Context-Aware Cognitive Radio Using Deep Learning

Francisco Paisana, Ahmed Selim, Maicon Kist, Pedro Alvarez, Justin Tallon, Christian Bluemm, Andre Puschmann, Luiz DaSilva

CONNECT, Trinity College Dublin, Ireland

Email: {paisanaf, selimam, kistm, pinheirp, tallonj, blummc, puschmaa, dasilval}@tcd.ie

Abstract—This paper describes the design, experimental assessment and Software Defined Radio (SDR) implementation of a Secondary User (SU) link for the IEEE DySPAN Challenge 2017. The objective is to successfully discern the behavior of and coexist with a Primary User (PU), whose channel access patterns vary over time. For that end, we utilize sensing, deep learning and dynamic optimization.

Keywords—Software-Defined Radio, Deep Learning, Cognitive Radio, Spectrum Sharing, Spectrum Sensing.

I. INTRODUCTION

The challenge is to design a high throughput secondary user (SU) system that can coexist with minimal interference with a primary user (PU) by detecting its channel utilisation pattern. The competition is divided into two phases. The first is the Situational Awareness (SA) phase, when SUs try to discern the current PU’s access pattern based on its transmissions and a table of all possible patterns/scenarios. The second phase, entitled Agile SU (ASU), focuses on techniques that SUs can employ to maximise their throughput without causing harmful interference. The scores of the SA and ASU phases are calculated as follows,

\[
\text{score}_{SA} = \frac{D}{10 \cdot 60 \cdot 10^4} \\
\text{score}_{ASU} = T_{SU} \cdot e^{-\frac{2T_{PU} - T_{SU}}{T_{PU}}} 
\]

(1)

(2)

Here \( D \) is the number of 1 ms time-slots when the SU correctly identified the PU’s access pattern scenario during the SA phase. \( T_{SU} \) and \( T_{PU} \) are the throughput of the SU and PU, respectively. \( T_{PU} \) is the offered throughput of the PU.

Based on our previous solution to the DySPAN Challenge 2015 [1], we have devised a SU-Tx system that can be subcategorized into four parts: (i) spectrum sensing, (ii) scenario estimation using deep convolutional neural networks, and (iii) decision-making. Parts (i)-(ii) are described in Section II, and part (iii) in Section III. We conclude this paper by discussing the implementation considerations we took into account in this work.

II. SITUATIONAL AWARENESS

The situational awareness phase including spectrum sensing as well as the estimation of the scenario that corresponds to current PU activity. For the latter, we use deep Convolutional Neural Networks (CNNs). We describe both functions in this section.

A. Spectrum Sensing

The SU-Tx senses an instantaneous bandwidth of 10 MHz (4 x 2.5MHz channels) to assess the spectrum occupancy of each channel. To achieve this, the SU-Tx gathers IQ samples from the radio environment, converts them to the frequency domain through an FFT block, and applies a magnitude square operation on the complex output to obtain the power of each FFT bin. The FFT bins are then grouped into 12 sections, each section defined by a channel index (1-4), and whether it belongs to the PU’s useful, left guard, or right guard band of the channel. The bins within the same section are then averaged to obtain a section’s estimated received power. These powers then enter as input in the CNN module for PU’s scenario estimation, and in the channel occupancy detector that will provide a list of the available channels.

As the PU’s transmissions leak to other channels, employing simple energy detection may lead to very high false alarm rates. For that reason, as a first stage of our channel occupancy detector, we compensate any noise uncertainty in each channel by dividing the useful band section powers by the average of the powers obtained from the left and right guard band sections. The end result is an array of 4 relative received powers, which can be compared against a threshold to detect the arrival of a packet.

B. PU Scenario Estimation Using Deep Convolutional Neural Networks

Each PU’s scenario is characterized by a unique set of characteristics such as packet duration, inter-packet delay, channel occupancy, frequency hopping pattern, and transmission bandwidth. In this paper, we introduce a strategy for recognizing the PU scenario that does not require the estimation of the parameters above. Instead, we train a deep CNN model to perform the classification directly from spectrograms. The fact that each PU scenario has unique characteristics is reflected as a unique set of spectrograms per class. Hence, the detection of PU scenarios becomes an image classification task that can be solved with CNNs. For each PU scenario, we generate 2000 spectrograms for training and 500 spectrograms for testing. Each spectrogram covers the 4 channels for 50 msec. We picked these values to create 10 mutually exclusive classes. Such a property is essential for reliable classification.

Figure 1 shows the layout of our CNN model. The input is a 64 × 64 gray-scale image. The network consists of 5 convolutional layers equipped with 48, 128, 192, 192, and 128 filters, respectively. Each convolutional layer is accompanied...
by a rectified linear unit (ReLU) and followed by a max-pooling layer. The output of these convolutional layers is then passed through 3 fully connected layers with 1024, 1024, and 10 neurons, respectively. The last 10 neurons are fed to a softmax layer to compute the probability $P(y = k|x; \theta)$ for $k \in \{1, 2, ..., 10\}$, where $x$ denotes the input spectrogram, and $\theta$ denotes our model parameters. The CNN model is trained on 20K spectrograms (2000 per class) and tested on 5K spectrograms (500 per class), achieving classification accuracy of 98.48%. During the competition, our trained CNN model will be used to predict the most likely PU scenario based on spectrograms generated by the SU. The model will be used during the SA and the ASU phases.

III. AGILE SU

In the ASU phase, the goal is to maximise the aggregate throughput of the PU ($T_{PU}$) and SU ($T_{SU}$), according to the aggregate score $S$, shown in (2). One of the tasks in the implementation is the optimisation of the three SU’s parameters: channel hopping pattern, SU-Tx Power ($P_{SU,Tx}$), and modulation order. The hopping pattern will be selected based on the PU’s activity defined by the CNN model, and the channel occupancy detector described in Section II. We illustrate in Figure 2 our implemented SU-Tx avoiding interference with the PU by hopping to the empty channel 3.

To operate at the optimal power, we adapt the gain of the SU-Tx, based on PU’s throughput feedback obtained from the database, until an equilibrium is found. This operation has to be performed continuously as the PU-Tx and PU-Rx will change their transmit power and position multiple times throughout the phase II of the challenge.

To adapt the modulation, during an initial phase, the SU-Tx will continuously increase the modulation order, starting from 4-QAM up until the SU’s throughput degrades. The obtained throughputs for each modulation are registered on a table for later consultation. After this calibration, this table can consulted whenever the SU-Tx gain is changed.

IV. IMPLEMENTATION CONSIDERATIONS

The chosen SDR platform for the SU system is an X310 USRP from Ettus Research [2] in combination with a general purpose processor, i.e. a host-computer. The frontends in use are of type SBX-120.

A. FPGA design

The standard design for the Kintex 7 FPGA of the X310 USRP supports low level radio functionality including a DUC chain, a DDC chain, and control functions [3]. For lowering the CPU stress and data rate of the host-computer, the core functionality of the SU-Tx spectrum sensing, as described in Section II-A, is added to the FPGA design by modifying an existing FFT RFNoC (RF Network on Chip) block. Only the last step of spectrum sensing is left to the host-computer, which is the threshold comparison of the power averages corresponding to the 4 channels. For later identification by the host-computer, those power averages are transferred with their corresponding time stamp from the FPGA. All FPGA-based spectrum sensing functionality is executed permanently without differentiating between in-band or out-band sensing. With an FFT size of 512 and a sample rate of 10 MHz, a maximum spectral resolution of about 19.5 kHz can be achieved. A 512 bin Hanning filter is applied at the input of the FFT, in order to reduce leakage effects due to the rectangular signal cutout of the FFT itself [4].

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