Sound Source Localization and Reconstruction Using a Wearable Microphone Array and Inertial Sensors

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Introduction

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- Hearing aid applications

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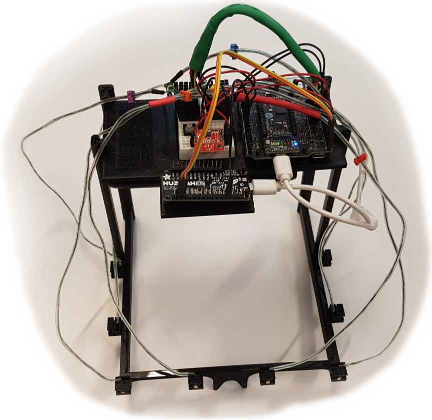
- Parallelisation

Array Frame Prototype

- 8 microphones



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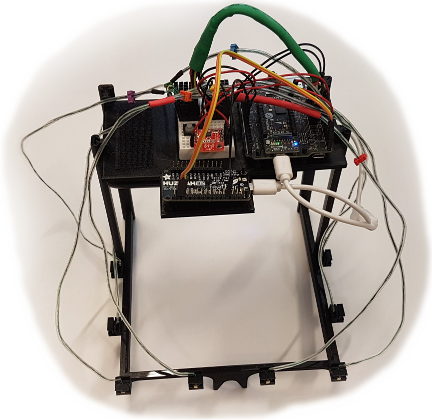

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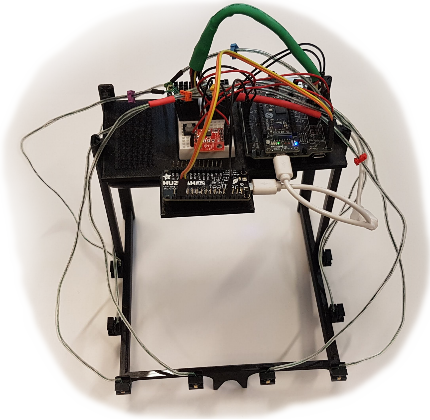

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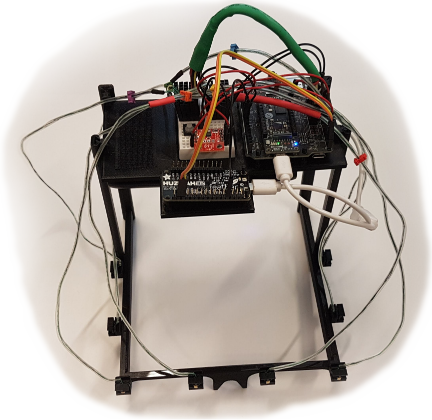

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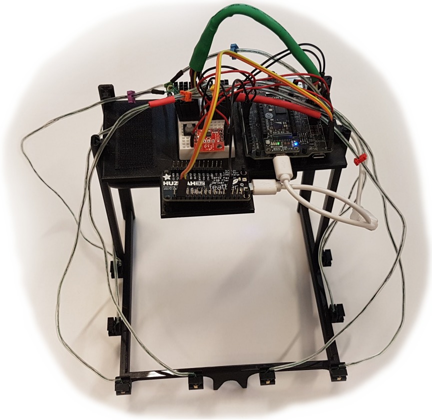

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- 8 microphones
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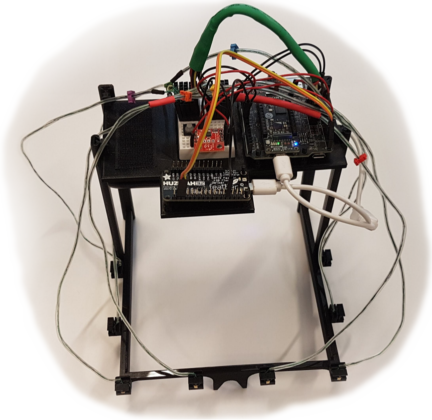
- Open source and design



Signal Models

Signal Models - Single Source

The signal model used in the single source case is

$$
\begin{aligned}
&y^n(t) = s(t + \tau_n) + e^n(t), \quad n = 1, \dots, N, \\
&e^n(t) \sim \mathcal{N}(0, \sigma_s^2).
\end{aligned}
$$

Signal Models - Taylor Series Expansion

An Lth order Taylor series expansion of the signal gives

$$s(t+\tau) \approx \sum_{l=0}^{L} \bar{\tau}_l \, s^{(l)}(t)$$

where $\bar{\tau}_l = \dfrac{\tau^l}{l!}$

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An Lth order Taylor series expansion of the signal gives

$$s(t+\tau) \approx \sum_{l=0}^{L} \bar{\tau}_l \, s^{(l)}(t) = \mathbf{h}^T(\tau)\mathbf{x}(t),$$

where $\bar{\tau}_l = \dfrac{\tau^l}{l!}$, the vector of signal derivatives is

$$\mathbf{x}(t) = \begin{bmatrix} s(t) & s^{(1)}(t) & \dots & s^{(L)}(t) \end{bmatrix}^T,$$

and the vector of delays is

$$\mathbf{h}(\tau) = \begin{bmatrix} 1 & \tau & \bar{\tau}_2 & \dots & \bar{\tau}_L \end{bmatrix}^T.$$

Signal Models - Approximation

The signal model

$$\begin{aligned} y^n(t) &= s(t+\tau_n) + e^n(t), \qquad n = 1, \dots, N, \\ e^n(t) &\sim \mathcal{N}(0, \sigma_s^2). \end{aligned}$$

Signal Models - Approximation

The signal model is then approximated as

$$y^n(t) = \mathbf{h}(\tau_n)\mathbf{x}(t) + e^n(t), \qquad n = 1, \ldots, N,$$
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The signal model is then approximated and discretized as

$$y_k^n = \mathbf{h}(\tau_n)\mathbf{x}_k + e_k^n, \qquad n = 1, \dots, N,$$
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In vector form the model reduces to

$$\mathbf{y}_k = \mathbf{H}(\boldsymbol{\tau})\mathbf{x}_k + \mathbf{e}_k,$$
$$\mathbf{e}_k \sim \mathcal{N}(\mathbf{0}, \sigma_r^2 \mathbf{I}_N), \qquad k = 1, \ldots, K.$$

where $\mathbf{y}_k \triangleq \begin{bmatrix} y_k^1 & \ldots & y_k^N \end{bmatrix}^T$ and $\boldsymbol{\tau} \triangleq \begin{bmatrix} \tau_1 & \ldots & \tau_N \end{bmatrix}^T$.

Estimation

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Estimation - LinDoA

Least-squares solution gives, for $k = 1, \dots, K$,

$$\hat{\mathbf{x}}_k(\boldsymbol{\tau}) = (\mathbf{H}^T(\boldsymbol{\tau})\mathbf{H}(\boldsymbol{\tau}))^{-1}\mathbf{H}^T(\boldsymbol{\tau})\mathbf{y}(t),$$
$$\text{cov}(\hat{\mathbf{x}}_k(\boldsymbol{\tau})) = (\mathbf{H}^T(\boldsymbol{\tau})\mathbf{H}(\boldsymbol{\tau}))^{-1}\sigma_r^2.$$

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Each estimate is independent from other samples in time.

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To enforce consistency, constraints in time are added on the form

$$\underline{\mathbf{I}}\mathbf{x}_{k+1} = \underline{\mathbf{F}}\mathbf{x}_k,$$

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where $\underline{\mathbf{I}}$ is the identity matrix with the last row removed. $\underline{\mathbf{F}}$ can, e.g., be

$$\underline{\mathbf{F}} = \begin{bmatrix} 1 & T & \bar{T}_2 & \dots & \bar{T}_L \\ 0 & 1 & T & \dots & \bar{T}_{L-1} \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & 0 & \dots & 1 & T \end{bmatrix}.$$

Estimation - Constrained LinDoA

This results in the following Constrained Least-Squares problem

$$(\hat{\mathbf{x}}_1(\boldsymbol{\tau}), \ldots, \hat{\mathbf{x}}_K(\boldsymbol{\tau})) = \underset{\mathbf{x}_1, \ldots, \mathbf{x}_K}{\arg\min} \quad \sum_{k=1}^{K} \|\mathbf{y}_k - \mathbf{H}(\boldsymbol{\tau})\mathbf{x}_k\|^2,$$

$$\text{s.t.} \quad \underline{\mathbf{I}}\mathbf{x}_{k+1} = \underline{\mathbf{F}}\mathbf{x}_k, \quad k = 1, \ldots, K-1.$$

Estimation - Time-Delay Estimation

The time delays can be estimated as

$$\hat{\boldsymbol{\tau}} = \arg\min_{\boldsymbol{\tau}} \sum_{k=1}^{K} \|\mathbf{y}_k - \mathbf{H}(\boldsymbol{\tau})\hat{\mathbf{x}}_k(\boldsymbol{\tau})\|^2,$$

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This can be solved using, e.g., numerical search.

Estimation - Multiple Sources

By superposition, M sources are incorporated as,

$$y^n(t) = \sum_{m=1}^{M} s_m(t + \tau_{nm}) + e^n(t), \quad n = 1, \ldots, N.$$

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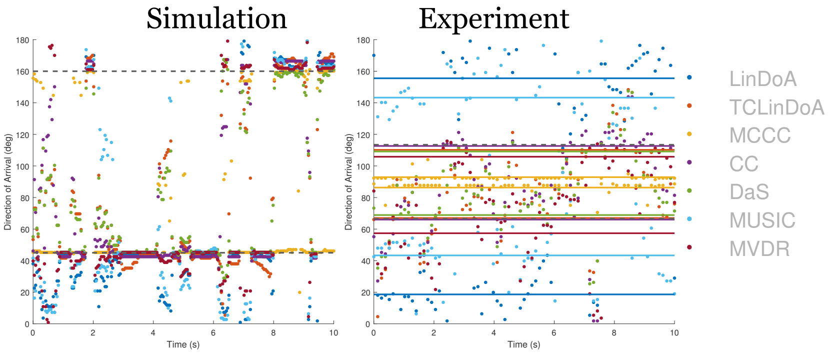
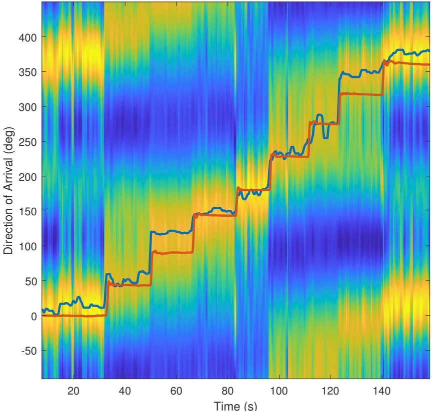
However, the signals are still observable using Constrained LinDoA.

Results

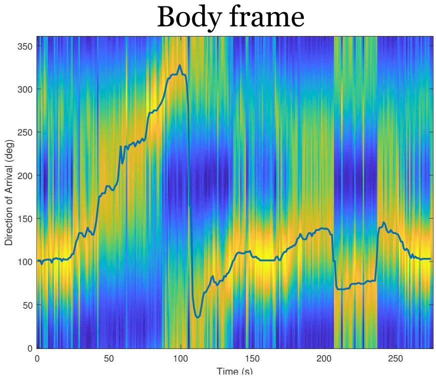
Two Sources Direction of Arrival



Single Source Constrained LinDoA compared with IMU



Single Source DoA with IMU Integration



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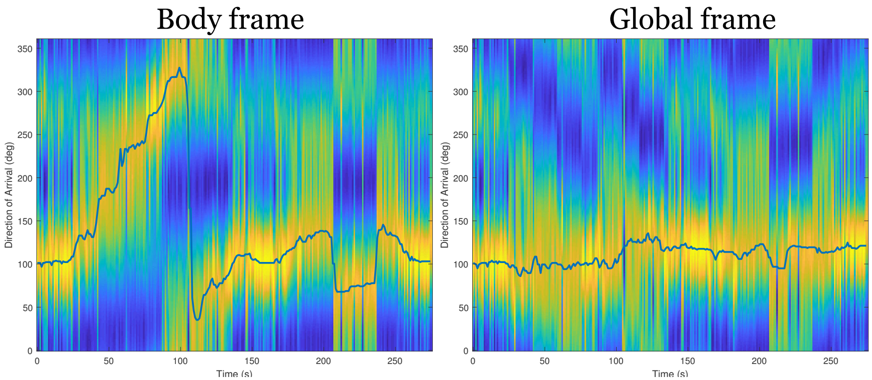

Source Separation

Delay and Sum

	Estimated Left	Estimated Right
True Left	0.7863	0.3114
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Constrained LinDoA

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True left	0.8942	0.0975
True right	0.1061	0.9534

Conclusion

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- LinDoA capable of tracking a single source in reverberant environment.
- Sound source separation of two sources performs well.

Possible Directions for Future Work

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- Multi-target tracking framework

Thank you for listening!

`gitlab.liu.se/veiback-public/lindoa`
`gitlab.liu.se/veiback-public/array-frame`

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