

Context

Previous work performed joint control and state-estimation of a robot arm under the Active Inference framework [1].

The AIC was compared to state-of-the-art methods and showed adaptive behaviour. However, it requires the definition of several parameters including covariance matrices.

In this work we learn the covariance matrices thus creating **'self-tuning' controllers**.

Background

Similar to [1], we assume Gaussianity on the observation and transition models. We then obtain the following cost function for the **free-energy F**:

$$F = \frac{1}{2}(\epsilon_o^\top \Sigma_o^{-1} \epsilon_o + \epsilon_{o'}^\top \Sigma_{o'}^{-1} \epsilon_{o'} + \epsilon_\mu^\top \Sigma_\mu^{-1} \epsilon_\mu + \epsilon_{\mu'}^\top \Sigma_{\mu'}^{-1} \epsilon_{\mu'}) + \ln |\Sigma_o| + \ln |\Sigma_{o'}| + \ln |\Sigma_\mu| + \ln |\Sigma_{\mu'}| + C.$$

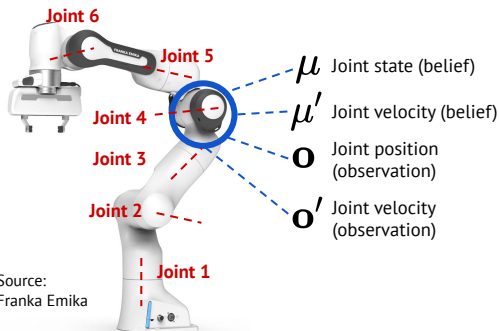
Actions and state-estimates are obtained using **gradient descent on F**.

Method

In our approach we learn the inverse covariance matrices (precision matrices).

Similar to control and state-estimation we obtained **update rules for the associated covariances** of the observation models. This allowed us to **adapt our controller online**.

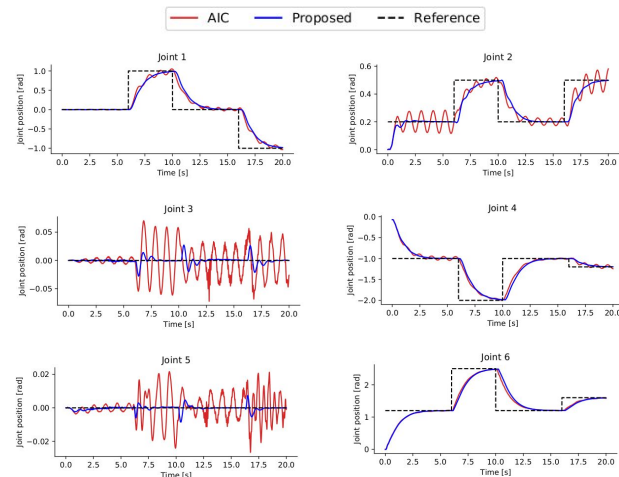
$$\dot{\Sigma}_o^{-1} = -\kappa_\sigma \frac{\partial F}{\partial \Sigma_o^{-1}}, \quad \dot{\Sigma}_{o'}^{-1} = -\kappa_\sigma \frac{\partial F}{\partial \Sigma_{o'}^{-1}}$$



Source:
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Results

We compared with [1] in a manipulation scenario. [1] performs well when the covariances are properly tuned, but performs poorly when if the initial covariance are perturbed. Our approach is 're-tuned' during run time using the update rules we derived.



Video



Code