
Relational Particle Filtering

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1 Introduction

The explicit recognition of relationships between interacting objects can improve the understanding of their dynamic model. Consider, for example, the situation in which we have a group of people walking in a park. If we know they are walking together (i.e. if we have a certain belief over their relation), we know they will have a similar behavior and this will help us in tracking them [1], especially in the presence of limited or noisy sensors (e.g., occlusions). Moreover, taking into account the relations between objects can also allow us to recognize complex activities like, for example, the activity of “going to a pub together”: single persons walking can be a simple fragment of a more complex activity that includes some people meeting, going in the same direction, waiting each other at different points and entering together into the pub.

In our work, we use the *relationships* between objects in two principal ways: (1) we use relations to *improve the efficiency of the tracking*; this information can improve prediction, resulting in a better estimation of objects trajectories and (2) we monitor relations to *improve activity recognition*.

We use Relational Dynamic Bayesian Networks [2] to represent the dependencies between objects’ behaviors in the context of multi-target tracking. We propose a new formulation of the transition model and we extend the Particle Filter algorithm in order to directly track relations between targets. Many applications, for instance activity recognition, traffic monitoring, strategic analysis and sport coaching, can benefit from this work.

2 Relational Particle Filter

A *relational domain* consists of a set of objects and relations (propositions about the objects). We call the state s_t of a relational domain *relational state*, and we define it as the set of instantiations of all the objects and their relations in the domain at time step t . Therefore, we can divide the relational state into two parts: the *state of the objects* s_t^o and the *state of the relations* s_t^r ; we write: $s_t = [s_t^o, s_t^r]$.

In order to make inference in a multi-target setting, we need to extend the conventional algorithms to represent relations. As in classic tracking, the aim is to estimate the current posterior distribution of the state s_t conditioned to the sequence of observations $z_{1:t}$ up to time t : $Bel(s_t) = p(s_t|z_{1:t})$. The tracker *predicts* the probability distribution of the state s_t , given the knowledge about the current state s_t , with a *state transition model* $p(s_t|s_{t-1})$. Once measurements about the state at time t (z_t) are acquired, the state is *filtered* using the *sensor model* $p(z_t|s_t)$ that relates (potentially noisy)

measurements to the state. To extend the traditional tracking algorithms to represent relations we introduce the following components:

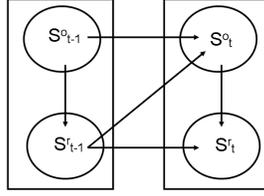


Figure 1: Relational Transition Model. Arrows indicate probabilistic dependence between variables.

The relational transitional model $p(s_t|s_{t-1}) = p(s_t^o, s_t^r|s_{t-1}^o, s_{t-1}^r)$, is a joint probability of the state of all instances and relations. We assume that the state of relations is not directly affected by the state of the objects at the previous time step, therefore the transition model can be rewritten as:

$$p(s_t^o, s_t^r|s_{t-1}^o, s_{t-1}^r) = p(s_t^o|s_{t-1}^o, s_{t-1}^r)p(s_t^r|s_{t-1}^r, s_t^o). \quad (1)$$

The sensor model $p(z_t|s_t)$, gives the probability of the state at time t given the measurements obtained at the same time step. We assume the relations to be not directly measurable, so the observation z_t is independent of the relations between objects:

$$p(z_t|s_t) = p(z_t|s_t^o, s_t^r) = p(z_t|s_t^o). \quad (2)$$

Under the Markov assumption and the conditional independence of the data given the state, we can use a *Bayesian filter algorithm* to compute the belief of the relational state:

$$bel(s_t) = \alpha p(z_t|s_t^o) \int p(s_t^o|s_{t-1}^o, s_{t-1}^r)p(s_t^r|s_{t-1}^r, s_t^o)bel(s_{t-1})ds_{t-1}. \quad (3)$$

where α is a normalization constant.

The specific and complex probabilistic nature of the presented setting makes it impossible to use filters that require a probabilistic function in closed form, such as the Kalman filter. To resolve this issue we integrate the relational transitional model introduced in Equation (1) in a new *Relational Particle Filter* (RPF), shown in Algorithm (1).

Algorithm 1: Relational Particle Filter algorithm

- $bel(s_t) = RPF(bel(s_{t-1}), z_t)$
- for all** $m = 1 : M$ **do**
1. $x_{t,(m)}^o \sim p(s_t^o|s_{t-1}^o, s_{t-1}^r)$; hypothesis for the state of instantiations
 2. $x_{t,(m)}^r \sim p(s_t^r|s_{t-1}^r, s_t^o = x_{t,(m)}^o)$; hypothesis for the state of relations
 3. $\omega_{(m)} = p(z_t|x_{t,(m)}^o)$; weights computation
- for all** $m = 1 : M$ **do**
4. $\tilde{\omega}_{(m)} = \frac{\omega_{(m)}}{\sum_{m=1}^M \omega_{(m)}}$; weights normalization
 5. Resample $bel(s_t)$ from $\{[x_{t,(m)}^o, x_{t,(m)}^r]\}$ according to weights $\{\tilde{\omega}_{(m)}\}$ with repetition.
-

A particle $(x_{t,(m)})$ is a representation of the state. In our setting, it is divided into two parts: the part of the objects $x_{t,(m)}^o$ and the part of the relations $x_{t,(m)}^r$. The part of the particle relative to the instantiations is sampled according to $p(s_t^o|s_{t-1}^o, s_{t-1}^r)$ (Line 1), subsequently the part of the particle relative to the relations is sampled according to the second part of the relational transition model (Line 2). When the measurement is acquired, particles are weighted according to the sensor model (Line 3). The sensor model takes into account only the part of the particles relative to the objects. Since the particles are composed of two parts, also the parts associated to the relations are weighted. After the weighting step, weights are normalized (Line 4) and particle are resampled (Line 5).

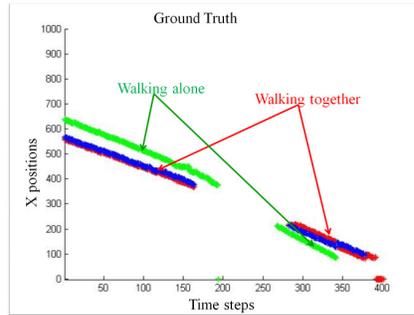
3 Experiments

We validate our approach on two problems. The first one is the problem of activity recognition in the sea navigation domain. We compared the performance of our RPF for the recognition of the activity of “rendezvous” between two ships, with the performance of a Hidden Markov Model (HMM). Our RPF distinguishes between positive (“rendezvous”) and negative examples much better than an HMM, resulting in an F-measure that is almost 20% higher than that obtained with HMM.

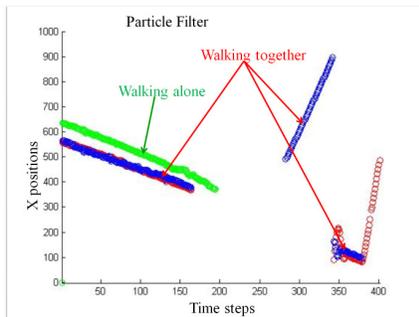
The tracking ability of the RPF is evaluated on the problem of tracking three people: two people are walking together and enter a “blind spot” first but the one person, walking alone, exits the “blind spot” first (i.e., in the blind spot the three people exchange order). The graphs in Figure 3 show that our RPF, taking into account the fact that people that are walking together are most likely to continue to walk together and has a similar motion, have a performance that is higher than a standard PF.



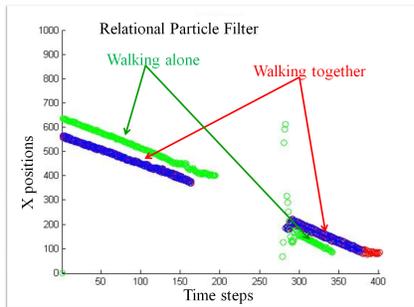
(a) A video clip of the problem.



(b) The real tracks of the three people.



(c) A standard Particle Filter.



(d) Our Relational Particle Filter.

This paper is the first to provide a model of the dynamic of the relations between moving objects in the scene. The algorithm introduced provides a solution to the problem of multi target tracking and activity recognition for objects that show joint behaviors. Moreover, modeling relations solves the problem of associating objects with observations during time in situations of lack of information (e.g. the blind spot example).

References

- [1] Manfredotti, C.E., Messina, E.: Relational dynamic bayesian networks to improve multi-target tracking. In Blanc-Talon, J., Philips, W., Popescu, D.C., Scheunders, P., eds.: ACIVS. Volume 5807 of Lecture Notes in Computer Science., Springer (2009) 528–539
- [2] Manfredotti, C.: Modeling and Inference with Relational Dynamic Bayesian Networks. PhD thesis, Computer Science Department, University of Milano-Bicocca, Italy (2009)