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Monte Carlo Exploration for Active Binaural Localization

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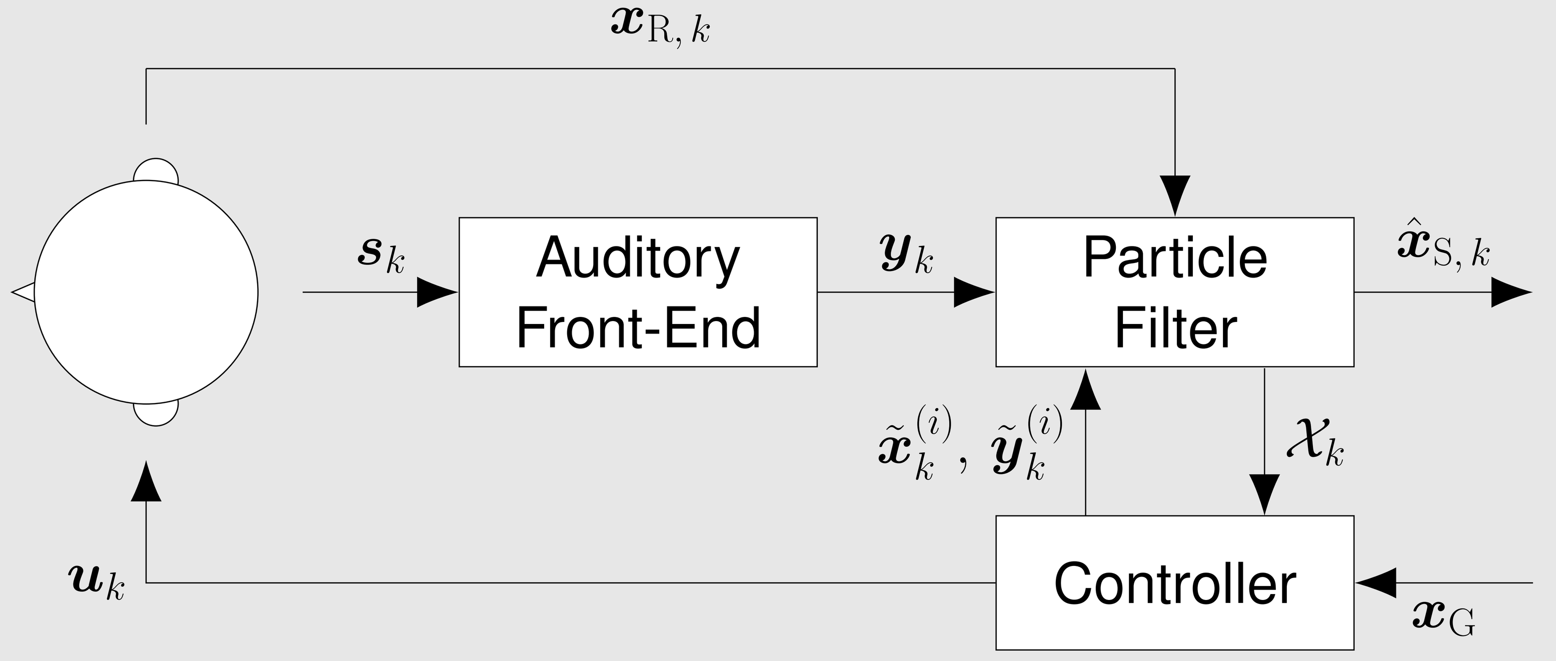
Introduction

- This study introduces a novel framework for active binaural localization on a mobile robotic platform.
- A binaural localization model exploiting azimuth and distance-related cues by means of particle filtering is proposed.
- Robot motion is controlled based on Monte Carlo exploration (MCE) [1] in a one-step look ahead scheme.

System Description

Overview



System Dynamics

$$\boldsymbol{x}_k = \begin{bmatrix} \boldsymbol{x}_{\mathrm{S},k} \\ \boldsymbol{x}_{\mathrm{R},k} \end{bmatrix} = \begin{bmatrix} \boldsymbol{x}_{\mathrm{S},k-1} \\ f(\boldsymbol{x}_{\mathrm{R},k-1},\, \boldsymbol{u}_k) \end{bmatrix} + \boldsymbol{v}_k$$

Measurement Model

$$\boldsymbol{y}_k = \boldsymbol{W}^T \boldsymbol{\Phi}(\boldsymbol{x}_k) + \boldsymbol{n}_k$$

$\boldsymbol{x}_k$	: System state	s_k	: Binaural signal	$\boldsymbol{v}_k$	: Process noise
$\boldsymbol{x}_{\mathrm{R},k}$	: Robot pose	$\boldsymbol{y}_k$	: Binaural meas.	$\boldsymbol{n}_k$	: Meas. noise
$\hat{\boldsymbol{x}}_{\mathrm{S},k}$	: Est. source position	$\mathcal{X}_k$	: Particle set	$\boldsymbol{W}$	: Regression coeff.
$\boldsymbol{x}_{\mathrm{G}}$	: Goal position	$\tilde{\boldsymbol{x}}_k^{(i)}$	: Predicted state	$\boldsymbol{\Phi}(\boldsymbol{x}_k)$	: Regressors
$\boldsymbol{u}_k$	: Control signal	$\tilde{\boldsymbol{y}}_k^{(i)}$	: Predicted meas.		

State Estimation and Control

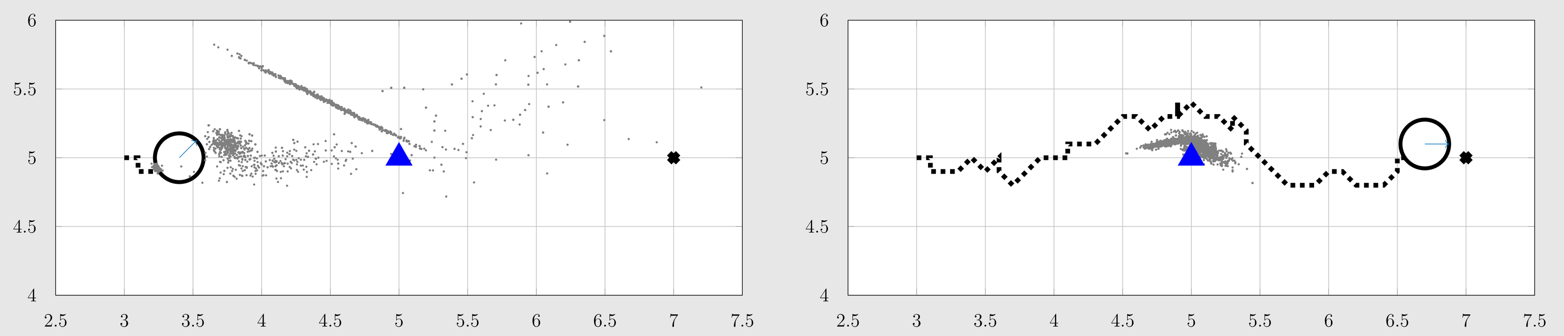
Particle Filter

- Estimation of state posterior $p(\boldsymbol{x}_{\mathrm{S},k} \,|\, \boldsymbol{y}_{1:k},\, \boldsymbol{u}_{1:k})$ using Gaussian mixture sigma point particle filter (GMSPPF) [2].
- Estimation uncertainty is modeled by entropy of the conditional mean state estimate $\hat{\boldsymbol{P}}_k = E\{(\boldsymbol{x}_{\mathrm{S},k} - \hat{\boldsymbol{x}}_{\mathrm{S},k})(\boldsymbol{x}_{\mathrm{S},k} - \hat{\boldsymbol{x}}_{\mathrm{S},k})^T\}$ at each filtering step:

$$H(\boldsymbol{x}_{\mathrm{S},k}) = \frac{1}{2} \log \left((2\pi e)^D \cdot |\hat{\boldsymbol{P}}_k| \right)$$

MCE Algorithm

- Control policy for subsequent timestep obtained by MCE with a discrete set of N_u possible controls $\mathcal{U} = \{\boldsymbol{u}_{k+1}^{(1)}, \ldots, \boldsymbol{u}_{k+1}^{(N_u)}\}$.
- Trade-off parameter λ balances exploration and goal-directed movements.



Initialize: $\rho(\boldsymbol{u}_{k+1}^{(j)}) = 0 \;\forall j$
for $i = 1$ *to* N do
  Sample $\tilde{\boldsymbol{x}}_{\mathrm{S},k} \sim p(\boldsymbol{x}_{\mathrm{S},k} \,|\, \boldsymbol{y}_{1:k},\, \boldsymbol{u}_{1:k})$
  for $j = 1$ *to* N_u do
    $\tilde{\boldsymbol{x}}_k = \left[\tilde{\boldsymbol{x}}_{\mathrm{S},k} \; \boldsymbol{x}_{\mathrm{R},k} \right]^T$
    Sample $\tilde{\boldsymbol{x}}_{k+1} \sim p(\tilde{\boldsymbol{x}}_{k+1} \,|\, \tilde{\boldsymbol{x}}_k,\, \boldsymbol{u}_{k+1}^{(j)})$
    Sample $\tilde{\boldsymbol{y}}_{k+1} \sim p(\tilde{\boldsymbol{y}}_{k+1} \,|\, \tilde{\boldsymbol{x}}_{k+1})$
    Compute $p(\boldsymbol{x}_{\mathrm{S},k+1} \,|\, \boldsymbol{y}_{1:k+1},\, \boldsymbol{u}_{1:k+1})$ using GMSPPF
    $\rho(\boldsymbol{u}_{k+1}^{(j)}) = \rho(\boldsymbol{u}_{k+1}^{(j)}) - \lambda \|\boldsymbol{x}_{\mathrm{R},k+1} - \boldsymbol{x}_{\mathrm{G}}\|_2 - (1-\lambda) H(\tilde{\boldsymbol{x}}_{\mathrm{S},k+1}^{(i)})$
  end
end
Return $\boldsymbol{u}_{k+1} = \arg\max_j \rho(\boldsymbol{u}_{k+1}^{(j)})$

Algorithm 1: MCE for selecting the subsequent control input $\boldsymbol{u}_{k+1}$.

Evaluation

Data

- Audio data: Speech and non-speech sounds from DCASE challenge 2016 [3].
- Head-related impulse responses: Recordings of KEMAR dummy head from CIPIC database [4].

Binaural Simulation

- Online rendering of binaural room impulse responses using the image-source method [5].
- Fixed room dimensions (10m x 10m x 3m) with four different reverberation times (anechoic, 250ms, 500ms and 750ms) were evaluated.
- 50 simulations were conducted in each condition with randomly selected initial robot poses and goal positions.

Results

Table 1: Median localization errors in [m], Time-to-goal (TTG) in [s] and percentage of goal positions reached (GPR) achieved for different trade-off parameters in all acoustic conditions. Experiments were conducted using a measurement model based on azimuth and distance (AD) and a bearing-only measurement model (A) for comparing localization performance (TTG and GPR omitted in this case).

Model	λ	Anec.	250ms	500ms	750ms	Avg.	TTG	GPR
AD	0.00	0.58	0.72	1.63	2.82	1.44	-	-
AD	0.25	**0.51**	**0.63**	**0.70**	**0.77**	**0.65**	38.31	60.00
AD	0.50	0.63	0.67	1.05	1.29	0.91	14.49	98.00
AD	0.75	0.87	0.91	1.18	1.44	1.10	9.94	**100.00**
AD	1.00	1.09	1.08	1.36	1.37	1.23	**9.44**	**100.00**
A	0.25	0.82	0.84	0.87	0.89	0.86	-	-

References

[1] S. Thrun, W. Burgard, and D. Fox, *Probabilistic Robotics*, The MIT Press, 2005.

[2] R. van der Merwe and E. Wan, "Gaussian mixture sigma-point particle filters for sequential probabilistic inference in dynamic state-space models," in *IEEE International Conference on Acoustics, Speech, and Signal Processing*, 2003.

[3] "IEEE DCASE 2016 Challenge," http://www.cs.tut.fi/sgn/arg/dcase2016/.

[4] V. R. Algazi, R. O. Duda, D. M. Thompson, and C. Avendano, "The CIPIC HRTF database," in *2001 IEEE Workshop on the Applications of Signal Processing to Audio and Acoustics*, 2001.

[5] J. B. Allen and D. A. Berkley, "Image method for efficiently simulating small room acoustics," *The Journal of the Acoustical Society of America*, vol. 65, no. 4, 1979.

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