Multiple Objects Tracking by Using Magnetic Inertia Potential Model

Hemanth
Student,
Dept.Of CSE,
Jntuk, Kakinada, India

Smt. D.Neelima
Asst.Professor,
Dept.Of CSE,
Jntuk, Kakinada, India

Abstract: Magnetic inertia potential model is one of the new system is used to track the moving objects on chronological particle filtering on graphs is to removes the unwanted materials in moving videos or on any moving objects particle filtering is also known as Sequential Monte Carlo methods (SMC). This is a classical technique for density function estimation of non-linear and non-Gaussian systems. In particle filtering, random samples called particles are generated from a proposal density function and are used to evaluate the importance weights. By using ‘magnetic-inertia potential model’ to improve fastness and reduce, the computational complexity associated with particle filtering on graphs with a large number of complex cycles. There are issues in multiple objects tracking as if similar object appearance can result in tracking failure when the objects are in close proximity or present occlusions.

We proposed to extend the magnetic Inertia Potential model for extracting multiple objects for handles the “error merge” and “labeling” problems in a particle-filtering framework. Instead of using a joint state space, representation and performing the joint data association in multi-object tracking, interactively distributed framework with linear complexity for real-time applications are used.

Keywords: Multiple object tracking, Kernel, Interaction Model Distributed Tracking, Object Detection, Particle Filtering (Numerical Methods), Filtering, Magnetic Separation Particle Filters Particle, Tracking, Robustness.

I. Introduction

Particle filtering is a classical technique for density function estimation of nonlinear and non-Gaussian systems, and also known as Sequential Monte Carlo methods (SMC). Random samples are generated from a proposal density function and are used to evaluate the importance weights. Particle filtering has emerged as one of the most popular methods for video tracking. The interaction among objects and solve the data association namely, by establishing the correspondence between objects and observations. The conventional particle filter can be used for MOT as a single object tracker. Without an effective scheme to model the interaction and solve the data association both multiple independent trackers and conventional particle filter cannot perform well for MOT. Trackers usually suffer from the well known “error merge” problem that the tracker loses its associated object and falsely coalesces with others and as well as “labeling” problem. A widely accepted approach to MOT that addresses many of the difficulties inherent in this complex task is by exploiting a joint state space representation, which concatenates all of the object’s states together to form a large Meta state. The centralized approach can handle the “error merge” problem and track multiple objects that undergo partial and complete occlusion. It requires a tremendous computational cost due to the complexity introduced by the high dimensionality of the joint state representation. Due to the complexity of interaction among objects in the event of occlusion existing methods either use joint data association or rely on a joint state space representation. Collaborating among filters by modeling the objects’ joint prior using a Markov Random network to solve the “error merge” problem.
As shown in the figure 1 we illustrate our dynamic graphic model with two consecutive frames for multiple interactive objects and it comprises of two layers. Hidden layer are circle nodes that represent the states of objects X. Moreover, the observable layer represents the observations Z associated with the hidden states. The likelihood observation ration of hidden layer over the observable layer is P (Z|X). The spatial relations of objects are roughly determined in each frame, and the structure of its observable layer is fixed. We also inherit the common assumption that the observations in different frames are conditionally independent. Particle filtering relies on a first-order state-space model, which refers to the Hidden Markov Model (HMM). Although the assumption of a first-order Markov model leads to a simple expression of the posterior density propagation and efficient implementation for applications.

a. The first-order Markov model is an approximation that does not accurately represent the dynamics of moving objects.

b. Particle filtering based on a first order Markov model is extremely sensitive to loss of particle information from the previous time instant.

Previous efforts to incorporate higher-order dynamic models and graphical representations have been introduced for various applications. Currently, graphical models are used as a powerful tool for application in pattern recognition and machine learning. Graphs provide a simple and intuitive way to visualize the structure of the probability model and conditional dependence properties can be obtained directly by inspection of the graph. We aim to extend particle filtering beyond first-order HMM models to high-order Markov chains and general graphs in order to improve the performance and robustness of video tracking. A widely accepted approach in video tracking to address the problems of interaction and data association among multiple objects is based on a centralized solution.

II. Sequential Packet Filtering

Let us denote (P, ≤) as a partial order on a set. We have a ≤ b or b ≤ a when a set S ⊆ P is a chain if for a, b ∈ S. A dual of Dilworth’s chain decomposition theorem states that the size of the largest chain in a partial order (if finite) equals the smallest number of antichains into which the order may be partitioned. We use to denote the set of hidden states in graph i.e. V = {x₁, x₂, ⋯}. Let us use V₀, = {V₀, V₁, ⋯, Vₙ} to denote the collection of child sets up order l. V₀=0₁ order child set, Vₙ = l order child set. We could assign a partial order to the nodes beginning from layer 0 starting with order 0. Although therefore the order of the nodes in a graph will have many combinations and only use one predetermined order for a graph. We let S(vₙ,l) be to one plus the maximum order number in V₀, l₁.

Let us define a root node to be a node that has no parents. We define a specific partial order (V, ≤) on V such that the nodes xᵢ and xⱼ satisfy the xᵢ ≤ xⱼ. We now define the anti chain decomposition provided by the partition V₀, V₁, V₂ ⋯ Vₙ with respect to the partial order. The moral graph associated with a directed graph is the undirected graph on the same vertex set and with an edge set obtained by including all edges in the directed graph together with all edges necessary to eliminate forbidden Wermuth configurations. By utilizing the Markov properties on the moral graph of a directed cycle-free graph we can obtain

$$\mathcal{O}_m, l\mathcal{O}_1: l - 1\{V_m, l V_0: l - 1\}; \mathcal{O}_m, l\mathcal{O}_0: l - 1\{V_m, l V_0: l - 1 - Pa(v_m, l)\} \{1\} Pa(v_m, l)$$

Now the core problem is how to model the density propagation for the interactive objects. The posterior will estimate of $$x^l_i$$ based on all involved observations $$p(x^l_i|z^{l}_{1:t})$$ instead of $$p(x^l_i|z^{l}_{1:t})$$. There is no direct link between $$x^l_i$$ and $$z^l_i$$ at any time.

There is no interaction between $$z^{l}_{1:t}$$ and $$p(x^l_i|z^{l}_{1:t}, z^{l}_{1:t}) = p(x^l_i|z^{l}_{1:t})$$. The conditionally independent assumption between the consecutive observations $$z^{l}_{1:t-1}$$ is conditionally independent with $$z^{l}_{1:t}$$. The local likelihood $$p(z^l_i|z^l_i)$$ characterizes the “gravitation” between interactive observations, which produces “error merge” problem as discussed. We have the same likelihood model as the conventional particle filter, for the interactive prior density of $$x^l_{0:t-1}$$.

$$p(x^l_i|z^{l}_{0:t-1}, z^{l}_{1:t-1}) = p(x^l_i|z^{l}_{0:t-1}, z^{l}_{1:t-1}) p(x^l_i|z^{l}_{1:t-1}, z^{l}_{1:t-1})$$
$$= p(x^l_i|z^{l}_{1:t-1}, z^{l}_{1:t-1}) p(x^l_i|z^{l}_{1:t-1}, z^{l}_{1:t-1})$$

By analyzing the above two equations the assumption that $$x^l_i$$ only depends on $$x^{l}_{1:t-1}, x^{l}_{1:t-2}$$ as illustrated in the fig.2.

![Figure 2. Inertia Markov chain.](image-url)
Magnetic Repulsion Model

We want to introduce a “repulsion” force to resist the excessive attraction among the interactive observations. Consider a simple case, which has only pairwise interaction. Assume the two objects to be two magnetic monopoles with same polarity. These assumptions are consistent with former assumptions in the graphic model states (magnets here) at a certain time are independent while interaction only lies between observations. The equilibrium between magnetic repulsion and gravitation cannot achieve at a draught but after a process of oscillation. Fig.3 illustrate half of one repulsion iteration cycle where only the particles of object i which means $x_{i,t,k}^n$ and are repelled by the j object is to temporary estimate $x_{j,t,k}^n$.

Figure 3. Magnetic repulsion weighting in half of one repulsion iteration cycle.

We first get the new temporary estimate of object $i[x_{i,t,k}^n]$ and then use it to repel the particles of object $j[x_{i,t,k}^n]$ back to complete one iteration cycle. The dash circles represent the particles while the solid circles represent the temporary estimates of states. The two objects’ estimates are first roughly decided by using independent trackers. Our motivation now is to model the inertia function that is related with two posteriors $P(x_{t-2}|x_{t-1})$ and $P(x_{t-1}|x_{t-2})$. Inertia Law in physics states that “An object at rest tends to stay at rest and an object in motion tends to stay in motion with the same speed and in the same direction unless acted upon by an unbalanced force”. The analysis of one object’s motion in three consecutive frames where $x_{t-1}, x_{t-2}$ are the object’s states in previous two frames.

III. Distributed Sequential Particle Filtering and Markov Chain Object Tracking

An orientation of a graph G is an assignment of a direction to each edge. We could split the graph into multiple directed cycle-free subgraphs and apply the proposed sequential updating scheme distributively. The process of finding directed cycle-free subgraphs for a general graph is also called acyclic orientation of graphs. We could get multiple directed cycle-free subgraphs G1, G2, G3, ----GW, W≥1. The distributed solution to particle filtering on general graphs relies on multiple particle filters that are updated sequentially. The iterative updating process begins from an arbitrary subgraph, and relies on the results in all other subgraphs to update the current subgraph.

Compared with the traditional first-order particle filters derived based on the first-order Markov chain. If the state-space model is a th-order Markov chain, the current state $x_t$ depends on the past n states. We have

$$p(x_t | x_{t-1}, x_{t-2}, \ldots, x_0) = p(x_t | x_{t-1}, x_{t-2}, \ldots, x_m)$$

By inspection of the graphical model of high-order Markov chain with each layer having one node only. We could utilizing the proposed sequential particle filtering on directed cycle-free graphs to solve the problem of visual tracking on high-order Monte Carlo Markov chain.

IV. Multi Object Interaction In MIPM

We utilize the proposed distributed sequential particle filtering on general graphs for distributed multiple object tracking. Consider high-order dependencies for the nodes that will improve the tracking performance. For simplicity reason and to concentrate on the interactions of multiple objects, we still consider a first-order dependency for each object. As shown in the fig.4 graphical model of multiple object tracking is given. Interacting objects generate an undirected link between the objects’ states, and each undirected link forms a cycle in the directed graph.

Figure 4. Graphical model of multiple object tracking.
The proposed distributed multiple object-tracking algorithm based on sequential particle filtering on a multi-object graphical interaction model as graphical multiple object tracking (GMOT). It has been widely accepted that a better importance density according to different criteria could give more particles that are efficient and thus improves the tracker’s performance. We accept the most common choice that is intuitive and simple for implementation and allows us to perform a better comparison among different methods.

\[ q(X_i,k|\{Pa(X_i,k)\}n,Z_i,k) = p(X_i,k|X_i,k-1) \]

V. Experimental Analysis

We use a four-dimension parameter representation of an ellipse to model objects \( X = [x_c, y_c, b, \rho]^T \), where \((x_c, y_c)\) is the center of the ellipse, \(b\) is the minor axis, \(\rho\) is the major axis. The ratio of the major and minor axis of the ellipse is assumed a constant, which is computed in the initialization. The color histograms are used as the cue for computing the particle likelihood. We use 50 particles for each object for all methods. The number of tracked objects is therefore pre-determined and the objects are assumed to have a uniform prior distribution.

![Figure 5. Tracking results of synthetic sequence Football: MIPF (first row), MFMC (second row) and GMOT (third row).](image)

The dynamics of the object is considered as a random walk and the noise variance the same for all comparative methods.

a. Synthetic Videos: The synthetic sequence Football is a gray scale image sequence. The dynamics of the objects is pre-defined. As shown in the fig.5 different algorithms show the tracking results. Fig.6 shows the root mean squared error of the centers of the four balls.

b. Real Videos: The Walkway video clip contains persons dressed with clothes of similar colors moving across each other. The resolution is 320 240 and the frame rate is 30 frames per second.

c. Computational Cost Analysis and Discussions: compared with MIPF, the GMOT algorithm requires additional computational time to compute the interaction probabilities. The added time required is negligible compared with other particle filtering operations. The computational burden of MFMC is higher than GMOT because of the complexity introduced by its message calculation.

![Fig. 6. RMSE of the objects' center in Football sequence.](image)

VI. Conclusion

By using ‘magnetic-inertia potential model’ to improve fastness and reduce, the computational complexity associated with particle filtering on graphs with a large number of complex cycles. There are issues in multiple objects tracking as if similar object appearance can result in tracking failure when the objects are in close proximity or present
occlusions. When the objects are in close proximity or present occlusions a magnetic-inertia potential model is used to handle the "error merge" and "labeling" problems in a particle-filtering framework. Instead of using a joint state space, representation and performing the joint data association in multi-object tracking, interactively distributed framework with linear complexity for real-time applications are used. Nevertheless, it can be seen that most of computation time is spent on local likelihood weighting using image features. However, it is better to reduce the likelihood weighting computation time.

References


About Authors:

I am Hemanth pursuing final Mtech. My interesting research in data mining and cloud computing.

Mrs. D. Neelima received B.Tech and M.Tech in computer science and engineering from Jawaharlal Nehru Technological University of Hyderabad And currently pursuing Ph.D. in JNTU Kakinada, Andhra Pradesh, India. She is presently working as Assistant professor in Computer Science & Engineering department in Jawaharlal Nehru Technological University Kakinada, Andhra Pradesh, India. She has 13 years of experience in teaching Computer Science and Engineering related subjects. She is a research scholar and her area of interest and research includes Video Image Processing. She has published several research papers out of which 12 are international Journals and 2 papers in various international conferences. She has guided more than 70 students of Bachelor degree, 30 Students of Master degree in Computer Science and Engineering in their major projects.