Comparing Resampling Techniques for Multitarget Tracking using Particle Filtering

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Abstract

Particle filters are a popular option for target tracking, however, they are known for being bad at maintaining multiple modes. Therefore, normal particle filters have problems with multitarget tracking. We tested 4 different resampling methods to address this problem on a dataset of 20 ants. These methods were the standard Systematic resampling, two versions of Clustered resampling and a method that uses multiple instances of a regular particle filter that we call MPF. The results showed that the MPF method was the most successful at tracking the ants but had lingering particles where no ants were present. The Clustered resampling using Lloyd's algorithm for clustering came in second place. The systematic resampling method was by far the worst resampling method.

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 [4]. 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) [4]. 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 [7], 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 methods for PF in the context of multitarget tracking in videos. The video used for evaluating the methods was a 1 minute video of ants from [5]. The resampling methods tested Systematic resampling, a simplified Cluster resampling and Multi Particle Filter (MPF) resampling. The Cluster resampling was tested with two different algorithm for clustering, Lloyd's algorithm and EM algorithm.

The results shows that Systematic resampling was the worst method and the MPF resampling was the best but has some issues. The MPF resampling suffers from having negligible sub particle filters with negligible particles and ended up having particles where no ants were present. Results also showed that the performance of MPF resampling increased with more sub filters. The Cluster resampling methods proved to be moderately good with no negligible particles as in MPF but they were considerably slower. The Lloyd's version of clustering was faster and more accurate than the EM variant.

2 Related Work

Several papers have acknowledge the weakness of particle filtering methods to maintain multi-modality. The authors in [3] were the first to introduced clustered particle filters and the authors of [8] developed it further. The authors of [3] introduced clustering of particles for robot motion to guard against premature impoverishment of particles when there are several equally probable modes. This is done by first clustering the particles and independently track the clusters. Each cluster is assigned a probability at a higher level so that the cluster with the highest probability was to correspond to the true robot position. The authors of [8] applied an improved version to one synthetic problem and football player tracking problem. The resampling method successfully keep both modes in the synthetic problem and track all players in the football problem.

In the context of multi target tracking, there are many different algorithms used. These algorithms usually fall into two different categories. The first is multiple instantiations of the sample tracker as in [6]. The second category explicitly extends the state space to track multiple objects [2]. To incorporate a varying number of targets, the state space can be dynamically changed to incorporate new or remove old targets, or indicators can be used to signify if a target is present or not.

3 Resampling methods

3.1 Systematic Resampling

Systematic resampling 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:

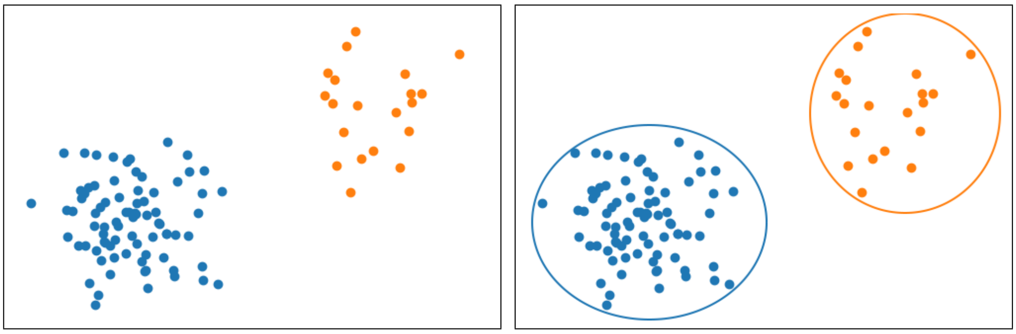
Algorithm 1 Systematic Resampling algorithm

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 inverse 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 of the particles before the resampling as it changes the cumulative distribution function.

3.2 Cluster Resampling

The idea behind cluster resampling is that we are not interested in particles, we are interested in the high probability areas the particles represent. One of the main problems of systematic resampling is that sampling variance can eliminate all particles in one area (figure 1a). Cluster 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 cluster, thus if an cluster have 10% of the weight, we draw 10% of the particles from that cluster (figure 1b).



(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.

3.2.1 Algorithm

The generic algorithm for ones step of cluster resampling is the following:

step 1: Propagate particles
step 2: Weight update
step 3: Resample particles
step 4: Calculate particles clusters

where the step 3 and 4 can exchange place.

3.2.2 Mixture Representation

In cluster resampling, we represent the target distribution as an M-component mixture model. Let z_t denote the state at time t and let $y^t = \{y_1, y_2, \cdots, y_t\}$ be the observations. Then the target distribution $p(z_t|y^t)$ is the following,

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

where $\sum_{m=1}^{M} \pi_{m,t} = 1$.

The particle filter approximation of the mixture model represents each mixture as a cluster of particles. Let the particles $\{z_t^i\}_{n=1}^N$ be clustered into M different clusters $\mathcal{I}_{m,t}$ representing the mixture components m. Let each particle z_t^i belong to one and only one cluster m and let $c_{t,i} = m$. The mixture components $p_m(z_t|y^t)$ are approximated by:

$$q_m(z_t|y^t) = \sum_{i \in \mathcal{I}_{m,t}} w_t^i \delta_{z_t^i}(z_t) \tag{2}$$

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

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

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

$$w_t^i = \frac{\hat{w}_t^i}{\sum_{i \in \mathcal{I}_{m,t}} \hat{w}_t^i}, \quad \hat{w}_t^i = p(y_t | z_t^i) w_{t-1}^i \tag{4}$$

$$\pi_{m,t} = \frac{\pi_{m,t} w_{m,t}}{\sum_{m'=1}^{M} \pi_{m',t} w_{m',t}}, \quad w_{m,t} = \sum_{i \in \mathcal{I}_{m,t}} \hat{w}_t^i. \tag{5}$$

It can be shown that this approximation is identical to the approximation used in normal particle filtering. For a complete derivation, see [8].

3.2.3 Resampling step

The main difference between standard resampling methods (e.g. systematic resampling), and the cluster resampling is that we draw samples from mixture components. When drawing samples from one mixture, we can use standard resampling methods such as systematic resampling. When drawing n samples from a mixture component m, it is important to note that the samples are drawn independently of other components, thus the new particles weights are $\frac{1}{n}$.

3.2.4 Clustering step

Clustering is the task to group objects in such a way that objects in the same group are more similar to each other than other groups. The algorithms we are interested in are two versions of the k-means clustering algorithms, Lloyd's algorithm and the EM algorithm.

Lloyd's algorithm Given an initial set of M centroids $m_1, m_2, \ldots, m_M$, the k-means algorithm proceeds in two steps:

> **Assignment:** Every object z^i is assigned to the nearest centroid k. The distance is measured with the euclidean distance.
>
> **Update:** New centroids m'_k are calculated by taking the mean of each object z^i that belongs to k; that is, $m'_k = \frac{1}{|\mathcal{I}_k|} \sum_{i \in \mathcal{I}_k} z^i$, where $\mathcal{I}_k$ is the set of objects assigned to centroid k.

this is done iteratively until the assignments no longer changes.

EM algorithm The algorithm starts with an initial initial set of mean vectors $m_1, m_2, \ldots, m_M$. Then the EM algorithm proceeds in 2 steps:

> **Expectation:** Every object i is partially assigned to each mixture k, this is represented by a weight $w_k^i = \frac{p_k(z^i)}{\sum_{k'=1}^{M} p_{k'}(z^i)}$ where $p_k(z^i) = \mathcal{N}(z^i | m_k, \sigma^2 I)$.
>
> **Maximization:** New means m'_k are calculated by taking the weighted mean of each object z^i; that is, $m'_k = \frac{\sum_{i \in \mathcal{I}_k} w_k^i z^i}{\sum_{i \in \mathcal{I}_k} w_k^i}$.

this is repeated until convergence. The EM algorithm for clustering is based on the EM algorithm for GMM.

Both algorithms suffers from local minima; that is, the optimal clustering is not found. Because of the local minima problem, the algorithms may need to be run several times with different initializations to find a better clustering. They algorithms are also biased towards spherical or hyper-spherical clusters. The EM algorithm is in general better than Lloyd's algorithm since it has fewer local minima, however, Lloyd's algorithm is easier to implement and faster. The EM algorithm will always assign at least one sample to every mixture, therefore one cluster that should be represented by one mixture may end up being represented by more than one mixture.

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3.3 Parallel Particle Filter

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3.4 Multi Particle Filter Resampling

The Multi Particle Filter (MPF) resampling method is based on the idea that we have a collection of particle filters, each of which will hopefully converges on different modes of the target distribution. This filter is represented by

$$p(z_t|y^t) \approx \frac{1}{M}\sum_{m=1}^{M} \tilde{p}^m(z_t|y^t) \tag{6}$$

where M is the number of sub particle filters and $\tilde{p}^m(z_t|y^t)$ is the approximation made by the m'th particle filter. ¿¿¿¿¿¿¿ Stashed changes

The problem with this method is modes might disappear resulting in particle filters with negligible particles. We will remove those sub particle filters in the following way:

1. For each sub particle filter m calculate

$$\eta_{m,t} = \frac{w_{m,t}}{w_{m,t}}, \; w_{m,t} = \sum_{i=1}^{N} z^i_{m,t} \tag{7}$$

   where M is the number of sub particle filters and N is the number of particles per filter.
2. If $\eta_{m,t} < \tau$ remove particle filter m. τ is threshold that should be chosen so that only negligible particle filters are removed.

4 Experiment

Dataset The dataset used for the comparison is the ant video dataset from [5]. The video consists of 20 ants wandering in a baking dish. With the video, a set of ground truths for the ants' positions is provided. Minutes 2-5 of the video was used to generate images for training an observation model. The first minute was used to test the accuracy of the algorithms.

Performance metric The accuracy of the algorithms at time t was calculated as:

$$\text{Accuracy}_t(A, P) = \frac{1}{20}\sum_{n=1}^{20} \text{Represented}(A_n, P) \tag{8}$$

Figure 2: A frame from the ant dataset [5].

where A is the coordinates of the ants and P is the set of particles. Represented(A_n, P) returns 1 if there is a particle $p \in P$ that is not more than 16 pixels away from ant n. This means that one particle can classify more than one ant as represented.

Particle model Each particle represents a possible location of the ant. $z_t^i = (x, y)$ where (x, y) is the coordinate of the particle on the frame. The observation model is deep neural network consisting of two hidden layers with fan-out 32 using ReLu as activation function. The observation model takes a 32×32 pixel gray scale frame with (x, y) in the center, this is enough to cover a possible ant. The motion model is:

$$D(x_t|x_{t-1}) = \mathcal{N}(x_t|x_{t-1}, \mathrm{I}_2 5^2) \tag{9}$$

where I_2 is a 2×2 identity matrix.

Resampling methods The resampling methods tested were Systematic resampling, Cluster resampling with Lloyd's algorithm and EM algorithm and the Multi Particle Filter (MPF) resampling. The number of particles used were 400, this is 20 particles per ant. For the cluster resampling methods, the number of clusters were set to 20 and 40, and the number of particles per cluster was set to be proportional to the total likelihood of the particle in the cluster. To simplify the algorithm, the cluster weights were ignored since we don not use them for tracking the ants, only the presence of the clusters was needed. For the MPF resampling, the number of parallel particle filters were set to 20 and 40 and the elimination threshold τ was set to 10^{-6}.

5 Results

The results shows that the Systematic resampling method is the worst of the methods tested, and the best method is the Multi Particle Filter (MPF) resampling but it has some problems. The Systematic resampling method is by far the worst method, most of the time it manages to represent only one ant (see figure 3). The Cluster resampling method is better when used with Lloyd's algorithm for clustering (see figure 5 and 4). Increasing the number of clusters makes the EM variant much worse at representing ants, the Lloyd variant is only slightly affected. The MPF method is much better at representing the ants, increasing the number of particle filters makes it even better (see figure 6). However, the MPF method have one significant drawback, it needs a carefully selected threshold in order to eliminate bad particle filters, as seen in figure 7, some clusters of particles are not near any ant.

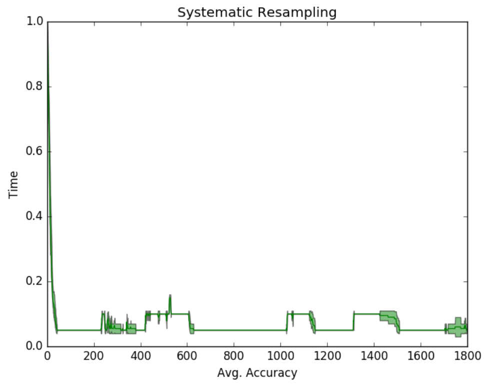

Figure 3: Accuracy of Systematic resampling. The filter was run 10 independent times, the green line is the mean, the area is one standard deviation away from the mean.

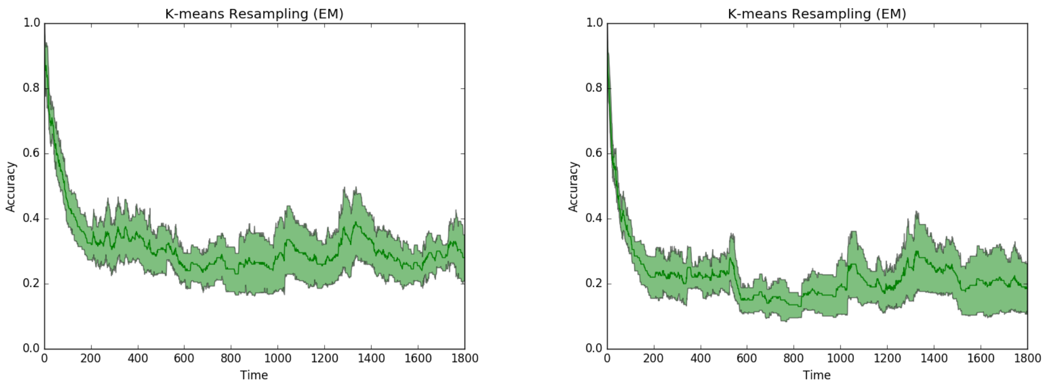

Figure 4: Accuracy of Cluster resampling using EM algorithm for clustering. The filter was run 10 independent times, the green line is the mean, the area is one standard deviation away from the mean. Left: 20 clusters. Right: 40 clusters.

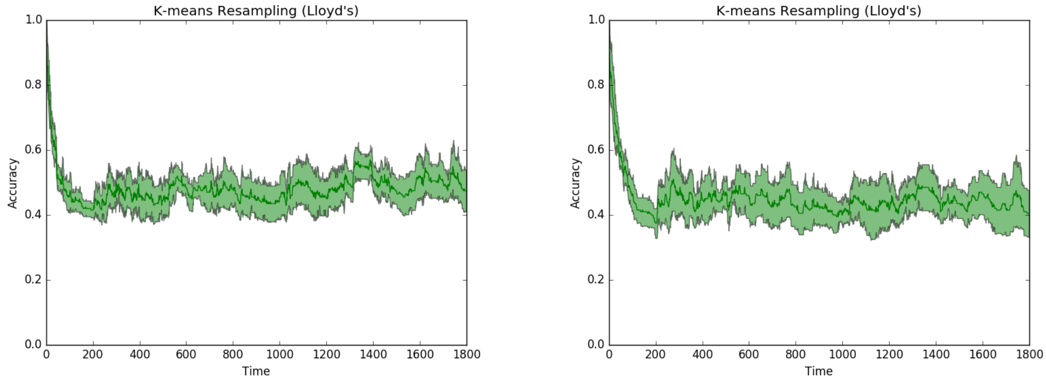

Figure 5: Accuracy of Cluster resampling using Lloyd's algorithm for clustering. The filter was run 10 independent times, the green line is the mean, the area is one standard deviation away from the mean. Left: 20 clusters. Right: 40 clusters.

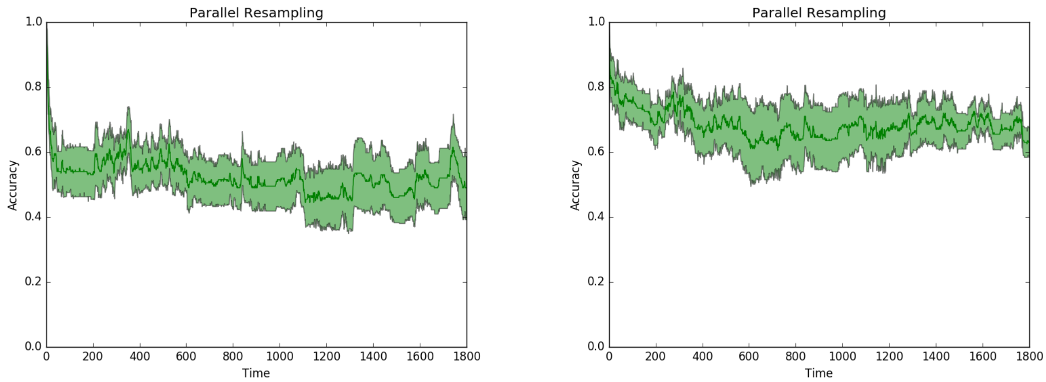

Figure 6: Accuracy of MPF resampling. The filter was run 10 independent times, the green line is the mean, the area is one standard deviation away from the mean. Left: 20 particle filters. Right: 40 particle filters.

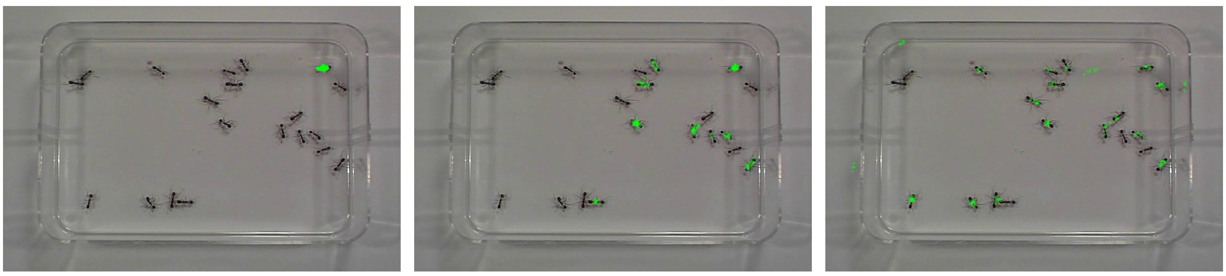

Figure 7: Particles locations after 10 seconds for three different algorithms. From the left: Systematic resampling, Cluster resampling (Lloyd's), and MPF resampling. Note that the MPF Resampling have several particle clusters not close to ants.

6 Summary and Conclusions

We compared four different particle filter resampling methods, Systematic Resampling, two versions of Cluster Resampling and Multi Particle Filter (MPF) Resampling. The comparison was made by tracking ants on a video feed. The MPF Resampling method performed the best were 50-80% of the ants were detected. In the second place were Cluster Resampling using Lloyd's algorithm to form clusters, it detected 40-50% of the ants. The second variant using EM for clustering performed worse, detecting about 20% of the ants. The absolute worst method was Systematic Resampling, detecting only one ant.

The MPF Resampling have some issues, it suffers from having negligible sub particle filters and thus ended up with particles in locations where no ants are present. This was partially solved by having a threshold τ such that any sub particle filter with normalized weight less than τ were removed. Setting the value τ is difficult, setting it too high can decimate the number of particle filters, and if it is too low, it does not remove enough particle filters.

The Cluster Resampling methods were moderately good with no negligible particles as with the MPF method but they were considerably slower. The Lloyd's version of clustering was both faster and more accurate than the EM variant. The reason it is more accurate might be due to the EM variant will always assign at least one particle to a cluster, therefore it might end up splitting one cluster into many smaller clusters that becomes relatively negligible in size. A solution might be to partially assign particles to all clusters using the EM algorithm and thereafter resampling is done cluster by cluster using normalized partial assigned weights; that is, the weight used for cluster n is $c_{i,n}w_t^i$ where $c_{i,n}$ is the partial assignment of particle i to cluster n.

The Cluster Resampling method might improve if a constant number of particles were kept for each cluster as it now depends on the total weight of the cluster. However, if the size is constant we might get problems with negligible clusters. The solution could be a threshold for each cluster as in MPF Resampling.

The Cluster Resampling for the ant dataset performed notably worse what [8] used for tracking football players, this is probably due to that the ants were tracked in gray scale so they blend in with the background, and there were 20 ants tracked compared to 4 football players. Other things were that we used a simpler version of the algorithm where cluster weights were neglected.

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