Stochastic Robot Behaviors through Extended Hidden Markov Models

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***Abstract*—Traditional approaches to robot navigation, such as Hidden Markov Models (HMMs) and Markov Decision Processes (MDPs), primarily focus on capturing uncertainty and stochasticity in the operational environment while maintaining deterministic actions based on the robot's belief state. We propose a methodology embracing uncertainty also in the reactive behavior of the robot, resulting in stochastic behavior, thus making the robot act differently under the same conditions. We argue that this produces rich information, often sufficient for effective navigation without explicit maps. This approach significantly reduces the computational burden on the agent and simultaneously mitigates undesirable behaviors arising from deterministic policies under environmental perception uncertainty. We control the reactive navigation of a mobile robot using a Probabilistic Finite-State Machine implemented as an Extended Hidden Markov Model (EHMM). We build the EHMM behaviors using a genetic algorithm to find the best models. We compare this approach with a robot behavior implemented with an MDP, whose parameters are also found by a genetic algorithm. Our method outperforms the MDP one in some cases.**

***Index Terms*—Robot Behaviors, Hidden Markov Models, Markov Decision Process, Evolutionary Algorithms.**

I. Introduction

OVER the course of extensive research in robot navigation spanning many years, numerous algorithms have emerged for robot exploration in unfamiliar environments. Many of these algorithms rely on finite-state machines (FSMs). In these algorithms, a robot, assuming minimal or no errors in sensor readings and motion, and operating under identical initial conditions, should consistently follow a deterministic path due to the controlling algorithm's predictability. This deterministic approach suffers from two drawbacks. On the one hand, while a deterministic behavior proves beneficial for certain applications, it is often preferable, especially in the context of exploring novel environments, for the robot to exhibit a varying behavior under similar conditions. For instance, this variation allows the robot to construct a comprehensive map of its surroundings by systematically aggregating uncharted areas. On the other hand, a deterministic FSM may yield undesirable behaviors caused by the random nature of the input variables, such as making the FSM go to a wrong state or generating a wrong ouput. We study the use of a probabilistic finite-state machine (PFSM) for solving both these problems. Not only is a PFSM able to produce the desired variability in behavior, but is better suited for handling randomness of the inputs.

We constructed these behaviors by adapting hidden Markov models (HMMs), and used an optimization procedure employing genetic algorithms to identify the most effective models. To evaluate this approach, we conducted a comparison with a mobile robot behavior that relies on a Markov decision process (MDP), where the parameters are likewise determined through a genetic algorithm. Our initial step involved training both evolved systems within a simulated environment. Subsequently, we assessed the performance of the top-performing models across various unfamiliar scenarios. This evaluation enabled us to contrast the effectiveness of each system, specifically the evolved PFSMs versus the MDPs, revealing the superior performance of the former in some cases over the latter.

The remaining of the paper is structured as follows: After presenting related work in II we review FSMs in Section III. Section IV describes the creation of navigation behaviors using our proposed extended version of HMMs. Section VI describes the creation of navigation behaviors using MDPs. The finding of optimized parameters of the PFSMs and MDPs for mobile robots behaviors using genetic algorithms (GAs) is in Section VII. We proceed, in Section VIII, with the experiments and results. This contribution finishes with a summary of results in Section IX and concluding remarks in Section X.

II. Related work

Within the realm of mobile robotics, behaviors play a crucial role in facilitating navigation, with some of these methods being implementable through state machines. In the 1980s, Brooks introduced a novel robotics paradigm aimed at controlling robots [1]. This paradigm involves the creation of robot behaviors through augmented state machines (AFSMs). By interconnecting these AFSMs, each housing a specific behavior, robots can attain emergent intelligence. In this architecture, the influence of each robot behavior, represented by AFSMs, is contingent on their position within the system hierarchy, as well as their inputs and outputs, making it possible for certain AFSMs to override others. One way to implement FSM behaviors is using recurrent neural networks (RNNs) [2]. In

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