



Active Robot Learning for Efficient Body-Schema Online Adaptation

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Motivation

The aim of this work is to estimate the body-schema parameters (DH parameters) of 7 joints of the iCub arm, using an Extended Kalman Filter and active learning for movement and sampling efficiency.

Robots rely on their body-schema to be able to predict the location and orientation of their body parts.

Results

We compared the performance of the proposed method with random sampling and active learning with no movement restrictions.

The position and orientation errors are computed between the actual and predicted poses of the end-effector.



Online body-schema learning:

- Allows the robot to adapt to accumulated errors.
- Increases robot's autonomous time.

Active learning methods have been successfully employed to optimise the number of training samples for learning tasks.

DH Parameters Estimation

The DH parameters are denoted by:

 $\boldsymbol{x} = \left[\boldsymbol{D}\boldsymbol{H}^{(0)}; \ \boldsymbol{D}\boldsymbol{H}^{(1)}; \cdots; \boldsymbol{D}\boldsymbol{H}^{(6)} \right],$

where $DH^{(i)}$ is a vector of size 4, containing the DH parameters of the *i*th joint.

Estimation done using an Extended Kalman Filted (EKF). Main loop of the algorithm:



The error evolution was evaluated

 At each iteration to perceive the quality of the samples:



Cost-Sensitive Active Learning

This work aims to choose joint configurations to sample the endeffector pose to reduce:

- Body-schema error
- Movement performed while calibrating.

It achieves these objectives by:

With respect to movement performed by the arm joints to \bullet perceive the movement efficiency:





Movement $\cdot 10^{4}$

- Selecting joint configurations, minimising the cost function $C(\boldsymbol{\theta}) = \mathbb{E}[tr(P_{k+1})|z_{1:k}, \boldsymbol{\theta}_{1:k}]$
- Adding constraints to the optimisation problem

$$\theta_k^* = \operatorname{argmin}_{\substack{\theta \in \left[\theta_{k-1}^* - \Delta, \theta_{k-1}^* + \Delta\right]}} C(\theta)$$

$$\Delta = \delta \cdot \mathbf{1}_n$$

Conclusions





This work was supported by FCT with the LARSyS - FCT Project UIDB/50009/2020 and the PhD grant PD/BD/135115/2017.

