Testing A Particle Filtering Approach as a Means of Data Assimilation for Agent-Based Modelling *

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Abstract. XX ABSTRACT

Keywords: Agent-based modelling · Particle Filter · Uncertainty · Data assimilation · Bayesian inference

1 Introduction

XXXX Introduction

2 Background

– How people have tried to do state (and parameter?) estimation in ABMs before
– Difference between normal parameter estimation with a (e.g.) GA and dynamic state estimation
– Data assimilation methods, focussing on Particle Filter
– Data assimilation methods in ABM (will be brief!)

3 Method

– Intro to station sim. Point to ODD
– Intro to particle filter
– Outline of experiments, including criteria to measure 'success' of the PF

3.1 StationSim

XXXX outline stations sim

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3.2 Data Assimilation - Introduction and Definitions

XXXX Outline how data assimilation method works broadly (e.g. *update* and *predict*) and define general concepts / objects.

Here, the *state vector* contains all the information that a transition function needs to iterative the model forward by one step, including all of the agent ($i = \{0, 1, \ldots, N\}$) parameters ($\overrightarrow{p_i}$) and variables ($\overrightarrow{v_i}$) as well as global model parameters $\overrightarrow{P}$:

$$S = \left[\, \overrightarrow{p_0} \; \overrightarrow{v_0} \; \overrightarrow{p_1} \; \overrightarrow{v_1} \; \ldots \; \overrightarrow{p_N} \; \overrightarrow{v_N} \; \overrightarrow{P} \,\right] \tag{1}$$

The *observation vector* contains all of the observations made from the 'real world' (in this case the pseudo-truth model) that the particle filter uses to predict the current true state, with the addition of some Gaussian noise, ϵ:

$$O = \left[\, x_0 \; y_0 \; x_1 \; y_1 \; \ldots \; x_n \; y_n \,\right] \tag{2}$$

In this paper, the particle filter is not used to estimate the state of the models variables ($\overrightarrow{v_i}$), not any of the parameters ($\overrightarrow{p_i}$ and $\overrightarrow{P}$) – although it is worth noting that parameter estimation is technically feasible and will be experimented with in later iterations of this work. Here a further vector is required to map the observations to the state vector that the particle can actually manipulate. We define the partial state vector S_{partial} to match the shape of O, i.e.:

$$S_{\text{partial}} = \left[\, x_0 \; y_0 \; x_1 \; y_1 \; \ldots \; x_n \; y_n \,\right] \tag{3}$$

4 Experiments

4.1 Experiments with Uncertainty

Purpose here is basically to see how the particle filter behaves when we give it l

1. Randomness in particles
2. Measurement noise (external)
3. Internal randomness (e.g. in agent behaviour)
4. (Simultaneous combinations of different randomness)

4.2 Experiments with Measurement Noise

1. Reduce the amount of information given to the particle filter (e.g. only allow it to optimise half of the state vector).
2. Aggregate the measurements (e.g. counts per area rather than individual traces).

5 Conclusion

XXXX Conclusion