

A Review of Spectrum Sensing Techniques Based on Machine Learning

Andres Rojas

 <https://orcid.org/0000-0003-1773-8514>

Instituto Nacional de Astrofísica, Óptica y Electrónica, Mexico

Gordana Jovanovic Dolecek

 <https://orcid.org/0000-0003-1258-5176>

Instituto Nacional de Astrofísica, Óptica y Electrónica, Mexico

INTRODUCTION

Wireless communication systems use the radio frequency (RF) spectrum as their propagation medium. RF spectrum is divided into several bands occupying electromagnetic frequencies from 30 kHz to 300 GHz. The necessity of RF spectrum uses increases constantly due to the rapid growth of modern wireless communication systems. Several technologies, especially the deployment of the 5G network and the Internet of Things (IoT), cause high demand for resources from the wireless spectrum for many devices (Xu et al., 2020).

Most of the available RF spectrum has already been assigned to existing wireless systems resulting in only an insignificant part of this spectrum can be given to new applications.

Cognitive radio (CR) aims to reinforce the utilization of the underutilized RF spectrum. These frequency bands are assigned to licensed or primary users (PU) but are not utilized in some locations or time instants. Therefore, unlicensed, or secondary users (SU) can use this spectrum.

One of the principal operations of CR is spectrum sensing (SS), consisting of dynamic monitoring and employing underutilized spectrum without interfering with PUs.

This chapter proposes a survey of current spectrum sensing (SS) research involving the application of machine learning techniques. The extensive review included in this document mainly focuses on deep learning architectures and image processing techniques that can help improve CR systems' detection probability to maximize the underutilized RF spectrum in 5G. This article aims to check the newest research about spectrum sensing techniques reported in the literature, which apply images or time series as input for different deep learning architectures whose main task is to classify the spectrum as occupied or non-occupied.

A current trend, automatic classification modulation (AMC), is also included in this review. It is closely related to SS by recognizing the spectrum availability and classifying the signal type currently using the licensed band of interest. This chapter is helpful for comparison of the current tendencies in spectrum sensing in terms of signal simulation, including different analog and digital modulation types, image-based approaches such as covariance matrix or spectrogram, and wireless channel simulations.

DOI: 10.4018/978-1-6684-7366-5.ch050

This article, published as an Open Access article in the gold Open Access encyclopedia, Encyclopedia of Information Science and Technology, Sixth Edition, is distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>) which permits unrestricted use, distribution, and production in any medium, provided the author of the original work and original publication source are properly credited.

BACKGROUND

Cognitive radio is a new design paradigm of wireless communications systems that aims to maximize the use of the underutilized RF spectrum. Simon Haykin defines cognitive radio as a wireless communications system that is intelligent and aware of its environment. It uses a methodology by which it learns from the environment and adapts to statistical variations in the input stimulus (Captain & Joshi, 2021; Haykin, 2005). This definition has two main objectives:

- Highly reliable communication when and where needed, and
- Efficient use of the radio spectrum.

Cognitive radio intends to manage and execute real-time operations to adjust its behavior and deal with the increasing demands of RF spectrum and spectrum shortage caused by fixed frequency assignments (Prasad et al., 2008). SU or CR users are allowed access to bands of licensed spectrum assigned to PUs if they do not cause destructive interference. In a cognitive radio network (CRN), the SU or unlicensed user can temporarily access the spectrum not occupied by the PU; therefore, it is critical to determine whether the PU is present or not, and spectrum sensing is a crucial prerequisite for CR (Xu et al., 2020). Three possible cognitive radio implementation models exist: interweave, underlay, and overlay. Due to the popularity of the interweave model and standardization efforts by IEEE on IEEE 802.11 and IEEE 802.11af standards, this type is detailed below (Captain & Joshi, 2021).

Interweave model: In this model, secondary users can access the licensed spectrum only when primary users do not use it. A licensed spectrum that is not in use is called a spectrum hole. Secondary users must dynamically identify spectrum holes. Once the primary user begins transmitting on the licensed band again, the secondary user must immediately abandon the licensed spectrum without any interference with PU.

Spectrum Sensing

One of the purposeful requirements of the SU is to exploit the underutilized spectrum without destructive interference to PU. In addition, a PU is not required to share the spectrum with SUs. Therefore, SUs must be able to detect holes in the spectrum independently of PU before using the licensed spectrum. During the use of that band, the SU needs to monitor constantly if any PU is active in that band, and if that is the case, it needs to abandon that band immediately. As a result, efficient spectrum sensing techniques are required to minimize interference with the PU while maximizing spectrum utilization (Captain & Joshi, 2021). There are three types of spectrum sensing, narrowband spectrum sensing, wideband spectrum sensing, and cooperative spectrum sensing.

Narrowband Spectrum Sensing

Narrowband spectrum sensing finds whether a single PU-licensed band is available for SU. The simplified signal detection problem can be explained in terms of two hypotheses H_0 and H_1 . Hypothesis H_0 means that only noise is received while the PU signal is missing. Similarly, the hypothesis H_1 states that not only noise but also PU signals are observed. Denoting the received signal at the signal detector as $y(n)$ and the PU signals observed by SU as $x(n)$, we have:

19 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:

www.igi-global.com/chapter/a-review-of-spectrum-sensing-techniques-based-on-machine-learning/322771

Related Content

Social Structures for Access, Use, and Development

Sarah Parkinson (2008). *Global Information Technologies: Concepts, Methodologies, Tools, and Applications* (pp. 2495-2505).

www.irma-international.org/chapter/social-structures-access-use-development/19126

Factors Influencing Chinese Online Health Service Use: A Valence Framework Perspective

Lin Xiao, Jian Mou and Lihua Huang (2021). *Journal of Global Information Management* (pp. 138-160).

www.irma-international.org/article/factors-influencing-chinese-online-health-service-use/279668

Technology Transfer Means and Processes: Improving the System of Transmitting Scientific Knowledge and Know-How to Recipient Emerging Nations

Ngozi C. Kamalu and Johnson A. Kamalu (2012). *Disruptive Technologies, Innovation and Global Redesign: Emerging Implications* (pp. 300-314).

www.irma-international.org/chapter/technology-transfer-means-processes/63836

Understanding Internet Banking Adoption and Use Behavior: A Hong Kong Perspective

Siu-cheung Chan and Ming-te Lu (2004). *Journal of Global Information Management* (pp. 21-43).

www.irma-international.org/article/understanding-internet-banking-adoption-use/3610

Outsourcing Information Technology: The Role of Social Capital

James J. Hoffman, Eric Walden and Mark L. Hoelscher (2008). *Global Information Technologies: Concepts, Methodologies, Tools, and Applications* (pp. 530-537).

www.irma-international.org/chapter/outsourcing-information-technology/18988