



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

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Cognitive  
Signal Processing

# Outline

- 1** Introduction
- 2** Acoustic SLAM
- 3** Potential-field-based exploration
- 4** Evaluation

# Outline

## 1 Introduction

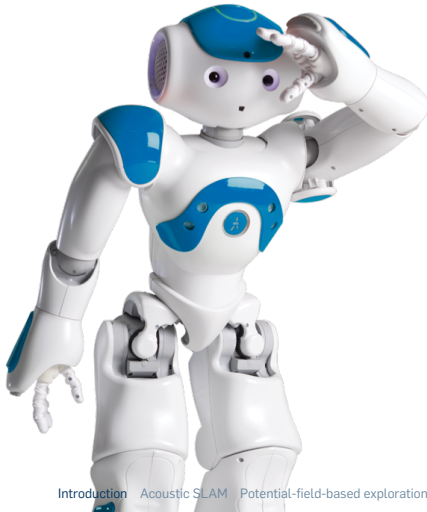
## 2 Acoustic SLAM

## 3 Potential-field-based exploration

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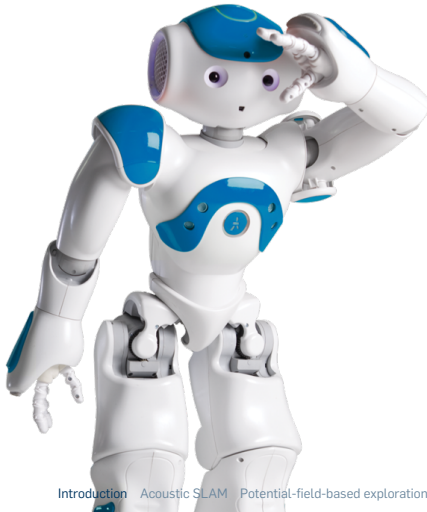
## Problem setting



- Acoustic SLAM aims at creating a map of acoustic sources within the environment of a moving microphone array (e.g. a robot).
- The position/trajectory of the acoustic sensors in the map is not known a-priori and has to be estimated from measurements.
- **Question:** can the motion trajectory of the acoustic sensors be controlled to improve map quality w.r.t. localization accuracy?

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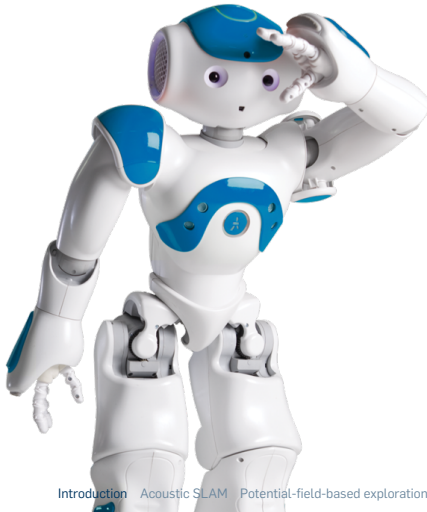
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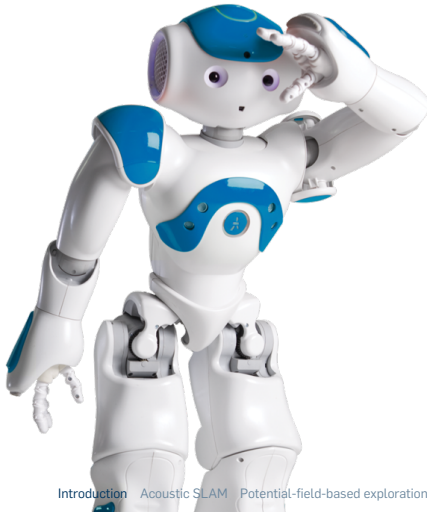
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### Some recent approaches to active exploration in robot audition

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

Potential extensions and improvements:

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

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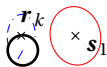
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# Acoustic SLAM

## Overview

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



- SLAM system state:

$$\begin{aligned} \mathbf{x}_k &= [\mathbf{r}_k \quad \mathbf{s}]^T \\ &= [r_{x,k} \quad r_{y,k} \quad r_{\theta,k} \quad s_1^T \quad \dots \quad s_N^T]^T \end{aligned}$$

- Motion dynamics:

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

- Measurement model:

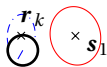
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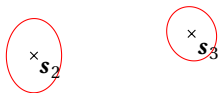
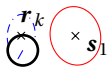
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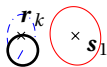
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# Acoustic SLAM

## State estimation and map management

- Only direction-of-arrival (DoA) measurements  $y_k^{(n)}$  available. Inverse depth parameterization for source states is used.<sup>4</sup>
- State estimation is performed recursively using an unscented Kalman filter.
  - 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.
- Deletion of unreliable source position estimates from the map using the log-odds ratio method<sup>5</sup>.

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## Potential-field-based exploration

### Potential field method<sup>6</sup>

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

$$U(\mathbf{q}_k) = U_a(\mathbf{q}_k) + U_r(\mathbf{q}_k)$$

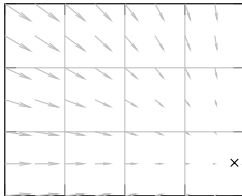


Figure: Attractive potential field.

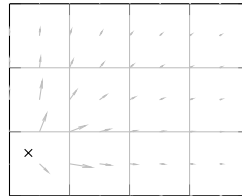


Figure: Repulsive potential field.

<sup>6</sup>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.

$$U_a(\mathbf{q}_k, n^*) = \frac{\beta_a}{2} \|\mathbf{q}_k - \mathbf{m}_{n^*}\|^2, \quad n^* = \arg \max_n H(\mathbf{m}_n)$$

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

$$U_{r_1}(\mathbf{q}_k) = \frac{\beta_{r_1}}{2} \sum_{n=1}^N \begin{cases} \left( \frac{1}{\|\mathbf{q}_k - \mathbf{m}_n\|} - \frac{1}{d_0} \right)^2 & \text{if } \|\mathbf{q}_k - \mathbf{m}_n\| \leq d_0 \\ 0 & \text{otherwise} \end{cases}$$

$$U_{r_2}(\mathbf{q}_k) = \frac{\beta_{r_2}}{2} \sum_{n=1}^N \left[ 1 - \cos^2 \left( \phi_n(\mathbf{q}_k) - \frac{\pi}{2} \right) \right]$$

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## Potential-field-based exploration

### Control signal generation

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

$$F(\mathbf{q}_k) = -\nabla U(\mathbf{q}_k) = -\nabla \left( U_a(\mathbf{q}_k, n^*) + U_{r_1}(\mathbf{q}_k) + U_{r_2}(\mathbf{q}_k) \right)$$

- Motion trajectory update using gradient descent.
- Trajectory-update frequency can be adapted to the available computational resources.
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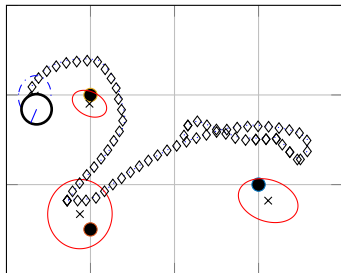


Figure: Proposed approach using the potential field method.

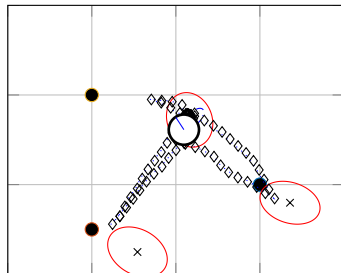


Figure: Trajectory generated using Monte Carlo exploration.

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## Experimental setup

- Monte Carlo simulations in a simulated “shoebox” room of size 5 m × 4 m × 3 m at three different reverberation times (anechoic, 0.5 s, 1 s).
- Three speech sources present in each scenario.
- Simulated 4-channel microphone array with geometry identical to a NAO robot.
- DoA measurements obtained using multiple signal classification (MUSIC).
- Simplified two-wheel differential-drive motion kinematics.
- Proposed approach compared to Monte Carlo exploration and one-step look-ahead information-based feedback control strategies.
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# Evaluation

## Experimental setup

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

$T_{60}$	Anechoic		0.5 s		1 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	<b>0.86</b>	<b>0.79</b>	<b>0.83</b>	<b>0.75</b>	<b>0.78</b>	<b>0.70</b>

Table: Localization gross accuracies  $A_L$  and  $F_1$  scores.

	IBF	MCE	Proposed
$T_c$	8.73	57.26	<b>0.09</b>

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### Results

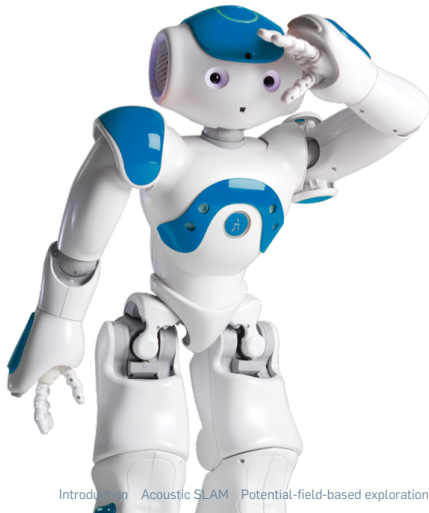
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## Conclusion and outlook



- 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!

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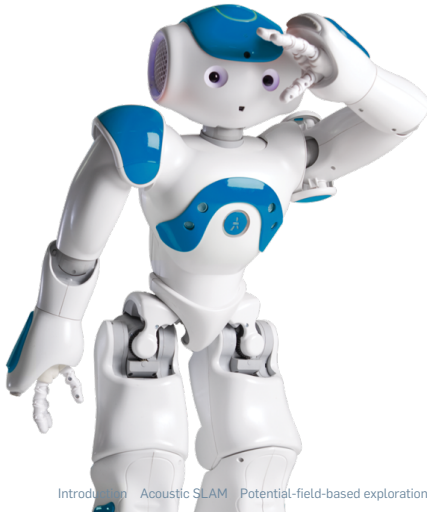


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