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Data assimilation in agent based simulation of smart environments using particle filters

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ABSTRACT

Agent-based simulations are useful for studying people's movement and to help making decisions in situations like emergency evacuation in smart environments. These agent-based simulations are typically used as offline tools and do not assimilate real time data from the environment. With more and more smart buildings equipped with sensor devices, it is possible to utilize real time sensor data to dynamically inform the simulations to improve simulation results. In this paper, we propose a method to assimilate real time sensor data in agent-based simulation of smart environments based on Particle Filters (PFs). The data assimilation aims to estimate the system state, i.e., people's location information in real time, and use the estimated states to provide initial conditions for more accurate simulation/prediction of the system dynamics in the future. We develop a PF-based data assimilation framework and propose a new resampling method named as component set resampling to improve data assimilation for multiple agents. The proposed framework and method are demonstrated and evaluated through experiments using a sparsely populated smart environment.

1. Introduction

Location information of occupants in building structures is useful for supporting decision makings such as scheduling efficient energy utilization and developing emergency evacuation strategies. Agent-based simulation is an important tool for studying the dynamics of people's movement in building structures [6,20]. It uses a bottom up approach to model individuals' behavior and their interactions with the environment, and can provide valuable information for helping system design. While many agent-based simulations have been developed, they are typically used as offline tools and do not utilize real time data of building environments. With advances of sensor and communication technologies, more and more building environments are equipped with sensors that provide real time information about the environment. In this paper, we refer to indoor building environment equipped with sensors as smart environment. With real time data provided by sensors, how to dynamically assimilate these data into simulation to support real time decision making becomes an important research topic.

Data assimilation refers to the process of incorporating observation data into a running model to produce improved estimates of interested state variables [29,30]. It is made necessary by the fact that no model is perfect, and therefore there is a need to obtain the best estimates of states (which are usually unobservable) of a dynamic system by incorporating

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observations into a model of the system. Data assimilation has gained much success in weather forecast and many geoscience fields. In this paper, we develop a data assimilation method for agent-based simulation of smart environments. The data assimilation aims to dynamically adjust the simulation to achieve more accurate simulation/prediction of people's movement in smart environments and thus to support real time decision makings. This is in contrast to traditional off-line simulation, where a simulation starts from an initial state and is not influenced by real time data during the simulation. With data assimilation, real time sensor data are assimilated to estimate the "current" system state. The estimated system states are then used to provide initial conditions for running simulations that simulate/predict the system dynamics in the future. Because the initial states are dynamically estimated from real time sensor data, simulations starting from these initial states will lead to more accurate simulation/prediction results. We note that this work is different from the work of dynamically calibrating or modifying the agent-based model based on real time data. In our work, the model is not dynamically changed. Instead, the simulation is dynamically reset to start from initial conditions that are estimated from real time sensor data, and thus the simulation/prediction results are dynamically adjusted in real time. Also note that even though this work does not calibrate the agent-based model over time, it is possible to treat some of the model parameters as part of the system state and dynamically estimate (calibrate) those parameters based on real time sensor data.

Data assimilation relies on several elements to work, including the sensor data that provides real time observation of the system under study, the simulation model that captures the system dynamics, and the data assimilation algorithm for carrying out state estimation. Various sensor devices exist in smart environments. High resolution sensor devices such as video cameras provide more precise measurement; however they are often intrusive and incur high cost. In this paper, we consider binary proximity sensors that are low cost and provide non-intrusive information. Besides sensor data, the quality of the agent-based simulation model also has an impact on data assimilation results. Many agent-based simulation models have been developed in the literature for simulating people's movement. Since the main focus of this paper is on the data assimilation framework instead of the agent-based model, we develop data assimilation based on a relatively simple agent-based model. In this model, each agent is specified by several basic behaviors that simulate people's movement in smart environments. We note that the developed data assimilation framework is not restricted to the agent-based model and sensor data used in this paper – it can be adapted to work with other models and sensor data. The state estimation algorithm is another key component of data assimilation. A unique feature of the agent-based simulation model is that the model is specified by behaviors or rules and lacks the analytic structures (e.g., those in partial differential equation models) from which functional forms of probability distributions can be derived. This makes it difficult to apply conventional state estimation techniques such as Kalman filter and its variances. In our work, we carry out state estimation using Particle Filters (PFs), which are a set of sample-based methods that use Bayesian inference and stochastic sampling techniques to recursively estimate the state of dynamic systems from some given observations [8,27]. PFs approximate the sequence of probability distributions of interest using a large set of random samples, named particles, each of which represents an estimation of the system state. PFs are non-parametric filters and thus work well with the agent-based simulation model.

Based on PFs, this paper develops data assimilation for agent-based simulation of smart environments. We first present the data assimilation framework based on the bootstrap filter algorithm [8]. Within this framework, the system state is composed from the states of all agents, and the state transition function is defined based on the agent-based simulation model. One issue associated with the standard bootstrap filter algorithm is that it suffers from the particle deprivation problem due to the high dimensional system state associated with multiple agents. In this paper, observing that the high dimensional system state is composed from states of individual agents (where each agent's state variables can be thought of as one component of the overall system state), we propose a PF algorithm with a new resampling method named as *component set resampling*. In the proposed component set resampling, instead of resampling each particle as a whole as in standard particle filters, we divide the system state into sub-components and resample at the component level to "construct" new particles. The goal is to use the same number of particles to represent more possible combinations of system state variables, and thus alleviate the particle deprivation problem. We show how the component set resampling can work together with the standard resampling to support data assimilation for agent-based simulation of smart environments. Experiment results based on a sparsely populated smart environment are provided to demonstrate the proposed data assimilation framework and method. This paper makes contributions in the following two aspects: (1) it develops a data assimilation framework for agent-based simulation of smart environments and (2) it proposes a new resampling method (the component set resampling) to improve data assimilation for multiple agents. As far as we know, this is one of the first efforts that assimilate real time sensor data in agent-based simulation of smart environments.

The rest of this paper is organized as follows: Section 2 presents the related work. Section 3 describes the smart environment and the agent-based model used in this work. Section 4 presents the data assimilation framework. Section 5 shows experiment results and analysis. Section 6 provides some discussions of this work, and Section 7 concludes this work.

2. Related work

A smart environment is equipped with sensors that provide information about the environment to help accomplishing tasks such as navigation, energy consumption scheduling, activity notification, and evacuation planning. Occupants' location information is one of the most important information that one would like to derive from the sensors because occupancy is directly related to many aspects of the contextual information of a building. One research topic related to deriving moving