Stein methods for Robot Navigation

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Abstract

Robot navigation problems to date rely extensively on particle filters for state estimation and thus inherit many of their associated artifacts. Resampling, which aims to solve the particle degeneracy problem in filters itself often leads to the sample impoverishment or path degeneracy problem where the diversity of particles greatly diminishes. While solutions like *adaptive resampling*[6] and *backward simulation*[5] have been suggested to recover this lost diversity, these tend to be either computationally expensive or heuristic-driven. In contrast, in *Stein Variational Gradient Descent (SVGD)*, the nature of the propagation of the particles in time is a deterministic transform of the particles at the previous timestep. Thus, filtering through Stein Methods similar to [3] should alleviate this issue altogether. Additionally, since the expression for the gradient factors in a repulsion term between the particles, we could implicitly get high diversity, or loosely speaking, a high *effective sample size(ESS)* of particles.

While recent work [7] shows that with Stein Methods we experience mode collapse in higher dimensions, this isn't a problem since state spaces are typically small in robotic navigation tasks (less than 10 dimensions). [7] also provides a solution to the mode collapse problem through an approach that leverages the conditional independence structure of probabilistic graphical models. It approximates the global inference problem by local inference using message passing on the Markov blankets of nodes. Since such an approximation yields the most computational benefit for graphs that are sparsely connected, robotic state estimation stands to benefit the most since this connectivity structure is very typically seen in pose graphs which are almost universally used for localization.

Simultaneous Localization and Mapping (SLAM) is the computational problem of constructing a map of an unknown environment while simultaneously localizing the agent within it. SLAM is one such problem where many state of the art solutions [2] rely on Rao-Blackwellized particle filters. In addition to the aforementioned problem of resampling, an additional problem needs to be tackled, where agents are often assumed to have either uni-modal (gaussian) or parametric multi-modal (sum of gaussians) measurement models. This turns out to be a restrictive assumption since the distribution of associations between current and the past states(the sensor/measurement model) in a confusing environment with repeating structures is highly multi-modal, with the distribution of modes largely depending on the environment's layout and the sensors used. This assumption is adopted in practice partly to enable the computation of intractable integrals for partition functions that arise in the derivation of these posterior measurement distributions. Stein Methods show great promise in being applied in solutions to approximating these non-gaussian posteriors, which have previously been dominated by strictly MCMC methods. In my ongoing work I am exploring formulations for navigation and recursive state estimation which exploit certain desirable characteristics of these methods. These include the ability to approximate un-normalized densities along with the ability to construct adaptive importance samplers [4] giving better proposal distributions which quickly converge to the target distribution.

References

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