ROBUST MULTIPLE OBJECT TRACKING BY DETECTION WITH INTERACTING MARKOV CHAIN MONTE CARLO

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ABSTRACT

This paper presents a novel and computationally efficient multi-object tracking-by-detection algorithm with interacting particle filters. The proposed online tracking methodology could be scaled to hundreds of objects and could be completely parallelized. For every object, we have a set of two particle filters, i.e. local and global. The local particle filter models the local motion of the object. The global particle filter models the interaction with the other objects and scene. These particle filters are integrated into a unified Interacting Markov Chain Monte Carlo (IMCMC) framework. The local particle filter improves its performance by interacting with the global particle filter while they both are run in parallel. We indicate the manner in which we bring in object interaction and domain specific information into account by using global filters without further increase in complexity. Most importantly, the complexity of the proposed methodology varies linearly in the number of objects. We validated the proposed algorithms on two completely different domains 1) Pedestrian Tracking in urban scenarios 2) Biological cell tracking (Melanosomes). The proposed algorithm is found to yield favorable results compared to the existing algorithms.

Index Terms— Tracking, Detection, Particle Filters.

1. INTRODUCTION

Object tracking is a well-studied problem in the computer vision community [1]. Recently, tracking by detection methodologies have been gaining more popularity due to the advancements in object detection [2, 3]. Several multiple object tracking-by-detection algorithms optimize detection responses across several past and future frames. These approaches find the optimal target configurations by solving the linear assignment problem [4, 2, 5]. These methods do not scale to large number of objects. In contrast, online tracking algorithms provide a scalable solution. However, online multiple object tracking still remains as a challenging problem. Tracking algorithm tuned for one domain might completely fail in another domain. For example, tracking algorithm modeled for crowded urban environment cannot be directly applied to biological cell tracking problem. We propose a novel online multiple object tracking-by-detection framework that takes domain information into account and can be seamlessly used in different domains. Figure 1 shows visual snapshots from two completely different domains.

Sequential Monte Carlo methods [6, 7] have been widely used in several object tracking algorithms and it provides a framework for online tracking by applying Markovian principle such that only the past frame is taken into account. For multiple object tracking, some of the existing methodologies represent the state space of all the objects jointly [8]. Khan et al. [9] use joint particle filter for all the objects and impose MRF priors for modeling the object interactions with efficient MCMC sampling. The joint state space representation introduces tremendous computational complexity. Therefore, recent methods use separate filter for each object [10, 3, 11, 12]. Qu et al. [10] use independent particle filter for each object and relax the first-order Markov chain assumptions by using "Inertia" Markov chain. Kwon et al. [11] combined several basic motion models and each of them covered different types of motions i.e. one for smooth and another for abrupt motions. Within a scene, different objects might exhibit different motion behaviors and single motion model may not be sufficient. Therefore, they form a compound tracker using several basic trackers and combine them using Interacting Markov Chain Monte Carlo (IMCMC) framework [13] and show significant improvements over the existing algorithms in some challenging sequences. However, they do not model the interaction between objects and also do not take additional domain specific information into account [14].

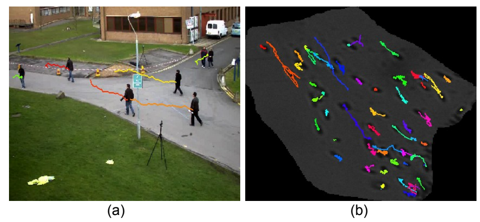

Fig. 1. **Datasets from completely different domains showing tracked object trajectories:** (a) PETS-2009 pedestrian dataset (b) Melanosomes from bright-field microscopy. Best viewed in color.

In this paper we propose a novel multiple object tracking-by-detection framework that can be applied to different domains [1]. A set of detections is obtained at every frame and we use the Hungarian algorithm for assigning detections to tracklets [2]. For every object, we use two kinds of particle filters i.e. local and global with MCMC sampling. For local particle filters, the observation likelihood is computed using the associated detection and it does not model scene information. For global particle filters, the observation likelihood is computed based on detections of nearby objects and domain specific information. Similar to [11], each filter operates either in parallel or interactive mode. By separating the local and global models, we can easily account for domain specific information into the global model. We provide extensive experimental results on two completely different application domains.

[1] not to be confused with cross-domain learning in Machine Learning community

Compared to existing works, following are the main contributions of this paper:

1. A unified MCMC approach to combine local and global models. Global models capture multi-object interaction and domain specific information.
2. A novel and computationally efficient approach for probabilistic multiple object tracking-by-detection using MCMC framework with independent filters for each object.

2. BAYESIAN TRACKING FORMULATION

In this section, we explain the basics of particle filter based object tracking. Let the object configuration be represented by $\mathbf{X}_t = [x_t, y_t, s_t]$ where x_t, y_t and s_t indicate the x, y position and scale of the object respectively. The goal is to find the best object configuration $\mathbf{X}_t$ given the observations $\mathbf{Y}_t$. Given the observation up to time "t", $\mathbf{Y}_{1:t}$, we estimate the state of the object $\mathbf{X}_t$ at time "t" with the following Bayesian formulation:

$$p(\mathbf{X}_t|\mathbf{Y}_{1:t}) \propto p(\mathbf{Y}_t|\mathbf{X}_t) \int p(\mathbf{X}_t|\mathbf{X}_{t-1}) p(\mathbf{X}_{t-1}|\mathbf{Y}_{1:t-1})\ d\mathbf{X}_{t-1}, \tag{1}$$

the best object configuration $\hat{\mathbf{X}}_t$ is obtained by Maximum a Posteriori (MAP) estimation:

$$\hat{\mathbf{X}}_t = \arg\max_{\mathbf{X}_t}\ \ p(\mathbf{X}_t|\mathbf{Y}_{1:t}) \tag{2}$$

with "Sequential Importance Resampling" (SIR) particle filters, the posterior at time "$t-1$" is approximated by a set of weighted particles given by:

$$p(\mathbf{X}_{t-1}|\mathbf{Y}_{t-1}) \approx \{\mathbf{X}_{t-1}^{(r)}, \pi_{t-1}^{(r)}\}_{r=1}^{N} \tag{3}$$

where r is the particle index and N is the number of particles. The particle weight is given by, $\pi_t^{(r)} = p(\mathbf{Y}_t|\mathbf{X}_t^{(r)})$. The integral in the equation 1 can be approximated by:

$$p(\mathbf{X}_t|\mathbf{Y}_t) \approx p(\mathbf{Y}_t|\mathbf{X}_t) \sum_{r=1}^{N} \pi_{t-1}^{(r)} p(\mathbf{X}_t|\mathbf{X}_{t-1}^{(r)}) \tag{4}$$

In this paper, we use MCMC sampling instead of the standard "importance resampling". The MCMC based particle filter is very efficient compared to "importance resampling" based particle filter [9]. Also, "importance resampling methods suffer from particle impoverishment and degeneracy. MCMC methods work by defining a Markov chain over the space of configurations $\mathbf{X}_t$, such that the stationary distribution of the chain is equal to the posterior distribution, $p(\mathbf{X}|\mathbf{Y})$. In MCMC based particle filter, the posterior is represented by set of un-weighted samples i.e. $p(\mathbf{X}_t|\mathbf{Y}_t) \approx \{\mathbf{X}_t^{(r)}\}_{r=1}^{N}$.

3. TRACKING BY DETECTION WITH IMCMC

This paper proposes a novel tracking algorithm to combine local and global models in a computationally efficient manner. The objects detection yields fully automated tracker initialization. A new tracker is initialized for every detection that is neither associated to any of the existing trackers nor occluded. Given the set of detections $\mathcal{D}_t = \{d_{jt}\}$ at every time step t, where j is the detection index, we explain the proposed tracking algorithm in the following.

3.1. Data Association

At time t, a matching algorithm is used to associate detections to existing trackers. We use the Hungarian algorithm to associate one detection to at least one tracker and we create a new tracker for every unassociated detection. Let $\{tr_{it}\}$ be the set of trackers at time t, where i is the tracker index and each tracker independently tracks one object. The score matrix (S) captures the affinity of matching a detection d_{jt} to the existing set of trackers $\{tr_{it}\}$ as given below:

$$S(i,j) = p_{size}(d_{jt}|tr_{it}) \cdot p_{pos}(d_{jt}|tr_{it}) \cdot p_{appr}(d_{jt}|tr_{it}) \tag{5}$$

where $p_{size}(d_{jt}|tr)$, $p_{pos}(d_{jt}|tr_{it})$, and $p_{appr}(d_{jt}|tr_{it})$ are the likelihoods based on size, position, and appearance. $p_{size}(d|tr)$ and $p_{pos}(d|tr)$ are drawn from the Normal distribution such that $p_{size}(d|tr) \sim \mathcal{N}(size(d); size(tr), \sigma_{size}^2)$ and $p_{pos}(d|tr) \sim \mathcal{N}(pos(d); pos(tr), \Sigma_{pos})$ respectively. σ_{size}^2 and Σ_{pos} are variance and co-variance for size and position respectively. $p_{appr}(d_{jt}|tr_{it})$ captures appearance likelihood based on the problem domain (color or shape based model).

3.2. MCMC based Local Particle Filter

The local particle filter captures the local information with respect to the object and it does not take object interactions nor domain information into account for modeling the object motion. After computing the associated detection for the given tracker, the observation likelihood is evaluated with respect to the associated detection d. The following observation model is used for the local particle filter:

$$p_l(\mathbf{Y}_t|\mathbf{X}_t) = \overbrace{\mu(d, \mathbf{X}_t)}^{Detection-Score}\ \ \overbrace{p_{pos}(d|\mathbf{X}_t)}^{Position} \tag{6}$$

where $\mu(\cdot)$ is based on the pascal visual object challenge (VOC) detection score [15]. With the detected bounding box B_d and the predicted bounding box B_x, the pascal VOC detection score is given by:

$$\mu(d, \mathbf{X}_t) = \frac{area(B_d \cap B_x)}{area(B_d \cup B_x)} \tag{7}$$

and $p_{pos}(\cdot)$ is a likelihood measure based on the distance between the centroids. We approximate the local motion model with the Normal distribution such that $p_l(\mathbf{X}_t|\mathbf{X}_{t-1}) \sim \mathcal{N}(\mathbf{X}_t; \mathbf{X}_{t-1}, \Sigma_l)$.

The local particle filter finds the MAP estimate defined in equation 2 by sampling via Metropolis Hastings algorithm [6]. The algorithm consists of two steps, a proposal step and an acceptance step. In the proposal step, the new state is proposed with the following proposal density:

$$Q_l(\mathbf{X}_t^*; \mathbf{X}_t) = p_l(\mathbf{X}_t^*|\mathbf{X}_t) \tag{8}$$

where Q_l denotes the proposal density function based on the local particle filter's motion model and $\mathbf{X}_t^*$ represents the new state proposed by Q_l at time t. Given the proposed state, the local filter accepts the new state with the acceptance ratio given by:

$$\alpha_{parallel} = \min\left[1, \frac{p_l(\mathbf{Y}_t|\mathbf{X}_t^*) Q_l(\mathbf{X}_t; \mathbf{X}_t^*)}{p_l(\mathbf{Y}_t|\mathbf{X}_t) Q_l(\mathbf{X}_t^*; \mathbf{X}_t)}\right] \tag{9}$$

3.3. MCMC based Global Particle Filter

The global particle filter captures interactions with the other objects and also with the scene. Also, it provides an efficient way to enforce higher level constraints without increasing the overall complexity of the tracking algorithm. Given the associated detection d_i for the tracker tr_i, observation model, $p_g(\mathbf{Y}_t|\mathbf{X}_{it})$, for the global particle filter is given by:

$$p_g(\mathbf{Y}_t|\mathbf{X}_{it}) = \overbrace{p_{appr}(d_i|\mathbf{X}_{it})}^{Appearance} \cdot \overbrace{\prod_{k \neq i} \psi(\mathbf{X}_{it}, d_k)}^{Interaction} \cdot \overbrace{\phi(d_i, \mathbf{X}_{it})}^{Domain} \tag{10}$$

where $p_{appr}(\cdot)$ is the appearance likelihood based on the domain. $\psi(\mathbf{X}_{it}, d_k)$ encodes the interaction likelihood based on the associated detections of the other objects in the scene and it is based on the Magnetic repulsion potential [10]:

$$\psi(\mathbf{X}_{it}, d_k) = 1 - \frac{1}{\beta} \exp(-\frac{dist(\mathbf{X}_{it}, d_k)}{\sigma_i^2}) \tag{11}$$

where β is the normalization constant and σ_i^2 characterizes the allowable maximum interaction distance. $\phi(d_i, \mathbf{X}_{it})$ is based on the domain, it encodes the domain knowledge into the observation model. We approximate the global motion model with the Normal distribution such that $p_g(\mathbf{X}_t|\mathbf{X}_{t-1}) \sim \mathcal{N}(\mathbf{X}_t; \mathbf{X}_{t-1}, \Sigma_g)$. Similar to the local particle filter defined in section 3.2 we drive the global particle filter using the Metropolis Hastings algorithm based MCMC sampling.

3.4. IMCMC based Tracking Algorithm

At each time step, during the sampling, the local particle filter interacts with the global particle filter as described in Fig. 2. In order for the local particle filter to communicate to the global particle filter we use IMCMC framework [13]. On the other hand, the global particle filter operates in parallel mode completely. Similar to [11], the proposed tracking algorithm operates in either parallel or interactive mode. In parallel mode, the local and global particle filters act as the parallel Metropolis Hastings algorithm explained in the previous subsections. In interaction mode, the local particle filter communicates with the global particle filer and seeks the better state of the object. The local particle filter accepts the state of the global particle filter as its own state with the probability as given by:

$$\alpha_{interacting} = \frac{p_g(\mathbf{Y}_t|\mathbf{X}_{it})}{p_l(\mathbf{Y}_t|\mathbf{X}_{it}) + p_g(\mathbf{Y}_t|\mathbf{X}_{it})} \tag{12}$$

Algorithm 1 explains the proposed multi-object tracking methodology with IMCMC framework. It explains how the MAP estimate is obtained with the local particle filter by communicating with the global particle filter while they both operate in parallel.

3.5. Missed Detections and Occlusion Handling

In some scenarios, objects might not be detected due to various reasons such as lighting changes, illumination effects, occlusion, and missing features. For a given tracker, if the object is neither detected nor associated, the global particle filter proceeds with the prediction step and performs an update using other available detections and domain specific information. On the other hand, the local particle filter operates completely in interactive mode. The tracker pauses its operation after a specified number of continuously missed detections between frames (in our experiments, we set the threshold to 20 frames).

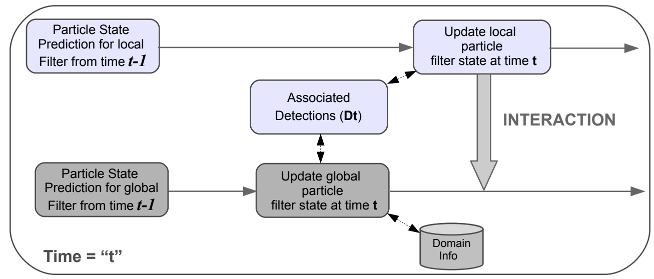

Fig. 2. **Interactive MCMC based tracking at time "t":** The local particle filter interacts with the global particle filter about the best configuration of the object.

Algorithm 1: Multi-Object Tracking with IMCMC

Input: $\mathbf{X}_t, \gamma$

Output: $\hat{\mathbf{X}}_t$

1: **rand()** returns a random number between 0 and 1.

2: **if** ***rand()*** $< \gamma$ **then**

  Accept the new state with the probability (12)

else

  Propose the new state using (8)

  Accept the new state with the probability (9)

end

3: Estimate the MAP state $\hat{\mathbf{X}}_t$ using (2)

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4. EXPERIMENTS

We evaluated the proposed algorithm on two completely different datasets. For all the experiments, we set the number of particles $N = 50$. The IMCMC interaction threshold (γ) was set to 0.2. Finally, the interactive likelihood constants in the global particle filters were set to $\beta = 1$ and $\sigma = 100$.

4.1. Pedestrian Tracking

We used a sequence from PETS-2009 (S2-L2) [16] for evaluating the proposed algorithm on pedestrian dataset. The sequence is 35 frames long and consists of 7 objects in the field of view. We used HOG based pedestrian detector to detect objects in every frame [17]. For appearance modeling in the global particle filter, we used "HSV" based color histogram obtained by binning in the values into a three dimensional space. Bhattacharya distance metric was used to compare the histograms and the final probability measure was obtained by weighting the Bhattacharya distance with the VOC detection score of the detection bounding box. For modeling the domain specific information, we used Kernel density estimator to model the probability density function on trajectories of the objects that moved over the scene for a period of time [14].

For both local and global particle filters, we used the Brownian motion model with variances $\sigma_x = 30, \sigma_y = 30$ and $\sigma_s = 0.2$. For comparison metrics, we used "Root Mean Square" (RMS) pixel error and pascal VOC detection scores. We compared the proposed algorithm with Mean-shift (MS) [18] and Visual Tracking Decomposition (VTD) [11]. Table 1 shows the average RMS pixel error and

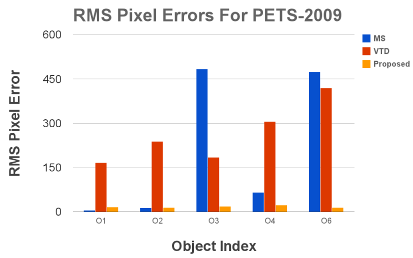

Fig. 3. **Experiment 1:** Average Root Mean Square (RMS) pixel error v/s object index. Best viewed in color.

Table 1. Average RMS errors and VOC detection scores for PETS-2009 Dataset.

Metric	MS	VTD	Proposed
RMS	304	278	**17**
VOC	0.34	0.0332	**0.39**

VOC detection score for the sequence (Best performing algorithm is highlighted by bolded text). Figure 3 compares RMS pixel errors for different algorithms for the objects in the scene. Due to the partial occlusion caused by the lamp post pole, the detector failed to detect objects around that region. Hence the objects "O3" and "O4" were completely guided by the global particle filter using the domain information and also by the location of the other tracked objects through interactive likelihood. Whereas, both Mean-shift and VTD trackers failed to capture object appearance changes during the occlusion and completely lost track of the object. Figure 4 shows the visual tracking results obtained using the proposed algorithm.

Fig. 4. **PETS-2009 Evaluation:** In this experiment, most of the other tracking methods failed due to the partial occlusion caused by the lamp pole. In the global particle filter, domain specific information learned from previous trajectories over the time is helpful in predicting the object position during the partial occlusion. Best viewed in color.

4.2. Biological Cell Tracking

Melanosomes carry dark pigment and they are imaged using Bright-Field microscopy. Our dataset is obtained from mouse retina. Tracking is very challenging on this dataset since most of the cells are out of focus and also the scalability is an issue for tracking multiple cells in parallel (see Figure 1(b) for melanosomes with trajectories marked in color). In our experiments, we used a sequence that is 360 frames long and consisted of approximately 56 melanosomes. At every frame, melanosomes are detected by thresholding followed by connected component analysis. For both local and global particle filters, we used Brownian motion model with variances $\sigma_x = 30, \sigma_y = 30$ and $\sigma_s = 0.2$. The velocity distribution of melanosomes follow

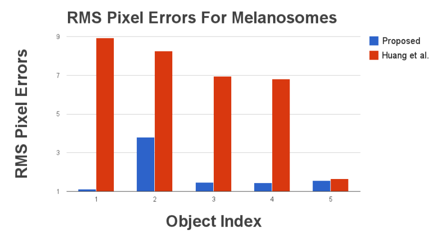

Fig. 5. **Experiment 2:** Average Root Mean Square(RMS) pixel error v/s object index for melanosomes dataset (average width and height of melanosomes is approximately 20 pixels.)

Langevin equation and it could be modeled using the Brownian motion model [19]. Therefore, we did not explicitly use domain specific information in the global particle filter. For appearance information, we used histogram of Local Binary Patterns computed within a neighborhood radius of 4 pixels. Similar to pedestrian tracking, Bhattacharya distance metric was used to compare the histograms and the final probability measure was obtained by weighting the Bhattacharya distance with the VOC detection score of the detection bounding box. Figure 6 shows the trajectories obtained by tracking different melanosomes over time. Figure 5 shows the RMS pixel errors compared to Huang et al. [2] for different melanosomes.

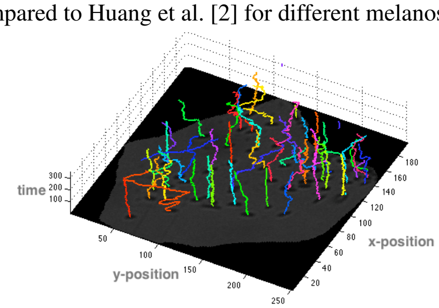

Fig. 6. **Experiment 2:** Trajectories obtained by tracking different melanosomes in a time lapse sequence. Best viewed in color.

5. CONCLUSION

An efficient multiple object tracking by detection algorithm with IMCMC framework is proposed. For every object, we used a set of two particle filters i.e local and global. The local particle filter models the local information with respect to the object of interest and does not take multi-object interaction into account. The global particle filter models the interaction with the other objects and scene i.e. consistent across the scene. Both of these particle filters are integrated into one using an efficient Interacting Markov Chain Monte Carlo (IMCMC) framework. The proposed algorithm is tested on some challenging datasets and validated with objective results. Our algorithm is very fast and could be parallelized completely, it takes approximately 300 milliseconds to track 50 objects per frame on a 2.4 GHz machine. We plan to extend the pedestrian tracking to multiple cameras [20] and melanosomes tracking to a larger sequence containing several hundreds of cells with quantitative analysis.

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