An Adaptive QoE-Based Network Interface Selection for Multi-homed eHealth Devices

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Abstract. Conventional network control mechanisms are no longer suitable for Internet of Things (IoT) because they don't allow scalability with a guarantee of Quality of Experience (QoE) especially when it comes to the health sector characterized by its real time and critical life aspects. That's why we need to think differently about control. One aspect consists of improving the network accessibility by considering Multi-homed terminals using multiple network access points simultaneously. In this paper we present a new Q-Learning-based adaptive network interface selection approach. Experimental results show that the proposed approach involve QoE compared to a simple linear programming approach. *abstract* environment.

Keywords: Reinforcement Learning · Q-learning · Quality of Experience · Mean Opinion Score (MOS) · Multi-homed devices · ICT health · Internet of Things (IoT)

1 Introduction

ICT health is a part of a new paradigm called the Internet of Things (IoT) [1]. The role of IoT in the current networks are expanding in terms of communicating things such as smart devices, gadgets, on-body sensors, cameras, and also in terms of applications and services (see Fig. 1).

Therefore, conventional network control mechanisms are no longer suitable because they don't permit scalability with a guarantee of Quality of Experience (QoE) especially when it comes to the health sector, which is characterized by its real time and critical life aspects. That's why we need to think differently about control mechanisms and protocols in the perspective of adaptive and autonomous aspects, that guarantee the high QoE. To achieve this goal, we shall improve the network accessibility by considering Multi-homed terminals using multiple network access points simultaneously (see Fig. 2). The Multi-homed methodology [2] provides the flexibility to select the best available network access points (e.g. wired or wireless include WiFi, 3G, 4G, WLAN, Satellite, etc.) for efficiently transport of information data. In such environment, the major issue is Always

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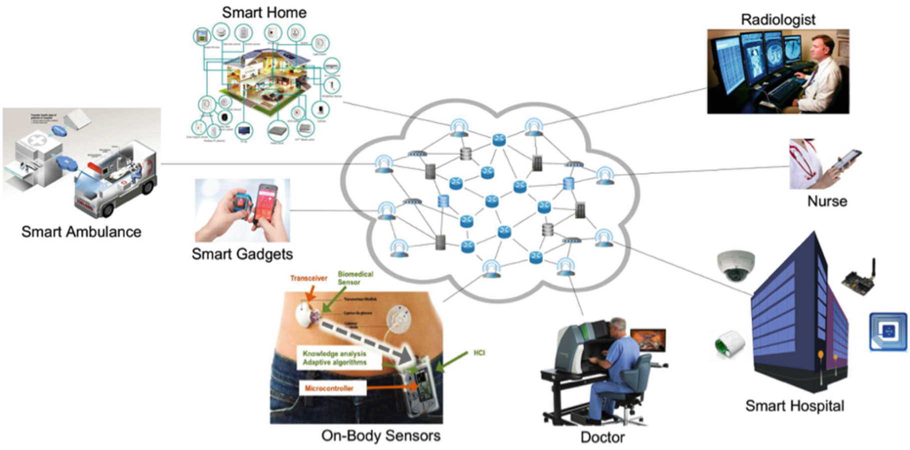

Fig. 1. IoT health network

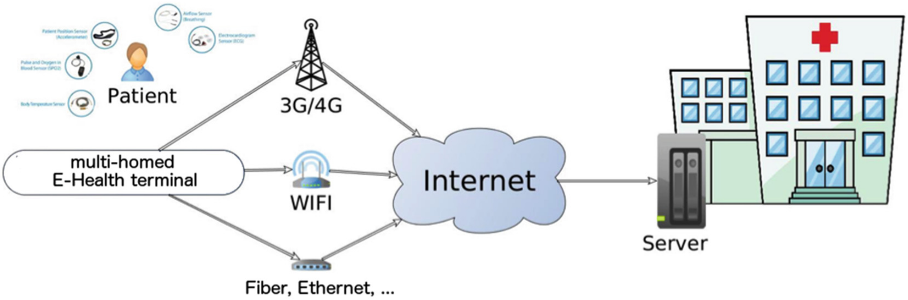

Fig. 2. Multi-homed IoT health device

Best Connected (ABC), which means that the mobile nodes rank the network interfaces and select the best one at anytime and anywhere. In this article, we present an adaptive ABC approach depending on QoE.

This paper is organized as follows: (i) The next section defines the ABC problem and describes a simple solution to address it. (ii) Then, Sect. 3 explains the proposed adaptive ABC approach depending on an estimated Mean Opinion Score (MOS) based on real time network measurements. (iii) Finally, the last section summarizes the evaluation results and demonstrates the performance of the proposed adaptive approach.

2 The ABC Problem

The evolution of mobile terminals with multiple access network interfaces give mobile users the possibility of being "Always Best Connected", where mobile users can switch between different network technologies, and connect to the best one that satisfies their service requirements at anytime and anywhere. In case of eHealth application, disaster or emergency situations, the Multi-homed method is an efficient solution to overcome the shortage of limited network access points. In fact, it is not always possible for patients to be whiting a healthcare facility due to several factors such as, emergency, remote location, limited mobility, being part of daily routine (patients with chronic conditions), or simply because it is a tedious expensive task for some simple procedures; this is where e-health fits in, with a multi-homed, easy-to-use, wearable devices in order to check blood pressure, heart rate, blood glucose level, oxygen levels, weight and health status, and sends the data to the server for doctor's diagnosis.

A simple solution to solve ABC problem is a Linear programming (LP; also called linear optimization). It is consist of a method to achieve the best outcome (such as maximum profit or lowest cost) [3]. Linear programming is a special case of mathematical programming (mathematical optimization). More formally, linear programming is a technique for the optimization of a linear objective function, subject to linear equality and linear inequality constraints. Its feasible region is a convex polyhedron, which is a set defined as the intersection of finitely many half spaces, each of which is defined by a linear inequality. Its objective function is a real valued affine function defined on this polyhedron. A linear programming algorithm finds a point in the polyhedron where this function has the smallest (or largest) value if such a point exists. In our case, the objective function consist of maximizing MOS by selecting the most suitable network interface. The problem of this method is that a choice made at time "t" may be inappropriate at time "t+1". That's why an adaptive model is needed.

3 An Adaptive Approach to Address the ABC Problem

Our proposed adaptive approach to address ABC problem is based on Reinforcement Learning (RL) which is an area of machine learning inspired by behaviorist psychology, concerned with how software agents ought to take actions in an environment so as to maximize some notion of cumulative reward.

Q-learning [4] is a model-free reinforcement learning technique (see Fig. 3). Specifically, Q-learning can be used to find an optimal action-selection policy for any given (finite) Markov decision process (MDP). It works by learning an action-value function that ultimately gives the expected utility of taking a given action in a given state and following the optimal policy thereafter. When such an action-value function is learned, the optimal policy can be constructed by simply selecting the action with the highest value in each state. One of the strengths of Q-learning is that it is able to compare the expected utility of the available actions without requiring a model of the environment. Additionally, Q-learning can handle problems with stochastic transitions and rewards, without requiring any adaptations. It has been proven that for any finite MDP, Q-learning eventually finds an optimal policy.

The algorithm therefore has a function which calculates the Quality of a state-action combination: Before learning has started, Q returns an (arbitrary)

$$Q_{t+1}(s_t,a_t) = \underbrace{Q_t(s_t,a_t)}_{\text{old value}} + \underbrace{\alpha_t(s_t,a_t)}_{\text{learning rate}} \times \left[\overbrace{\underbrace{R_{t+1}}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \underbrace{\max_{a} Q_t(s_{t+1},a)}_{\text{estimate of optimal future value}}}^{\text{learned value}} - \underbrace{Q_t(s_t,a_t)}_{\text{old value}} \right]$$

Fig. 3. Q-learning equation

fixed value, chosen by the designer. Then, each time the agent selects an action, and observes a reward and a new state that both may depend on both the previous state and the selected action. The core of the algorithm is a simple value iteration update. It assumes the old value and makes a correction based on the new information. In our case the states are the current interface and the reward is the estimated MOS.

4 The Evaluation of Network Interface Selection Approches

In order to evaluate our work, we emulated the network behavior by varying the main network metrics based on realistic models. For the packet loss, we used a gilbert eliot loss model [5], for the latency we used a normal distribution model [6] and for bandwidth we used a random variation model. We connect our

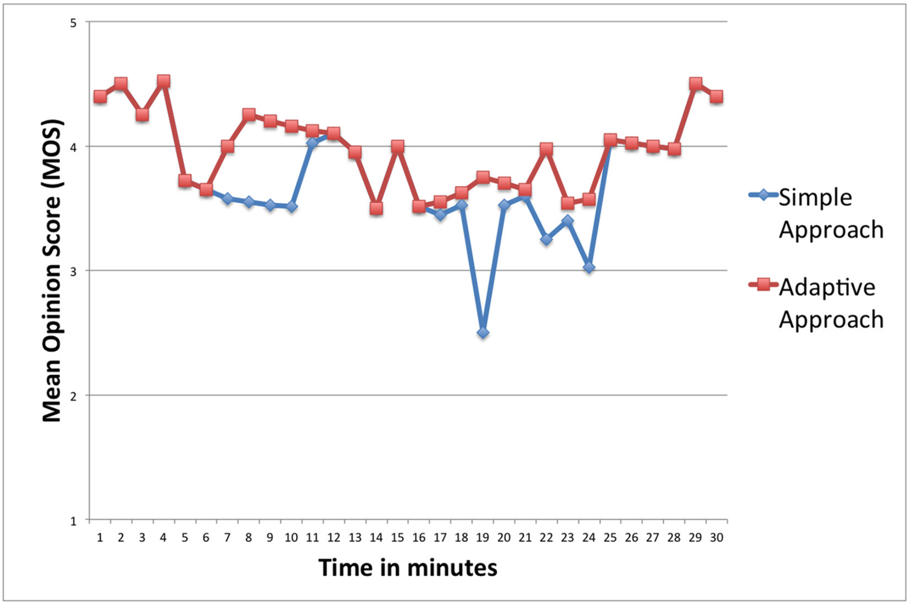

Fig. 4. Network interface selection approches

multi-homed box to network emulator throw three interfaces that represented three kind of network accesses: Wi-Fi, Ethernet and 3G/4G. In addition, we implemented in this box a module that continuously measures the delay, the bandwidth and the packet loss in order to estimate the MOS. To switch from one interface to another, the system takes only few milliseconds (around 30 ms). This lost time is nothing comparing to the gain made by changing the interface. The total experimentation duration is 30 min.

Figure 4 show the experimentation results. It represents the MOS variation through time and compares the score obtained by the simple approach based on Linear programming (LP) to the one obtained by our adaptive approach based on Q-learning. Indeed, the simple approach consists in selecting the best interface (based on MOS) and continues with that interface independently of network parameters evolution while the adaptive selection algorithm changes the network interface based on the estimated MOS calculated from the current network metrics values. The proposed algorithm gives the same score when the first interface selected gives the best score, otherwise, the proposed algorithm gives the best measured score.

5 Conclusion

Selecting the network over which data should be sent is important, and it depends on multiple criteria. In case of a patient with a chronic condition, periodic vital signs measurements are needed, and network with average bandwidth/delay is suitable for such a situation, where a sudden rise in those signs should be reported in real time through a high bandwidth/low delay network. In this paper, we present an adaptive approach to address the “Always Best Connected” issue. Experimental results show that this approach, based on a Q-Learning model, improves Quality of Experience compared to a simple non adaptive approach.

As a perspective, we intend to improve the information transportation in an efficient manner without changing the existing hardware components of the core network. To address this challenge, we think to use a new paradigm called Software Defined Networking (SDN).

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