Simulation-Based Behavior Tracking of Pedestrians in Partially Observed Indoor Environments

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ABSTRACT

Tracking and understanding moving pedestrian behaviors is of major concern for a growing number of applications. This problem, known as difficult, is more complex when the considered environment is not fully under sensory coverage. Classical approaches either focus on location estimation or attempt to build the relationship between possible activities in the environment and reason on it, which may turn out to be inadequate. In this paper, we propose an approach based on behavioral models from the situated artificial intelligence field, which aim to realistically reproduce human behaviors within complex environments. We focus on the special case of a single target and experimentally show that we are performing well even in case of long periods of occlusion.

Keywords

Behavior Tracking - Autonomous Agent-based simulations - Situated Artificial Intelligence - Particle filter

1. INTRODUCTION

The ability of using sensor networks to track and understand the behavior of moving human beings is of great importance for surveillance applications. When sensors are cameras, this implies retrieving behavioral information from image analysis. This is not a trivial task to perform, even for humans, and interpretation errors are common.

Moving pedestrians are usually driven by an inner motivation in relation with the activity they want to perform. Therefore, location and intent (motivation) are contextually dependent, and the knowledge of one may help predict the other. In the literature, people tracking has usually been addressed using Bayesian filters [2], which require the use of models representing the target's behavior. It is a common consensus that the more realistic the models used, the better the tracking results.

Nowadays, the use of simulators to generate realistic human behaviors in indoor environments has become very popular. Works from the situated artificial intelligence field have focused on designing virtual agent control architectures (behavior models) based on sensorimotor loops [1] whose purpose is to define, at any time, the action an agent will perform according to his perceptions, thus making him adaptive and autonomous in fulfilling a sequence of activities (subgoals) aiming at a particular goal.

In this paper, we consider integrating simulators implementing such architectures within a Bayesian filter (approximated by a particle filter) for the analysis of people intents. We focus on the single-target case and experimentally show that we are able to infer relevant information regarding the target behavior even with long periods of occlusion.

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2. AGENT-BASED BEHAVIOR TRACKING

2.1 Process Overview

The proposed solution is represented in Fig. 1. The simulator is assumed to handle virtual-agent navigational features and object-agent interactions (e.g., escalators). It is used during the prediction step to estimate the belief regarding both the aimed location and the activity of the target.

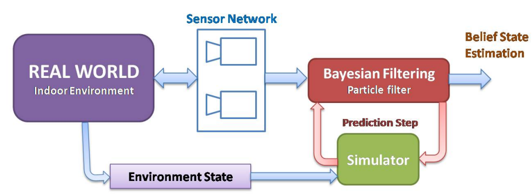

Figure 1: Process overview

Observations received from the sensors are typically noisy location data of the detected target. Furthermore, the simulator is fed with changes occurring in the real world (e.g., escalator failures, fire alerts) in order to preserve coherence with the simulated environment.

Next, we describe the models used in the filter.

2.2 Models

2.2.1 *System Dynamics*

Given a behavioral model, a state $\mathbf{x}_t$ of an agent contains all the attributes that are taken into account during the decision-making process. We assume that an agent cannot change the state of objects he may interact with. The system dynamics is fully encoded within the simulator. The latter takes as input the agent state $\mathbf{x}_t$ and the environment state $\mathbf{E}_t$ and modifies the agent's inner attributes, that is

$$\mathbf{x}_{t+1} \sim f(\mathbf{x}_t, \mathbf{E}_t),$$

where f is the implemented simulator stochastic function.