Piecewise Constant Sequential Importance Sampling for Fast Particle Filtering

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Abstract. Particle filters are key algorithms for object tracking under non-linear, non-Gaussian dynamics. The high computational cost of particle filters, however, hampers their applicability in cases where the likelihood model is costly to evaluate, or where large numbers of particles are required to represent the posterior. We introduce the piecewise constant sequential importance sampling/resampling (pcSIR) algorithm, which aims at reducing the cost of traditional particle filters by approximating the likelihood with a mixture of uniform distributions over pre-defined cells or bins. The particles in each bin are represented by a dummy particle at the center of mass of the original particle distribution and with a state vector that is the average of the states of all particles in the same bin. The likelihood is only evaluated for the dummy particles, and the resulting weight is identically assigned to all particles in the bin. We derive upper bounds on the approximation error of the so-obtained piecewise constant function representation, and analyze how bin size affects tracking accuracy and runtime. Further, we show numerically that the pcSIR approximation error converges to that of sequential importance sampling/resampling (SIR) as the bin size is decreased. We present a set of numerical experiments from the field of biological image processing and tracking that demonstrate pcSIR’s capabilities. Overall, we consider pcSIR a promising candidate for simple, fast particle filtering in generic applications, especially in those with a costly likelihood update step.

1. Introduction

Since their inception, sequential Monte Carlo (SMC) resampling methods (a.k.a., particle filters) [1][2] have emerged as a useful tool to estimate and track targets with non-linear and/or non-Gaussian dynamics. Unlike the Kalman filter [3] and its variants [4], particle filters (PF) do not use a fixed functional form of the posterior probability density function (PDF). Instead, they employ a finite number of points, called “particles”, to discretely approximate the posterior probability density function (PDF) in state space [5].

A standard PF algorithm consists of two parts: (i) sequential importance sampling (SIS) and (ii) resampling [2]. A popular combined implementation of these two parts is the sequential importance resampling (SIR) algorithm. Depending on the application, SIR may need a large number of particles to adequately sample the state space. This demands substantial computational resources that scale linearly with the number of particles and may hinder actualization of many practical real-time applications.

Here, we introduce the piecewise constant SIR (pcSIR) algorithm, which reduces the computational cost of SIR while providing tracking accuracy comparable to standard SIR. The main idea behind pcSIR is to group particles in state space (i.e., creating bins) and to represent each group of particles by a single representative particle. Only the weight of this representative dummy particle is then updated. We choose the dummy particle to sit in the center of mass of the group of particles it represents and to carry the mean properties of all the particles in the respective group. This is inspired by first-order multipole expansions from particle function approximation theory [6]. Once the weight of the dummy particle is computed, all other particles in the same group receive the same weight, which is copied from the dummy instead of being re-computed through the likelihood model for each individual particle, as in the original SIR. This way, an pcSIR-based PF can outperform a classical SIR-based PF by orders of magnitude in overall runtime in applications where evaluation of the likelihood is computationally expensive. Expensive likelihoods are particularly common when tracking objects in images, where each likelihood evaluation entails a numerical simulation of the image-formation process (see, e.g., Ref. [7]).

We outline the mathematical roots of pcSIR and derive an upper bound on the expected approximation error with respect to the chosen bin (i.e., Cartesian mesh cell in 2D) size. This error stems from the point-wise approximation of the likelihood function and is quantified using mid-point Riemann-sum error analysis [8][9]. We numerically quantify the errors in the state estimates (based on the posterior distribution) obtained by SIR and pcSIR as a function of the number of particles used, and show that there is almost no difference between SIR and pcSIR in terms of tracking accuracy. Furthermore, with a focus on biological image processing, we show that relating the bin size to the pixel size of an image provides satisfactory, and sometimes even higher-quality results in pcSIR compared with standard SIR.

The structure of this manuscript is as follows: Section 2 summarizes similar approaches to PF for state estimation. Section 3 recapitulates the classical SIR algorithm, whereas Section 4 introduces our new pcSIR method, discusses the theoretical framework behind pcSIR, and provides detailed
2. Related Works

Recent years have seen great interest in challenging tracking problems where the targets usually have non-linear and/or non-Gaussian dynamics. Two nonparametric algorithms, namely the histogram filters (HF) and particle filters (PF), stand out amongst others as main classes of algorithms that successfully tackle difficult tracking problems [5]. In both variants, posterior distributions are approximated by a finite set of values. Amongst others as main classes of algorithms that successfully tackle difficult tracking problems [5], the histogram filters (HF) and particle filters (PF), stand out in terms of tracking accuracy, runtime, and error convergence.

3. The Classical SIR Particle Filter

Recursive Bayesian importance sampling [13] of an unobserved and discrete Markov process \( \{ \mathbf{x}_k \}_{k=1,...,K} \) is based on three components: (i) the measurement vector \( \mathbf{z}^k = \{ z_1, \ldots, z_k \} \), (ii) the dynamics (i.e., state transition) probability distribution \( p(\mathbf{x}_k | \mathbf{x}_{k-1}) \), and (iii) the likelihood \( p(\mathbf{z}_k | \mathbf{x}_k) \). Then, the state posterior \( p(\mathbf{x}_k | \mathbf{z}^k) \) at time \( k \) is recursively computed as:

\[
\begin{align*}
\frac{p(\mathbf{x}_k | \mathbf{z}^k)}{p(\mathbf{x}_k | \mathbf{z}^{k-1})} & = \frac{p(\mathbf{z}_k | \mathbf{x}_k) p(\mathbf{x}_k | \mathbf{x}_{k-1})}{p(\mathbf{z}_k | \mathbf{z}^{k-1})},
\end{align*}
\]

where the prior is defined as:

\[
p(\mathbf{x}_k | \mathbf{z}^{k-1}) = \int p(\mathbf{x}_k | \mathbf{x}_{k-1}) p(\mathbf{x}_{k-1} | \mathbf{z}^{k-1}) \, d\mathbf{x}_{k-1}.
\]

In the PF approach, the posterior at each time point \( k \) is approximated by \( N \) weighted samples (i.e., particles) \( \{ \mathbf{x}_i^k, w_i^k \}_{i=1,...,N} \). This approximation is achieved by drawing a set of particles from an importance function (i.e., proposal distribution) \( \pi(\cdot) \) and updating their weights according to the dynamics PDF and the likelihood. This process is called sequential importance sampling (SIS) [2]. However, SIS suffers from the weight degeneracy, where small particle weights become even smaller and do not contribute to the posterior any more. To overcome this, a resampling step is performed [2] whenever the sample size falls below a preset threshold. Using the standard notation, as in Refs. [2][4], the complete SIR algorithm is given in Algorithm 1.

Algorithm 1 Sequential Importance Resampling (SIR)

1: procedure SIR
2: for \( i = 1 \rightarrow N \) do \( \triangleright \) Initialization, \( k=0 \)
3: \( w_i^0 \leftarrow 1/N \)
4: Draw \( \mathbf{x}_i^0 \) from \( \pi(\mathbf{x}_0) \)
5: end for
6: for \( k = 1 \rightarrow K \) do
7: for \( i = 1 \rightarrow N \) do \( \triangleright \) SIS step
8: Draw a sample \( \mathbf{x}_i^k \) from \( \pi(\mathbf{x}_i^k | \mathbf{x}_{i-1}^k, \mathbf{z}^k) \)
9: Update the importance weights \( w_i^k \leftarrow w_i^{k-1} \frac{p(\mathbf{z}_k | \mathbf{x}_i^k) p(\mathbf{x}_i^k | \mathbf{x}_{i-1}^k)}{\pi(\mathbf{x}_i^k | \mathbf{x}_{i-1}^k)} \)
10: end for
11: for \( i = 1 \rightarrow N \) do \( \triangleright \) Calculate the effective sample size
12: \( \hat{N}_{\text{eff}} \leftarrow 1/\sum_{j=1}^{N} (w_j^k)^2 \)
13: if \( \hat{N}_{\text{eff}} < N_{\text{threshold}} \) then \( \triangleright \) Resampling step
14: Sample a set of indices \( \{ s(i) \}_{i=1,...,N} \) distributed such that \( \Pr[s(i) = l] = w_l^k \) for \( l = 1 \rightarrow N. \)
15: for \( i = 1 \rightarrow N \) do \( \triangleright \) Reset the weights
16: \( \mathbf{x}_i^k \leftarrow \mathbf{x}_{s(i)}^k \)
17: \( w_i^k \leftarrow 1/N \)
18: end for
19: end if
20: end for
21: end procedure

4. The Piecewise Constant SIR Particle Filter

In classical SIR, all particle weights are updated according to the likelihood, which may impart a high computational load. Moreover, the computational cost scales linearly with the number of particles. Therefore, depending on the application, the likelihood evaluation often constitutes the most time-consuming part of a PF.

To address this problem, we propose the pcSIR algorithm, which aims at reducing the computational cost of importance weight update by exploiting the nature of the particle function approximation underlying SIR [6]. We do this by grouping the particles into non-overlapping multi-dimensional bins...
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(i.e., Cartesian mesh cells in higher dimensions), which are then represented by only a single dummy particle positioned at the center of mass of the real particles in that bin. The center of mass is computed using the state vectors and weights of all particles within the bin and is solely used to represent that bin by a single dummy particle. This amounts to a first-order multipole expansion of the PDF approximated by the particles [6]. Higher-order approximations are easily possible by storing on the dummy particle not only the mean, but also higher-order moments of the particle distribution in the bin. However, the overall error of a PF is dominated by the Monte-Carlo sampling error, which is of order 1/2. A first-order function approximation is hence sufficient.

The importance weight update is then only applied to the dummy particle. All other particles in the same bin are assigned the same weight that the dummy particle received. Thus, we approximate the likelihood by a mixture of uniform PDFs and bypass the costly likelihood update step for all particles. The pcSIR algorithm differs from SIR only in the SIS part, where the particles are binned and several averaging operations are performed. This makes it straightforward to implement pcSIR in any existing SIR code. The detailed pseudo-code is given in Algorithm 2.

The final function approximation used in pcSIR is related to BPF, where the box support is also approximated by a mixture of piecewise constant functions [15]. However, the theoretical motivation and the algorithmic implementation of this piecewise constant approximation is very different in pcSIR and in BPF. Gning et al. [12, 15] used interval analysis [11] to show that the uniform PDF approximation of the posterior becomes more accurate as the number of intervals increases. In pcSIR, the piecewise constant approximation of the likelihood is rooted in particle function approximation theory and can be understood as a first-order multipole expansion [6]. This dispenses with the need for interval analysis and provides a different algorithmic implementation and error analysis.

Unlike BPF, pcSIR still uses point particles. Thus, state estimation problems that result in narrow posterior densities can easily be handled by pcSIR, which is not the case for BPF. With pcSIR, we provide a simple way of using uniform PDFs to approximate the likelihood function, which eventually results in a satisfactory posterior representation through the Bayesian formulation. Moreover, it requires only few modifications to the classical SIR, which makes pcSIR an attractive choice for practical implementations.

4.1 Theoretical framework

The pcSIR algorithm is a function-approximation algorithm. It divides the n-dimensional state space into n-dimensional bins. In each bin, a sufficiently differentiable likelihood function is approximated by a constant value. The error analysis of such piecewise constant approximations is well understood on the basis of Taylor’s theorem for multivariate functions.

For the sake of example, we present the theoretical framework of pcSIR with a focus on image processing. When processing a sequence of 2D images, the likelihood function

\[ p(z_k|x_k) \]

is typically a two-dimensional function that is discretized over a finite set of particles. In SIR, the likelihood is approximated by N particles, where the particle number \( N \) defines the accuracy for the specific application. Therefore, the approximation error of SIR is denoted \( E_{SIR}(N) \).

With pcSIR, in the considered application, only the positions of the particles play a role in the likelihood update. This allows pcSIR to bin the state space. Therefore, the approximation error in \( p(z_k|x_k) \) depends on both the number of particles \( N \) and the maximum lengths of the bins \( l_x \) and \( l_y \) in both dimensions. Hence, the overall approximation error of pcSIR is denoted \( E_{pcSIR}(N, l_x, l_y) \).

First, we analyze the effect of bin size on \( E_{pcSIR}(N, l_x, l_y) \). For that purpose, we consider two cases: The first considers bins of varying rectangular shapes (i.e., \( l_y \neq l_x \)). In this setting, we fix \( N \) and let the approximation error depend on the bin lengths in both dimensions, hence \( E_{pcSIR}(l_x, l_y) \). In the second case, all cells are squares of edge length \( l \). The pcSIR approximation error can then be expressed as \( E_{pcSIR}(l) \).

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**Algorithm 2 Piecewise Constant Sequential Importance Resampling (pcSIR)**

1: procedure pcSIR
2: for \( i = 1 \rightarrow N \) do \( \triangleright \) Initialization, \( k=0 \)
3: \( w_0^i \leftarrow 1/N \)
4: Draw \( x_0^i \) from \( \pi(x_0) \)
5: end for
6: Create \( B \) bins of equal size \( l_1 \ldots B \)
7: for \( k = 1 \rightarrow K \) do
8: for \( i = 1 \rightarrow N \) do \( \triangleright \) piecewise constant SIS step
9: Draw a sample \( \tilde{x}_k^i \) from \( \pi(x_k | x_{k-1}, Z^i) \)
10: Assign \( \tilde{x}_k^i \) to a bin
11: end for
12: for \( j = 1 \rightarrow B \) do \( \triangleright \) Visit all bins
13: Create a representative particle that has the mean values of the state vector of all particles in the same bin
14: \( x_{k_{dum}} \leftarrow \text{mean}\{x_k^1, \ldots, x_k^N\} \)
15: Update the importance weights
16: \( w_{dum, k} \leftarrow w_{dum, k-1} \frac{p(x_k | x_{k_{dum}}) p(x_{k_{dum}} | x_{k_{dum}})}{p(x_k | x_{k_{dum}}) p(x_{k_{dum}} | x_{k_{dum}})} \)
17: for all \( x_k^i \) in bin \( l_j \) do
18: \( w_k^i \leftarrow w_{dum} \)
19: end for
20: end for
21: \( \tilde{N}_{eff} \leftarrow 1/\sum_{i=1}^{N} (w_k^i)^2 \)
22: if \( \tilde{N}_{eff} < N_{\text{threshold}} \) then \( \triangleright \) Resampling step
23: Sample a set of indices \( \{s(i)\}_{i=1}^{N} \) distributed such that \( \Pr(s(i) = l) = w_k^l \) for \( l = 1 \rightarrow N \),
24: for \( i = 1 \rightarrow N \) do
25: \( x_k^i \leftarrow x_k^{(s(i))} \)
26: \( w_k^i \leftarrow 1/N \) \( \triangleright \) Reset the weights
27: end for
28: end if
29: end for
30: end procedure
The particle locations in a cell cannot be determined directly - switching between motion types occurs (see Section 5.1). In this comparison, we assume Gaussian and uniform priors of different sizes. A smooth likelihood function is approximated by SIR and pcSIR and later applied to the prior. Thus, we obtain the estimation errors for the state. We call this experiment "pseudo" - tracking, since by eliminating the explicit dynamics PDF, we can focus on the approximation error and its convergence with increasing N.

4.2 The effect of cell size on \(E_{\text{pcSIR}}\)

The particle locations in a cell cannot be determined a priori since the movement of the particles depends on the data. We hence assume that for small cells and statistically large numbers of particles, we have a uniform particle distribution an a cell. The approximation errors introduced by the pcSIR algorithm in 2D are described in detail in the Appendix.

In pcSIR, the state space is decomposed into non-overlapping cells. Choosing an appropriate cell size is hence crucial for pcSIR. Similar to histogram filters [5], the accuracy of pcSIR is determined by the cell size. In the highest possible resolution, there is one particle per cell, which recovers the classical SIR algorithm.

In image processing, it is convenient to choose the image pixels as the cells of pcSIR. This constitutes a good choice since in typical image-processing applications, the pixel size already reflects the sizes of the objects represented in the image in order not to under-sample the objects and not to store unnecessary data. We call pcSIR with single-pixel cells pcSIR-1x1. Due to the characteristics of the likelihood function, however, there may be cases where sub-pixel resolution or higher accuracy is needed. Therefore, we also investigate pcSIR-2x2, where each pixel is divided into four cells. In the following Section, we empirically benchmark the effect of cell size on pcSIR performance and accuracy.

5. Experimental Results

We study the performance of pcSIR by considering a biological image-processing application: the tracking of sub-cellular (here, "cell" refers to the biological cell being imaged and is not to be confused with the pcSIR bin cells) objects imaged by fluorescence microscopy [16–18]. There, intracellular structures such as endosomes, vesicles, mitochondria, or viruses are labeled with fluorescent dyes and imaged over time with a confocal microscope. Many biological studies start from analyzing the dynamics of those structures and extracting parameters that characterize their behavior, such as average velocity, instantaneous velocity, spatial distribution [19, 20], motion correlations, etc.

5.1 Dynamics model

The motion of sub-cellular objects can be represented by a variety of dynamics models, ranging from random walks to constant-velocity models to more complex dynamics where switching between motion types occurs [21, 22]. Here, we use a nearly-constant-velocity model, which is frequently used in practice [7, 23]. The state vector in this case is \(x = (\hat{x}, \hat{\bar{y}}, v_x, v_y, \hat{l}_0)^T\), where \(\hat{x}\) and \(\hat{\bar{y}}\) are the \(x\)- and \(y\)-positions of an object, \((v_x, v_y)\) its velocity vector, and \(\hat{l}_0\) its fluorescence intensity.

5.2 Likelihood / Appearance model

Many sub-cellular objects are smaller than what can be resolved by the microscope, making them appear in a fluorescence image as diffraction-limited bright spots with an intensity profile given by the impulse-response function of the microscope, the so-called point-spread-function (PSF) [24, 25].

In practice, the PSF of a fluorescence microscope is well approximated by a 2D Gaussian [24, 25]. Object appearance in a 2D image is hence modeled as:

\[
I(x, y; x_0, y_0) = I_0 \exp \left( -\frac{(x-x_0)^2 + (y-y_0)^2}{2\sigma_{\text{PSF}}} \right) + I_{\text{bg}}, \tag{3}
\]

where \((x_0, y_0)\) is the position of the object, \(I_0\) is its intensity, \(I_{\text{bg}}\) the background intensity, and \(\sigma_{\text{PSF}}\) is the standard deviation of the Gaussian PSF. Typical microscope setups yield images with pixel edge lengths corresponding to 60 to 200 nm real-world length in the imaged sample. For the images used here, the pixel size is 67 nm and the microscope has \(\sigma_{\text{PSF}} = 78\) nm (or 1.16 pixels). During image acquisition, the "ideal" intensity profile \(I(x, y)\) is corrupted by measurement noise, which in the case of fluorescence microscopy has mixed Gaussian-Poisson statistics. For the resulting noisy image \(z_k = Z_k(x, y)\) at time point \(k\), the likelihood \(p(z_k|x_k)\) is:

\[
p(z_k|x_k) \propto \exp \left( -\frac{1}{2\sigma_z^2} \sum_{(x_i, y_i) \in S_k} \left| Z_k(x_i, y_i) - I(x_i, y_i; \hat{x}, \hat{\bar{y}}) \right|^2 \right), \tag{4}
\]

where \(\sigma_z^2\) controls the peakiness of the likelihood, \((x_i, y_i)\) the integer coordinates of the pixels in the image, \((\hat{x}, \hat{\bar{y}})\) are the spatial components of the state vector \(x_k\), and \(S_k\) defines a small region in the image centered at the object location specified by the state vector \(x_k\). Here, \(S_k = [\hat{x} - 3\sigma_{\text{PSF}}, \hat{x} + 3\sigma_{\text{PSF}}] \times [\hat{\bar{y}} - 3\sigma_{\text{PSF}}, \hat{\bar{y}} + 3\sigma_{\text{PSF}}]\).

5.3 Experimental setup

We focus on single sub-cellular object tracking (a problem which is related to the “track-before-detect” problem [26]) and compare pcSIR with SIR in two test cases, which differ in the size of the tracked object. We consider two different object sizes in order to compare cases where the likelihood is computationally cheap to evaluate with cases where this is more costly. 20 synthetic image sequences of different quality (i.e., signal-to-noise ratios, SNR) are generated by simulating a microscope. Each sequence is composed of 50 frames of size 512×512 pixels. The movies show a single object moving according to the dynamics model. Examples are shown in Fig. 4.
The two object sizes correspond to $\sigma_{\text{PSF}} = 1.16$ and $\sigma_{\text{PSF}} = 13$, and are named “small object tracking” and “large object tracking”, respectively (Fig. 1(a-c)). The positions and directions of motion of the objects are randomly chosen within the image plane. The speed (i.e., the displacement in pixels per frame) is drawn uniformly at random over the interval $[2, 7]$ for large objects and over $[2, 4]$ for small objects. The SNR of the images of large objects is 2 (ca. 6 dB), that for small objects is 4 (ca. 12 dB). We use the SNR definition for Poisson noise [27].

Knowing the ground-truth object positions and those estimated by the PF, we quantify the tracking accuracy by the root-mean-square error (RMSE) in units of pixels. The likelihood kernel for the large objects has a support of $65 \times 65$ pixels and is correspondingly costly to evaluate. The kernel for the small objects has a support of $9 \times 9$ pixels and is cheaper to evaluate. Examples of noise-free and noisy object profiles, together with their likelihood kernels, are shown in Fig. 2.

Using double-precision arithmetic, a single PF particle requires 52 KB (i.e., six doubles and one integer) of computer memory. The particles are initialized at the ground-truth location and all tests are repeated 50 times for different realizations of the image-noise process on a single core of a 12-core Intel® Xeon® E5-2640 2.5 GHz CPU with 128 GB DDR3 800 MHz memory on MPI-CBG’s MadMax computer cluster. All algorithms are implemented in Java (v. 1.7.0_13) within the Parallel Particle Filtering (PPF) library [28]. The results are summarized in Figs. 3 and 4 for large and small objects, respectively.

5.4 Results

When tracking large objects (Fig. 3), both pcSIR versions provide significant speedups over the classical SIR algorithm. For 12 800 particles, pcSIR-1x1 is more than two orders of magnitude faster than SIR with a 2.4% loss in tracking accuracy. pcSIR-2x2 provides an up to 5.8% better tracking accuracy than SIR while running over 50 times faster. Since SIR is also an approximation of the actual posterior distribution, in some cases pcSIR may provide a better representation of the posterior and thus a higher tracking accuracy. This phenomenon has been previously described [29].

When tracking small objects, the likelihood support requires sub-pixel resolution and the effect of bin size is more visible (Fig. 4). pcSIR-1x1 uses rather coarse bins compared to the likelihood support (Fig. 2), resulting in a pronounced loss of tracking accuracy. Visually, however, the trajectories produced by SIR and pcSIR-1x1 are virtually indistinguishable, since the tracking accuracy of pcSIR-1x1 is still in the sub-pixel regime (about 0.27 pixel). When finer bins (pcSIR-2x2) are used, the tracking accuracy of pcSIR is again better than that of SIR, and pcSIR runs more than five times faster than SIR.

5.5 Convergence of SIR and pcSIR

Both SIR and pcSIR employ particle approximations of a smooth, differentiable function, the order of accuracy of which depends on the number of particles $N$. In order to eliminate uncertainties resulting from the dynamics model, we assume the prior $p(s_k | Z_k^{t-1})$ to be either a uniform distribution over $3 \times 3$ or $5 \times 5$ pixels, or a Gaussian with $\sigma_{\text{prior}} = \{0.5, 0.8\}$, respectively. We then evaluate the likelihood in Eq. (4) with $\sigma_z = 20$ using both SIR and pcSIR. We call this a “pseudo”-tracking experiment. The object is a single PSF (Eq. (3)) with $\sigma_{\text{PSF}} = 1.16$. Visualizations of the object, likelihood, and prior are shown in Fig. 5.

We compare two versions of pcSIR, which differ in the placement of the dummy particles: In pcSIR-CoC, the dummy particles are placed at the geometric centers of the bins, whereas in pcSIR-CoM, the centers of mass of the state vectors of all particles inside that bin are used. Each convergence experiment is repeated 1000 times for different realizations of the random process, and the number of particles is increased up to 100 000. We quantify the RMSE of the state estimation.
The “pseudo”-tracking experiment: (a) the object with \( \sigma_{\text{pixel}} = 1.6 \), SNR=2; (b) the corresponding likelihood with \( \sigma_p = 20 \); (c) a uniform prior of support 5×5 pixel; (d) a Gaussian prior with \( \sigma_{\text{pixel}} = 0.5 \); (e) a uniform prior of support 3×3 pixel; (f) a Gaussian prior with \( \sigma_{\text{pixel}} = 0.8 \).

Thin white lines indicate the image pixel grid.

Figure 5. The “pseudo”-tracking experiment: (a) the object with \( \sigma_{\text{pixel}} = 1.6 \), SNR=2; (b) the corresponding likelihood with \( \sigma_p = 20 \); (c) a uniform prior of support 5×5 pixel; (d) a Gaussian prior with \( \sigma_{\text{pixel}} = 0.5 \); (e) a uniform prior of support 3×3 pixel; (f) a Gaussian prior with \( \sigma_{\text{pixel}} = 0.8 \).
a 50-frame 2D image sequence. pcSIR-1x1 needed only 2.3 seconds to accomplish the same task at the expense of a 2.4% smaller accuracy. pcSIR-2x2 completed the task in 5.3 seconds with a 5.8% better tracking accuracy than SIR. This improvement stems from the fact that for some posterior distributions, the piecewise constant likelihood approximate of pcSIR may be a more regular representation than that generated by SIR. This is a known phenomenon \cite{29}. The relative speedups of the two pcSIR variants over classical SIR were 130-fold and 57-fold for 12,800 particles, respectively. For larger numbers of particles, we expect even larger speedups.

For small-object tracking, both pcSIR variants showed an average 5-fold improvement in execution time for the largest tested particle number. However, the tracking accuracy of pcSIR-1x1 is greatly reduced, since the likelihood function has a narrow support that is not well sampled by the coarse bins. While the errors are in the range of 150%, they are barely visible in the final trajectories since the average RMSE is only about 0.27 pixels. Interestingly, pcSIR-2x2 shows improvements both in overall runtime (5-fold) and in tracking accuracy (1%), which suggests that pcSIR-2x2 may be a good algorithm for tracking small objects.

We believe that pcSIR can be used in many PF applications that require large numbers of particles, costly likelihood evaluations, or real-time performance. When tracking accuracy is not critical, pcSIR-1x1 can offer orders of magnitude speedup in image-processing applications. If a loss in tracking accuracy is undesired, pcSIR-2x2 still offers significant speedups while in some cases even improving accuracy over SIR. In other applications, one can adjust the size of the averaging bins according to the desired accuracy. Future improvements could involve adaptive bin sizes.

Appendix: Approximation error of pcSIR in 2D

Approximating integrable functions by piecewise constant functions is well understood in mathematics on the basis of Riemann integral theory \cite{8,9}. We formulate the approximation error $E_{pcSIR}(l_x,l_y)$ of pcSIR with rectangular cells and then simplify it to $E_{pcSIR}(l)$ for square cells. All results can be extended to higher-dimensional settings.

Let the likelihood $p(z_k | x_k)$ be a twice continuously differentiable function $f(x,y)$ within a domain $D$ in $\mathbb{R}^{[x_0,x_m] \times [y_0,y_m]}$, which is divided into $B = n \times m$ non-overlapping rectangular cells. Further, $l_{k_i}$ and $l_{k_j}$ denote the width (i.e., in $x$-direction) and the height (i.e., in $y$-direction) of cell $l_k$ in $D$, where $D = \bigcup_{k=1}^{B} \{l_k\}$. The indices $i$ and $j$ are given by $i = 1, \ldots, n$ and $j = 1, \ldots, m$, and the maximum side lengths in both dimensions are defined as $l_k = \max_{i} (l_{k_i})$ and $l_k = \max_{j} (l_{k_j})$ where $l_{k_i} = x_k - x_{k-1}$ and $l_{k_j} = y_k - y_{k-1}$. Then, the total approximation error $E_{pcSIR}(l_x,l_y)$ of the likelihood in $D$ obtained by pcSIR (Algorithm 2) is bounded by:

$$E_{pcSIR}(l_x,l_y) \leq \frac{1}{24} \left[ \max_{D} \left| \frac{\partial^2 f}{\partial x^2} \right| l_{k}^3 + \max_{D} \left| \frac{\partial^2 f}{\partial y^2} \right| l_{k}^3 \right],$$

where $\max_{[x_0,x_m]} \left| \frac{\partial^2 f}{\partial x^2} \right|$ and $\max_{[y_0,y_m]} \left| \frac{\partial^2 f}{\partial y^2} \right|$ are the maxima of the absolute values of $\frac{\partial^2 f}{\partial x^2}$ and $\frac{\partial^2 f}{\partial y^2}$ in $D$, respectively.

This result can be derived by mid-point Riemann-sum approximation of an integral. While the dummy particle does not have to be located at the center of a cell, for the sake of simplicity of the derivation, we assume that pcSIR uses the mid-point for piecewise constant likelihood approximation. Assume that $f(x,y)$ is twice continuously differentiable in region $D \in \mathbb{R}^{[x_0,x_m] \times [y_0,y_m]}$ and the following partial derivatives are defined: $\frac{\partial^2 f}{\partial x^2} = f_{xx}$, $\frac{\partial^2 f}{\partial y^2} = f_{yy}$ and $\frac{\partial^2 f}{\partial x \partial y} = f_{xy}$. The approximation error $E_{q_k}(l_x,l_y)$ can be calculated by integrating the multivariate Taylor approximation

$$E_{q_k}(l_x,l_y) = f(x,y) - f(a,b)$$

$$= f_x(a,b)(x-a) + f_y(a,b)(y-b)$$

$$+ \frac{1}{2!} [f_{xx}(a,b)(x-a)^2 + f_{xy}(a,b)(y-b)^2]$$

$$+ \frac{1}{2!} [f_{yy}(a,b)(x-a)(y-b)] \tag{5}$$

over the two-dimensional interval $l_k = [x_{k-1},x_k] \times [y_{k-1},y_k]$, where $a = \frac{x_{k-1}+x_k}{2}$, $b = \frac{y_{k-1}+y_k}{2}$, and $D = \bigcup_{k=1}^{B} l_k$, hence:

$$E_{q_k}(l_x,l_y) = f_x(a,b) \int_{l_k} (x-a) \, dx \, dy$$

$$+ f_y(a,b) \int_{l_k} (y-b) \, dx \, dy$$

$$+ \frac{1}{2!} \left[ f_{xx}(a,b) \int_{l_k} (x-a)^2 \, dx \, dy \right]$$

$$+ \frac{1}{2!} \left[ f_{yy}(a,b) \int_{l_k} (y-b)^2 \, dx \, dy \right]$$

$$+ \frac{1}{2!} \left[ f_{xy}(a,b) \int_{l_k} (x-a)(y-b) \, dx \, dy \right]. \tag{6}$$

Substituting $a$ and $b$ in Eq. (5), we find:

$$E_{q_k}(l_x,l_y) = \frac{1}{2!} \left[ f_{xx}(a,b) \int_{l_k} \left( x - \frac{x_{k-1}+x_k}{2} \right)^2 \, dx \, dy \right]$$

$$+ f_{yy}(a,b) \int_{l_k} \left( y - \frac{y_{k-1}+y_k}{2} \right)^2 \, dx \, dy \right]. \tag{7}$$

We substitute $l_k = x_k - x_{k-1}$, $l_{k_j} = y_k - y_{k-1}$ and evaluate the integrals. Then Eq. (7) becomes

$$E_{q_k}(l_x,l_y) = \frac{1}{24} \left[ f_{xx}(a,b) l_{k}^3 l_{k_j} + f_{yy}(a,b) l_{k_i}^3 l_{k_i} \right]. \tag{8}$$

Next, we sum the absolute values of the partial errors in all $l_k$ regions in order to provide an upper bound on the total approximation error in the closed region $[D]$ as:

$$E(l_x,l_y) \leq \frac{1}{24} \left[ \max_{D} \left| f_{xx} \right| \max_{l_k} (l_{k})^3 \max_{l_{k_j}} (l_{k_j}) \right.$$

$$+ \max_{D} \left| f_{yy} \right| \max_{l_{k_i}} (l_{k_i})^3 \max_{l_{k_i}} (l_{k_i}) \left. \right]. \tag{9}$$

By substituting $l_i$ and $l_j$ into Eq. (9), we find the total error in the closed region $[D]$:

$$E(l_x,l_y) \leq \frac{1}{24} \left[ \max_{D} \left| f_{xx} \right| l_{k}^3 l_{k_j} + \max_{D} \left| f_{yy} \right| l_{k_i}^3 l_{k_i} \right]. \tag{10}$$
For equi-sized square cells, a tighter bound for the approximation error can be derived by repeating the steps that lead to Eq. (10). The derivation diverges here by taking the minimum possible value for the side lengths $l_k$ and $l_j$, of the small interval $I_k$ in region $D \in \mathbb{R}^{[x_0,x_1] \times [y_0,y_1]}$, where $D = \bigcup_{k=1}^{B} I_k$. When $I_k$ is a square with $l = l_k = l_j = x_k - x_{k-1}$, we obtain the bound on $E_k(l)$ as:

$$E_k(l) \leq \frac{1}{24} [f_{xx} + f_{yy}], \quad (11)$$

By summing the absolute values of the errors in all $I_k$ regions, we get the total error in closed region $D$:

$$E(l) \leq \frac{1}{24} \left[ \max_{D} |f_{xx}| + \max_{D} |f_{yy}| \right]. \quad (12)$$

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