

Université libre de Bruxelles

Faculté des Sciences Appliquées OPERA - Wireless Communications Group

DISTRIBUTED SPECTRUM SENSING AND INTERFERENCE MANAGEMENT WITH LOW CAPACITY CONTROL CHANNELS FOR COOPERATIVE COGNITIVE RADIOS

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Abstract

Cognitive radios have been proposed as a new technology to counteract the spectrum scarcity issue and increase the spectral efficiency. In cognitive radios, the sparse assigned frequency bands are opened to secondary users, provided that interference induced on the primary licensees is negligible. Cognitive radios are established in two steps: the radios firstly sense the available frequency bands by detecting the presence of primary users and secondly communicate using the bands that have been identified as not in use by the primary users. In this thesis we investigate how to improve the efficiency of cognitive radio networks when multiple cognitive radios cooperate to sense the spectrum or control their interferences. A major challenge in the design of cooperating devices lays in the need for exchange of information between these devices. Therefore, in this thesis we identify three specific types of control information exchange whose efficiency can be improved. Specifically, we first study how cognitive radios can efficiently exchange sensing information with a coordinator node when the reporting channels are noisy. Then, we propose distributed learning algorithms allowing to allocate the primary network sensing times and the secondary transmission powers within the secondary network. Both distributed allocation algorithms minimize the need for information exchange compared to centralized allocation algorithms. In Chapter 2, we study the impact of the noise appearing on the control channels used by the secondary users to exchange their sensing information with the coordinator node. We model the control channel noise as noise coming from the two-bits non-uniform quantization of the energy measure at each node plus noise coming from the nonuniform bit flipping on the control channel. Using this model, we compute analytically the probability density functions of the noise, which allows to select the quantization step as well as the the bit flipping probabilities so as to reduce the impact of the error. A new optimal fusion rule is proposed for the iv Abstract

coordinator node, that takes into account the control channel noise distribution. Numerical simulations show that this new scheme outperforms the Maximum Ratio Combining scheme when different false alarm probabilities are used by the nodes. The sensing times, i.e. the number of samples used by the secondary nodes to sense the primary network, should be chosen high enough to ensure the correct detection of the primary emitter but low enough so that the nodes still have enough time to communicate. In Chapter 3, we propose a decentralized Q-Learning algorithm to allocate the sensing times of the cognitive radios in a way that maximizes the throughputs of the radios while simultaneously limiting the interference induced on the primary network. A rigorous proof of the convergence of the proposed algorithm is provided. Numerical results show that the algorithm converges faster than a reference distributed sensing time allocation algorithm, with a lower time and memory complexity. The average throughputs per node achieved with the proposed Q-Learning algorithm are inferior to those achieved with the optimal centralized sensing time allocation algorithm but superior to those achieved with the reference distributed allocation algorithm. In Chapter 4, we study how some form of cooperation

between cognitive radios allow to achieve efficient secondary communications. For this purpose we consider the scenario of an underlay network of multiple independent secondary cells using the same frequency and time resources as a primary network made up of one central primary emitter and several passive primary receivers whose positions are unknown. In order to protect the primary receivers from receiving harmful interference from the secondary users, a primary protection countour is defined on which the received primary Signal on Interference-plus-Noise Ratio (SINR) must be superior to a given threshold. To satisfy this constraint, the secondary transmission powers are controlled by the secondary base stations in order to guarentee that no harmful interference is induced on the primary receivers located inside the protection contour. In addition, as each secondary cell uses the same primary bandwidth, multiple secondary users from different cells may be interfering as well. To address this

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issue, we propose in Chapter 4 a new Q-Learning distributed power allocation algorithm that allows to maintain secondary transmission powers to reasonable levels in order to limit secondary-to-secondary interference. A rigorous proof of the convergence of the proposed algorithm is provided. Numerical results show that the implementation of a cost function that penalizes the actions leading to a higher than required secondary SINR gives better results than the implementation of a cost function without such penalty, in terms of level of harmful interference induced on both the primary and the secondary network.

Keywords

Cognitive Radios, Cooperation, Multi-Agent Q-Learning, Control Information, Control Channels

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