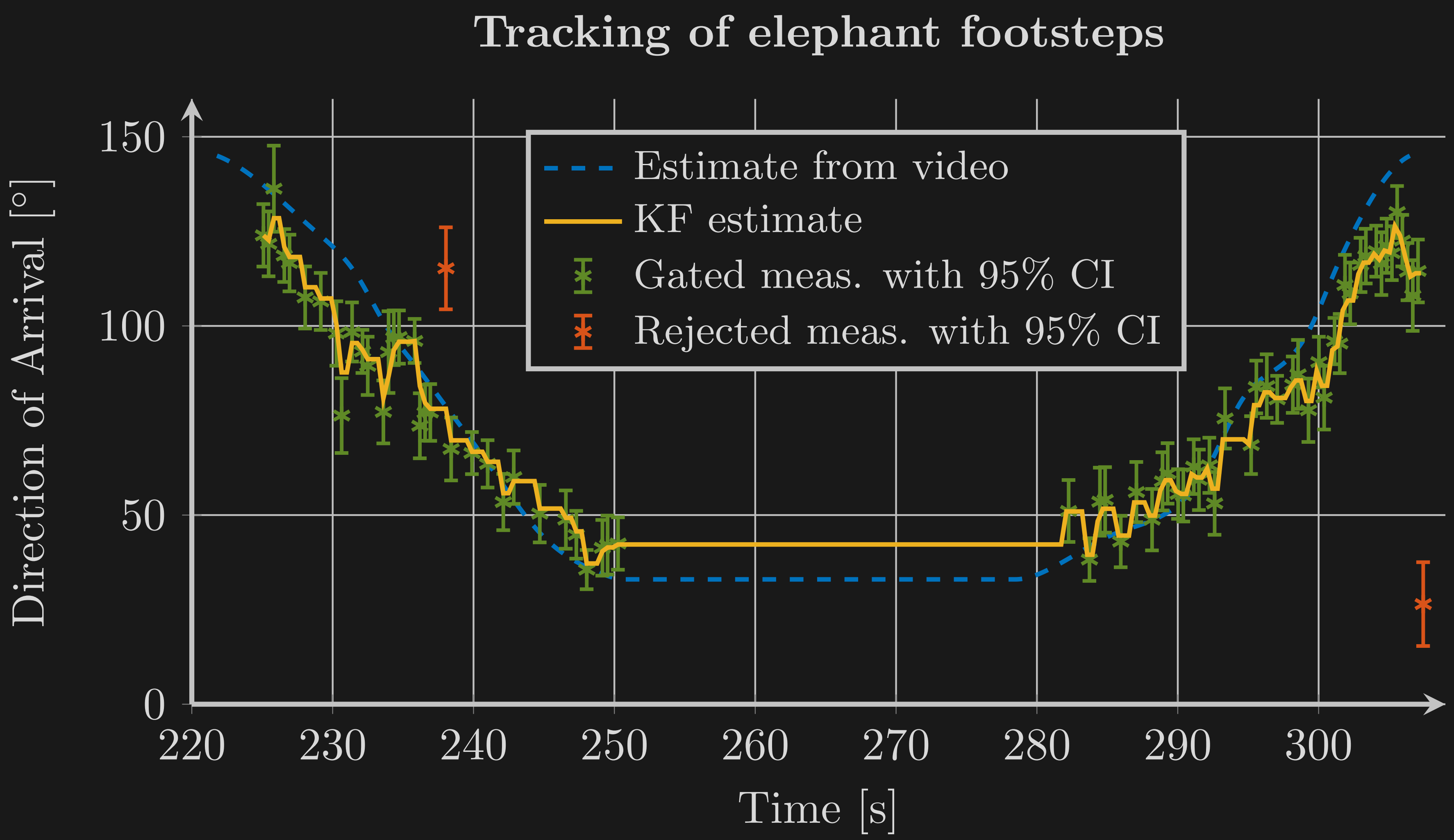
Signal Feature

- Fast Fourier transform.
- Normalized amplitude.
- Frequency content between 8 and 23 Hz.

$$\frac{\text{Energy in 8-23 Hz}}{\text{Energy in 4-30 Hz}}$$

Detection Results

Tracking Results



Tracking Results

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Conclusions

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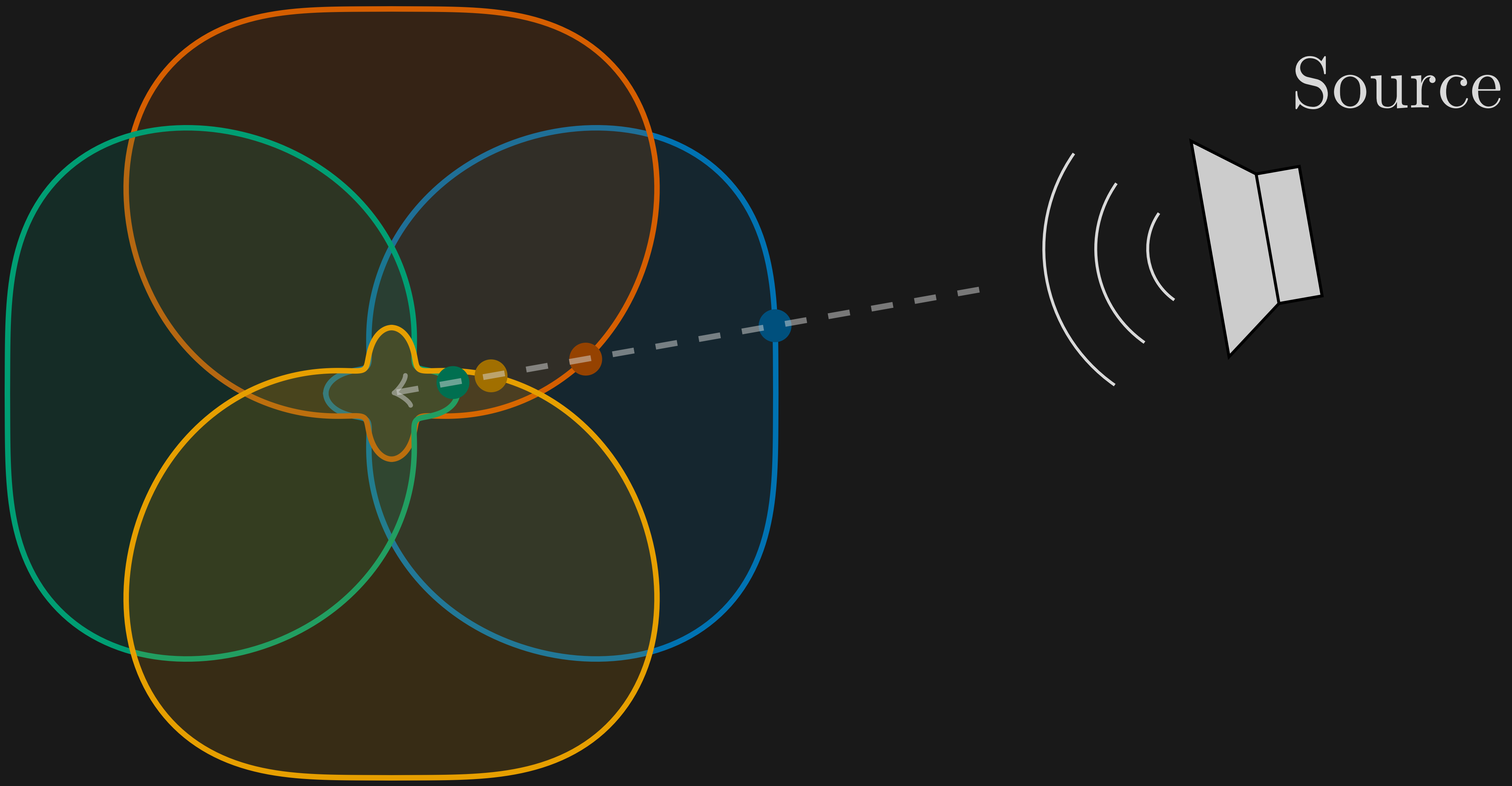
- Works well within 15-40 meters
- Direction of arrival estimate is accurate

Directional Sensitivity DOA



Motivation

- Classical methods rely on time-differences.
- Requries separation of the sensors in space.
- Placing them to far appart leads to ambiguity in DOA.
- Placing them to close decrease DOA resolution.

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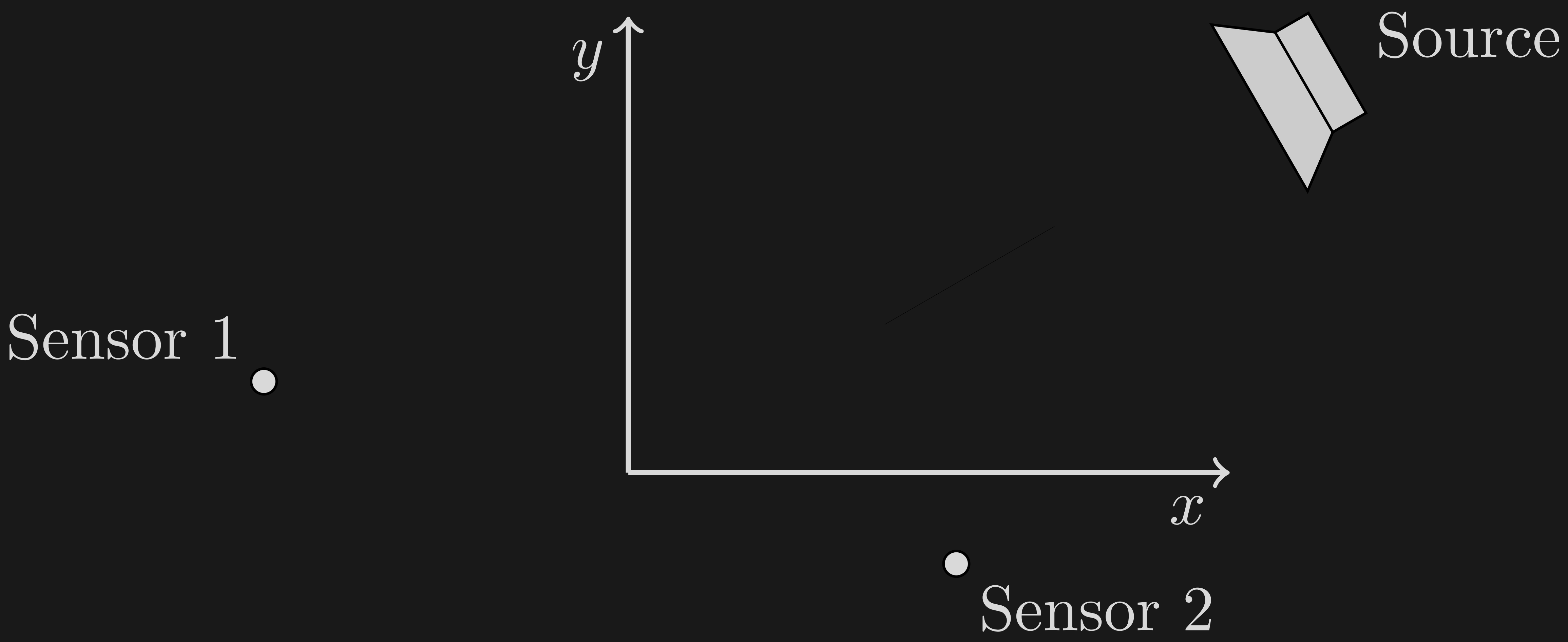

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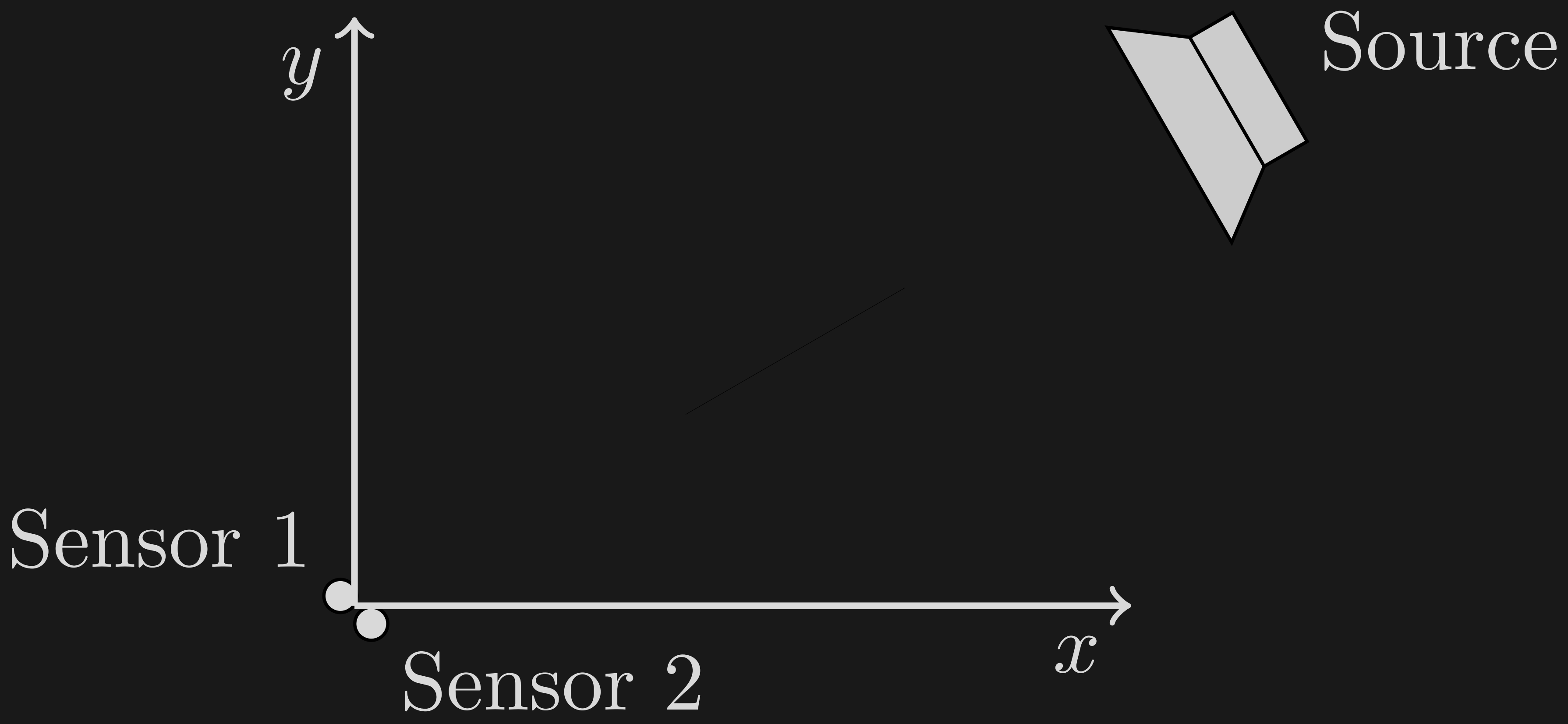

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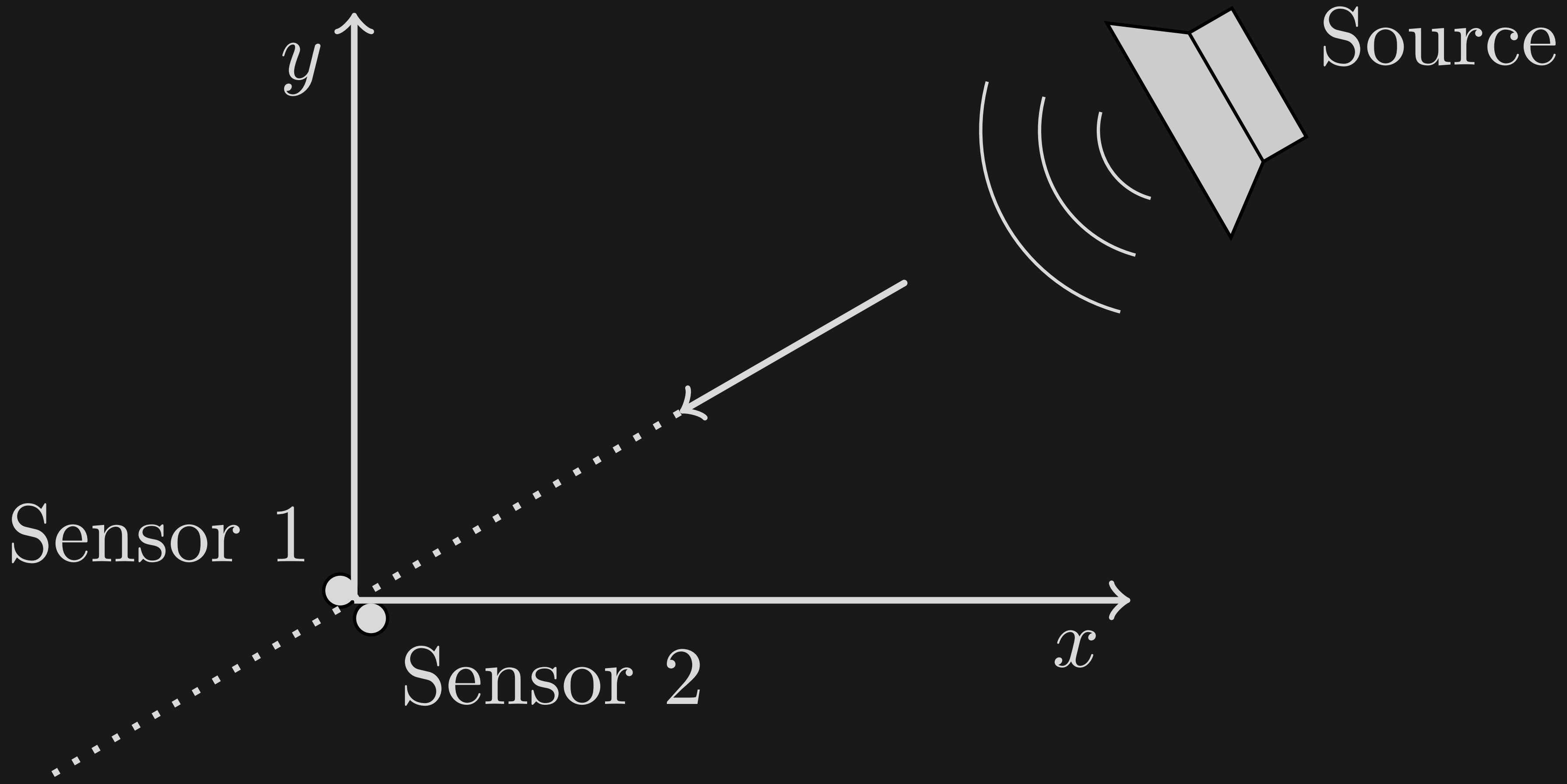

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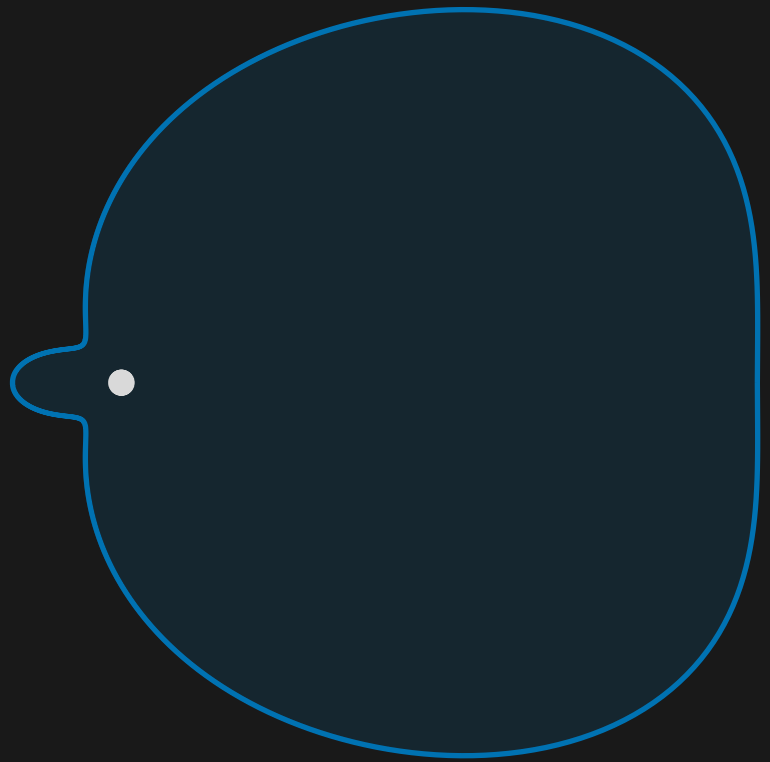

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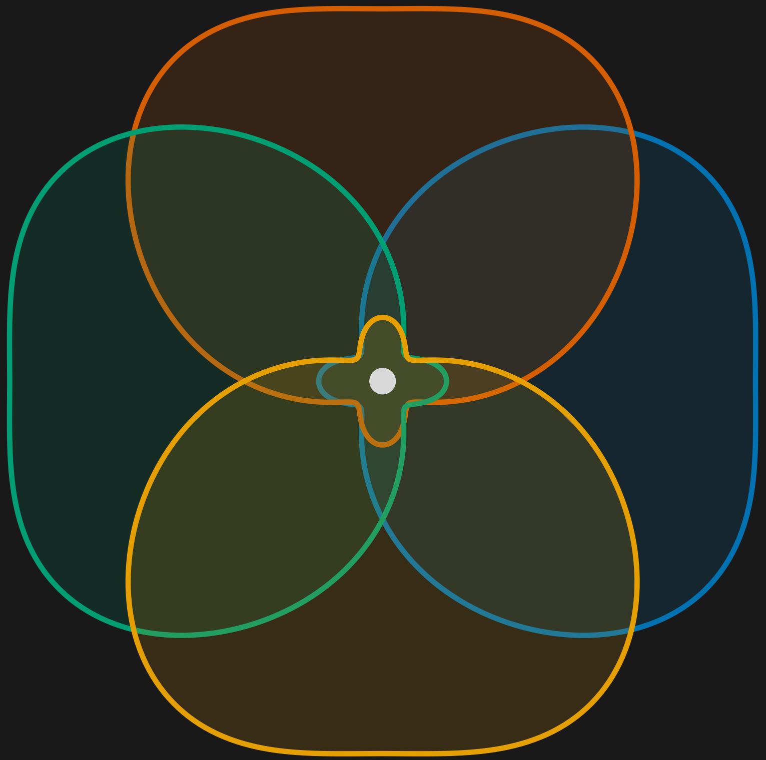

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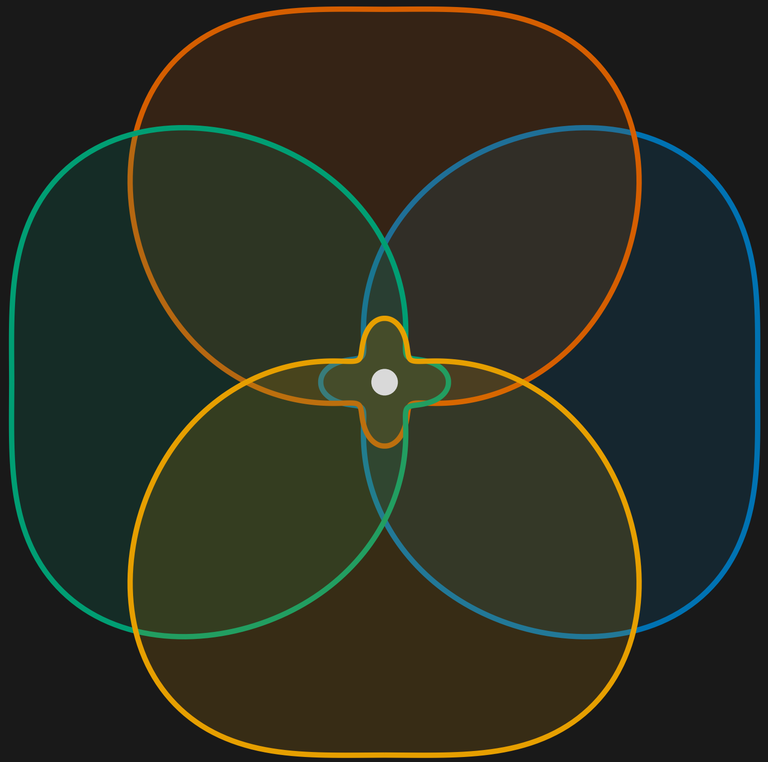

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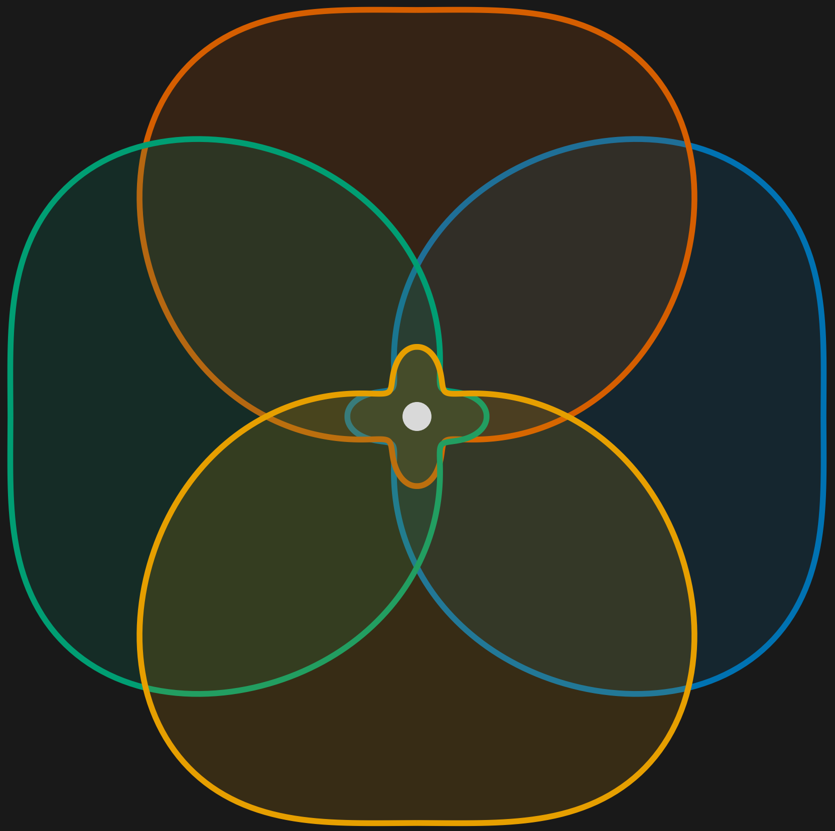

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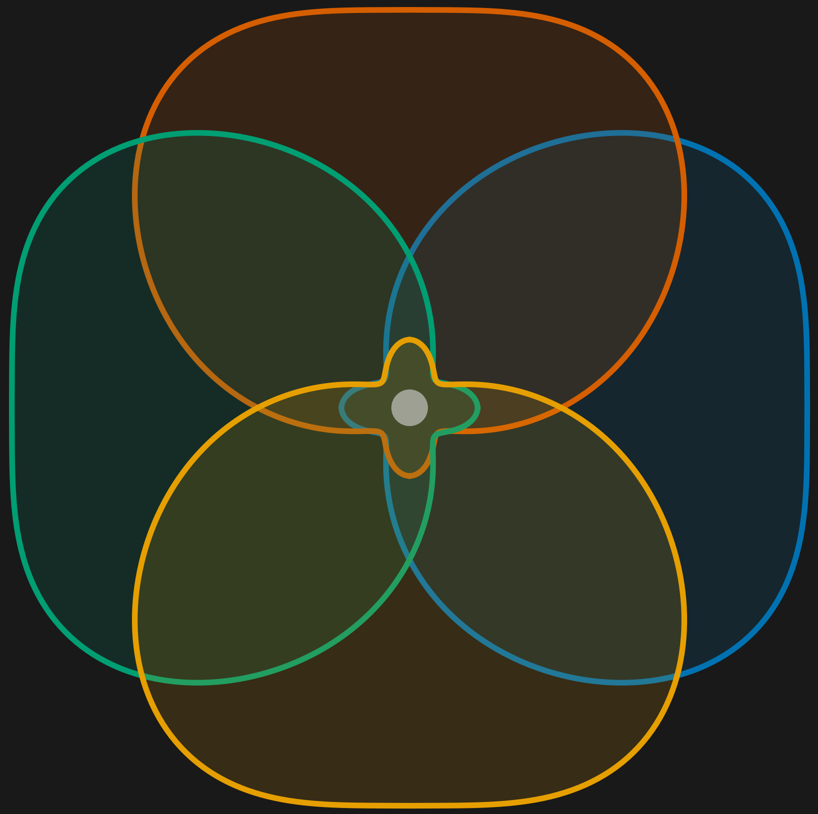

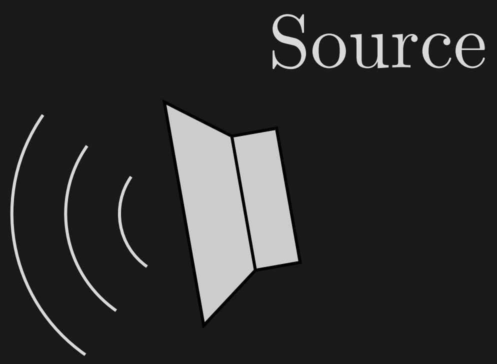

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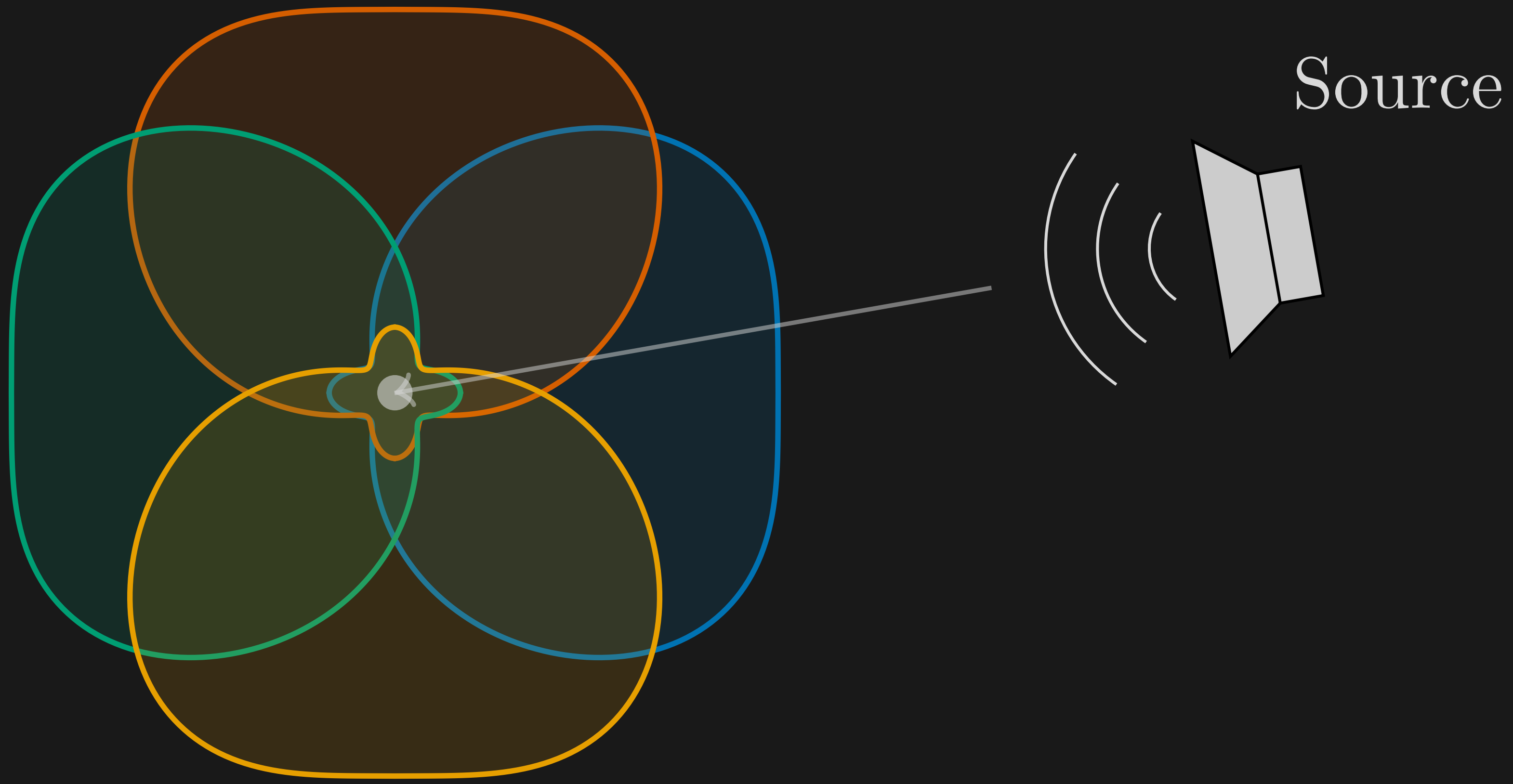

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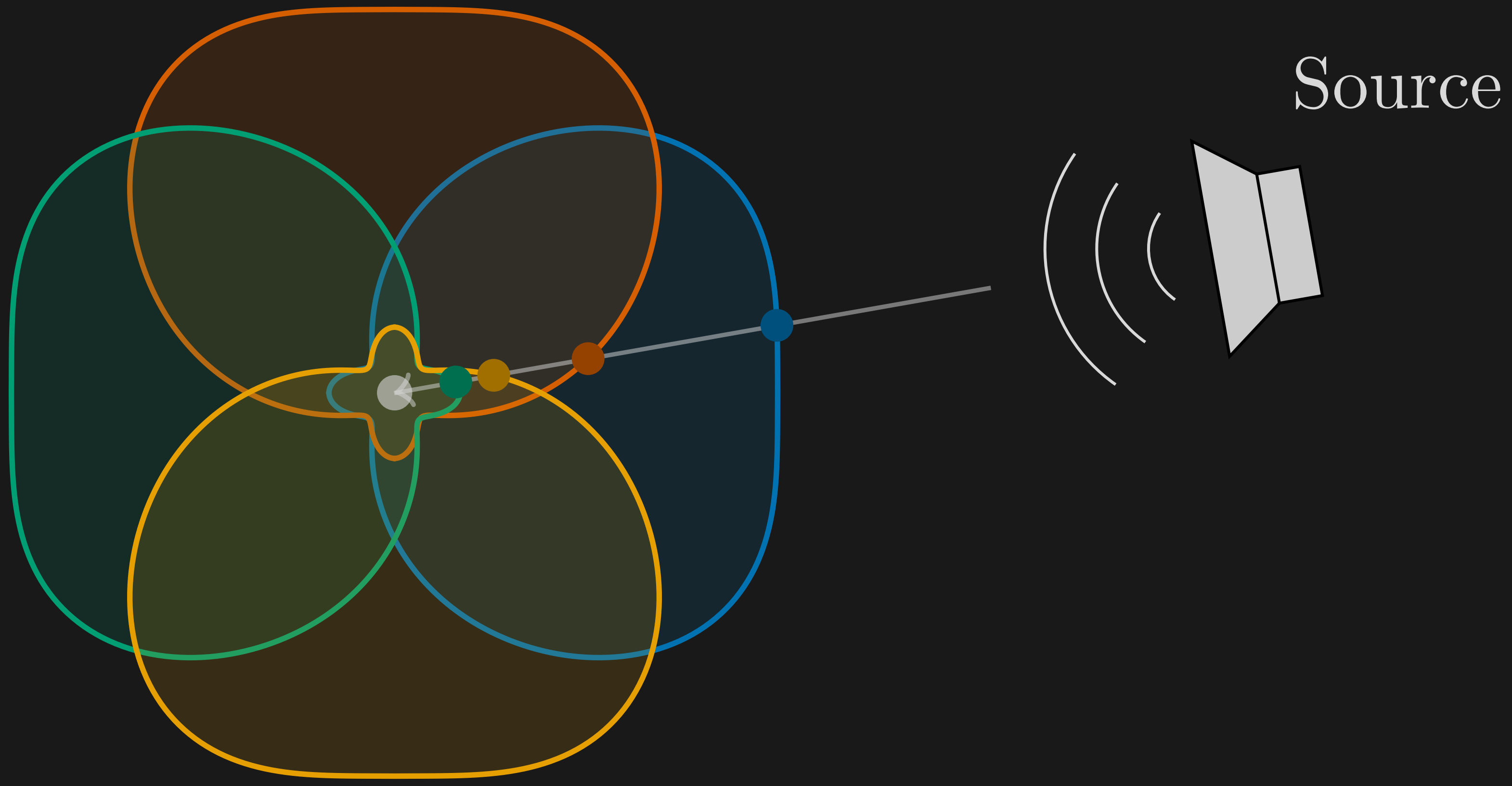

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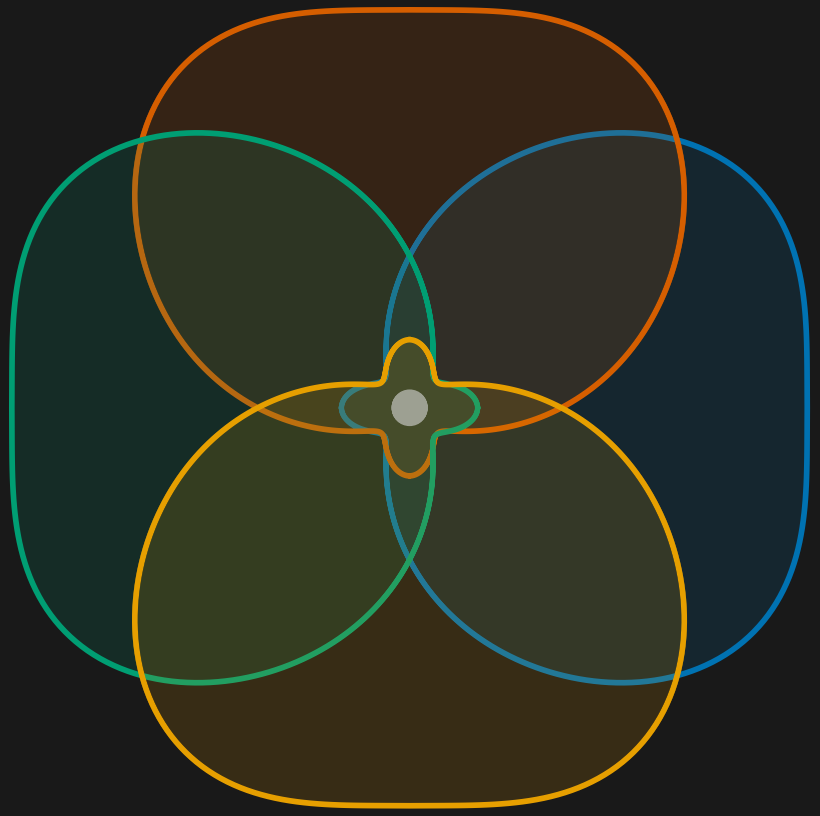

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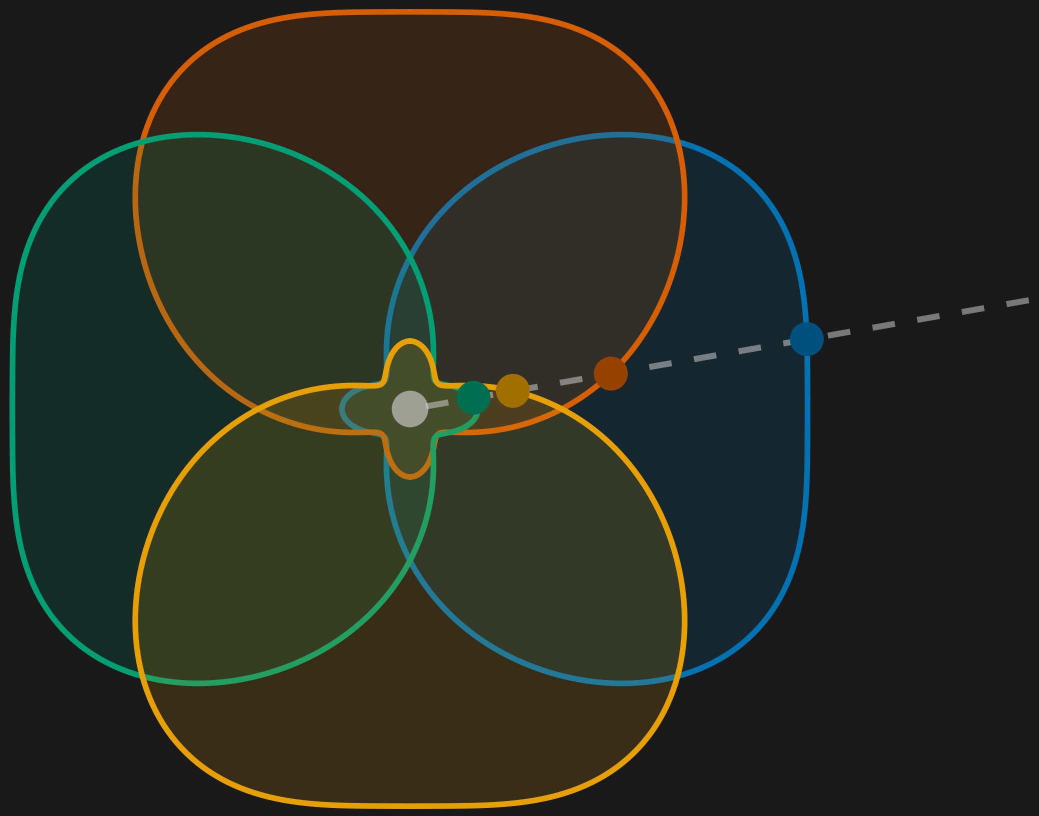

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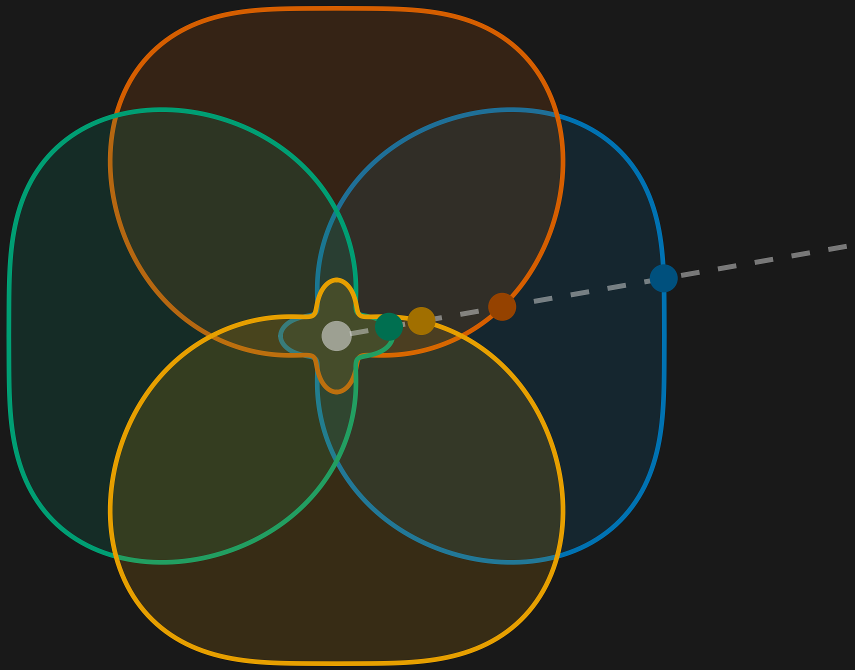

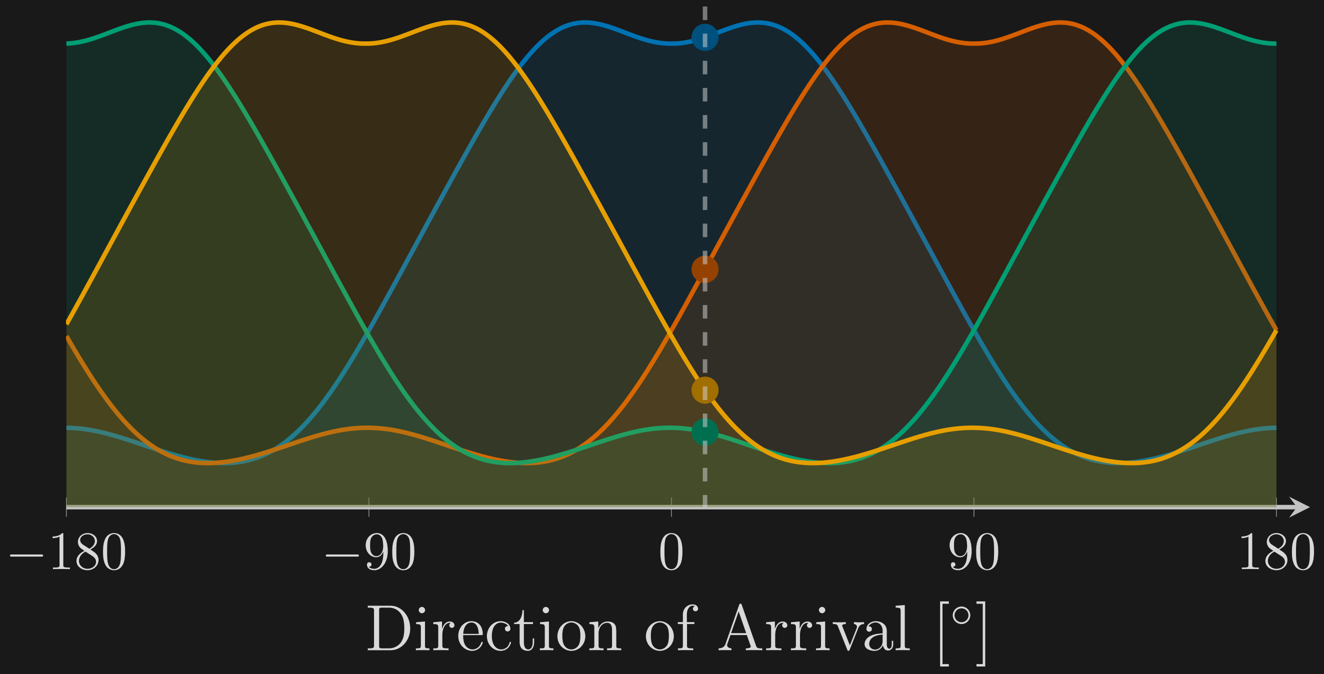

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$$P_m = \underbrace{\frac{1}{L}\sum_{l=1}^{L} s_m^2[l]}_{P_m^s} + \underbrace{\frac{1}{L}\sum_{l=1}^{L} 2 s_m[l] e_m[l]}_{P_m^{sw}} + \underbrace{\frac{1}{L}\sum_{l=1}^{L} e_m^2[l]}_{v_m},$$

Signal model

$$y_m[l] = s_m[l] + e[l], \quad e[l] \sim \mathcal{N}(0, \sigma_m^2)$$

$$P_m = \underbrace{\frac{1}{L}\sum_{l=1}^{L} s_m^2[l]}_{P_m^s} + \underbrace{\frac{1}{L}\sum_{l=1}^{L} 2 s_m[l] e_m[l]}_{P_m^{sw}} + \underbrace{\frac{1}{L}\sum_{l=1}^{L} e_m^2[l]}_{v_m},$$

Signal model

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$$P_m = \underbrace{\frac{1}{L}\sum_{l=1}^{L} s_m^2[l]}_{P_m^s} + \underbrace{\frac{1}{L}\sum_{l=1}^{L} 2s_m[l]e_m[l]}_{P_m^{sw} \to 0} + \underbrace{\frac{1}{L}\sum_{l=1}^{L} e_m^2[l]}_{v_m},$$

Signal model

$$y_m[l] = s_m[l] + e[l], \quad e[l] \sim \mathcal{N}(0, \sigma_m^2)$$

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Signal model

$$P_m = P_m^s + v_m$$

Signal model

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Signal model

$$P_m = P_m^s + v_m$$

$$P_m(\psi) = \alpha g_m h(\psi, \boldsymbol{\theta}_m) + v_m$$

α: absolute power level

g_m: gain of microphone m

$h(\psi, \boldsymbol{\theta}_m)$: directivity pattern

Fourier series Model

$$P_m(\psi) = \alpha g_m h(\psi, \boldsymbol{\theta}_m) + v_m$$

Fourier series Model

$$P_m(\psi) = \alpha g_m h(\psi, \boldsymbol{\theta}_m) + v_m$$

$$\begin{aligned} h\left(\psi, \boldsymbol{\theta}_m\right) &= \theta_0^m + \sum_{d=1}^{D} \theta_{d,c}^m \cos(d\psi) + \theta_{d,s}^m \sin(d\psi) \\ &= \boldsymbol{\Phi}(\psi)\boldsymbol{\theta}_m \end{aligned}$$

Training

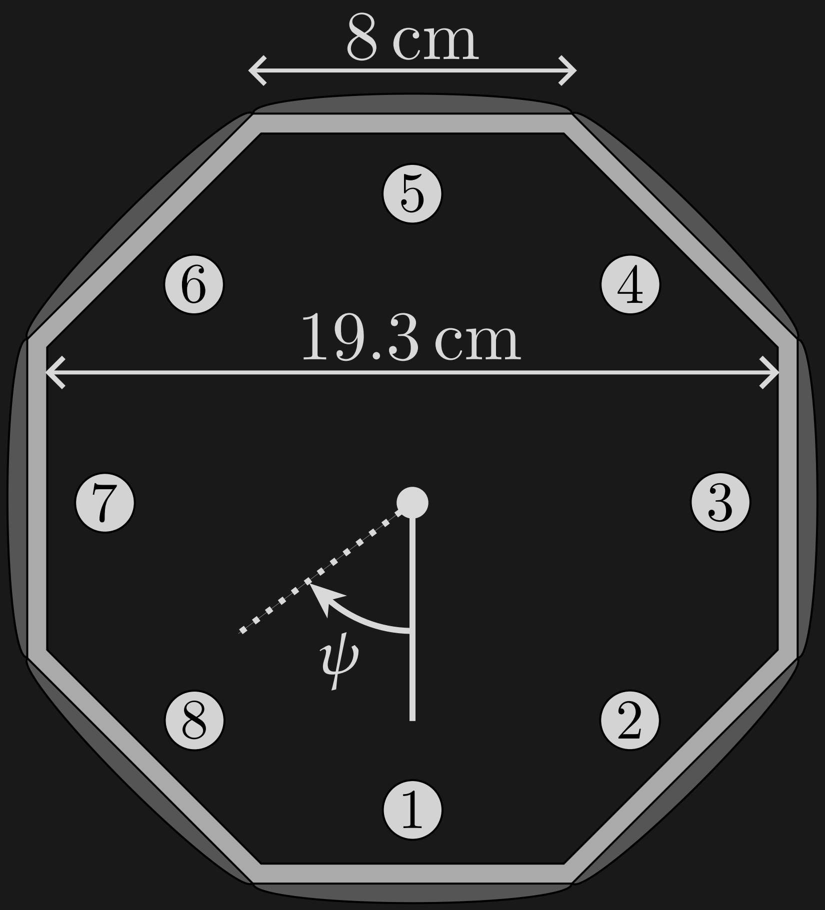
The parameters $\boldsymbol{\theta}_m, g_m$ are estimated by minimizing the error between the predicted and the measured power.

Training

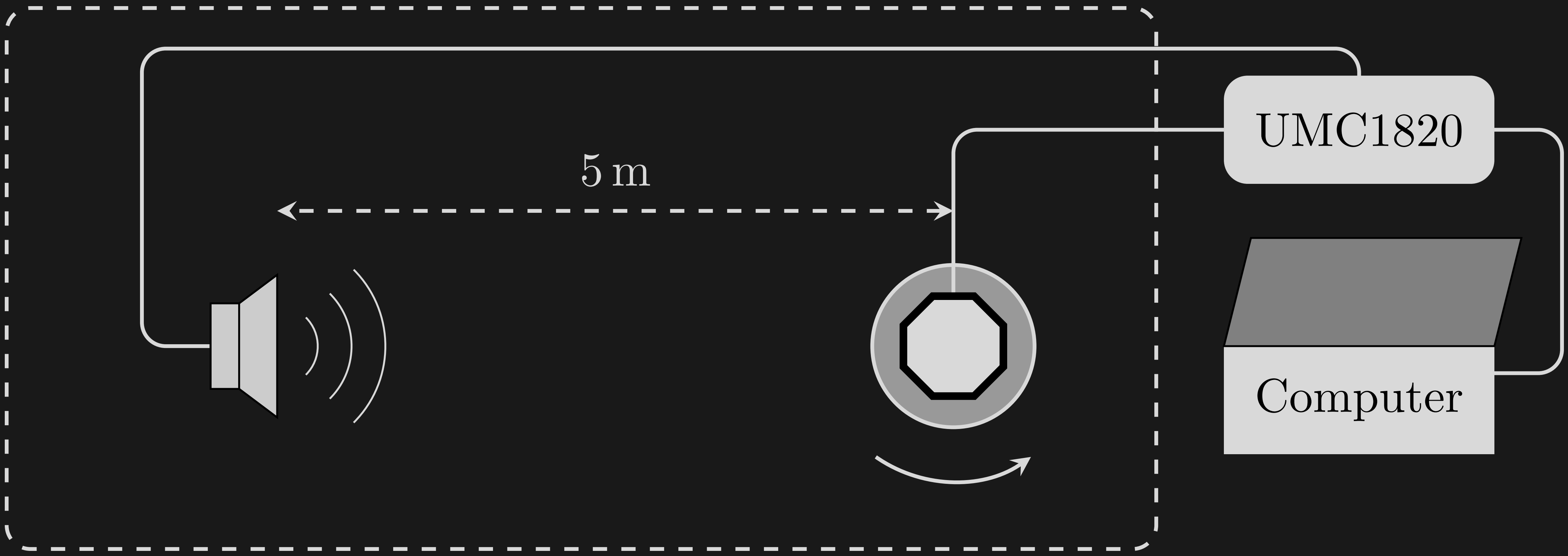
The parameters θ_m, g_m are estimated by minimizing the error between the predicted and the measured power.

$$
\begin{aligned}
\underset{\boldsymbol{\alpha},\, \boldsymbol{g}_{1:M},\, \boldsymbol{\theta}_{1:M}}{\text{minimize}} \quad & \sum_{m=1}^{M} \frac{1}{\eta_m} \sum_{k=1}^{K} \left(P_m(\psi_k) - \left(\alpha g_m h\left(\psi_k, \boldsymbol{\theta}_m\right) + \sigma_m^2\right)\right)^2 \\
\text{subject to} \quad & \alpha > 0 \\
& g_1 = 1 \\
& h\left(\psi_m, \boldsymbol{\theta}_m\right) = 1, \qquad \forall\, m = 1, 2, \ldots, M,
\end{aligned}
$$

Experimental Setup



Experimental Setup



19 different sounds

No.	Sound	Signal
1	Wideband noise	0:00 / 0:10
2-11	Sinusoids	0:00 / 0:10
12	Hovering drone	0:00 / 0:05
13	Elephant trumpet	0:00 / 0:02
14	Police Siren	0:00 / 0:10

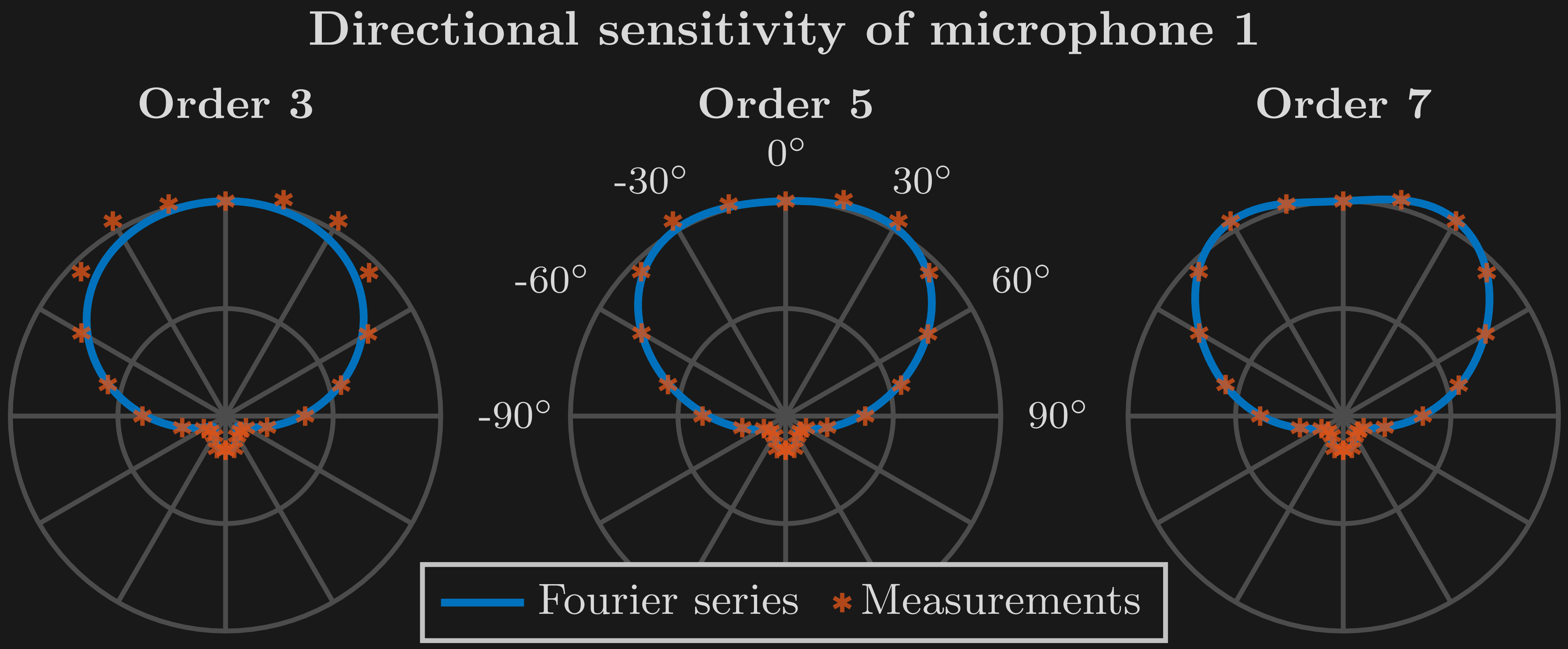
19 different sounds

No.	Sound	Signal
15	Woman Scream	0:00 / 0:01
16	Wideband noise low	0:00 / 0:10
17	Wideband noise high	0:00 / 0:10
18	Gunshot	0:00 / 0:00
19	Background noise	0:00 / 0:26

Data summary

	Training		Estimation	
	Signals	**# of angles**	**Signals**	**# of angles**
Anechoic	Signal 1	24	Signal 1-18	24
Outdoor	-	-	Signal 1-17	10

Fourier Series Order



DOA Estimation

$$\hat{P}_m(\psi) = \alpha \underbrace{\hat{g}_m \mathbf{\Phi}(\psi) \hat{\boldsymbol{\theta}}_m}_{\hat{h}_m(\psi)} + \sigma_m^2$$

DOA Estimation

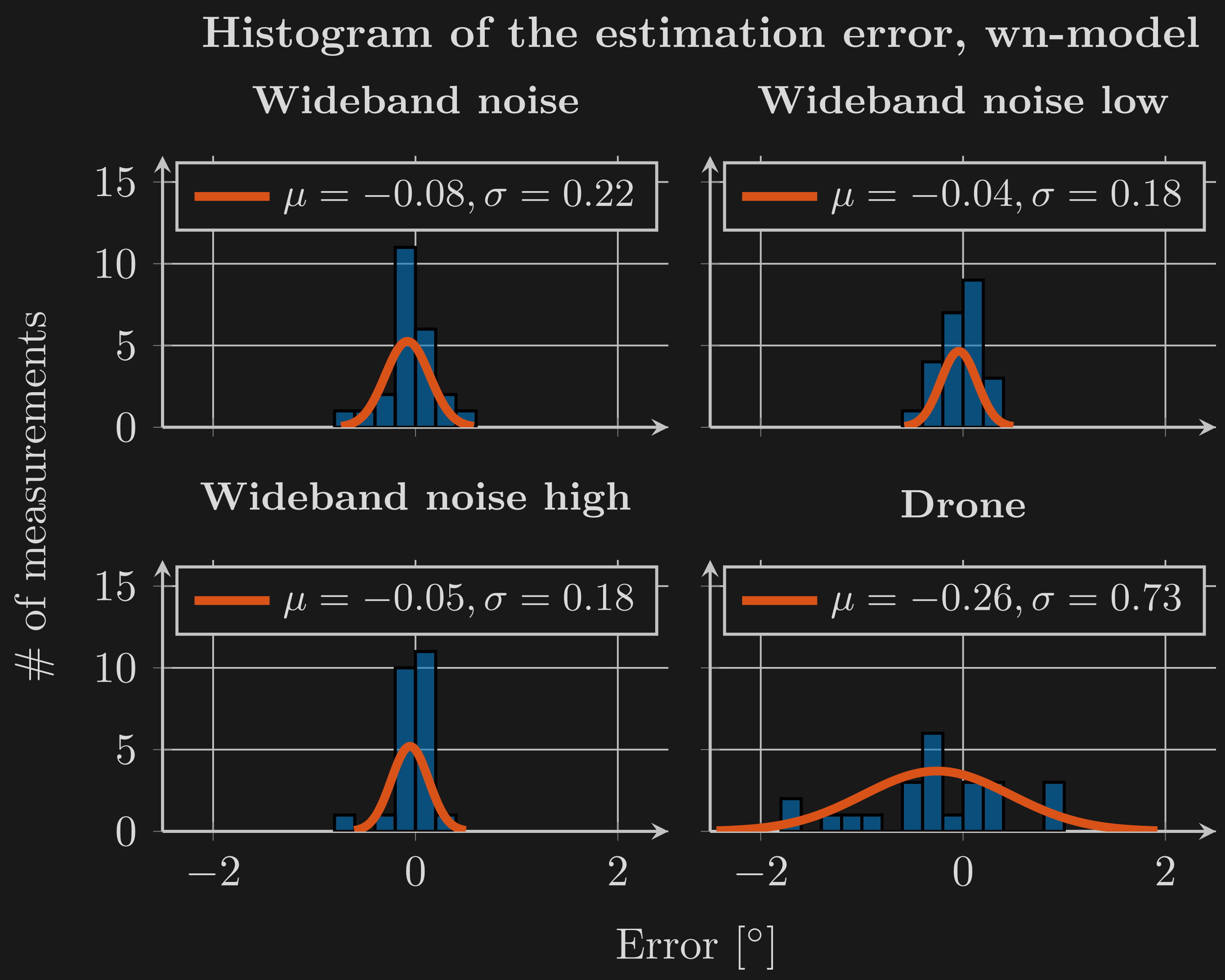
$$\hat{P}_m(\psi) = \alpha \hat{g}_m \boldsymbol{\Phi}(\psi) \hat{\boldsymbol{\theta}}_m + \sigma_m^2$$

$$\hat{h}_m(\psi)$$

$$\hat{\psi} = \arg\max_{\psi} \frac{\left(\sum_{m=1}^{M} \hat{h}_m(\psi)(P_m - \sigma_m^2)\right)^2}{\sum_{m=1}^{M} \hat{h}_m^2(\psi)}$$

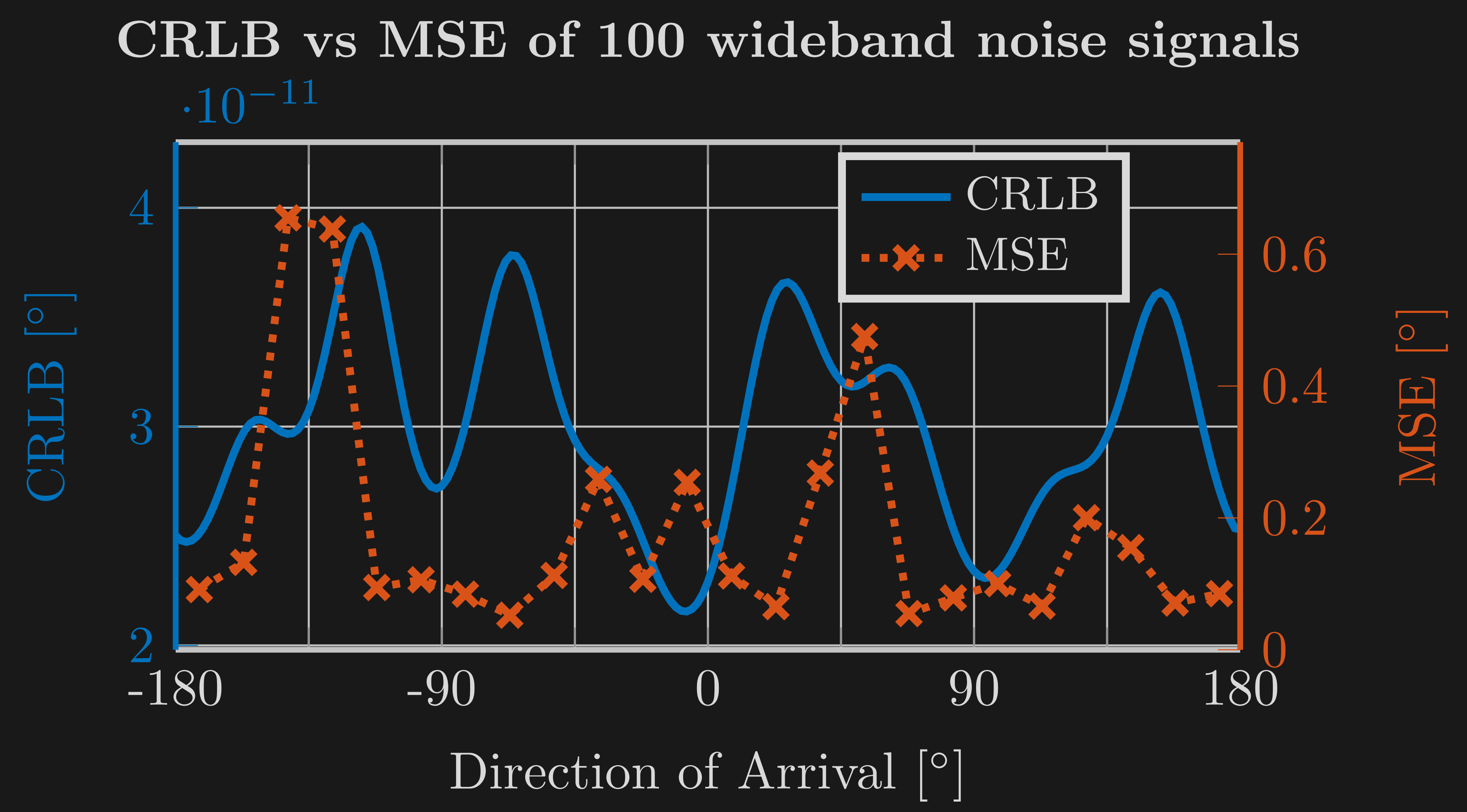
$$\hat{\alpha} = \frac{\sum_{m=1}^{M} \hat{h}_m(\hat{\psi})(P_m - \sigma_m^2)}{\sum_{m=1}^{M} \hat{h}_m^2(\hat{\psi})}$$

Result



Histogram of the estimation error, wn-model
Wideband noise
Wideband noise low
Wideband noise high
Drone
$\mu = -0.08, \sigma = 0.22$
$\mu = -0.04, \sigma = 0.18$
$\mu = -0.05, \sigma = 0.18$
$\mu = -0.26, \sigma = 0.73$
# of measurements
Error [°]
0
5
10
15
−2
0
2

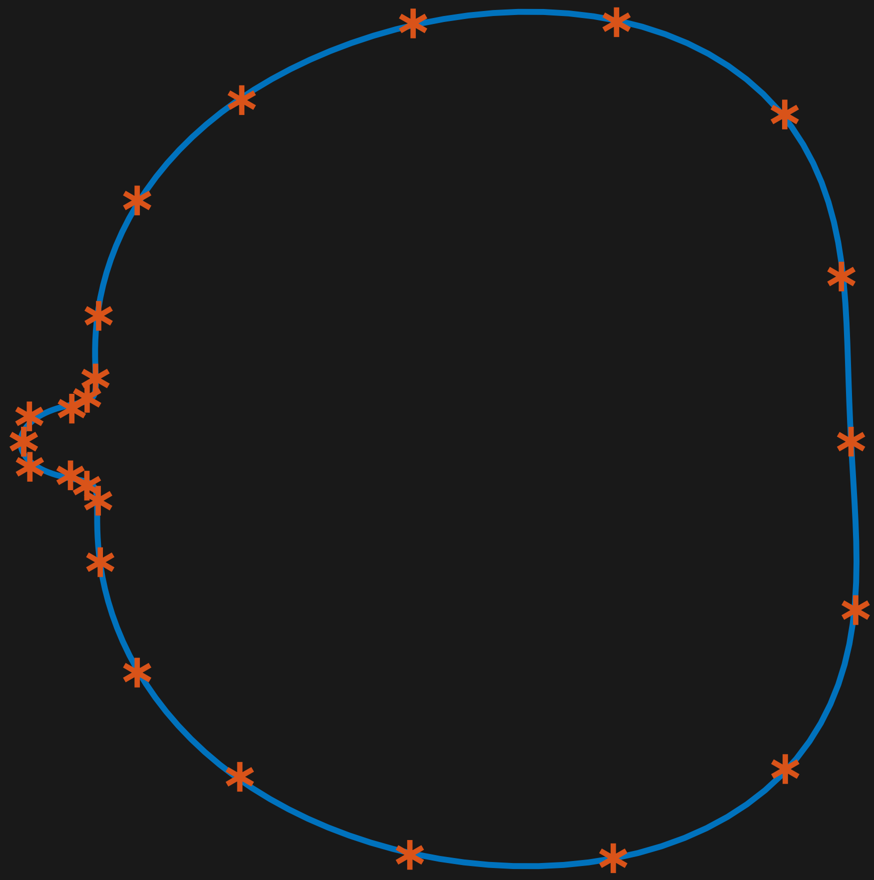
Cramér-Rao Lower Bound



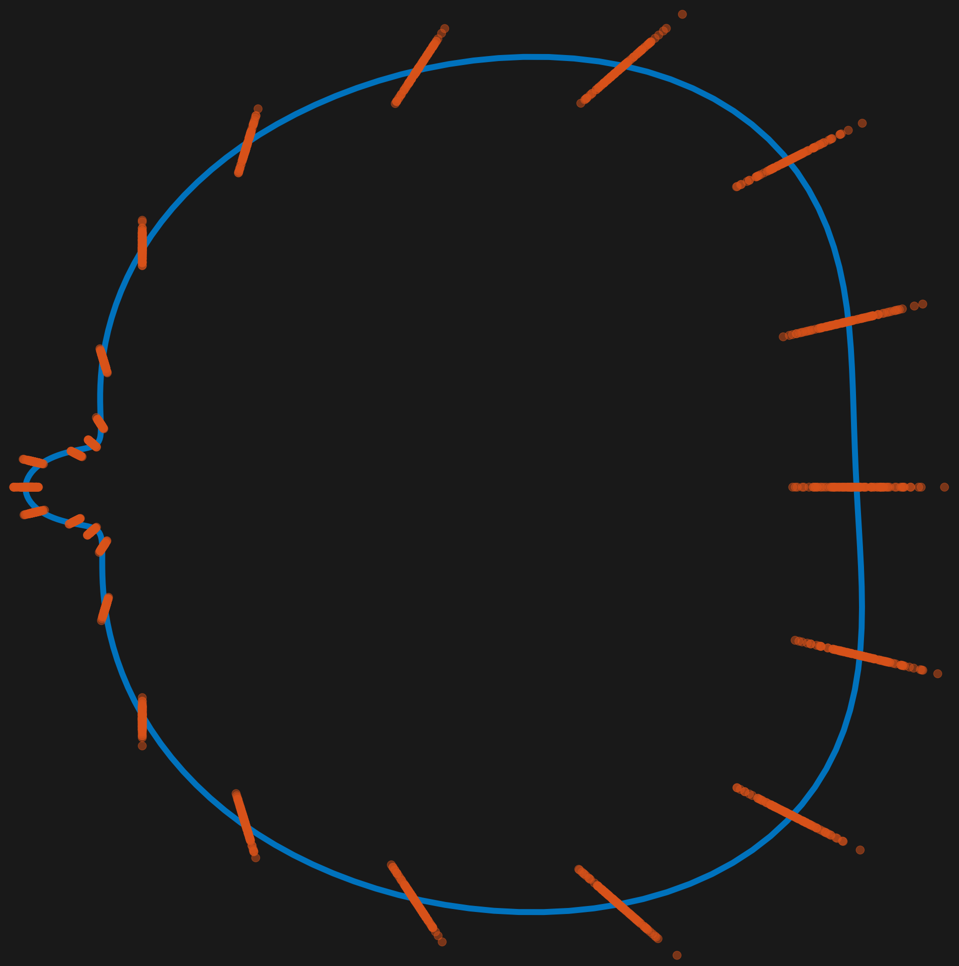
Noise distribution

$$P_m = \alpha g_m h(\psi, \boldsymbol{\theta}_m) + v_m, \quad v_m \sim$$

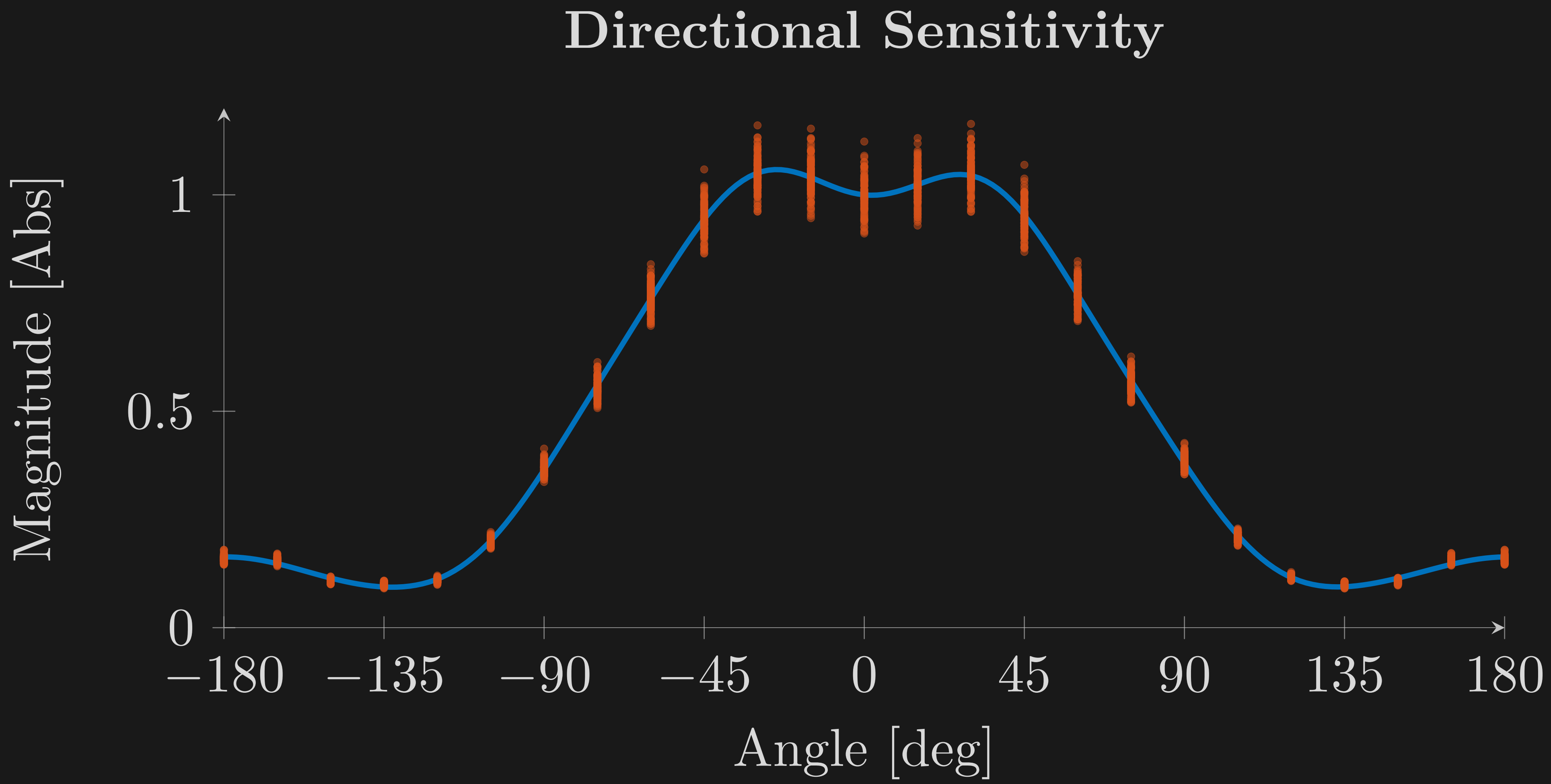
Noise distribution



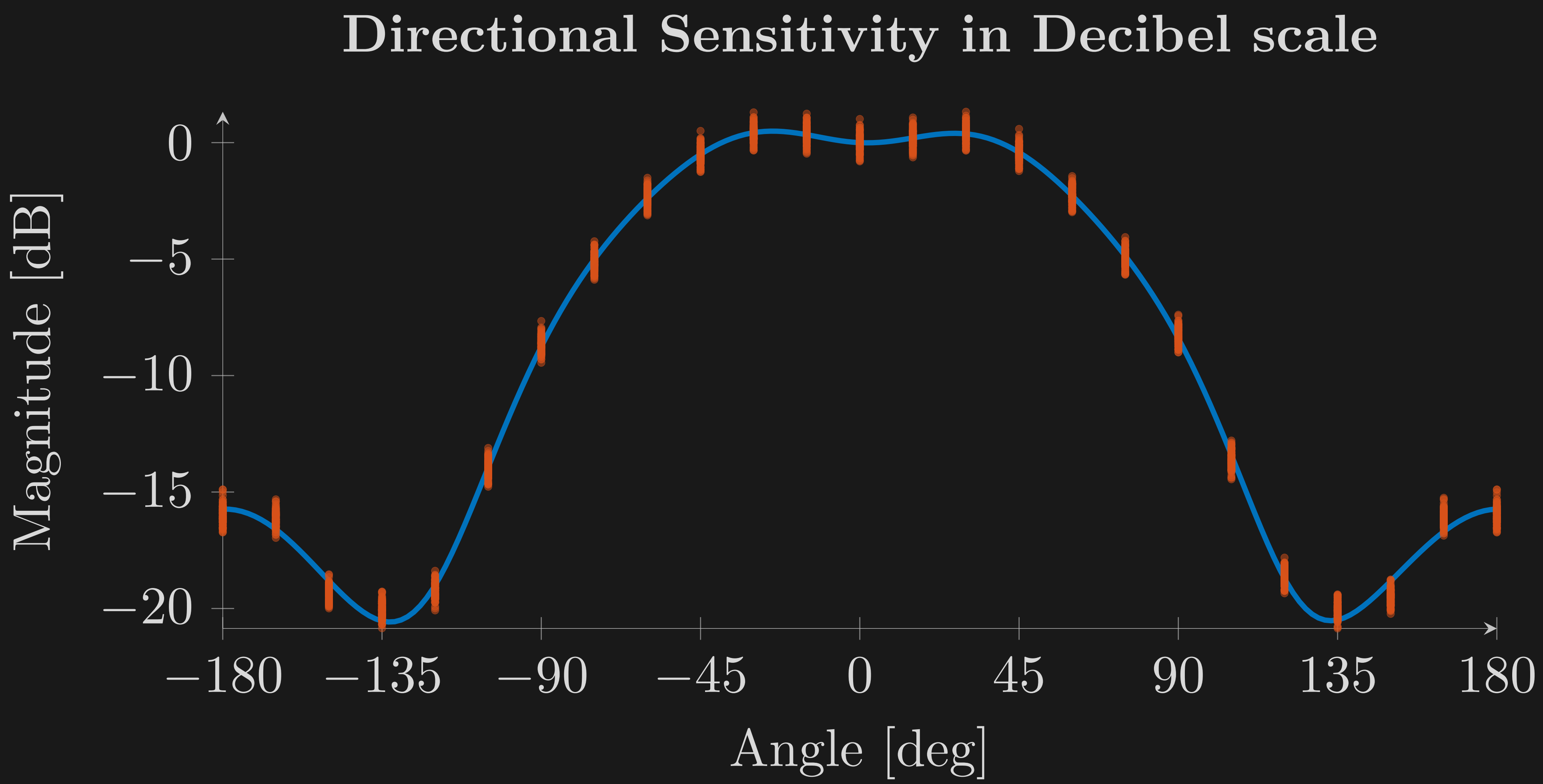
Noise distribution



Noise distribution



Noise distribution

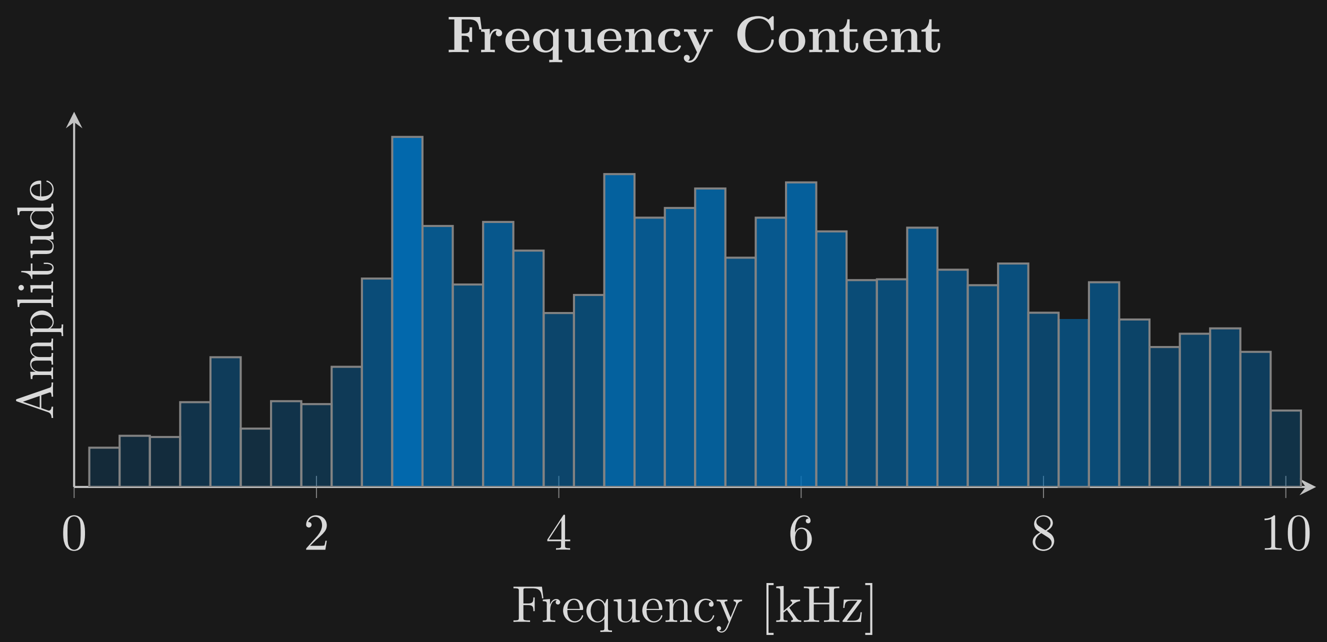


Noise distribution

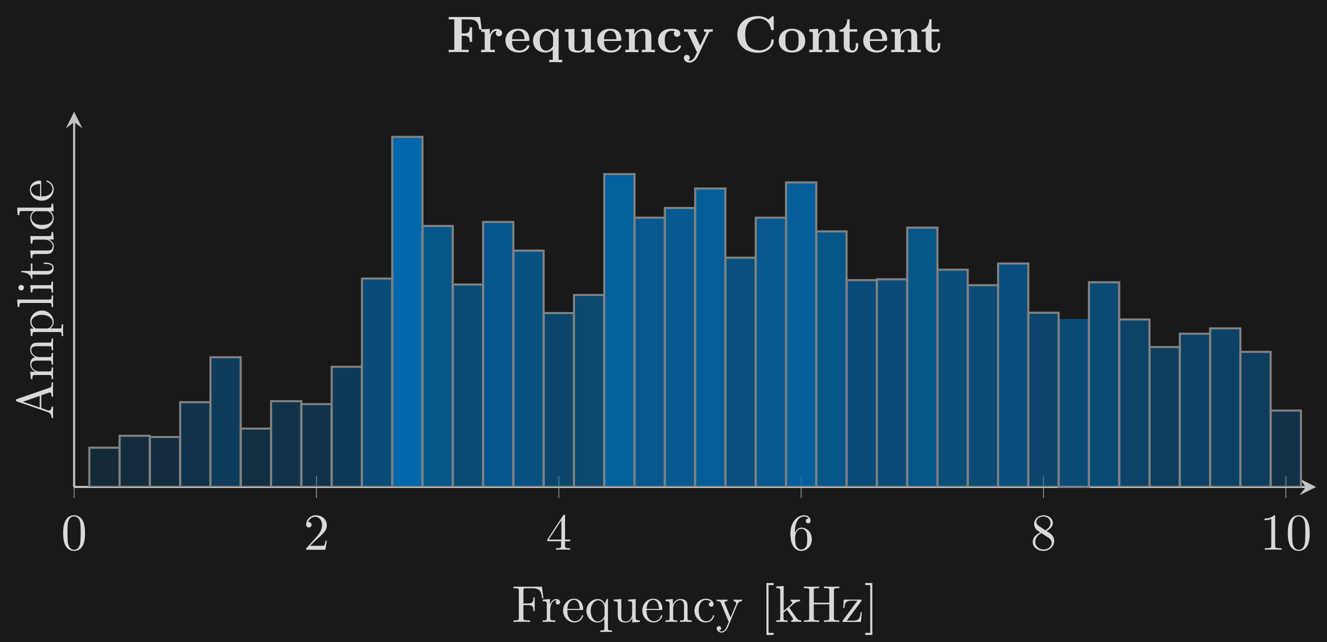
Introduce model in dB scale as

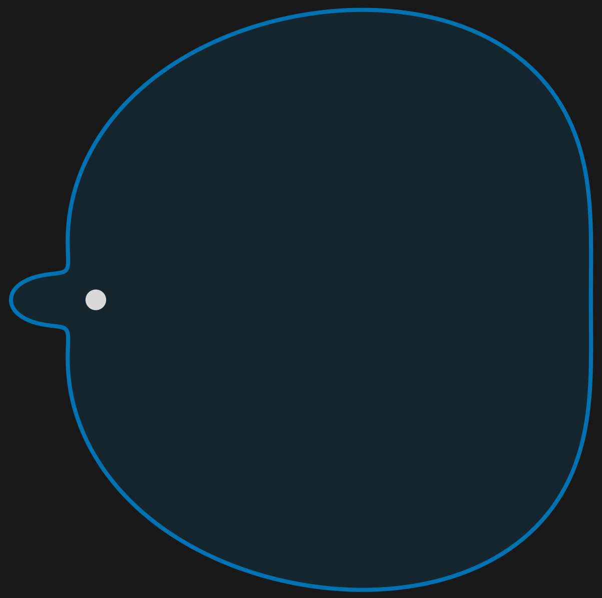
$$\bar{P}_m = \bar{\alpha} + \bar{g}_m + h(\psi, \bar{\boldsymbol{\theta}}_m) + \bar{v}_m,$$

Frequency Dependency



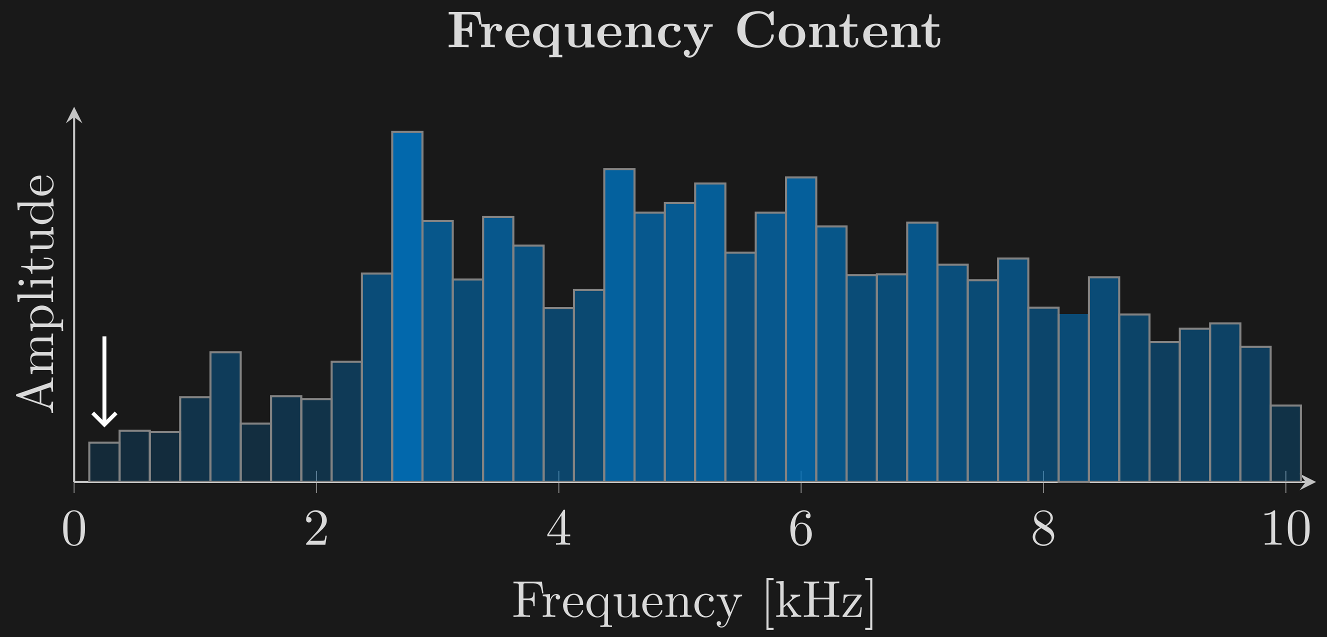
Frequency Dependency





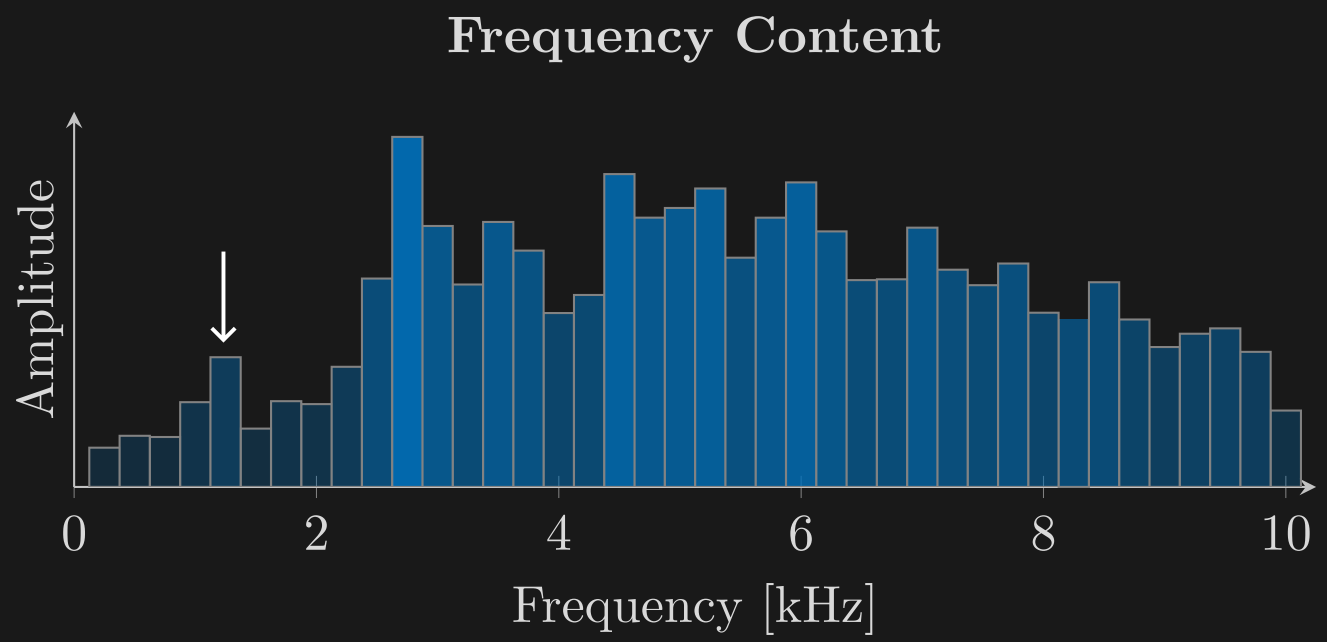
Wideband noise

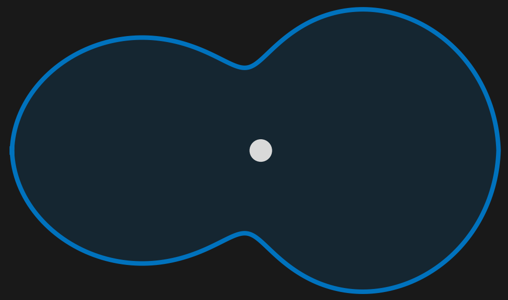
Frequency Dependency



250 Hz

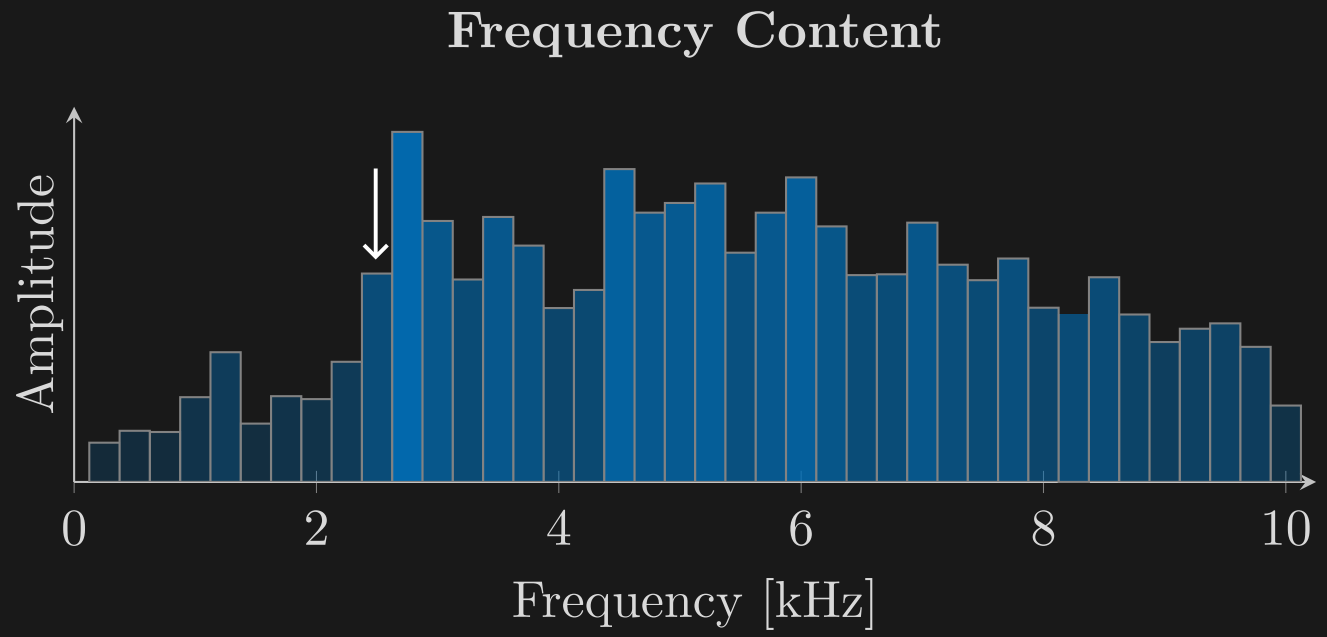
Frequency Dependency

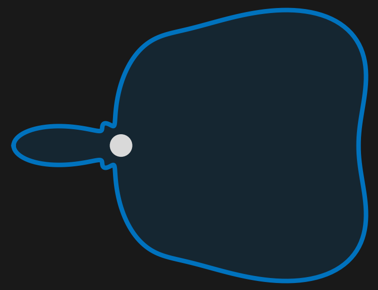




1250 Hz

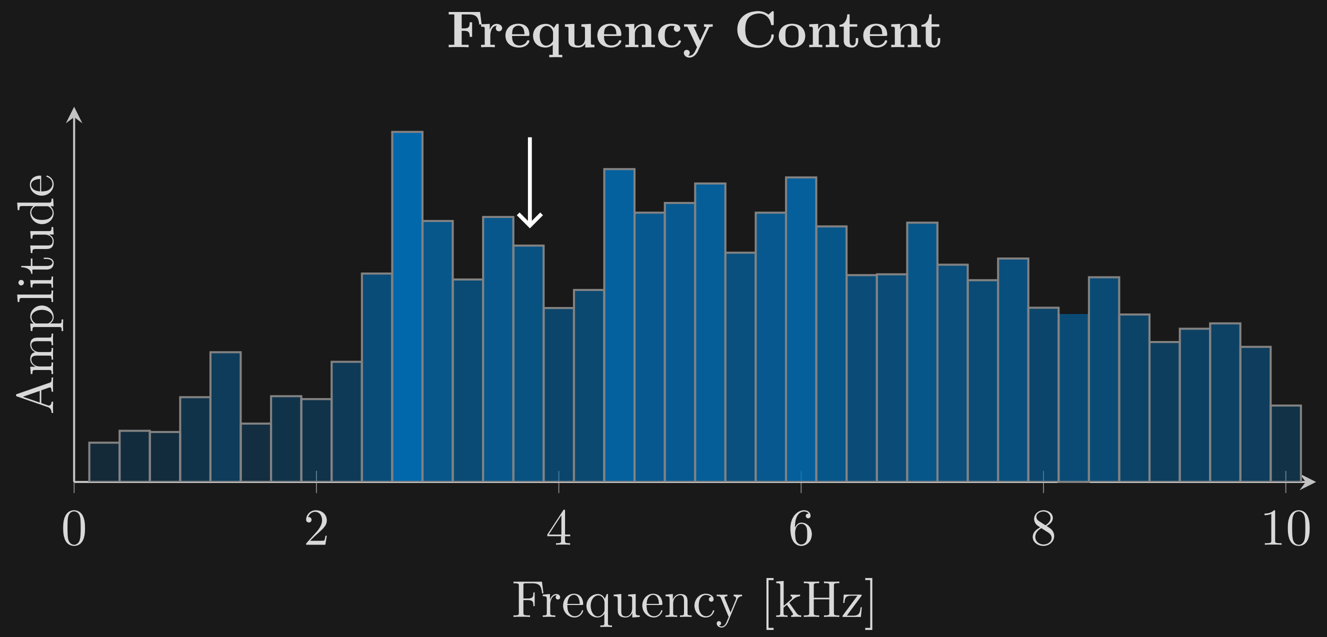
Frequency Dependency

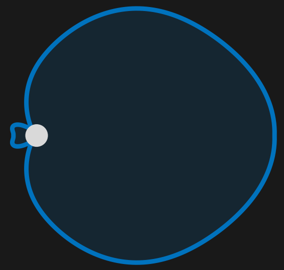




2500 Hz

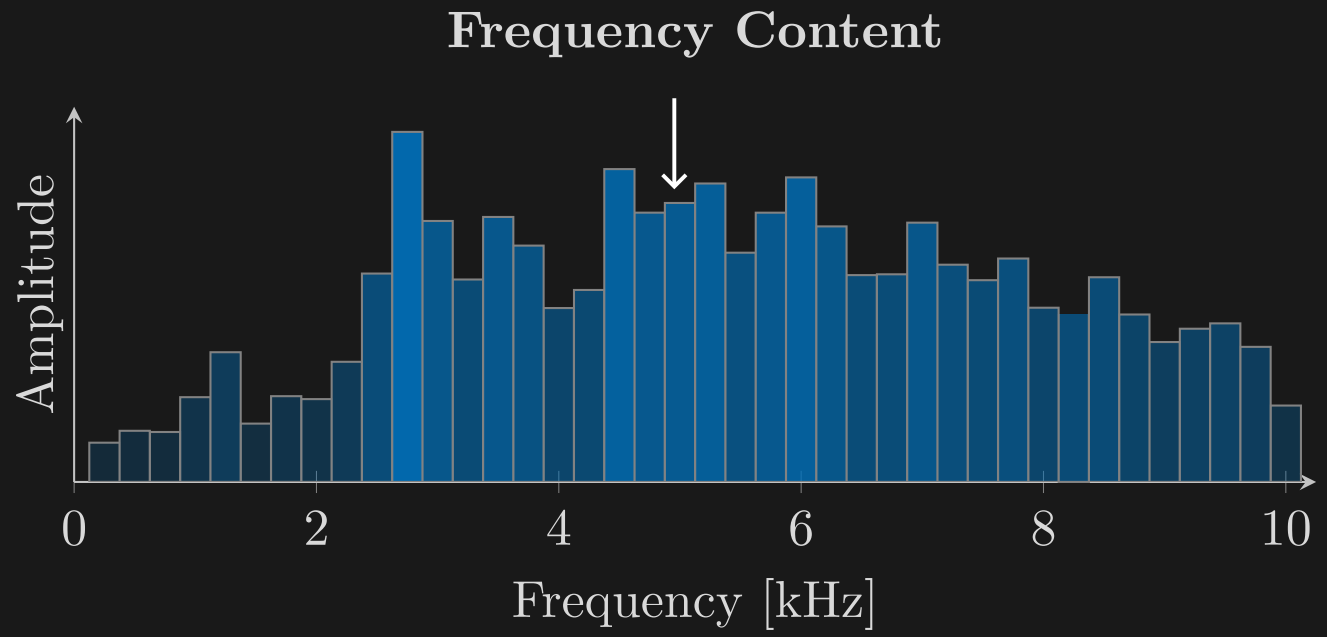
Frequency Dependency

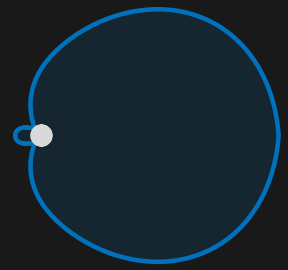




3750 Hz

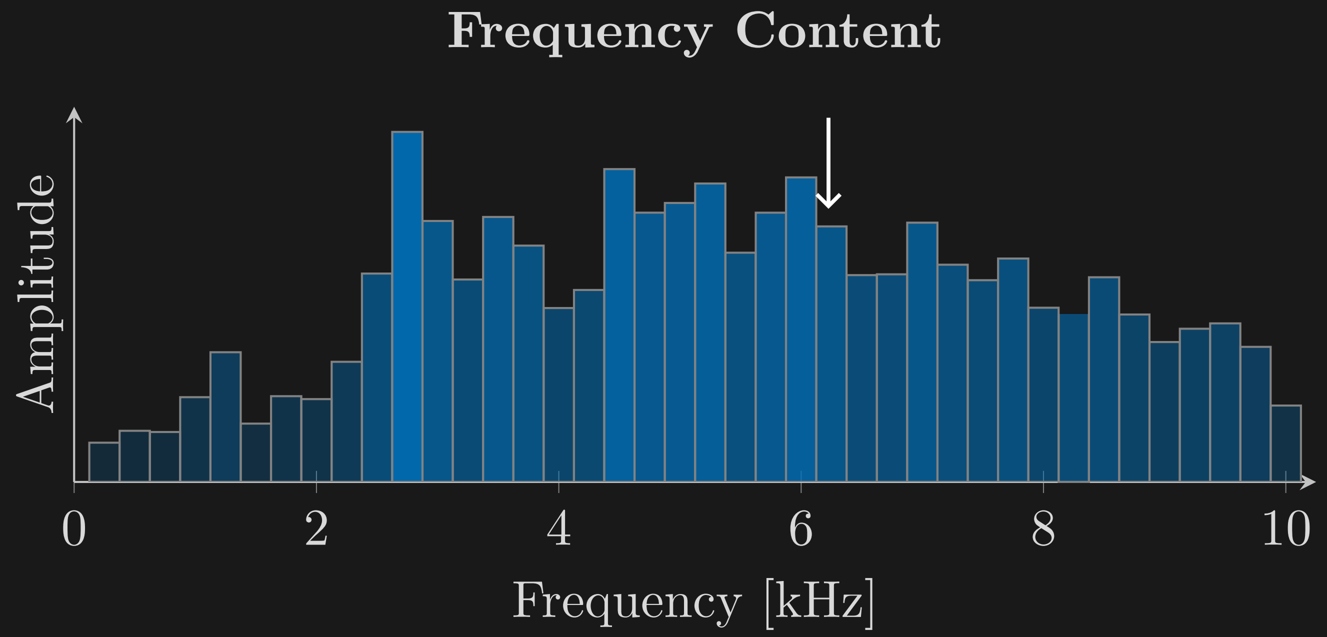
Frequency Dependency

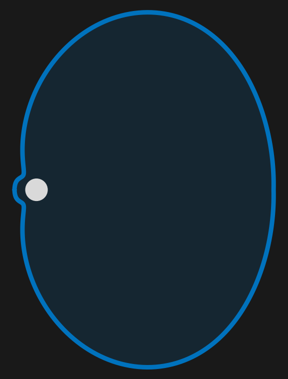




5000 Hz

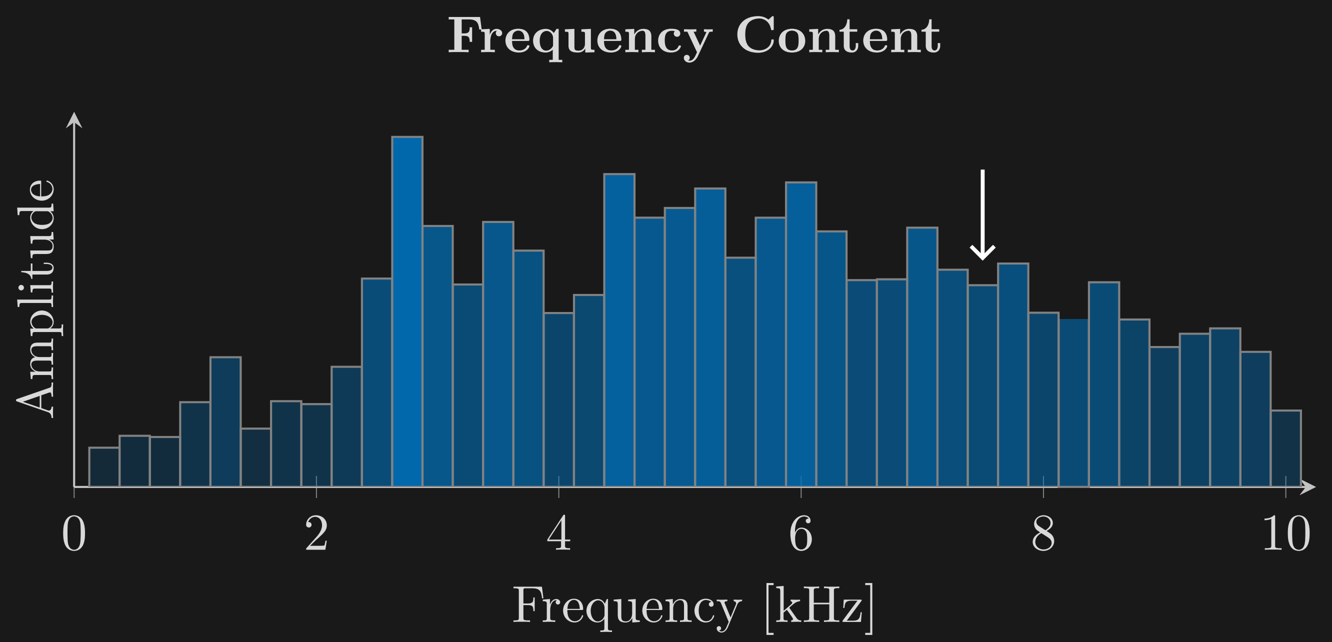
Frequency Dependency

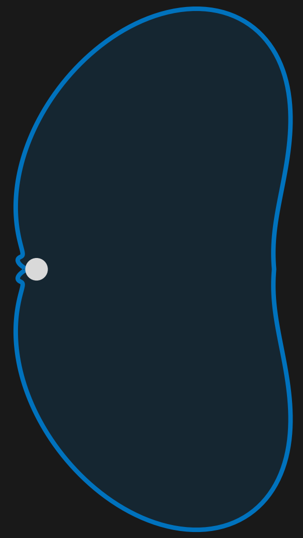




6250 Hz

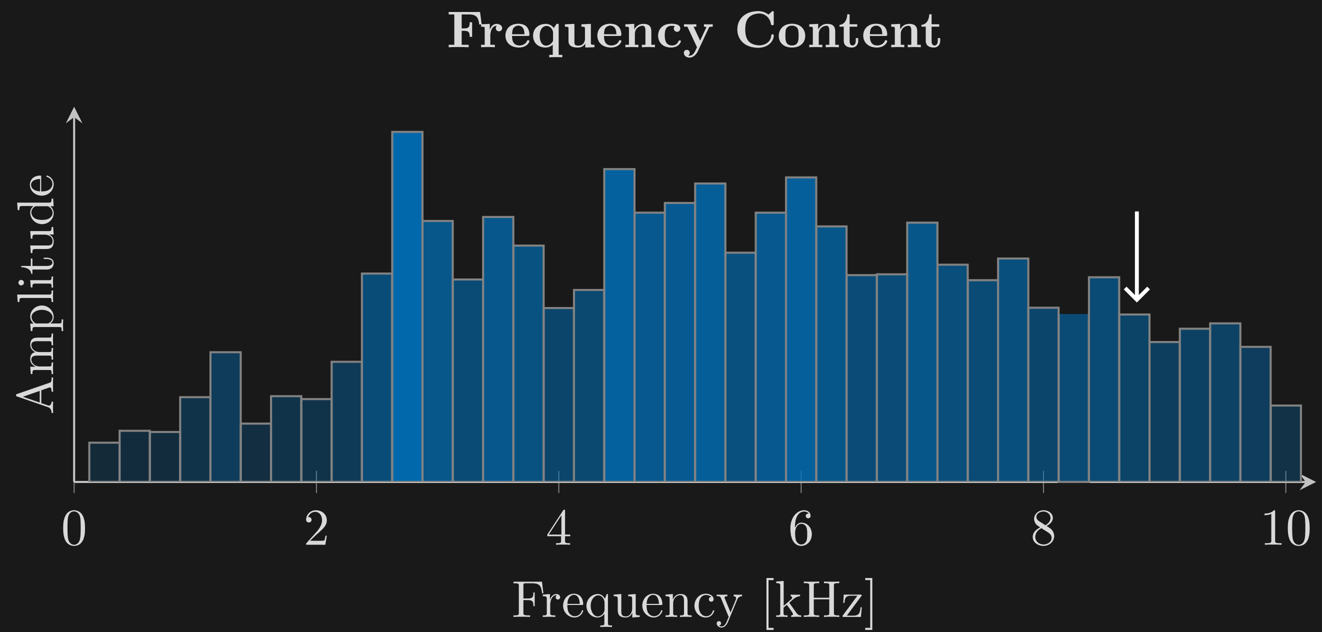
Frequency Dependency

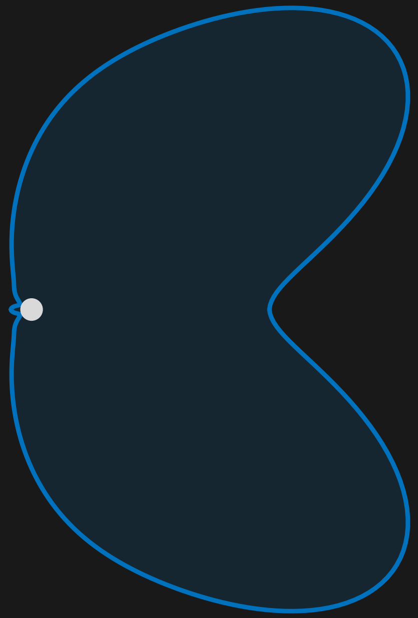




7500 Hz

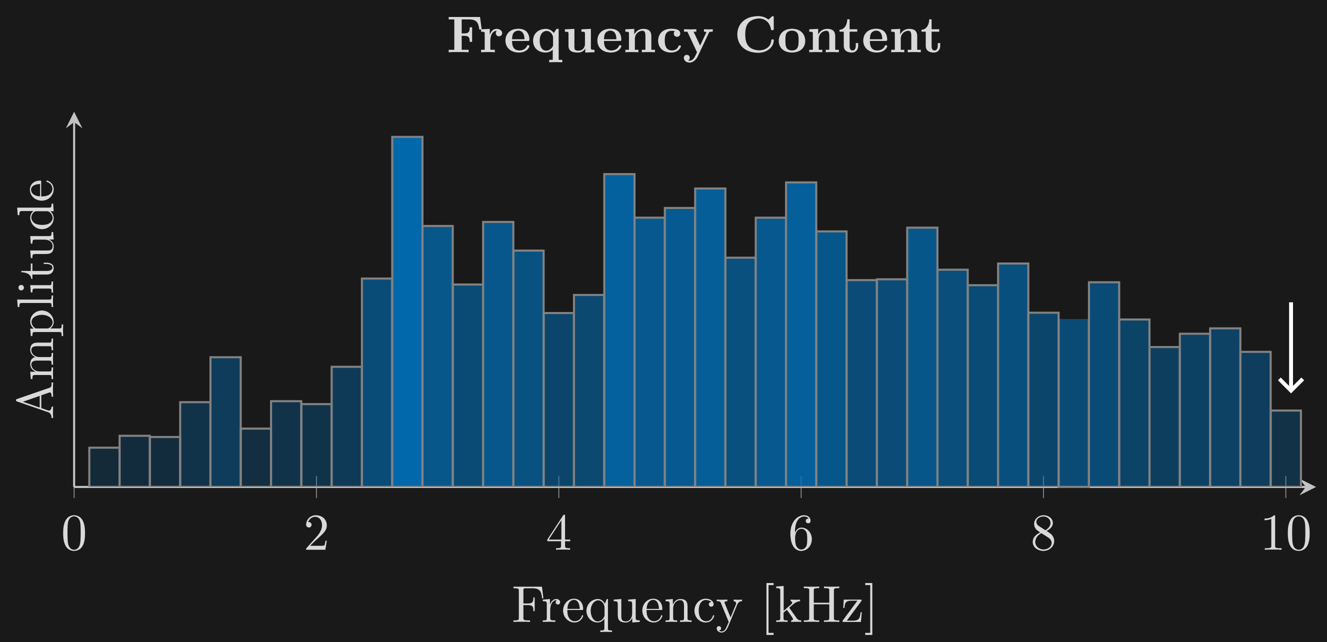
Frequency Dependency

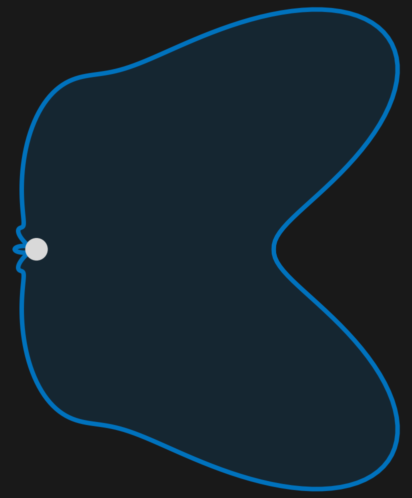




8750 Hz

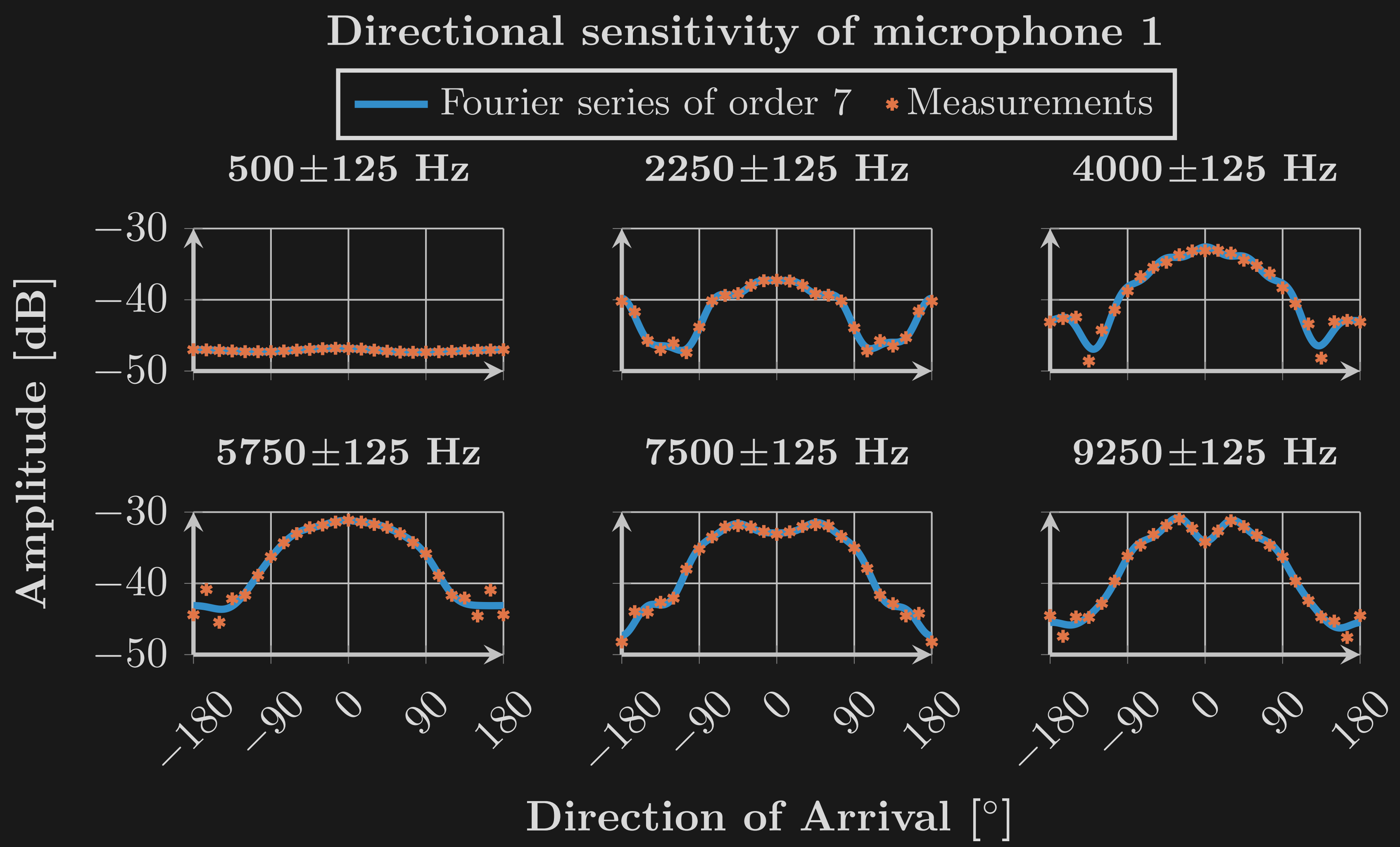
Frequency Dependency



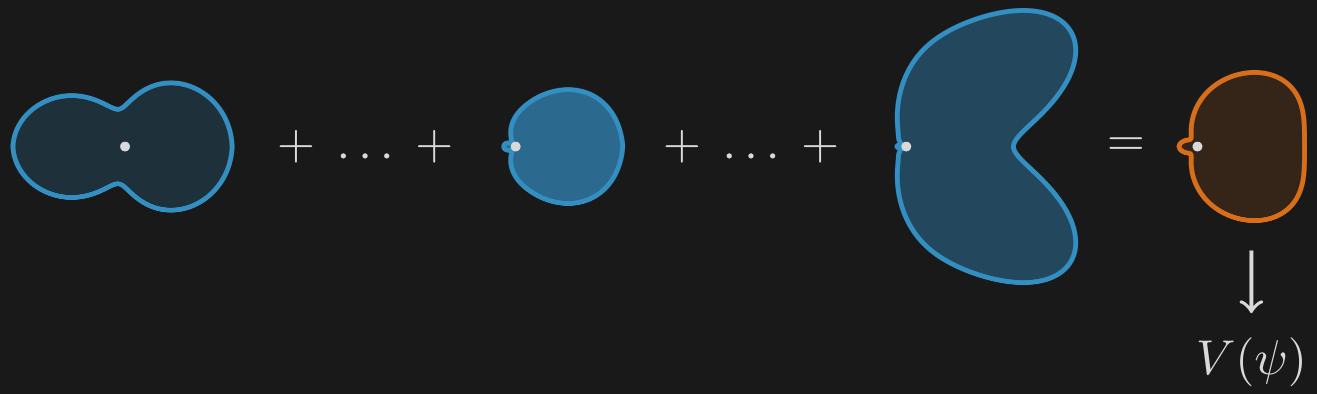


10 000 Hz

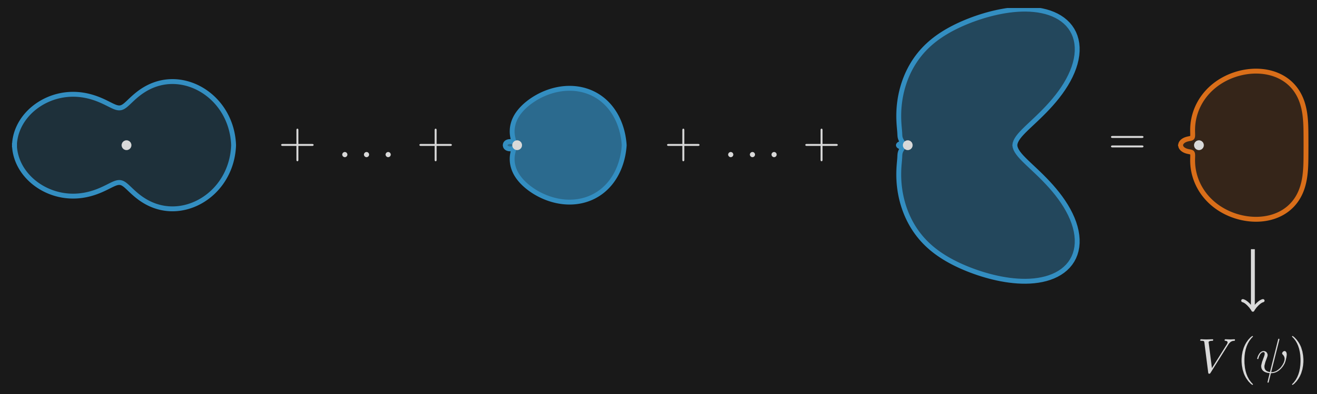
Frequency Dependency

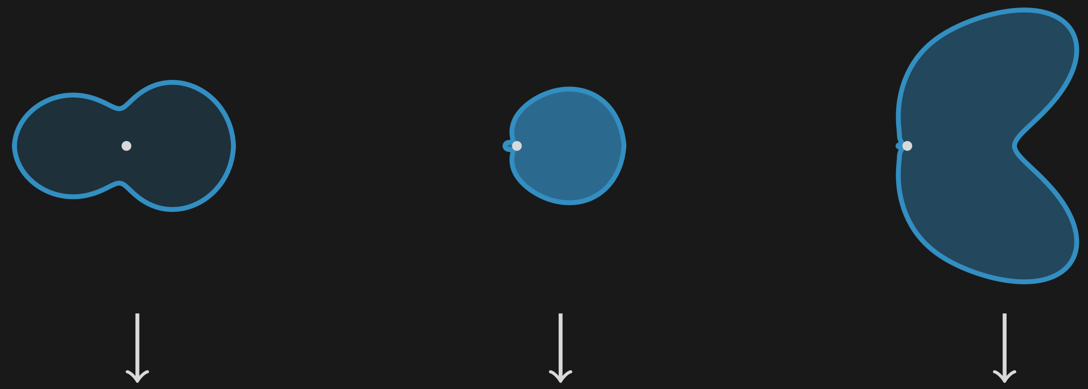


Frequency Dependency



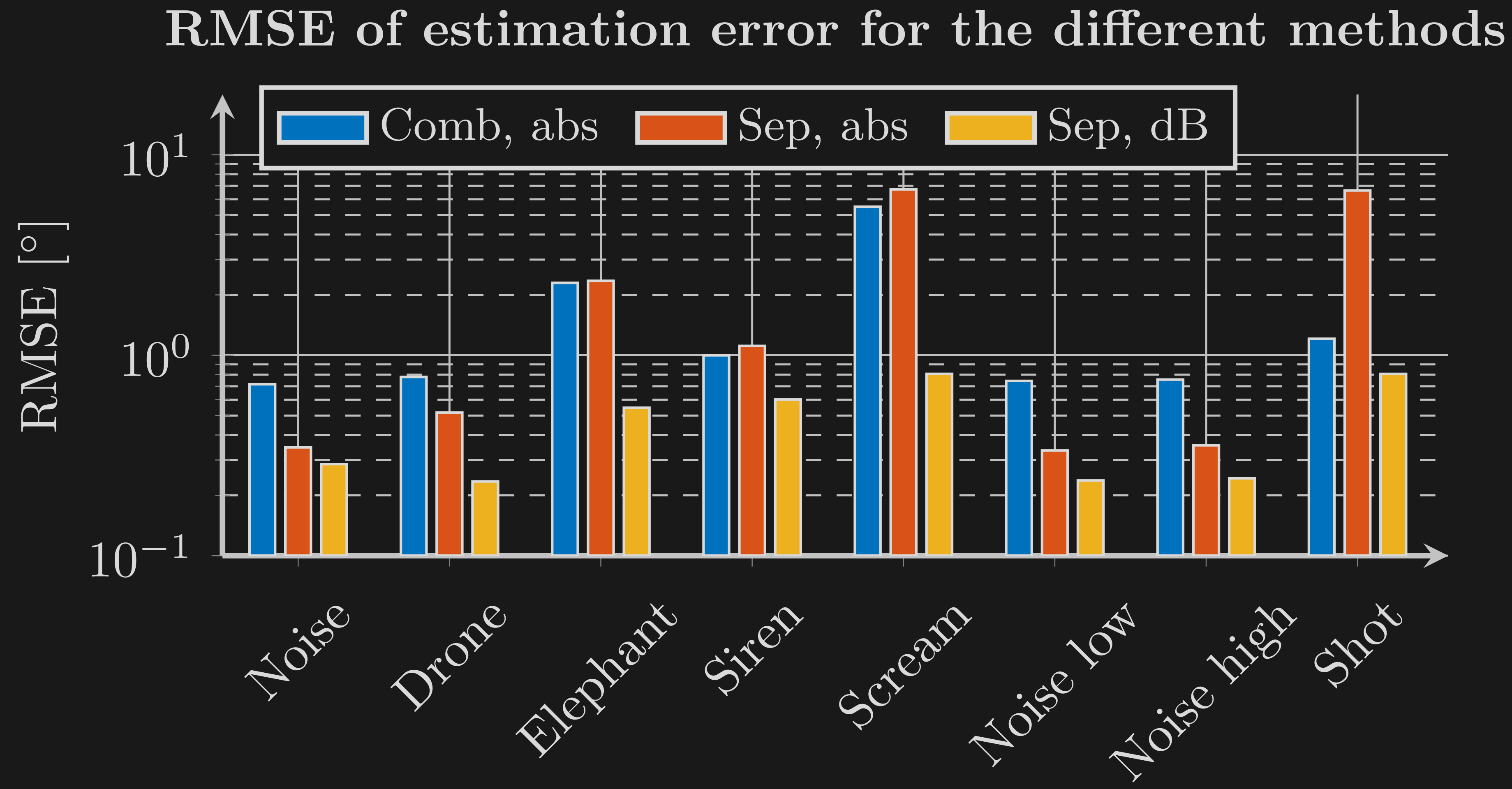
Frequency Dependency





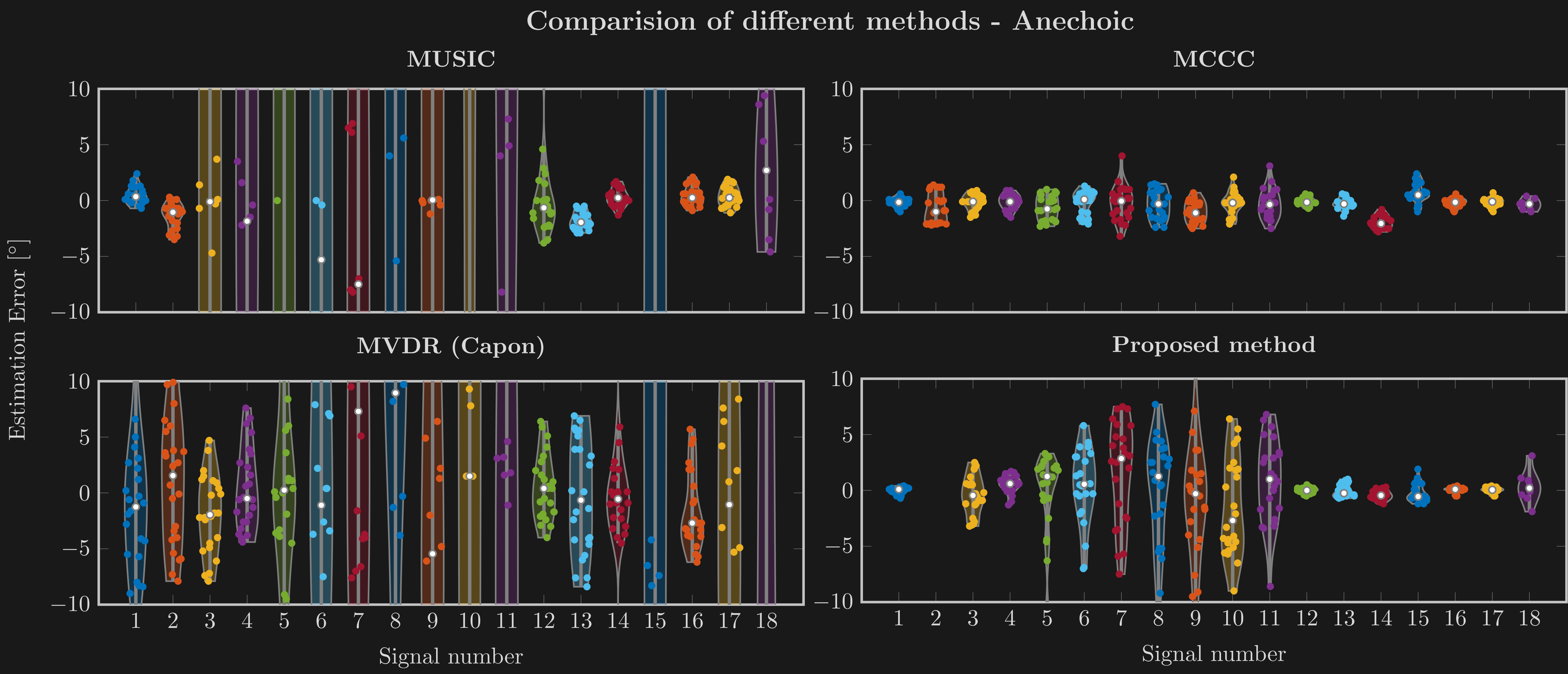
$$w_1 V_1(\psi) + \ldots + w_n V_n(\psi) + \ldots + w_F V_F(\psi) = V(\psi)$$

Results



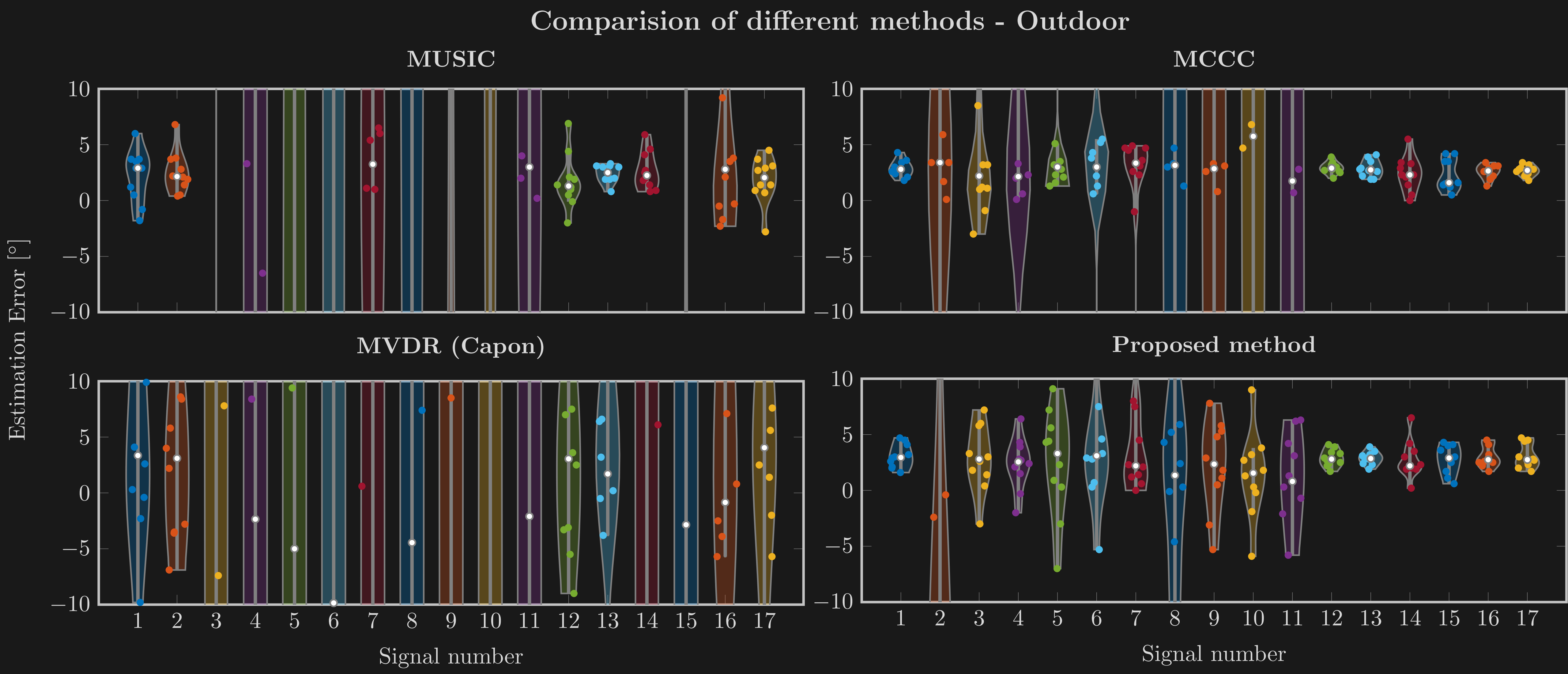
RMSE of estimation error for the different methods
Comb, abs
Sep, abs
Sep, dB
RMSE [°]
10^1
10^0
10^{-1}
Noise
Drone
Elephant
Siren
Scream
Noise low
Noise high
Shot

Results



Comparision of different methods - Anechoic
MUSIC
MCCC
MVDR (Capon)
Proposed method
Estimation Error [°]
10
5
0
−5
−10
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18
Signal number

Results

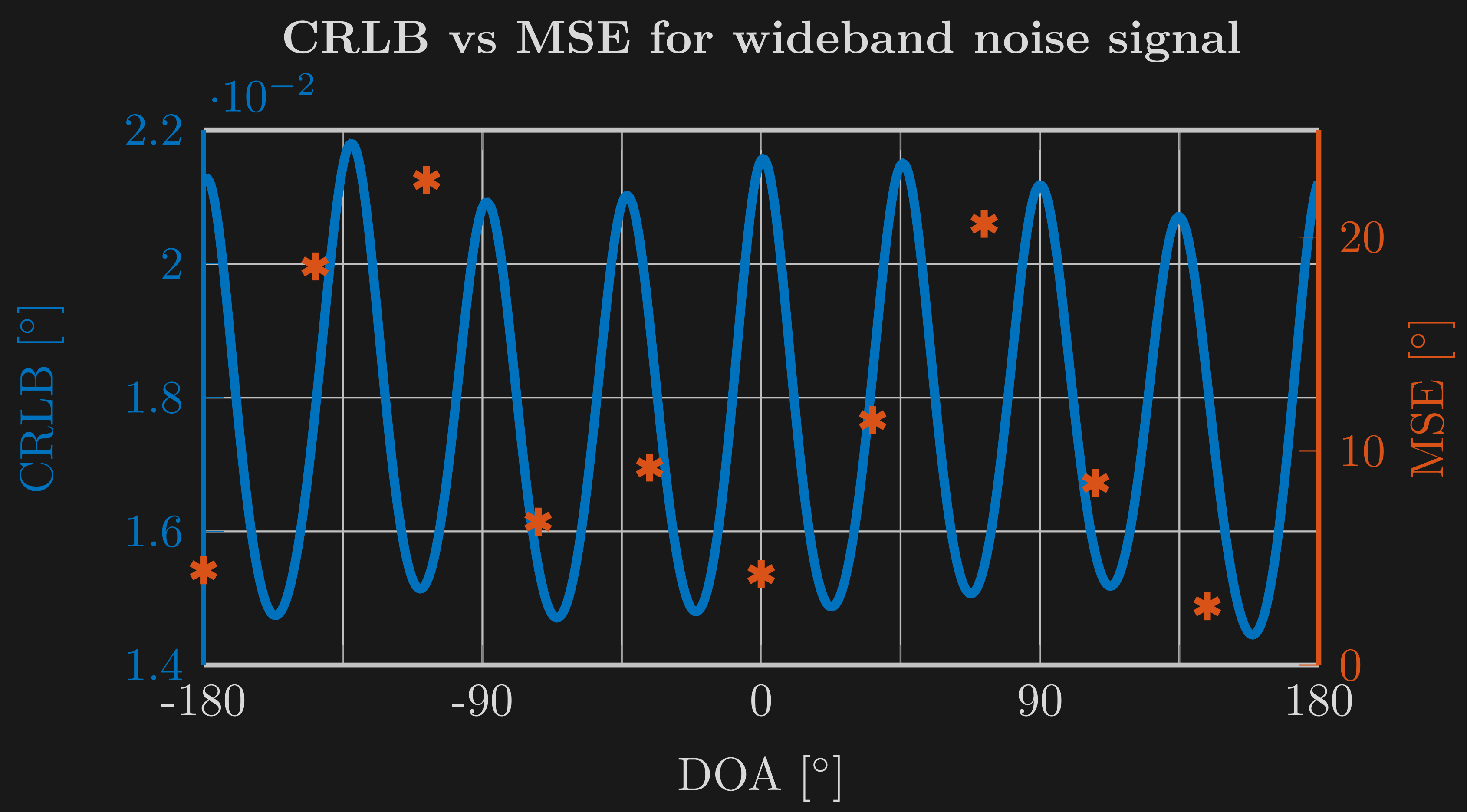


Comparision of different methods - Outdoor
MUSIC
MCCC
MVDR (Capon)
Proposed method
Estimation Error [°]
Signal number
Signal number
10
5
0
−5
−10
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17

Results

	Signal No.	Proposed	MUSIC	MVDR	MCCC
Anechoic	1-17	11.62	60.04	27.07	**0.99**
	1, 12-17	**0.45**	15.33	22.51	0.79
	18	1.42	9.68	92.43	**0.58**
Outdoor	1-17	**5.14**	74.25	76.08	42.03
	1, 12-17	3.10	29.15	59.23	**2.78**

Cramér-Rao Lower Bound



Conclusions

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- **Successful Experiments**: Eight-microphone array estimated DOA for 18 signal types, effective for frequencies above 1000 Hz.
- **Robust Performance**: Maintains accuracy over time and temperature; enables high-resolution DOA estimation with smaller arrays.

Future Work

- Investigate the effect of **reverberations** to potentially improve robustness and accuracy in complex acoustic environments.

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- Investigate the effect of **reverberations** to potentially improve robustness and accuracy in complex acoustic environments.
- Address **model errors** in microphone directional sensitivity to refine performance in diverse conditions.
- Test with more **complex signals** (e.g., speech) to evaluate real-world effectiveness.

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- Explore the method's applicability to detecting elephant footsteps, considering **variations in individual elephants** and multi-target tracking of herds.
- Study the influence of ground vehicles and **other large mammals** (e.g., humans, giraffes, rhinos) on detection accuracy.
- Assess the **method's range limitations** to improve its design for larger or open environments.

Thank you!