Rao-Blackwellized Marginal Particle Filtering for Multiple Object Tracking in Molecular Bioimaging

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Abstract. Modern live cell fluorescence microscopy imaging systems, used abundantly for studying intra-cellular processes in vivo, generate vast amounts of noisy image data that cannot be processed efficiently and accurately by means of manual or current computerized techniques. We propose an improved tracking method, built within a Bayesian probabilistic framework, which better exploits temporal information and prior knowledge. Experiments on simulated and real fluorescence microscopy image data acquired for microtubule dynamics studies show that the technique is more robust to noise, photobleaching, and object interaction than common tracking methods and yields results that are in good agreement with expert cell biologists.

Keywords: Bayesian estimation, particle filtering, multiple object tracking, Rao-Blackwellization, microtubule dynamics, fluorescence microscopy.

1 Introduction

Live cell imaging using time-lapse fluorescence microscopy has rapidly advanced in the past decade and has opened new possibilities for studying intra-cellular dynamic processes in vivo. Motion analysis of nanoscale objects, such as proteins, vesicles, or microtubules (Fig. 1), requires tracking of large and time-varying numbers of spots in noisy image sequences [1, 2, 3]. Manual analysis of such image data is laborious and often produces results with poor accuracy and/or reproducibility. Hence, the development of automated tracking methods is of great importance. Commonly used tracking methods fail to yield reliable results in the case of poor imaging conditions (SNR<5) [4], because the detection is usually based on simple intensity thresholding or model fitting, and available temporal information and prior knowledge are largely ignored. Alternative techniques, based on spatiotemporal segmentation [5], are also prone to errors in the case of very noisy images containing many objects at high densities.

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Recently, sequential Monte Carlo (SMC) methods \[6\], also known as particle filters (PF) \[7\], have become a popular tool to perform tracking in many fields. In this paper we extend our previous PF approach \[8\] and present a substantially more efficient Rao-Blackwellized marginal particle filter (RBMPF) for robust and accurate tracking of multiple nanoscale targets in two-dimensional (2D) and three-dimensional (3D) fluorescence microscopy image sequences. The RBMPF takes into account the analytical structure of the modeled processes and makes it possible to reduce the variance of the estimates in the case of high-dimensional state spaces, where standard PF fails. We compare the performance of standard PF and RBMPF with manual tracking using simulated as well as real image data acquired for microtubule dynamics studies.

## 2 Tracking Framework

Bayesian estimation for tracking aims at inferring knowledge about the unobserved state \( x_t \) of an object, which changes over time, using noisy measurements \( z_{1:t} \equiv \{z_1, \ldots, z_t\} \) up to time \( t \). The state evolution is modeled as a Markov process of initial distribution \( p(x_0) \) and transition prior \( p(x_t | x_{t-1}) \). The idea is to sequentially estimate the time evolving joint filtering distribution \( p(x_{0:t} | z_{1:t}) \) or the marginal filtering distribution \( p(x_t | z_{1:t}) \) and associated features, such as expectation. A recursive formula for the former is given by \[6\]

\[
p(x_{0:t} | z_{1:t}) \propto p(z_t | x_t) p(x_t | x_{t-1}) p(x_{0:t-1} | z_{1:t-1}). \tag{1}
\]

It is assumed that the initial pdf, \( p(x_0 | z_0) \equiv p(x_0) \) is available (\( z_{1:0} = z_0 \) being the set of no measurements). The distribution \( p(x_t | z_{1:t}) \) follows from (1) as

\[
p(x_t | z_{1:t}) \propto p(z_t | x_t) \int p(x_t | x_{t-1})p(x_{t-1} | z_{1:t-1}) dx_{t-1}. \tag{2}
\]