Forgetting-based Estimation of Stationary Parameters in Marginalized Particle Framework

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Particle filtering is a popular approximation of Bayesian filtering, i.e. on-line recursive evaluation of posterior distribution of unknown time-varying quantities. Its success is documented by a range of applications in object tracking, navigation, video processing, etc. A known weakness of the particle filtering is its inability to estimate stationary or slowly-varying quantities, which are typically called parameters. Theoretical studies suggest that this task is perhaps impossible as the posterior density degenerates in time [1, 4].

The marginalized particle filtering arise for specific problems that allow analytical marginalization over a part of the unknowns. If the marginalization is over the stationary parameters and the resulting marginal density has sufficient statistics, it is known as particle learning. In effect, each particle carries sufficient statistics of the parameters. This approach was believed to mitigate the problems with stationary parameters [2], however, extensions of the previous analytical results to this case points out the same degeneracy as in the non-marginalized case [3].

A heuristic approach to avoid degeneracy of the posterior density is the use of classical forgetting techniques developed for recursive estimation with sufficient statistics [5]. This approach has been shown to avoid the degeneracy problem in simulation [6]. In this contribution, we will demonstrate the degeneracy problem on some simulated examples. Various forgetting techniques, such as scheduling of the forgetting factor, will be compared. An informal theoretical justification of the use of the forgetting approach will be given as well as its potential limitations. In summary, estimation of the stationary parameters in particle filtering (as well as marginalized particle filtering) is still an open problem. Application of the forgetting technique allows to estimate slowly varying parameters. Its application to stationary parameters is suboptimal, however, it may be sufficient for many practical applications.

References

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