Integrating Spectrum Sensing and Channel Estimation for Wireless Communications

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***Abstract*—With the rising user demands to support multiple applications, the next-generation wireless communications exploit coexistence of licensed and unlicensed spectrum to much improve the spectrum efficiency. However, spectrum sharing is a crucial yet currently challenging element in enabling the coexistence of diverse technologies and functionalities in next-generation wireless network systems. While cognitive radio (CR) is one such prominent technology to identify the unused portions of the spectrum, it usually requires extra process or separate hardware for sensing. In this work we propose a novel approach to integrate spectrum sensing with the existing channel estimation process. In particular, we assume that channel estimation is implemented constantly for licensed spectrum usage for user equipment (UE). Based on channel reciprocity, adjacent unlicensed spectrum will be sensed for occupancy and also estimated if unoccupied simultaneously. The integration of spectrum sensing and channel estimation offers multiple benefits such as accurate resource allocation, reduced latency and processing load, faster decision making, and adaptable to real-time scenarios. Moreover, the proposed scheme can be applicable to most communication systems, e.g., the fourth-generation mobile network and onwards without extra hardware implementation. Evaluation results based on the open-source dataset is included to demonstrate the proposed concept and scheme.**

I. Introduction

The evolution of wireless technologies from a primitive first-generation to the current fifth-generation (5G) offered multiple services such as enhanced connectivity, reduced latency, and higher throughput [1]. However, the incessant introduction of sophisticated applications such as Cybersystems, and the elevation of traditional methods with advanced wireless communications such as smart grids necessitated the need to expand the wireless spectrum [2]. The limited spectrum of resources poses multiple challenges. For example, it leads to increased competition in the unlicensed bands such as Industrial, Scientific, and Medical (ISM) resulting in increased packet loss, and poor performance [3]. Advanced sophisticated applications such as tactile internet require higher frequency bands such as mmWave due to the higher bandwidth associated with it. However, a study of the spectrum resources by the Federal Communications Commission (FCC) reveals the sub-optimal use of spectrum resources [4]. In this work, we propose a scheme that can achieve spectrum sensing, as well as estimate the channel state information (CSI) simultaneously thereby improving spectrum efficiency with little hardware modification to the existing systems.

In the pursuit of enhanced spectrum resource utilization and innovation, LTE and 5G have incorporated a range of mechanisms to harness unlicensed spectrum with cognitive radio (CR) technology. For example, LTE-Unlicensed, LTE-Wi-Fi Aggregation and License Assisted Access enable an LTE device to use both licensed and unlicensed spectrum simultaneously to boost the capacity and other performance of the LTE network [5], [6]. Dynamic spectrum sharing enables the coexistence of 5G new radio and LTE [7]. Traditional CR mechanisms identify and allow the secondary users (SUs) to access the licensed spectrum of the primary users (PUs) when not in use [2]. In this manner, the efficiency of the spectrum utilization can be improved without impacting the functioning of the PUs. The spectrum sensing techniques in the literature can be categorized into cooperative and non-cooperative sensing [8]. In non-cooperative sensing, the SUs will not collaborate with others sensing the frequency band resulting in issues such as noises, and interference [8]. In the cooperative sensing technique, the SUs collaborate and make a final common decision. However, these traditional CR techniques either requires an extra process or separate hardware for spectrum sensing, making it lesser accessible to the current and next-generation wireless communication.

In this work, we propose to integrate spectrum sensing into the existing channel estimation process such that the two functions can be performed simultaneously with little hardware modification. For example, in the licensed spectrum utilized by the LTE the channel estimation is already implemented based on reference or the pilot signals [9]. Least-square (LS), and low rank approximation [10] are some of the traditional channel estimation techniques in addition to machine-learning used by the LTE [11]. In our proposed scheme design, spectrum sensing is performed on adjacent secondary downlink channels using the same signals received for primary downlink channel estimation. If available, an interpolation based channel estimation is utilized to estimate CSI of the secondary downlink channel using the current primary downlink channel or the primary uplink channel. Note that the uplink channel is usually narrower than a downlink channel. Moreover, the downlink pilot sequences to be transmitted increases with the increase in the user equipments (UEs). Such a scheme offers numerous advantages. First, the same resources are used for the spectrum sensing and channel estimation leading to efficient use of the limited computing resources. Second, ceding some of the excess downlink pilots to the new unoccupied channel can reduce latency on channel estimation, hence improving applications in real-time scenarios. In comparsion, most the existing works dwell on proposing techniques and schemes to identify spectrum holes while our work incorporates the spectrum sensing in traditional channel estimation methods.

Our contributions to this work can be summarized as follows. A novel approach integrating the spectrum sensing into the existing channel estimation method is proposed, and analyzed using evaluation results based on open-source datasets. The remainder of this paper can be organized as follows. Section II outlines the proposed integration of spectrum sensing and channel estimation for wireless communications. Section III presents the evaluation results, and Section IV concludes the paper.

II. Simultaneous Spectrum Sensing and Downlink Channel Estimation

A. Studied System Model

As shown in Fig. 1, a frequency division duplex (FDD) system is considered as the studied system model. In specific, UEs are both primary users (PUs) for the licensed spectrum and secondary users (SUs) for adjacent unlicensed spectrum. The UEs have unlimited access to the primary downlink and uplink channels, while they only have access to the secondary downlink channel when it is unoccupied. In the studied system, each CR UE comprises of M antennas to sense the spectrum that is currently utilized by N PUs, where $N \leq M$. Note that the signal at the m^{th} antenna, referred to as observed signal, can be given as follows:

$$x_m(n) = \sum_{j=1}^{N} h_{m,j} s_j(n) + w_m(n), \tag{1}$$

where n refers to the sample size; s_j refers to the transmitted signal; $h_{m,j}$ denotes the fading channel; and $w_m(n)$ refers to the additive noise. The observed signal $\mathbf{x}$ can be written in the vector format as follows:

$$\mathbf{x} = \mathbf{Hs} + \mathbf{w}. \tag{2}$$

The suitable secondary downlink channel can be identified during a typical channel estimation process of the primary downlink channel. The energy levels of the secondary channels are determined based on the energy levels of the primary received signal. By applying suitable thresholds, the unoccupied secondary channels can be determined. If unoccupied, channel estimation for the secondary downlink channel is also performed in addition to the primary downlink channel and fedback to the BS. In this manner, the spectrum sensing is integrated into the existing channel estimation process.

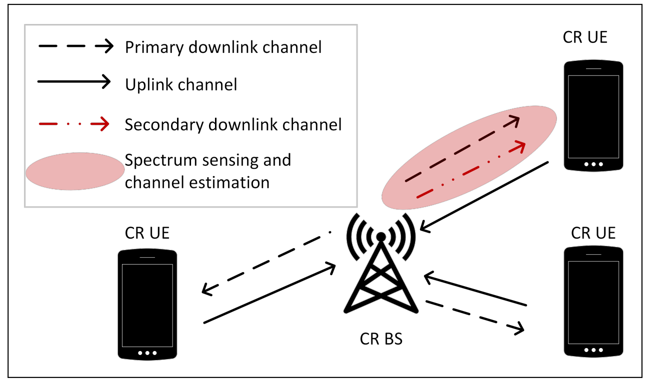


Fig. 1: Studied system model.

B. Primary Downlink Channel Estimation and Secondary Channel Spectrum Sensing

The primary downlink channel is estimated by transmitting the pilots from the CR BS to the CR UE. The channel is estimated using the LS method. From Eq. (2) we get,

$$\hat{h}_p^{LS} = s_p^{-1} x_p \tag{3}$$

where $\hat{h}_p^{LS}$ refers to the channel estimates at the pilot sub-carriers. With the knowledge of the channel, the transmitted signal can be estimated using,

$$\hat{s} = \{(H^{LS})^T \ H^{LS}\} \ (H^{LS})^T \ s \tag{4}$$

where $\hat{s}$ is the estimate of the transmitted signal s. The energy of the received signal E_x can be computed using [12]

$$E_x = \frac{1}{K} \sum_{n=1}^{K} |x(n)|^2, \tag{5}$$

where K is the total number of samples. E_x is also referred to as the energy of the primary downlink received signals denoted by E_{primary}. We assume that the principle of reciprocity holds good in our system model. Under similar transmission conditions and propagation paths, we can say, that energy of the secondary channels $E_{\text{secondary}}$ is inversely proportional to E_{primary}. With the knowledge of $E_{\text{secondary}}$ it is possible to estimate the unoccupied secondary channels. In other words, this entire process trickles down to a classic spectrum sensing problem that can be modeled as a hypothesis problem using [13],

$$x(n) = \begin{cases} \mathbf{H}_0: & w(n), \\ \mathbf{H}_1: & hs(n) + w(n), \end{cases} \tag{6}$$

where $\mathbf{H}_0$ that refers to the case when the secondary channel under study is unoccupied, while $\mathbf{H}_1$ when it is occupied. Traditional approaches to achieve spectrum sensing include energy detection, cyclostationary feature detection, and matched filter detection [14]. However, cyclostationary and matched filter detection suffer from limitations such as the need for a priori knowledge of PU, and high complexity. However, sensing the occupancy of the spectrum based on the reciprocity requires no prior knowledge, and is computationally less complex [14].

C. Secondary Downlink Channel Estimation

If the secondary downlink channel is unoccupied, the CR BS will estimate the channel by extrapolating the channel estimates of the primary channel. The extrapolation technique is utilized in this work for estimating the channel for the following reasons. First, channel extrapolation techniques reduce the overhead, and computational complexity. Second, by predicting the channel state it will be feasible for the BS to tune its parameters such as modulation standards to reduce the bit error rates. The channel response at a frequency f can be estimated with the knowledge of channel estimates $\hat{h}$. Using least-square (LS) method on Eq. 1, we can get [15],

$$\hat{h}_{LS} = h_m(f_k) + \frac{w_m(f_k)}{s(f_k)}, \tag{7}$$

for $k = \{0, 1, \ldots, K\}$, K refers to the channel estimates, $\hat{h}_{LS}$ denotes the channel estimated using LS method. Applying LMMSE estimator, the channel extrapolates at a frequency f can be determined [15].

$$\hat{h}_{\text{LMMSE}}(f) = \mathbf{p}^H(f)\ \hat{\mathbf{h}}_{LS}, \tag{8}$$

where $\mathbf{p}^H$ refers to the vector of coefficients, and it can be obtained my minimizing the MSE of the estimate.

The salient features of the proposed work are as follows. First, the integration of spectrum sensing and channel estimation steps eliminates the need for different computational and hardware resources resulting in efficient utilization of the spectrum resources. Second, the estimated seconday downlink CSI enables the BS to tune its modulation scheme to reduce the bit-error rates (BER) before switching the channels. Third, since both operations are working in tandem it is possible to reduce the latency involved in making transmission strategies decisions. Fourth, integrating both these processes results in simplified architecture, and it is extremely useful to support applications in the next-generation wireless networks.

III. Evaluation Results

A. Dataset and System settings.

The open-source Argos channel dataset was utilized to validated our approach [16]. The Argos dataset comprises of uplink pilot sequences corresponding to different scenarios such as static and dynamic environments stored in the form of In-phase and Quadrature (I/Q) components. The dataset corresponding to a 2.4 GHz static environment is used for testing in this work. More information about the dataset collection and storage can be inferred from [16]. The system settings are summarized in Table I.

TABLE I: System settings.

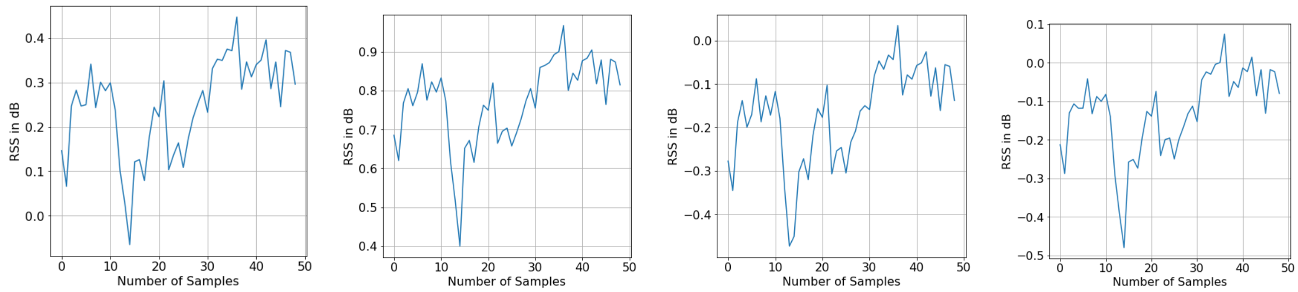
System configuration	96×8
# Samples per batch	50
Frequency band	2.4 GHz
SNR values	-20 to 20 dB, Δ = 5
# Channels studied	8 (Channels 1-8)
Uplink channel bandwidth	5 MHz, 10 MHz, 15 MHz, 20 MHz
Downlink channel bandwidth	10 MHz, 20 MHz, 30 MHz, 40 MHz
Dimension of the data	1000, 96, 8 , 52

B. Preliminary Results.

Initially, the I/Q measurements corresponding to different channels were processed to compute the received signal strength (RSS). Figures 2a- 2d presents the RSS measurements based on 50 samples corresponding to channels 1-4 respectively. The RSS provides important information about the wireless channels such as the signal strength and quality. For instance, Channel 2 has the highest strength among the four referenced channels. Post-processing of the raw measurements, pilot-based traditional channel estimation is performed using the primary downlink channel. Figures 3a- 3d depicts the channel estimation results with unequal UL and DL bandwidths. The results presented in the above-mentioned figures are based on channels 1 and 3 acting as primary downlink and uplink channels respectively. A simple examination of the figures provides the following inferences. First, the DL bandwidths are twice that of the UL to reduce the mean-squared errors (MSE). The MSE decreases with the increase in the DL bandwidth. For instance, from Figures 3a and 3d the MSE at -10 dB are -2.15 dB and -2.50 dB respectively. Second, due to the strong signal strength at higher SNRs the MSE decreases with the increase in the SNR. For instance in Fig. 3b the MSE decreased from -2.30 dB at -10 dB SNR to about -2.65 dB at 20 dB SNR. With the help of the channel information, it is feasible to determine the energy levels corresponding to each of these channels as illustrated in Figures 4a-4d. For instance, Channel 1 on average the highest signal strength when compared to others. With the help of extrapolation, the energy levels corresponding to the secondary channels are approximated based on the primary channels. The one with the lowest energy levels is the unoccupied secondary channel. However, if there are channels with the same energy as shown in Fig. 5 the process is repeated multiple times with different I/Q measurements till the ideal candidate is determined. For instance, in this work, the iteration was repeated nearly 8 times and results about the last three iterations are summarized in Table II.

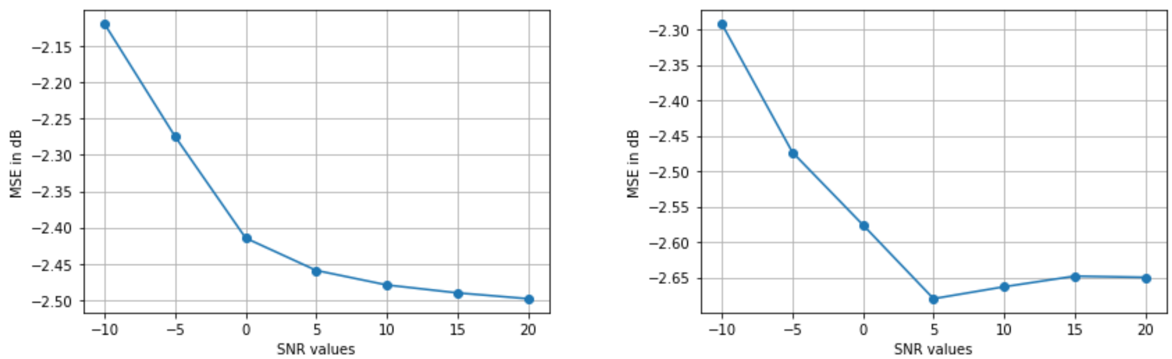
TABLE II: Evaluaion results for secondary channel detection.

Iterations	Threshold	Channels occupied
6	0.30	1, 2, 3,4,5,6,7,8
7	0.35	1,2,3,4,5,6,7,8
8	0.40	2,6,7

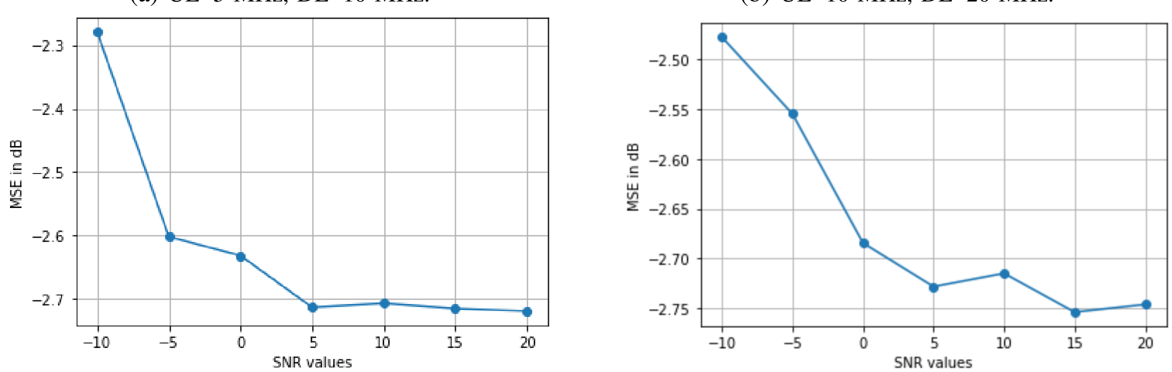


(a) Channel-1. (b) Channel-2. (c) Channel-3. (d) Channel-4.

Fig. 2: Raw RSSI measurements.

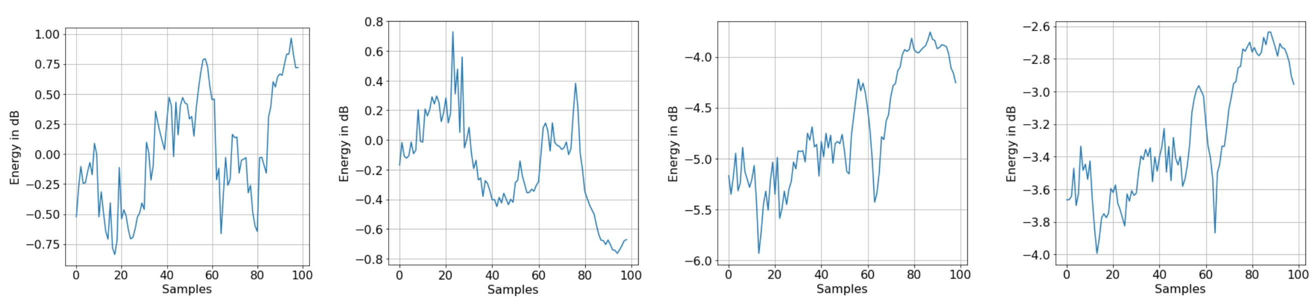


(a) UL=5 MHz, DL=10 MHz. (b) UL=10 MHz, DL=20 MHz.



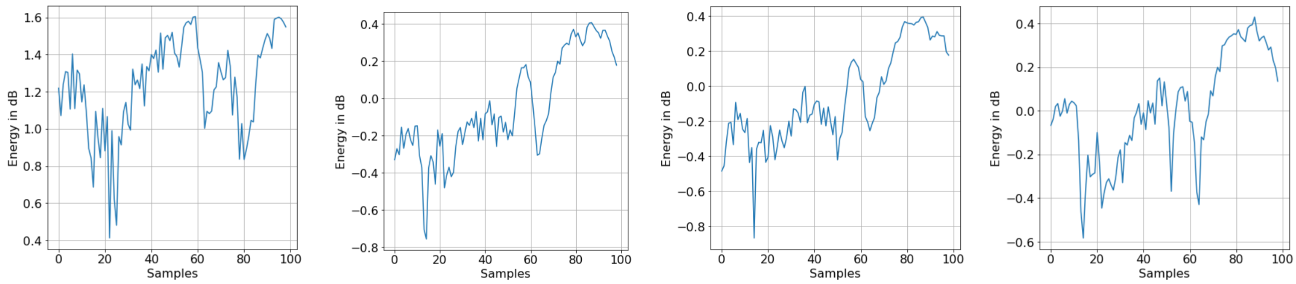
(c) UL=15 MHz, DL=30 MHz. (d) UL=20 MHz, DL=40 MHz.

Fig. 3: Channel estimation at different uplink and downlink bandwidths.



(a) Channel-1. (b) Channel-2. (c) Channel-3. (d) Channel-4.

Fig. 4: Energy levels of the received signals.



(a) Channel-1. (b) Channel-2. (c) Channel-3. (d) Channel-4.

Fig. 5: Energy levels of extrapolated secondary channels.

C. Discussions and Future Directions

The integration of spectrum sensing and channel estimation into a single step eliminates the need to run two different computationally intensive processes. Moreover, for the battery-powered devices such an integration would result in an energy-efficient operation. The objective of this work is to prove the concept such that spectrum sensing can be integrated into an existing channel estimation process with little hardware modification. However, there are a few limitations that we intend to address in our future works. First, the proposed approach is studied theoretically using an open-source dataset while it needs to be further verified using real experimental data. Second, an automated scheme is needed for the threshold to maximize the unoccupied channels. Third, currently, the downlink bandwidth should be at least twice that of the uplink to ensure reasonably accurate channel estimation results. Suitable schemes will be designed to improve the channel estimation when the above-mentioned condition is violated. Fourth, both these operations are performed independently in the current evaluation. It will be automated and integrated to reduce user interference. Last but not least, the proposed framework works for the static 2.4 GHz dataset, while it will be expanded to different available datasets.

IV. Conclusion and Future Works

In this work we proposed an integrated framework to improve the efficiency of the spectrum utilization by offering interpolation-based channel estimation and energy detection-based spectrum sensing techniques in one single step for wireless communications. The salient features of this work includes efficient utilization of resources, as well as expeditious computation of channel information. In addition to this, we demonstrated that a wider downlink channel can be estimated using narrower channels. Such benefits are critical in FDD systems that have uneven downlink and uplink channels. Moreover, the framework was validated and tested on open-source datasets. In the future, an extensive study of the proposed integrated approach will be conducted under different system configurations and datasets. Furthermore, it will be evaluated on real-time data using a software-defined radio based hardware platform.

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