



Inverse Cognition in Radars

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Complex and dynamic environments in many engineering applications require intelligent and autonomous agents that cognitively sense the environment, acquire the relevant information, and then use it to adapt in real-time for improved performance. In this context, inverse cognition --- wherein a 'defender' agent learns the information about itself sensed by a cognitive 'attacker' agent --- has recently gathered significant research interest. The problem is motivated by the need to design counter-autonomous adversarial systems.

A suitable example is a military surveillance application, where a target aircraft is tracked by a hostile but cognitive radar, which is equipped with a Bayesian tracker. It is then instructive for the target to become inversely cognitive and predict the actions of the radar and guard against them. This is precisely the objective of inverse Bayesian filtering, wherein given noisy observations, a posterior distribution of the underlying state is obtained.

We consider this problem in a non-linear setting and develop a family of inverse stochastic filters to address inverse cognition. We begin with the inverse extended Kalman filter (I-EKF) [1] and derive its theoretical stability guarantees using both bounded nonlinearity and unknown matrix approaches. We then generalize these formulations and results to the case of higher-order, Gaussian-sum, and dithered I-EKFs [2]. We then obtain a more robust approach to nonlinearities in the form of an inverse unscented Kalman filter (I-UKF) [3] [4] and extend it to inverse cubature/quadrature Kalman filters (I-CKF/I-UKF) [5]. For both I-EKF and I-UKF, we also consider the scenario when the radar's filter is unknown to the target. This work has strong connections with general approximate Bayesian inference approaches in machine learning. The UKF, QKF, and CKF are a special case of assumed density filters (ADF) or online Bayesian learning, which sequentially approximates the posterior distribution of the underlying state. We close this talk by discussing the recent advances in meta-cognitive radar.

References

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