Reinforcement Learning in Fog-based Internet-of-Things: Applications and Research Issues

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***Abstract*—Reinforcement learning (RL) algorithms are the platform for connecting intelligent Internet-of-Things (IoT) devices. The data provided by these intelligent devices can offer more insights about the overall futuristic functionalities in terms of usage and preferences. Machine learning algorithms have been widely used for predictions, with several optimization algorithms using reinforcement learning techniques to improve the performance and interaction of devices within a dynamic IoT ecosystem. In this paper, we present a comprehensive review of state-of-the-art RL techniques that have been applied to solve trending problems in the IoT and cyber-physical systems domain. Furthermore, we give an in-depth analysis into its applications in the emerging fog-based IoT networks. Finally, we propose alternative research directions that may yield better outcomes.**

***Index Terms*—Reinforcement learning (RL), Internet-of-Things (IoT), Fog-based IoT, Markov decision process (MDP), machine learning (ML).**

I. IDEAS1

A. Problem Formulation

Devices/agents in an IoT network are resource-constrained, as such, it will be proper to deploy lightweight RL-based techniques that will improve the performance of the network. Furthermore, we may have to experiment on a very dynamic environment considering factors that depict a realistic IoT scenario to meet strict quality-of-service requirements.

In this work, a finite-horizon MDP is considered with continuous state and action spaces defined by the tuple $\langle \mathcal{S}, \mathcal{A}, p, p_0, \mathcal{P}_{out}, \gamma \rangle$, where $\mathcal{S}$ is the set of states, $\mathcal{A}$ is the set of actions, $p : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to \mathbb{G}^+$ is the conditional probability density over successor states given the current state and action, $p_0 : \mathcal{S} \to \mathbb{G}^+$ is the probability density over initial states, $\mathcal{P}_{out}$ is a function that maps state to cost, and the discount factor is $\gamma \in (0, 1]$. In the RL techniques, the agent has a choice to take certain actions in each time step, causing the environment to respond with new conditions, and consequently, the agent receives reward for that action as a form of feedback. The reward could be positive, negative or even zero, and the main objective of the agent is to maximize the positive reward or minimize the negative reward (often the cost) over the entire time step N.

Our objective is to learn a stochastic policy $\pi^* : \mathcal{S} \times \mathcal{A} \to \mathbb{G}^+$, which is a conditional probability density over the present state, in such a way as to minimize the expected cumulative cost.

$$\pi^* = \arg\min_{\pi} \mathbb{E}_{s_0, a_0, s_1, a_1, \ldots, s_N} \left[\sum_{i=0}^{N} \gamma^i \mathcal{P}_{out}(s_i) \right], \quad (1)$$

We take the expectation over the joint distribution of all state-action pairs, with the density give as,

$$q(s_0, a_0, s_1, a_1, \ldots, s_N) = p_0(s_0) \prod_{i=0}^{N-1} \pi(a_i|s_i) p(s_{i+1}|s_i, a_i). \quad (2)$$

Fig. 1 shows a dynamic IoT environment with an IoT sensor attempting to request some services from a remote target fog agent/node through randomly deployed fog devices. The devices act as relays to forward traffic from the source

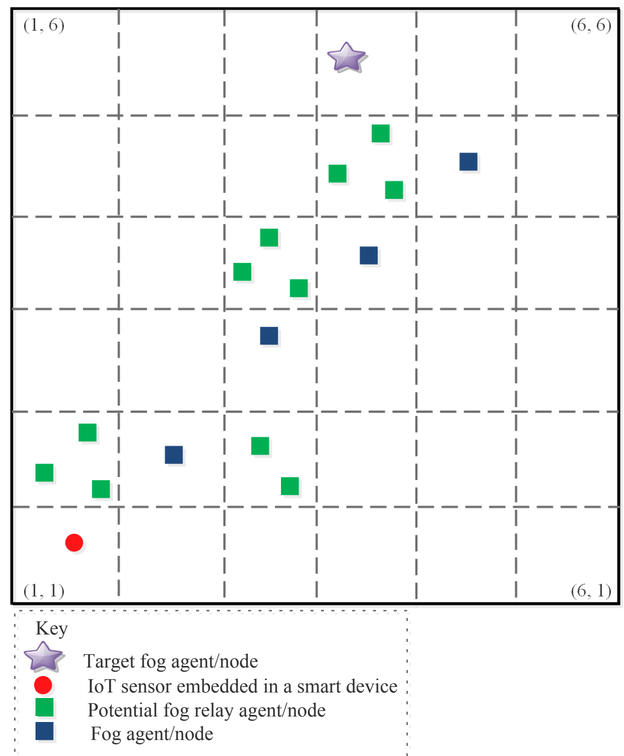

Fig. 1. System model depicting the role of fog agents in a dynamic and heterogenous IoT environment.

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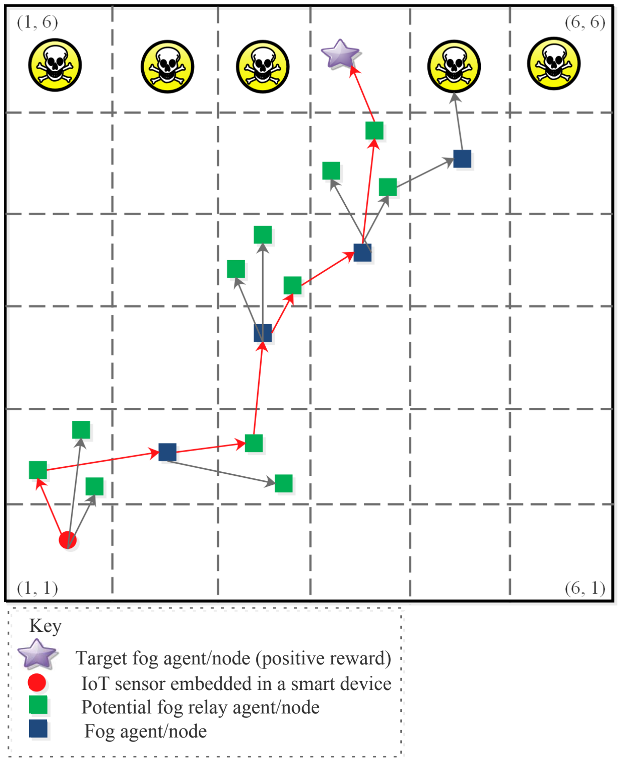

Fig. 2. System model depicting the role of fog agents in a dynamic and heterogenous IoT environment with a route policy in red.

to the destination. However, based on their position, line-of-sight(LoS) obstruction, which affect the conditions of the wireless channel, some degree of communication outage may occur. Our aim is to ensure that the agents are able to learn the optimal route to take through their experience with the environment.

II. Ideas2

III. Ideas3

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