Concurrent Particle Tracking Using an Iterative Kalman Filter Approach

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Abstract. Particle tracking is a widespread research question for quantitative biology. In contrast to other approaches, we developed a local greedy technique based on the Kalman filter. To overcome the problem of guessing the first state of a particle, the algorithm runs iteratively in forward and backward direction. The algorithm was successfully tested with simulated and real data.

1 Introduction

Main tasks for analyzing particles in microscopic images are segmentation and tracking. While there is a vast quantity of segmentation algorithms that can be successfully used, tracking algorithms often fail on difficult data. Our goal is to develop an algorithm, which can be applied to a wide range of tracking problems, especially on difficult data.

Cheezum et al. [1] compared different tracking algorithms and found that a Gaussian fit is the best algorithm when tracking single fluorophores. Godinez et al. figured out, that a probablilistic approach based on a particle filter outperforms deterministic algorithms [2] and that independant particle filters outperforms those using a mixture of particle filters [3]. Genovesio et al. [4] propose a method to track multiple moving biological spot-like particles using Bayesian filtering. Wu et al. [5] implemented their Bayesian framework using the Kalman filter [6]. While their approach handles only a single trajectory each run, our algorithm estimates all trajectories at once and additional has some improvements in the Kalman filter. To overcome the problem of invisible particles Li et al. [7] introduced a compiler linker which connects two tracks segments belonging together.

In our approach, the Kalman filter determines the individual transition probabilities between particle locations in two subsequent frames given a motion model. Starting from an initial guess of the first track position, the forward model finds, after a while a consistent track tail. In order to compensate an eventual incorrect starting position, a backward tracking is applied. Further, our method pays attention to all particle trajectories at once to obtain better results on images with lots of particles. Last but not least, it is able to introduce faked particles, to overcome the problem of missing particles.

2 Materials and methods

The particles visible in the microscopy images are first located using a local maxima selection followed by a Gaussian fit to get the intensity. While this is not an optimal method, it is sufficient for testing the algorithm with real data.

Thus, the information about every particle in each frame is its position and intensity. Based on these information, for each particle in a time-frame *t*, the most likely corresponding particle is chosen from the next timeframe *t+1* using the Kalman filter. This filter estimates the next state of a particle using the prior state like position, velocity and intensity, of the particle, and a mathematical model for the dynamics of the process to be estimated. All relevant parameters for the filter are set manual by the user.

If no corresponding particle is found, a fake particle is created to overcome the problem, that in some cases particles may not be visible due to image acquisition or segmentation issues. The state of the fake particle is estimated using the Kalman filter. When the estimation error is getting too high, the fake particle is destroyed and the trajectory ends at the point with the last real particle.

Our simulation data consists of an area with 500x500 pixels with two particle streams. The streams are crossing and each stream has 50 particles with different speed from 1.5 to 3 Pixels per frame. Since segmentation is not the emphasis of this paper the simulated data is made up of already segemented data. To take failures in segmentation into account, several parameters define the quality of the segmentation. The parameters μ and σ define the Gaussian noise, adding a small localization error to each particle position. α describes the percentage of non-segmented particles in a frame and β the ratio between false particles and real particles.

Eq (1) shows the calculation for the estimation error, where N is the total number of particles, *est* is an estimated particle and p the corresponding real particle. Several simulations were done, each with different simulation parameters, which simulate potential failures from image acquisition and segmentation.

$$err = \sqrt{\frac{1}{N}\sum_{k=1}^{N} \|est_k - p_k\|^2} \tag{1}$$

Each measurement was created using the average of 50 simulations with 100 timeframes each. The different versions of the algorithm are quoted with the abbreviations *F* for faked particles and *I* for the iterative version.

3 Results

The following table (Tab. 1) shows the results for the simulations. Each row represents one measurement. The values in the first three columns indicate the parameters used for the measurements and are expressed as percentages. In the next four columns the localization error *err* is shown for each different version

Table 1. Tracking errors for several measurements using different algorithms: (-) Standard approach, (F)aked particles, (I)terative approach, (F,I) faked particles and iterative approach.

	Parameters		Localization error				Correctly
Noise N(μ,σ)	Inv. part. α	Seg. error β	-	*F*	*I*	*F, I*	assigned particles
0/0.1	0.01	0.01	0.33	0.33	0.16	0.13	99
0/0.5	0.05	0.05	0.77	0.77	0.74	0.62	94
0/0.1	0.1	0.1	0.77	0.77	0.53	0.41	87
0/1	0.1	0.1	1.15	1.16	1.08	1.00	87
0/0.5	0.01	0.1	1.21	1.21	1.18	0.94	99
0/0.5	0.1	0.01	0.65	0.65	0.51	0.46	87

of the algorithm. The last column indicates the percentage of correctly assigned particles.

We tested the image using an image stack from a cell obtained from a Zeiss Axiovert 200 M. The results showed a good agreement with anticipated trajectories.

4 Discussion

Our algorithm performs visually correct on real microscopy images. For an evaluation of the robustness of the approach, simulated test cases were considered. According to the results the advantage of the additional forward and backward iteration of the algorithm can be clearly seen. While the amount of correct assigned particles changed only marginal (below one percentage), the estimation error *err* decreased significantly. It showed that the introduction of faked particles alone had no benefits, compared to the standard algorithm, but using the faked particles in addition to the iterative version of the algorithm the estimation error could be further decreased.

In the future the tracking algorithm shall be compared to manually tracked data. In order to ease setting up the parameters for the kalman filter a semi-automatic approach like in [7] using the expectation maximizating algorithm [8] could be used. Further the segmentation algorithm could be exchanged in order to take advantage of the characteristics of the specific microscopy images.

We have presented a robust method to track particles in microscopic images. The main advantage of this method over methods from state of the art, especially from Wu et al. [5] is the iterative processing and the use of faked particles. This way, the algorithm is more robust against failures in segmentation and noisy data.

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