Group Object Tracking with Sequential Monte Carlo Methods Based on a Parameterised Likelihood Function

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Outline

Motivation

Background (1)

- W. Koch and M. Feldmann. Cluster tracking under kinematical constraints using random matrices. *Robotics and Autonomous Systems*, 57(3):296 – 309, 2009.
- M. Baum, M. Feldmann, D. Fränken, U. D. Hanebeck, and W. Koch. Extended Object and Group Tracking: A Comparison of Random Matrices and Random Hypersurface Models. *In LNCS, 2010*.
- K. Gilholm and D. Salmond. Spatial Distribution Model for Tracking Extended Objects. *IEE Proc.-Radar, Sonar Navig.*, 152(5):364–371, 2005.

Background (2)

- M. Baum and U. D. Hanebeck. Extended Object Tracking based on Combined Set-Theoretic and Stochastic Fusion. In *Proc. of the International Conf. on Information Fusion*, 2009.
- D. Angelova and L. Mihaylova. Extended Object Tracking Using Monte Carlo Methods. *IEEE Transactions on Signal Processing*, 56(2):825–832, 2008.
- A. Gning, L. Mihaylova, S. Maskell, S.K. Pang, and S. Godsill. Group Object Structure and State Estimation With Evolving Networks and Monte Carlo Methods. *IEEE Trans. on Signal Processing*, 59(4):1383 –1396, 2011.
- PHD Filters - Mahler, Vo, Ristic, Willett, Clark, Koch, Gustafsson, etc.

Goals and Contributions

Goals

Set a framework for group object tracking based on:

- nonlinear system dynamics model,
- nonlinear measurement,
- arbitrary noise distribution.

Contributions

Introducing a sampling step for regions of interest in the group regions using the Sequential Monte Carlo approach.

Derivation of the likelihood function.

SMC Framework

$\boldsymbol{X}_k^g = \left(\boldsymbol{x}'_{1,k}, ..., \boldsymbol{x}'_{t,k}, ..., \boldsymbol{x}'_{n_T^g,k}, \boldsymbol{G}_k\right)'$, where

- $\boldsymbol{x}_{t,k}$ - the state vector of the t^{th} target, $t = 1, ..., n_T^g$, at time k
- $\boldsymbol{G}_k$ is a vector characterising the group

The system dynamics is given by:

$\boldsymbol{X}_k^g = f(\boldsymbol{X}_{k-1}^g, \boldsymbol{\eta}_{k-1})$, where $\boldsymbol{\eta}_k$ is the system noise.

The sensors measurements are described as:

$$\boldsymbol{Z}_k = h(\boldsymbol{X}_k^g, \boldsymbol{w}_k),$$

where $\boldsymbol{w}_k$ is the measurement noise and $\boldsymbol{Z}_k = \{\boldsymbol{z}_{m,k}\}_{m=1}^{M_k}$ is the set of measurements from the objects received at time step k.

Estimate: $p(\boldsymbol{X}_k^g | \boldsymbol{Z}_{1:k})$

SMC Framework

The posterior state PDF is estimated given the data $\boldsymbol{Z}_{1:k} = \boldsymbol{Z}_1, ..., \boldsymbol{Z}_k$, in two steps:

- prediction:

$$p(\boldsymbol{X}_k^g|\boldsymbol{Z}_{1:k-1}) = \int p(\boldsymbol{X}_k^g|\boldsymbol{X}_{k-1}^g)p(\boldsymbol{X}_{k-1}^g|\boldsymbol{Z}_{1:k-1})d\boldsymbol{X}_{k-1}^g,$$

- update:

$$p(\boldsymbol{X}_k^g|\boldsymbol{Z}_{1:k}) = \frac{p(\boldsymbol{Z}_k|\boldsymbol{X}_k^g)p(\boldsymbol{X}_k^g|\boldsymbol{Z}_{1:k-1})}{p(\boldsymbol{Z}_k|\boldsymbol{Z}_{1:k-1})},$$

where $p(\boldsymbol{Z}_k|\boldsymbol{Z}_{1:k-1})$ is the normalising constant.
The number of measurements $M_{t,k} \sim Poisson(\lambda_t)$

$$p(\boldsymbol{Z}_k|\boldsymbol{x}_{t,k}) = \prod_{m=1}^{M_{t,k}} p(\boldsymbol{z}_{m,k}|\boldsymbol{x}_k).$$

They are independent!

Likelihood Function Based on Surface Parametrisation

Using the Chapman-Kolmogorov equation we introduce the measurement sources $\boldsymbol{V}_k \in \mathcal{V}_k(\boldsymbol{X}_k^g, \boldsymbol{x}_{s,k})$,:

$$p(\boldsymbol{z}_{m,k}|\boldsymbol{X}_k^g) = \int_{\mathbb{R}^{n_\mathrm{V}}} p(\boldsymbol{z}_{m,k}|\boldsymbol{V}_k)p(\boldsymbol{V}_k|\boldsymbol{X}_k^g)d\boldsymbol{V}_k,$$

where

- $p(\boldsymbol{z}_{m,k}|\boldsymbol{V}_k)$ is the probability of receiving the measurement $\boldsymbol{z}_{m,k}$ if the actual source of it is $\boldsymbol{V}_k$;
- $p(\boldsymbol{V}_k|\boldsymbol{X}_k^g)$ is the probability of a point in the state space to be a source of measurement given the group object $\boldsymbol{X}_k^g$.

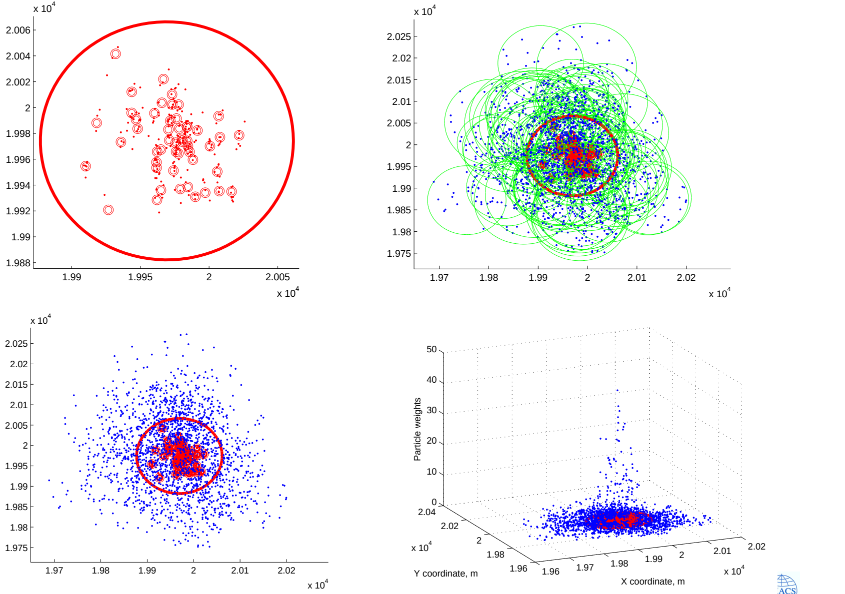
Parameterisation of the Visible Surface

$$p(\boldsymbol{z}_{m,k}|\boldsymbol{X}^{g(i)}_{k|k-1}) = \int_{\mathbb{R}^{n_x}} p(\boldsymbol{z}_{m,k}|\boldsymbol{V}_k)p(\boldsymbol{V}_k|\boldsymbol{X}^{g(i)}_{k|k-1})d\boldsymbol{V}_k$$
$$\approx \sum_{\ell=1}^{S} p(\boldsymbol{z}_{m,k}|\boldsymbol{V}^{(\ell)}_k)p(\boldsymbol{V}^{(\ell)}_k|\boldsymbol{X}^{g(i)}_{k|k-1}).$$

For example

$$p(\boldsymbol{z}_{m,k}|\boldsymbol{V}^{(\ell)}_k) = \frac{1}{\sqrt{2\pi||\boldsymbol{R}||}} e^{-\frac{(\boldsymbol{z}_{m,k}-\boldsymbol{z}^{(\ell)}_k)\boldsymbol{R}^{-1}(\boldsymbol{z}_{m,k}-\boldsymbol{z}^{(\ell)}_k)^T}{2}};$$

$$p(\boldsymbol{V}^{(\ell)}_k|\boldsymbol{X}^{g(i)}_{k|k-1}) = \mathcal{U}_{\mathcal{C}(x^{(i)}_{c,k},y^{(i)}_{c,k},r^{(i)}_{k|k-1})}\left(\sqrt{(x^{(\ell)}_k - x^{(i)}_{c,k})^2 + (y^{(\ell)}_k - y^{(i)}_{c,k})^2}\right).$$


x 10^4
2.006
2.004
2.002
2
1.998
1.996
1.994
1.992
1.99
1.988
1.99
1.995
2
2.005
x 10^4
2.025
2.02
2.015
2.01
2.005
1.995
1.985
1.98
1.975
1.97
2.01
2.02
Particle weights
50
40
30
20
10
0
2.04
Y coordinate, m
X coordinate, m
1.96

Scenario

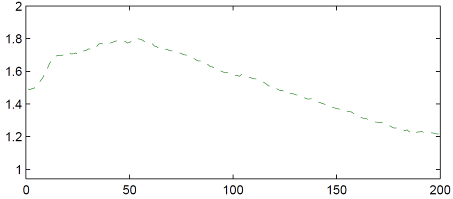
- one group of objects
- nearly constant velocity motion model for the individual targets;
- circular shape surrounding the group;
- range and bearing measurements;
- multiple sensors observe the objects in the group
- the number of measurements is $\sim$ Poisson(5);
- 200 time steps each repeated for 30 iterations;
- 100 group object particles;
- 20 samples per particle;

Results (video)

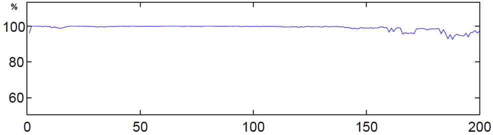
(Loading GroupExample.avi)

Results

Performance evaluation averaged over 30 runs:



Ratio between the estimated extent and the optimal extent



Percentage of targets inside the group extent

Summary

- In this paper we cope with the problem of having *multiple measurements* from a large number of objects with coordinated *group movement* by deriving an expression for the *likelihood function* based on *surface parametrisation*.
- The algorithm is presented in a general framework using *nonlinear measurements* and *nonlinear system model* as well as *noise with arbitrary distribution*.
- We show how the data *association problem* could be *facilitated* using the likelihood representation.

Future Work

- More complex target shapes (i.e. ellipse, freeform shapes)
- Better sampling in the group region
- Variable number of particle/samples, use of box particles
- Clutter scenarios
- Multiple groups and interactions between them
- Estimation of the number of targets

Thank you for your attention!