Comparing Resampling Techniques for Multitarget Tracking using Particle Filtering

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Abstract

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1 Introduction

The Particle Filter (PF), also known as Sequential Importance Sampling and Resampling (SISR), is a Monte Carlo, or simulation based algorithm, for recursive Bayesian inference [2]. The PF consists of particles and associated importance weights that are propagated through time to approximated a target distribution. It only needs a proposal distribution, a likelihood and a dynamic model. The PF is used in many areas such as tracking, parameter estimation, robotics, etc.

The PF is an improvement over the Sequential Importance Sampling (SIS) [2]. SIS have the problem of degeneracy; that is, after a few iterations, most of the particles will have negligible weight. The PF improves upon SIS by adding the resampling step where particles with low weight are eliminated and replaced by copies of the surviving particles. More specifically, the new set $\{\hat{z}_t^s\}_{s=1}^S$ is sampled from the distribution

$$p(z_t|y_{1:t}) \approx \sum_{s=1}^{S} w_t^s \delta_{z_t^s}(z_t).$$

However, this leads to another problem, particle deprivation.

Particle deprivation is when the particles do not cover regions of high probability [3], this is a significant problem of PF. This generally happens when the number of particles is not large enough and/or the target distribution is multi-modal. Particle deprivation occurs due to the sampling variance and thus the resampling step can wipe out all particles in the high density areas of the target distribution. The probability of this happening is non-zero at each re-sampling step and therefore it is only a matter of time until it happens. Solutions to particle deprivation is to add more particles, to randomly generated particles in each iteration, or use a better sampler.

Multitarget tracking (MTT) is the localization and recursive detection of objects of interest based on sequential measurements. Some examples are aircraft tracking using radar, and tracking people through a video feed. In practice, there are many factors that contributes to uncertainty of an objects location such as noise in measurement, clutter and environment. Therefore, a probabilistic approach to the problem is required. Popular approaches are Bayesian Monte Carlo Estimation such as particle filtering.

Particle filters have some problems with multitarget tracking. Due to that MTT problems are multi-modal, PF solutions tends to suffer from particle deprivation and will therefore lose targets. One of the solutions to this problem is use a sampler specifically made to track multiple targets.

This paper compares different resampling techniques for PF in the context of multi-target tracking.

2 Related Work

3 Resampling methods

3.1 Systematic Resampling

The systematic resampling method is widely used resampling method for particle filters. It is preferred because it is computationally simple and have good empirical performance [1]. The systematic resampling method have shown to be empirically comparable with other resampling methods such as stratified sampling and residual resampling which in turn have been shown to be better than multinomial resampling [1].

In practice it is implemented as follows:

Algorithm 1 Systematic Resampling algorithm

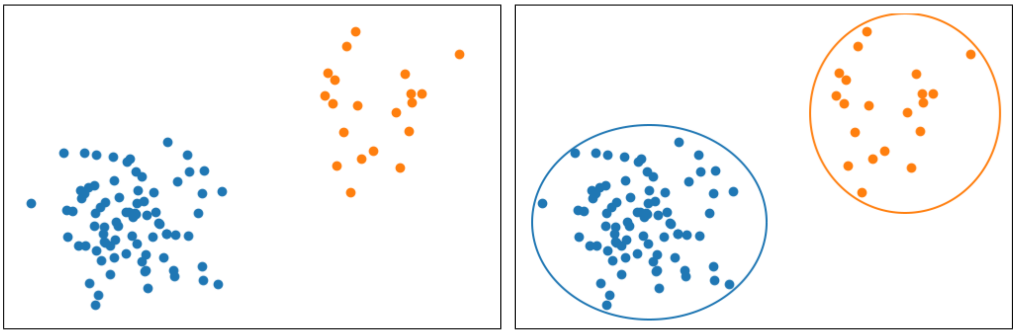
Draw: $r \sim U(0, 1)$
for $i = 0 : M - 1$ **do**
  $U^i \leftarrow (i + r)/M$
  $I^i \leftarrow D_w^{inv}(U_i)$
end for

Where D_w^{inv} is the inversion of the cumulative distribution function associated with the particle weights $\{w_t^i\}_{i=1}^N$, M is the number of samples to draw, and I^i is the index of the i'th sample. This resampling method is sensitive to the order particles before the resampling as that order changes the cumulative distribution function.

3.2 Mixture Resampling

The intuition behind mixture resampling is that we are not interested in resampling individual samples, but we are interested in sampling from high probability areas. One of the main problems of systematic resampling is that sampling variance can eliminate all particles in one area (figure 1a). Mixture resampling remedies this problem by representing areas as a cluster/mixture of particles and then resample particles from one cluster at the time. The number of particles resampled from one cluster is proportional to the weight of the area, thus if an area have 10% of the weight, 10% of the particles will be placed there (figure 1b).

Let the particles z_t^i be clustered into M different clusters $\mathcal{I}_{m,t}$ and each mixture $\mathcal{I}_{m,t}$ are assigned a weight $\pi_{m,t}$. When resampling, particles are draw from the following



(a) Standard resampling from this distribution can eliminate the all orange particles due to sampling variance since there is nothing preventing the resampler from only selecting blue particles.

(b) By clustering particles and thereafter resampling 10% of the particles from the orange cluster and 90% from the blue cluster, there will be exactly 10 orange and 90 blue particles in the new set.

Figure 1: 100 hundred particles to be resampled. 90% of the weight is in the blue particles and 10% is in the orange particles.

mixture distribution:

$$p(z_t|y^{t-1}) = \sum_{m=1}^{M} \pi_{m,t} p_m(z_t|y^{t-1}). \tag{1}$$

The mixture components $p_m(z_t|y^{t-1})$ is approximated by

$$\hat{p}_m(z_t|y^{t-1}) = \sum_{i \in \mathcal{I}_{m,t}} w_t^i \delta_{z_t^i}(z_t). \tag{2}$$

Inserting (2) into (1) gives us the following approximation of $p(z_t|y^{t-1})$

$$\hat{p}(z_t|y^{t-1}) = \sum_{m=1}^{M} \pi_{m,t} \sum_{i \in \mathcal{I}_{m,t}} w_t^i \delta_{z_t^i}(z_t) \tag{3}$$

where the weights $\pi_{m,t}$ and w_i^t are computed as follows:

$$\pi_{m,t} = \frac{\hat{\pi}_{m,t}}{\sum_{m'=1}^{M} \hat{\pi}_{m',t}}, \; \hat{\pi}_{m,t} = \sum_{i \in \mathcal{I}_{m,t}} \hat{w}_t^i \tag{4}$$

$$w_t^i = \frac{\hat{w}_t^i}{\hat{\pi}_{c_i,t}}, \; \hat{w}_t^i = p(y_t|z_t^i) w_{t-1}^i. \tag{5}$$

It can be shown that this approximation is identical to the approximation used in normal particle filtering, thus it is valid. For full derivation of the Mixture Particle Filter see [4].

The difference between the PF and the MPF comes from the resampling step where we draw samples from one mixture at the time.

4 Experimental Results

5 Summary and Conclusions

References

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