Particle Flow for Sequential Monte Carlo Implementation of Probability Hypothesis Density

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Abstract

• **Audio visual multi-target tracking** aims to track multi-target with audio information and visual information, even when the **number of targets is unknow**.

• The main disadvantage of sequential Monte Carlo (SMC) Implementation of Probability Hypothesis Density (PHD) filter is the weight **degeneracy problem**.

• We propose a novel SMC implementation for the PHD filter assisted by the **particle flow** (PF), which is called PF-SMC-PHD filter.

Particle flow

• The key idea of the particle flow is to migrate particles from the unnormalized prior density to the posterior density by a physical flow [1].

• λ is a step size parameter taking values from the set $[0, \Delta\lambda, 2\Delta\lambda, \cdots, 1]$ as the artificial time.

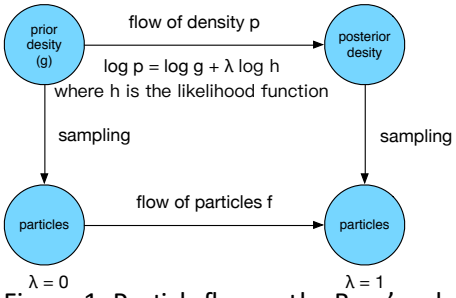

Figure 1. Particle flow as the Baye's rule.

Particle flow SMC-PHD filter

• We add an adjustment step between the prediction step and update step, where the particle flow is incorporated to adjust the states and weights of the particles by smoothly migrating them.

• We generate the same number of flows as that of the observations.

• We duplicate the set of the selected particles, and create the flow using only the duplicated particles as Figure 2.

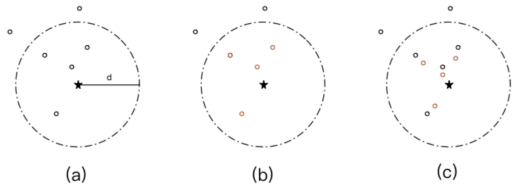

Figure 2 The adjustment step in PF-SMC-PHD. The star represents an observation.

Experiments

• We design an occlusion scenario, in which three targets move in the certain area and one target appears suddenly at frame 70.

• There are 50 random clutters in observations and their positions are set randomly.

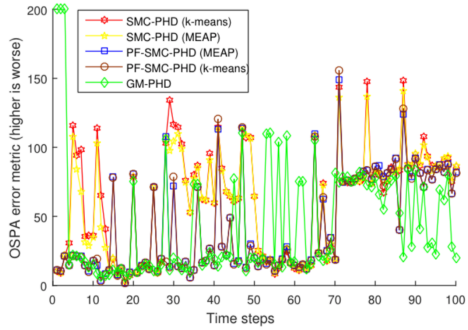

Figure 3 Optimal sub-pattern assignment of the compared filtering algorithms at each time step.

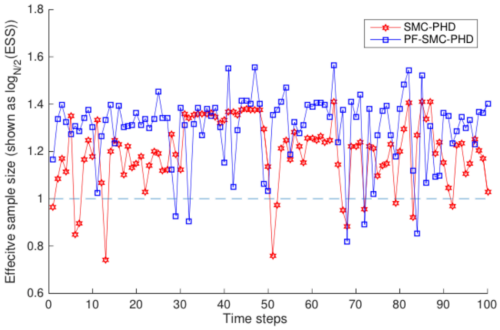

Figure 4 Effective sample size for SMC-PHD filter and PF-SMC-PHD filter.

Conclusion

• OPSA of the PF-SMC-PHD filter (24.8) is only 40% of that of the SMC-PHD filter (61.7).

• The SMC-PHD filter re-samples the particles 12 times while PF-SMC-PHD filter re-samples them only 5 times. Particle flow can mitigate the particle degeneracy problem.

References

[1] F. Daum and J. Huang, "Small curvature particle flow for nonlinear filters," in SPIE Defence, Security, and Sensing International Society for Optics and Photonics, 2012, pp. 83930A–1–83930A–12.

Ackownlegement

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