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Cognitive spectrum management in dynamic cellular environments: A case-based Q-learning approach

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ABSTRACT

This paper examines how novel cellular system architectures and intelligent spectrum management techniques can be used to play a key role in accommodating the exponentially increasing demand for mobile data capacity in the near future. A significant challenge faced by the artificial intelligence methods applied to such flexible wireless communication systems is their dynamic nature, e.g. network topologies that change over time. This paper proposes an intelligent case-based *Q*-learning method for dynamic spectrum access (DSA) which improves and stabilises the performance of cognitive cellular systems with dynamic topologies. The proposed approach is the combination of classical distributed *Q*-learning and a novel implementation of case-based reasoning which aims to facilitate a number of learning processes running in parallel. Large scale simulations of a stadium small cell network show that the proposed case-based *Q*-learning approach achieves a consistent improvement in the system quality of service (QoS) under dynamic and asymmetric network topology and traffic load conditions. Simulations of a secondary spectrum sharing scenario show that the cognitive cellular system that employs the proposed case-based *Q*-learning DSA scheme is able to accommodate a 28-fold increase in the total primary and secondary system throughput, but with no need for additional spectrum and with no degradation in the primary user QoS.

1. Introduction

One of the fundamental tasks of a cellular system is spectrum management. It is concerned with dividing the available spectrum into a set of resource blocks or subchannels and assigning them to voice calls and data transmissions in a way which provides a good quality of service (QoS) to the users. Flexible dynamic spectrum access (DSA) techniques play a key role in utilising the given spectrum efficiently in the face of an ever increasing demand for mobile data capacity. This has given rise to novel wireless communication systems such as cognitive radio networks (Sun et al., 2013) and cognitive cellular systems (Guizani et al., 2015; Sachs et al., 2010). Such networks employ intelligent opportunistic DSA techniques that allow them to access licensed spectrum under-utilised by the incumbent users.

The classical and most common application of spectrum sharing in cognitive radio networks to date is the use of the TV white spaces. Such networks reuse the spectrum allocated to TV broadcasters for other wireless communications, whilst eliminating harmful interference to the incumbent TV receivers, e.g. Ghosh et al. (2011) and Gurney et al. (2008). A more recent problem investigated by researchers, mobile network operators (MNOs) and regulators is Long Term Evolution (LTE) and LTE-Advanced spectrum sharing (Matinmikko et al., 2014). In many cases LTE spectrum sharing is required by two or more co-primary MNOs. This can be facilitated by an emerging framework known as licensed shared access (LSA) (Matinmikko et al., 2014). Here, licenses for the use of LTE spectrum are issued upon agreement for a specific geographical area and required time duration. Another type of LTE spectrum sharing actively investigated within the LTE research community, is resource allocation in heterogeneous networks (HetNets) consisting of LTE femto-cells overlapped by a high power macro-cell, e.g. Alnwaimi et al. (2015) and Hamouda et al. (2014). In these scenarios, the problem is often tackled by using game theory or machine learning principles. The LSA method is a static regulatory approach to spectrum sharing, whereas the HetNet problems normally consider a dynamic scenario, where the same LTE channel is used by both the macro-cell and the femto-cells. Both of these spectrum sharing scenarios are investigated in this paper.

Abbreviations: 2ON, Second order neighbourhood; CBR, Case-based reasoning; DSA, Dynamic spectrum access; eNB, Evolved node B (LTE base station); ICIC, inter-cell interference coordination; LSA, Licensed shared access; RL, Reinforcement learning; UE, User equipment; UT, User throughput; WoLF, Win-or-learn-fast

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An emerging state-of-the-art technique for intelligent DSA is reinforcement learning (RL); a machine learning technique aimed at building up solutions to decision problems only through trial-and-error, e.g. Malialis and Kudenko (2015) and Walraven et al. (2016). It has been successfully applied in a range of wireless network scenarios, such as cognitive radio networks (Jiang et al., 2011), small cell networks (Bennis et al., 2013; Morozs et al., 2016), cognitive wireless mesh networks (Chen et al., 2013), and wireless sensor networks (Chu et al., 2015). The most widely used RL algorithm in both artificial intelligence and wireless communications domains is *Q*-learning (Watkins, 1989). Therefore, most of the literature on RL based DSA focuses on *Q*-learning and its variations, e.g. Chen et al. (2013) and Morozs et al. (2015). The novel algorithm developed in this paper employs distributed *Q*-learning based DSA. The distributed *Q*-learning approach has advantages over centralised methods in that no communication overhead is required to achieve the learning objective, and the network operation does not rely on a single computing unit. It also allows for easier insertion and removal of base stations from the network, if necessary. For example, such flexible opportunistic protocols are well suited to disaster relief and temporary event networks. There, rapidly deployable network architectures with variable topologies are required to supplement the existing wireless infrastructure (Gomez et al., 2016).

The purpose of this paper is to propose an algorithm that combines distributed RL with case-based reasoning (CBR) to improve the stability of intelligent DSA algorithms in realistic, dynamically changing cellular environments, i.e. the type of environments rarely considered in the research literature. The key contributions of this paper are the following:

- First, we present a detailed formulation of the case-based RL framework designed for dynamic learning environments in general.
- We then use this framework to develop the case-based *Q*-learning algorithm for DSA in cellular networks with dynamically changing topologies.
- The proposed algorithm includes a novel network topology based case identification and retrieval mechanism; the two essential components of all CBR systems.
- Finally, we present the results of an extensive empirical evaluation of the proposed scheme using a novel simulation model of a large-scale dynamic wireless environment.

Similar combinations of RL and CBR have already been successfully applied to various decision problems, e.g. dynamic inventory control (Jiang and Sheng, 2009), RoboCup Soccer (Celiberto et al., 2012) and control of a simulated mountain car (Bianchi et al., 2015). For example, Jiang and Sheng (2009) propose an effective case-based RL algorithm, where CBR is used for analysing the similarity between different states of a dynamic multi-agent RL problem. Celiberto et al. (2012) and Bianchi et al. (2015) develop transfer learning algorithms that transfer knowledge between similar learning tasks whilst using CBR to make this process faster. However, the only example of applying this methodology in the wireless communications domain is proposed by us in Morozs et al. (2013). There, a DSA scheme is designed for an unrealistically small and generic cellular network with its own dedicated spectrum, i.e. without secondary spectrum sharing and the presence of the primary users.

The rest of the paper is organised as follows: Section 2 describes the dynamic cellular environments considered in this study, that justify the need for robust intelligent DSA algorithms. Section 3 introduces the classical distributed *Q*-learning approach to DSA. In Section 4 we propose our case-based *Q*-learning algorithm, including novel case identification and case retrieval mechanisms. The results from a number of large-scale simulation experiments are discussed in depth in Section 5. Finally, the conclusions are given in Section 6.

2. Dynamic cellular environments

The aim of this paper is to investigate the applications of intelligent DSA in dynamic cellular environments. This section introduces the problem that provides such a challenging learning environment for DSA algorithms.

2.1. Heterogeneous temporary event networks

The DSA problem investigated in this paper is currently considered in the EU FP7 ABSOLUTE project. It is designed for a stadium event scenario and involves a temporary cognitive cellular infrastructure that is deployed in and around a stadium to provide extra capacity and coverage to the mobile subscribers and event organisers involved in a temporary event, e.g. a football match or a concert (Reynaud et al., 2014). This scenario is depicted in Fig. 1. There, a small cell network is deployed inside the stadium to provide ultra high capacity density to the event attendees, and an eNodeB (eNB) on an aerial platform is deployed above the stadium to provide wide area coverage.

We consider two different spectrum management cases:

1. The stadium small cell network has access to its own dedicated 20 MHz LTE channel, e.g. it is granted a temporary LSA license for exclusive access to this spectrum for the duration of the event. In this case, its performance is assessed separately, not considering the aerial eNB (AeNB) and the primary eNBs (PeNBs).
2. The cognitive small cells and the AeNB have secondary access to a 20 MHz LTE channel, also used by a network of 3 local PeNBs. This represents a more challenging secondary spectrum sharing task, where, in addition to the performance of the stadium small cells and the AeNB, the primary user QoS guarantees have to be taken into account. We assume that the primary users are those that are served by the local PeNBs depicted in Fig. 1.

A key challenging aspect of the cellular environment considered in this paper is its dynamic nature. We assume that the stadium network is able to dynamically adapt its topology to temporal non-uniform variations in the stadium traffic load. In the secondary spectrum sharing scenario, the dynamic nature of the environment is also caused by periodic deployments of the AeNB. All of these paradigms are explained in more detail in the following subsections.

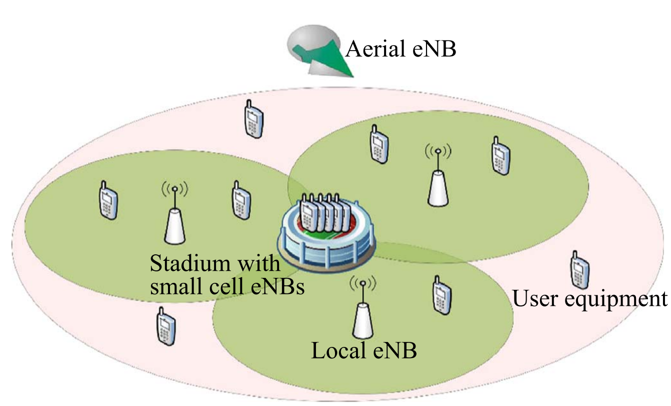

Fig. 1. Enhanced cellular network infrastructure during a stadium temporary event.