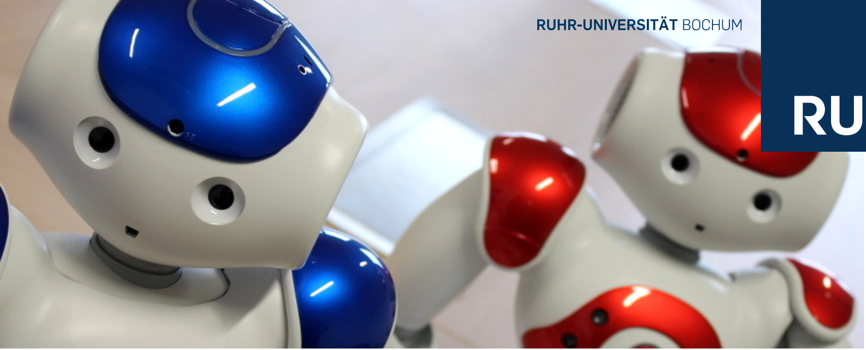


Potential-field-based active exploration for acoustic simultaneous localization and mapping

ICASSP 2018

Christopher Schymura, Dorothea Kolossa

April 19, 2018

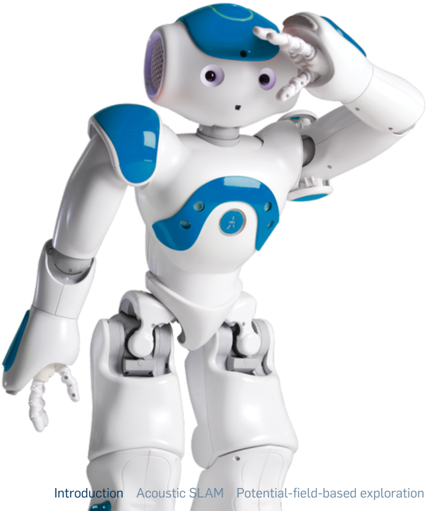
Cognitive
Signal Processing

Outline

Outline

Introduction

Problem setting



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- **Question:** can the motion trajectory of the acoustic sensors be controlled to improve map quality w.r.t. localization accuracy?

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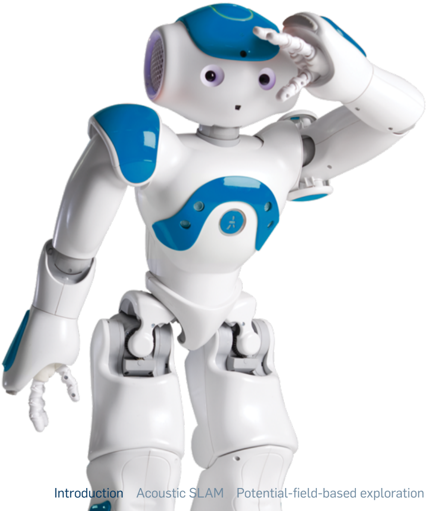

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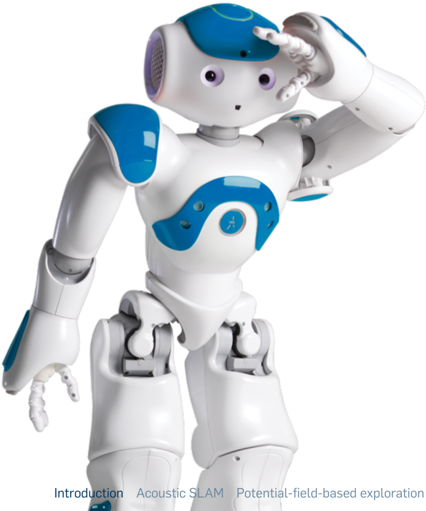

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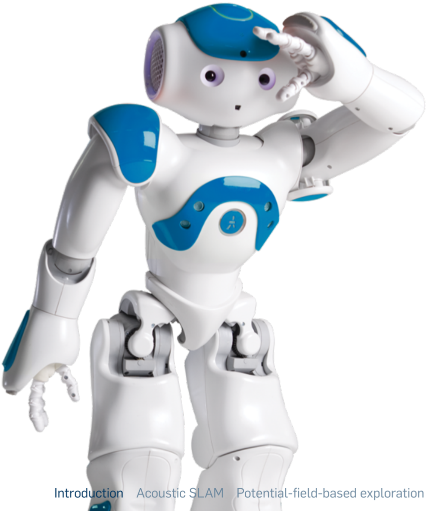

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Some recent approaches to active exploration in robot audition

- Information-based one-step look-ahead control for binaural localization[1].
- Monte Carlo exploration for sound source localization on a mobile robot[2].
- Multi-step ahead control based on Monte Carlo tree search[3].

Potential extensions and improvements:

- Full acoustic SLAM problem with multiple sources.
- Reduction of computational demands (e.g. real-time capabilities).

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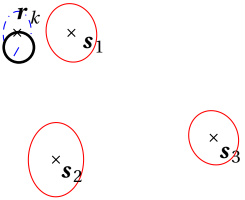
Overview

SLAM model is based on a conventional nonlinear state-space representation with additive Gaussian noise.



- SLAM system state:

$$\boldsymbol{x}_k = \begin{bmatrix} \boldsymbol{r}_k & \boldsymbol{s} \end{bmatrix}^{\mathrm{T}} = \begin{bmatrix} r_{\mathrm{x},k} & r_{\mathrm{y},k} & r_{\theta,k} & \boldsymbol{s}_1^{\mathrm{T}} & \cdots & \boldsymbol{s}_N^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}}$$

- Motion dynamics:

$$\boldsymbol{r}_k = f(\boldsymbol{r}_{k-1}, \boldsymbol{u}_k) + \boldsymbol{v}_k, \quad \boldsymbol{v}_k \sim \mathcal{N}(\mathbf{0}, \boldsymbol{Q}_k)$$

- Measurement model:

$$y_k^{(n)} = h(\boldsymbol{r}_k, \boldsymbol{s}_n) + \boldsymbol{w}_k, \quad \boldsymbol{w}_k \sim \mathcal{N}(\mathbf{0}, \boldsymbol{R}_k)$$

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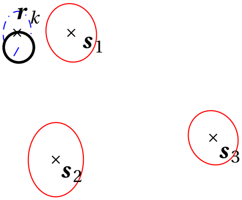

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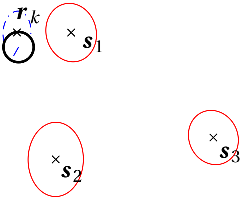

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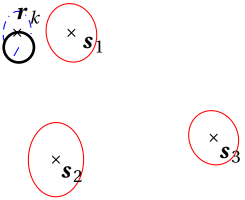

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Source state parameterization

Only direction-of-arrival (DoA) measurements $y_k^{(n)}$ available.

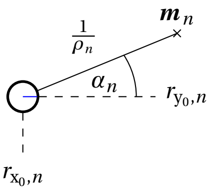
⇒ Source position initialization in Cartesian map-space is challenging.

Solution: inverse depth parameterization[4] of source states:

$$\boldsymbol{s}_n = \begin{bmatrix} r_{\mathrm{x}_0,n} & r_{\mathrm{y}_0,n} & \rho_n & \alpha_n \end{bmatrix}^{\mathrm{T}}$$

Actual Cartesian source position:

$$\boldsymbol{m}_n = \begin{bmatrix} m_{\mathrm{x},n} \\ m_{\mathrm{y},n} \end{bmatrix} = \begin{bmatrix} r_{\mathrm{x}_0,n} \\ r_{\mathrm{y}_0,n} \end{bmatrix} + \frac{1}{\rho_n} \begin{bmatrix} \cos(\alpha_n) \\ \sin(\alpha_n) \end{bmatrix}$$



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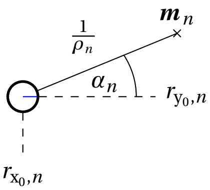

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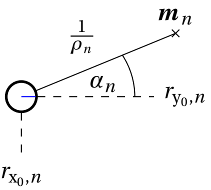

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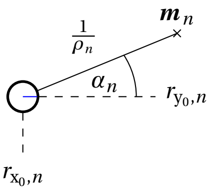

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State estimation and map management

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  - Each update yields estimates of the posterior mean $\hat{x}_k$ and covariance matrix $\hat{\Sigma}_k$ of the SLAM system state.
  - Computationally efficient.
- Initialization of new source positions based on maximum likelihood data association framework.
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Potential-field-based exploration

Potential field method[6]

Well-established approach to robotic path planning and navigation, based on a differentiable potential function

$$U(\boldsymbol{q}_k) = U_\mathrm{a}(\boldsymbol{q}_k) + U_\mathrm{r}(\boldsymbol{q}_k)$$

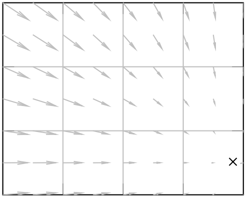

Figure: Attractive potential field.

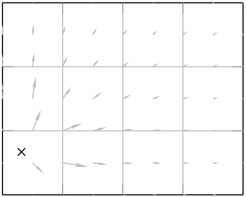

Figure: Repulsive potential field.

[6] Khatib (1986): *"The Potential Field Approach And Operational Space Formulation In Robot Control"*

Potential-field-based exploration

Active exploration using potential functions

- **Attractive potential:** move acoustic sensors towards the source in the map associated with the largest estimation uncertainty.

$$U_\mathrm{a}(\boldsymbol{q}_k, n^\star) = \frac{\beta_\mathrm{a}}{2} \|\boldsymbol{q}_k - \boldsymbol{m}_{n^\star}\|^2, \quad n^\star = \arg\max_n H(\boldsymbol{m}_n)$$

- **Repulsive potential:** maintain safe distance towards all sources in the map and enforce circular trajectories around detected sources to support triangulation.

$$U_{\mathrm{r}_1}(\boldsymbol{q}_k) = \frac{\beta_{\mathrm{r}_1}}{2} \sum_{n=1}^{N} \begin{cases} \left(\frac{1}{\|\boldsymbol{q}_k - \boldsymbol{m}_n\|} - \frac{1}{d_0}\right)^2 & \text{if } \|\boldsymbol{q}_k - \boldsymbol{m}_n\| \leq d_0 \\ 0 & \text{otherwise} \end{cases}$$

$$U_{\mathrm{r}_2}(\boldsymbol{q}_k) = \frac{\beta_{\mathrm{r}_2}}{2} \sum_{n=1}^{N} \left[1 - \cos\left(\phi_n(\boldsymbol{q}_k) - \frac{\pi}{2}\right)^2\right]$$

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Potential-field-based exploration

Control signal generation

Idea: generate motion trajectory along the steepest descent of the potential field gradient

$$F(\boldsymbol{q}_k) = -\nabla U(\boldsymbol{q}_k) = -\nabla\Big(U_{\mathrm{a}}(\boldsymbol{q}_k, n^\star) + U_{\mathrm{r}_1}(\boldsymbol{q}_k) + U_{\mathrm{r}_2}(\boldsymbol{q}_k)\Big)$$

- Motion trajectory update using gradient descent.
- Trajectory-update frequency can be adapted to the available computational resources.
- Control signals $\boldsymbol{u}_k$ have to be generated based on the planned trajectories.

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Method comparison

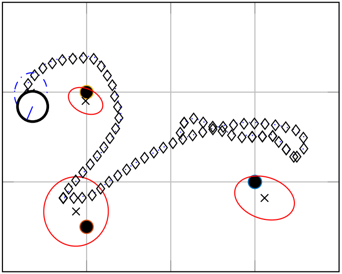

Figure: Proposed approach using the potential field method.

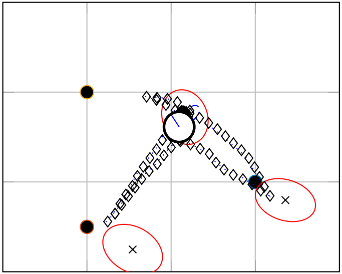

Figure: Trajectory generated using Monte Carlo exploration.

Outline

Evaluation

Experimental setup

- Monte Carlo simulations in a simulated “shoebox” room of size $5\,\mathrm{m} \times 4\,\mathrm{m} \times 3\,\mathrm{m}$ at three different reverberation times (anechoic, $0.5\,\mathrm{s}$, $1\,\mathrm{s}$).
- Three speech sources present in each scenario.
- Simulated 4-channel microphone array with geometry identical to a NAO robot.
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Evaluation

Experimental setup

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T_{60}	Anechoic		$0.5\,\mathrm{s}$		$1\,\mathrm{s}$	
	A_{L}	F_1	A_{L}	F_1	A_{L}	F_1
IBF	0.79	0.75	0.78	0.70	0.74	0.65
MCE	0.78	0.68	0.73	0.63	0.63	0.57
Proposed	**0.86**	**0.79**	**0.83**	**0.75**	**0.78**	**0.70**

Table: Localization gross accuracies A_{L} and F_1 scores.

	IBF	MCE	Proposed
T_{c}	8.73	57.26	**0.09**

Table: Average computation time for one control-update iteration T_{c} in ms.

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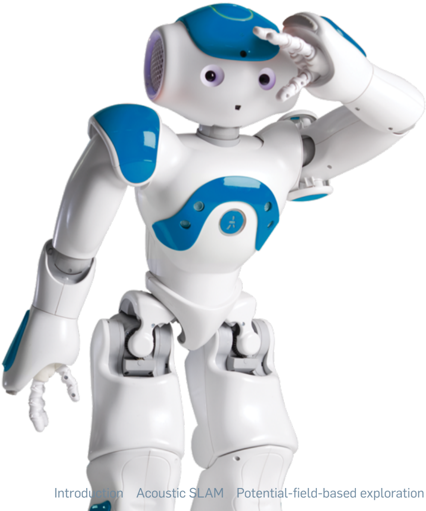
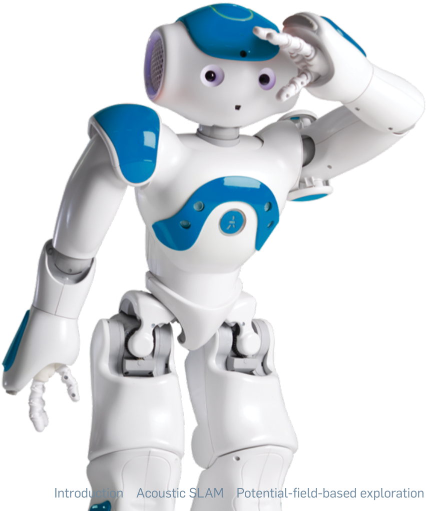
Conclusion and outlook



- An active exploration strategy for acoustic SLAM based on the potential field method was presented.
- The proposed approach achieves good localization performance with comparably low computational complexity.
- Further research: alternative potential functions, performance with more advanced SLAM frameworks, ...

Thank you!

Conclusion and outlook



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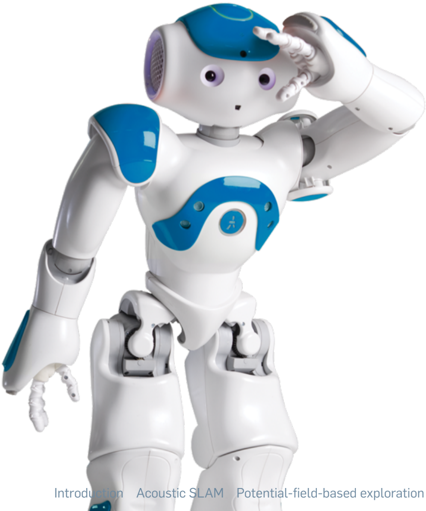

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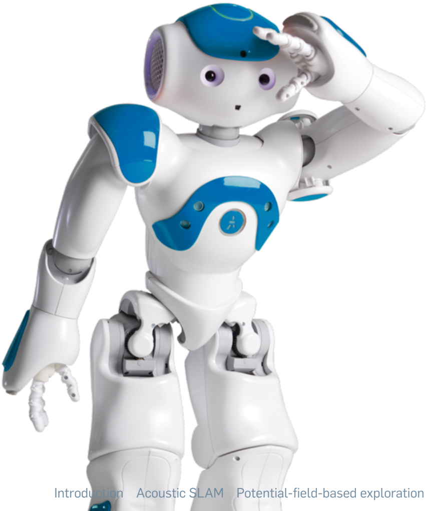

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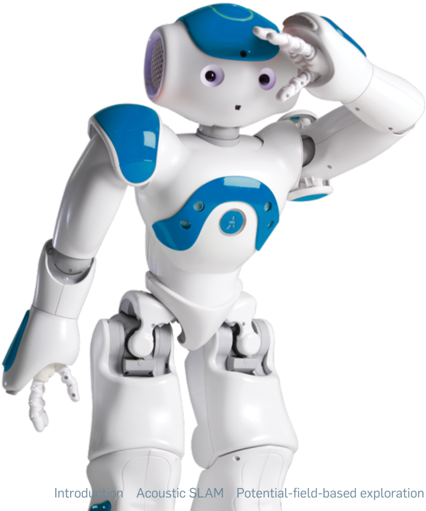

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