USRP-Based Prototype for Real-Time Estimation of Channel Activity Statistics in Spectrum Sharing

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***Abstract*—The statistical characteristics of the frequency spectrum play a key role in decision making in smart spectrum sharing systems. In such systems, the activity of the licensed users changes differentially over both time and frequency, hence, their statistical information changes accordingly. The performance of spectrum sharing systems is directly affected by the estimated channel activity statistics, therefore low spectrum utilisation may result from inaccurate estimation of these statistical parameters. In this context, this work presents a prototype design for real-time estimation of channel activity statistics based on a Software Defined Radio (SDR) platform using USRP. A detailed explanation of both hardware and software implementations is provided (with free open source code). The developed platform will enable a spectrum sharing system adapt its parameters smartly and instantaneously in accordance with the estimated channel statistics in real-time. Moreover, this prototype will serve researchers and engineers to conduct and validate further research developments in statistics estimation methods and algorithms for spectrum sharing systems through experiments and proof-of-concept.**

***Index Terms*—Spectrum sharing, dynamic spectrum access, spectrum sensing, primary channel activity statistics, Software Defined Radio (SDR), USRP.**

I. INTRODUCTION

Maximising spectral utilisation efficiency is one of the ongoing challenges in modern wireless communications that has been of interest in the recent research campaigns. Studying the statistical information of the spectrum utilisation patterns can play a key role in decisions making in various wireless communication systems, in particular spectrum sharing systems such as Dynamic Spectrum Access (DSA) [1]. In DSA, the (unlicensed) Secondary Users (SUs) are allowed to exploit the frequency bands that the (licensed) Primary Users (PUs) have priority to access, without causing any harmful interference. Spectrum sensing, using Energy Detection (ED) algorithm [2], [3], enables a SU to autonomously sense the state of the frequency channels, find unused spectrum, and access (without prior negotiation with the primary system or PU). Since PU activity varies over both time and frequency, it is very critical and inefficient for a SU to access the spectrum without having a proper knowledge about the activity patterns of the channel. Such knowledge can be acquired from exploiting the statistical information of the spectrum usage. These statistics can help SUs predict the future activity trends in the spectrum [4], [5], select the most opportunistic (underutilised) channel [6]–[8], and reduce the interference between SUs and PUs [9], [10].

Channel activity statistics can be obtained from spectrum sensing observations [11]. Although spectrum sensing is mainly used to sense the presence of the PU signal in the channel, its outcomes can also be exploited to provide an estimation of the channel activity statistics. In the literature, channel activity statistics estimation has been studied widely based on Perfect Spectrum Sensing (PSS) [11]–[13] and Imperfect Spectrum Sensing (ISS) [14]–[17]. However, the majority of the existing studies are conducted theoretically and validated by means of simulations. Few works such as [11], [14] have adopted the Prototype for the Estimation of Channel Activity Statistics (PECAS) proposed in [18] to validate the mathematical analyses of the channel activity statistics experimentally. PECAS model [18], however, has several hardware limitations in its transmitter and receiver. The PECAS transmitter (which acts as a PU with a particular activity pattern) is based on a Raspberry Pi with an ON-OFF Keying (OOK) modulator connected to it. The used OOK modulator can only operate at a central frequency of 433.92 MHz, thus limiting the experiments to such frequency band and making it impossible to conduct a wider range of experiments for different research purposes. In addition, the maximum modulation frequency supported by the modulator is 10 kHz, which limits the time resolution of the generated (PU activity) idle/busy periods to 0.1 ms. This limited time resolution is inconvenient since a reliable study requires the transmission and reception of a sufficiently large number of idle/busy periods, which may take unreasonably long times for many experiments under such limited time resolution. The PECAS receiver, on the other hand, (which acts as a SU) is based on the RTL-SDR platform, which supports a limited frequency range of 24 MHz–1766 MHz. Therefore, experiments on a higher frequency channel (e.g., 2.5 GHz and 5 GHz of the WLAN frequency bands) are not possible. In addition, the maximum sample rate that RTL-SDR can provide is 3.2 MS/s, which might not be sufficient when fast spectrum sensing is required.

While PECAS prototype is suitable for low-cost experiments on channel activity statistics, it might not be applicable on a wider range and sophisticated experiments. In addition, it has no capability of monitoring the channel activity statistics while the experiment is running in real-time (it only provides the statistical information after the execution of the experiment). In this context, this work overcomes the aforementioned

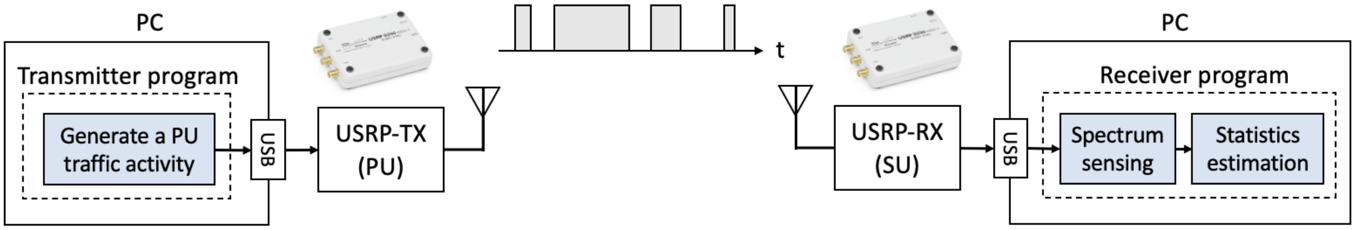


Fig. 1: Block diagram of the proposed prototype.

limitations of the PECAS prototype [18] by proposing a new sophisticated prototype based on the Universal Software Radio Peripheral (USRP). USRP is a readily available and widely used platform in the community, which enables other researchers and engineers to easily implement and reproduce our proposed system and benefit from its advantages (we provide free open source code in [19]). The contribution of this work, therefore, can be highlighted as follows:

1) A USRP-based prototype is developed to support a wide range of (sophisticated) experiments that help validating the theoretical analyses of the channel activity statistics under real-world conditions. In addition, it provides a real-time estimation of the channel activity statistics, which can be plotted instantaneously according to the PU's activity within the channel along with plotting the energy of the existing signals in the spectrum.
2) The proposed prototype's transmitter and receiver provide a high sample rate of at least 56 MS/s (and higher in some USRP models), which enables a better time resolution for generating idle/busy periods at the transmitter (with 17.8 ns compared to 0.1 ms for PECAS) and a faster spectrum sensing at the receiver (30 times faster than PECAS).
3) The proposed prototype can operate in a wide frequency range of 70 MHz – 6 GHz (or even larger for some USRP models), which supports a wide range of experiments such as those in 5G wireless communications. Meanwhile, PECAS prototype is restricted to the experiments at a central frequency of 433.92 MHz, which can be useful for proof-of-concept validations but is not suitable for more realistic experimental validations.
4) A Graphical User Interface (GUI) is developed for both transmitter and receiver in order to ease the configuration of the USRP used in this prototype, which will help researchers to conduct various experiments without the need to modify the source code.

The rest of the paper is organised as follows. Section II presents a general overview for the proposed prototype. Then the hardware and software implementations of the transmitter and receiver are explained in details in Sections III and IV, respectively. The performance of the proposed prototype is examined through an illustrative experiment shown in Section V. Finally, the paper is concluded in Section VI.

II. PROTOTYPE OVERVIEW

The proposed prototype consists of a transmitter and a receiver. For each, a host computer (PC) and a USRP are used as illustrated in Fig. 1. The transmitter acts as a PU, which transmits a sequence of idle/busy periods (with known statistical parameters) in a particular frequency channel in order to generate a PU channel activity. The receiver, on the other hand, acts as a SU, which performs spectrum sensing (using ED algorithm) in the same channel with a periodic sensing time T_s. The energy of each sensing event is compared with a threshod to decide whether the channel is idle or busy. Sensing decisions can then be used to calculate the durations of the PU idle/busy periods and based on these durations PU activity statistics can be estimated. By comparing the statistics of the generated periods at the transmitter (PU) with the estimated ones at the receiver (SU), it is possible to validate the accuracy of the estimation methods and algorithms, including those used in the literature to estimate channel activity statistics [11]–[17], under a realistic conditions of wireless channel impairments (i.e., noise, path loss, shadowing and fading) and hardware limitations of the transmitter and receiver.

III. HARDWARE IMPLEMENTATION

The hardware implementation of the proposed prototype comprises a USRP and a host PC at both sides of the system (transmitter and receiver). USRP is a Software Defined Radio (SDR) platform that is widely used to implement and prototype sophisticated radio communication systems. In this prototype, we adopt USRP B200mini Series [21], which is a small form factor and easily portable USB-powered USRP with 1 Tx and 1 Rx front ends as shown in its block diagram in Fig. 2. This USRP supports a wide frequency range from 70 MHz to 6 GHz, which enables a wide range of experiments (e.g., FM and TV broadcast, cellular, Wi-Fi and etc.). The USRP front end filter has an adjustable bandwidth of 200 kHz - 56 MHz and an available gain up to 89.8 dB (for the transmit front end) and 76 dB (for the receive front end). In addition, the ADC/DAC of this USRP can provide a maximum sample rate (master clock) of 61.44 MS/s (note that rates above 56 MS/s are possible, but not recommended). The I/Q samples of the USRP are streamed to/from a host computer PC for additional processing through a high-speed USB 3.0 bus (which has a transmission speed of up to 5 Gbit/s). Meanwhile, the host PC adopted in this prototype has the following specifications: Ubuntu 18.04.3 LTS operating

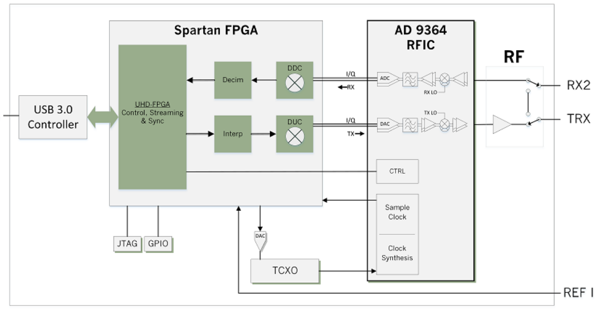


Fig. 2: USRP B200mini block diagram [21].

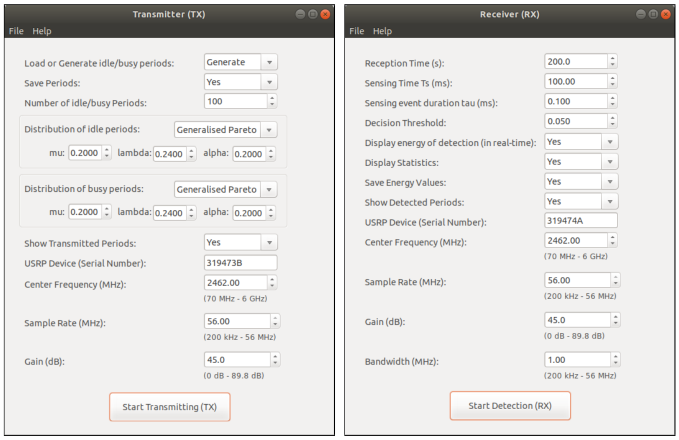
system, Intel Core i5-6500 CPU processor @ 3.20GHz and 8 GB memory. This host PC provides enough computational power to run a broad range of complex experiments in real-time with the developed software implementation, which is described in the following section.

IV. SOFTWARE IMPLEMENTATION

A. *Transmitter software*

The software of the transmitter aims to configure the USRP in order to operate as a PU. A program is developed using C language on the host PC to communicate with the USRP. First, the USRP Hardware Driver (UHD) is required to be installed on the PC in order to provide all the necessary controls and libraries used to transport I/Q samples to/from USRP hardware. Then the USRP-transmitter is programmed such that it generates a sequence of idle/busy periods in a frequency channel to represent PU activity. The busy period durations T_1 can be generated by letting the USRP transmit a signal for a desired duration of time T_1. Any modulation scheme can be used for the transmitted signal since signal modulation is irrelevant when energy detection method is used at the SU [2] (the purpose of this signal is to generate an energy activity in the channel rather than to transmit data). However, for simplicity, ON-OFF Keying (OOK) modulation is used by streaming a binary 1 data (i.e., I=1 and Q=0) for a duration of T_1. The code implementation allows to easily add sequences of random bits and more sophisticated modulations if desired. The maximum sample rate (56 MS/s) of USRP B200mini allows representing continuous values of busy periods with a time resolution of 17.8 ns (which significantly improves the accuracy of the generated periods using PECAS prototype [18] where the time resolution was 0.1 ms). The idle periods T_0, on the other hand, are produced by halting the transmission of the USRP for a duration of time T_0 using `nanosleep` function in C, in which an idle duration with nano seconds resolution is used to hold up the transmission before the next busy period.

The duration values of the idle/busy periods that are wanted to be transmitted can either be imported from a plain text file or generated by the transmitter program (in both cases the number of periods can be specified). If the later was selected, the program will generate random durations of idle/busy periods based on a distribution selected from a list of distributions that provide an accurate representation for the empirical data in a real system [22]. This list includes exponential, generalised exponential, Pareto, generalised Pareto, log-normal, gamma and Weibull distributions as shown in [22, Table I]. Note that a random value from any distribution can be obtained (based on the inversion method in [23, p. 28]) using uniform random number generator (e.g., `rand` function in C) and the inverse CDF [18]. A test mode is also included in the list of distributions to transmit a test sequence of 1 second idle and 1 second busy periods. Finally, a Graphical User Interface (GUI) is designed as shown in Fig. 3a to ease the configuration of the USRP transmitter and the created PU activity without the need to modify the original source code. Also, it will help other researchers to easily conduct relevant experiments on such platform for different research purposes.



Load or Generate idle/busy periods: Generate
Save Periods: Yes
Number of idle/busy Periods: 100
Distribution of idle periods: Generalised Pareto
mu: 0.2000 lambda: 0.2400 alpha: 0.2000
Distribution of busy periods: Generalised Pareto
mu: 0.2000 lambda: 0.2400 alpha: 0.2000
Show Transmitted Periods: Yes
USRP Device (Serial Number): 319473B
Center Frequency (MHz): 2462.00
(70 MHz - 6 GHz)
Sample Rate (MHz): 56.00
(200 kHz - 56 MHz)
Gain (dB): 45.0
(0 dB - 89.8 dB)

Reception Time (s): 200.0
Sensing Time Ts (ms): 100.00
Sensing event duration tau (ms): 0.100
Decision Threshold: 0.050
Display energy of detection (in real-time): Yes
Display Statistics: Yes
Save Energy Values: Yes
Show Detected Periods: Yes
USRP Device (Serial Number): 319474A
Center Frequency (MHz): 2462.00
(70 MHz - 6 GHz)
Sample Rate (MHz): 56.00
(200 kHz - 56 MHz)
Gain (dB): 45.0
(0 dB - 89.8 dB)
Bandwidth (MHz): 1.00
(200 kHz - 56 MHz)

(a) Transmitter GUI (b) Receiver GUI

Fig. 3: Designed GUI for the proposed USRP-based prototype.

B. *Receiver software*

Receiver software aims to configure the USRP in order to operate as a SU. Similar to the transmitter, a C program is developed on the receiver PC to control on the USRP via UHD library. The USRP-receiver is programmed such that it senses the activity of a frequency channel periodically every T_s sensing time (using ED algorithm); and then make a binary decision on whether the channel is idle or busy. At every sensing event a set of samples are captured from the desired channel for a time slot of τ as shown in Fig. 4. Note that τ must significantly be shorter than T_s such that the remaining time of $T_s - \tau$ would be reasonable to exploit in spectrum sharing systems (when the channel is idle). The number of samples N that can be captured during τ time slot depends on the sample rate of the USRP hardware and it is given by $N = \lceil \tau f_s \rceil$, where f_s is the sample rate configured for the USRP. Using the USRP's maximum sample rate of 56 MS/s enables capturing 1000 samples in $\tau = 17.8$ μs time (whereas PECAS model would require a time of $\tau = 312.5$ μs to capture the same number of samples, which slows down the process of spectrum sensing and thus the whole experiment, in particular when a large number of idle/busy periods is

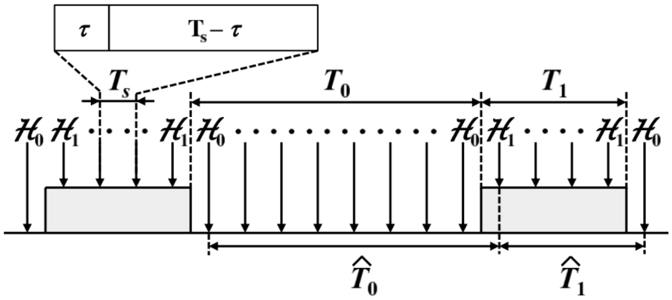


Fig. 4: Spectrum sensing decisions [18].

required). The energy of these samples is then calculated and compared with a predefined threshold as:

$$E_x = \sum_{n=1}^{N} |x[n]|^2 \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \lambda \qquad (1)$$

If the energy of the N samples is greater than the threshold λ a binary decision of $\mathcal{H}_1$ is made to indicate the channel is busy, otherwise $\mathcal{H}_0$ is made to indicate the channel is idle. Selecting threshold value will determine the operation of the system. The prototype can operate under PSS by selecting a threshold energy midway between idle and busy energies after adjusting the gain of the receiver to be sufficiently high in order to easily differentiate the energy between the two states without causing any sensing error. On the other hand, under ISS scenario, threshold value λ is selected to meet a predefined probability of false alarm P_{fa}, where only receiver's noise need to be known [3]. This threshold can be selected by configuring the program to save the energy of sensing events (when there is no signal in the channel but only noise, i.e., transmitter is off) to a file for post-processing. Energy values are then used to select a threshold that would cause a false decision with a probability P_{fa} for which the experiment wanted to be tested under ISS.

After obtaining the sensing decisions, they can be further exploited to provide statistical information of the channel activity as discussed in Section I. The program first estimates the durations of the idle/busy periods observed in the channel by computing the time difference between any two changes in the decision of sensing as shown in Fig. 4. The estimated periods can then be printed on the terminal window of the program in real-time (while the experiment is running) such that their accuracy can be examined instantaneously in comparison with the transmitted periods. They can also be saved into a text file for post-processing. Subsequently, the statistical parameters of the detected periods can then be calculated to find, for example, the minimum/maximum period, the mean and variance of periods, duty cycle and distribution of periods. These statistics are valuable information to enhance the performance of smart spectrum sharing systems. Receiver program is developed such that it can provide a real-time graphical illustration for the detected energy of the idle/busy periods as well as a real-time estimation for the statistical parameters of the channel activity. Every time the program detects a new period it updates the estimation of the statistics instantaneously. In addition, a user-friendly GUI is also designed for the receiver as shown in Fig. 3b to ease the configuration of the USRP that is performing spectrum sensing and processing the sensing decisions.

By comparing the estimated statistics in the receiver with the statistics used to generate the idle/busy periods in the transmitter, it is possible to evaluate the accuracy of the estimation methods and algorithms (such as those used in the literature [11]–[17]) under realistic conditions of wireless communication system imposed by channel impairments (noise, path loss, shadowing and fading) and hardware limitations of transmitter and receiver. In addition, the impact of the employed parameters of spectrum sensing (which include sensing period T_s, sensing time slot τ, probability of sensing errors and sample size N) on the estimation of the channel activity statistics can easily be examined using such prototype in real-time and under realistic conditions. Therefore, it provides an experimental platform to support future works on the channel activity statistics estimation.

V. ILLUSTRATIVE EXPERIMENT AND RESULTS

In this section we demonstrate the operation of the proposed prototype by carrying out an illustrative experiment to show the whole process which involves generating PU activity in a frequency channel (i.e., transmitting idle/busy periods), detecting the energy of the channel activity (i.e., spectrum sensing), estimating the idle/busy periods durations, and finally estimating their statistical information. All these operations take place in real-time while the experiment is running.

First, we configure the USRP of the transmitter and the receiver (using the designed GUI shown previously) such that they both operate on the same frequency channel. In this context, we run the experiment on 2.5 GHz WiFi band using channel 11 (2.451 GHz - 2.473 GHz) centred at 2.462 GHz. This was motivated as such experiment would not be possible to carry out using PECAS [18], which therefore emphasises the importance of this platform. In addition, we select channel 11 as such was less crowded in the WiFi environment where our experiment was tested. Selecting the less crowded WiFi channel (non-overlapping) allows us generate our own PU traffic with known statistics in order to be compared and validated with the statistics estimated at the SU. Therefore, in the GUI of the transmitter and receiver, we set the centre frequency of the USRPs to 2.462 GHz as shown in Fig. 3. In addition, the full functionality of the USRP is used to set the sample rate to its maximum 56 MS/s, which will help providing high resolution idle/busy periods at the transmitter and fast energy detection at the receiver. Placing the SU 1 meter apart from the PU and using a gain of 45 dB at both sides will be sufficient to detect the transmitted signal. The transmitter is configured to generate and transmit 200 periods (100 idle and 100 busy). These periods are produced from the Generalised Pareto distribution (which is the best desecription for the empirical data in real system [22]). This distribution can be selected from the GUI and its parameters

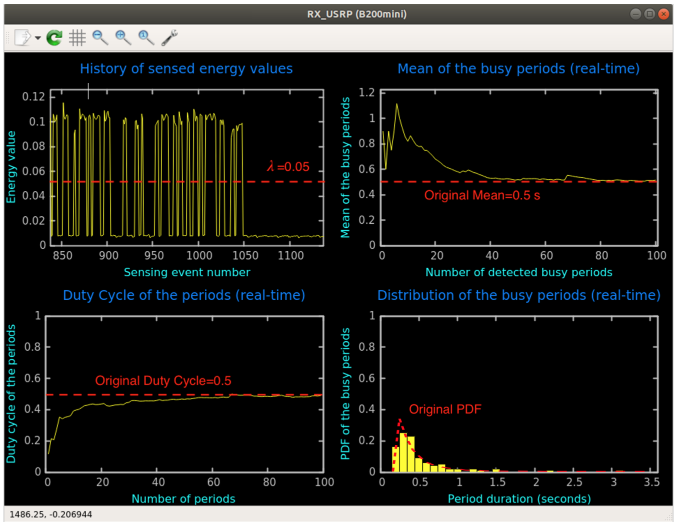


Fig. 5: Real-time energy detection and statistics estimation using the proposed prototype.

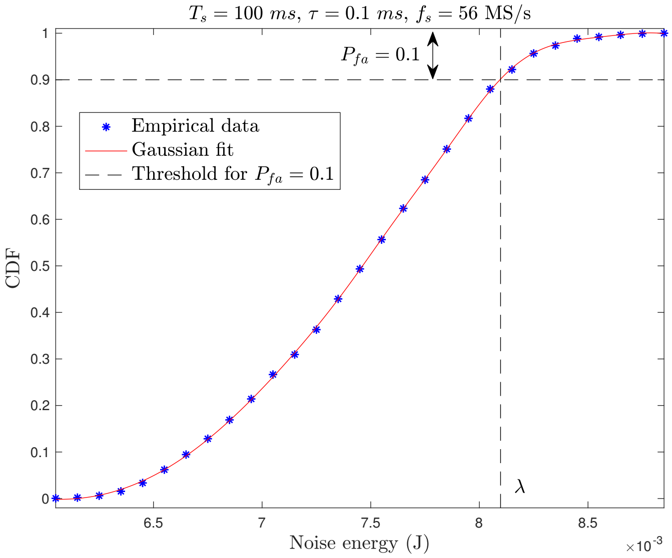


Fig. 6: Threshold selection from the CDF of the noise energy.

(for both idle and busy periods) can be configured as: location $\mu = 0.2$ s, scale $\lambda = 0.24$ s, and shape $\alpha = 0.2$. Based on which, the generated idle/busy periods will have (statistical parameters) a minimum period $\min(T_0) = \min(T_1) = 0.2$ s, a mean period $\mathbb{E}(T_0) = \mathbb{E}(T_1) = 0.5$ s, and a duty cycle $\Psi = 0.5$. Since these generated periods require 100 seconds to be transmitted, the reception time of the receiver is adjusted to be sufficiently high to detect the whole transmitted sequence. For example, a reception time of 200 s (with extra 50 s before starting the transmitter and extra 50 s after) can be used to guarantee all the periods will be detected properly. The receiver senses the channel periodically using a sensing time $T_s = 100$ ms, where T_s has to be smaller than the minimum transmitted period which is $\min(T) = 0.2$ s. Note that the minimum T_s that can be configured by the proposed prototype using the host PC specified in Section III (with Intel Core i5 processor) while still maintaining real-time operation is 0.33 ms (which is 30 times faster than PECAS [18] where its minimum T_s is 10 ms). At every sensing event ($T_s = 100$ ms) a set of samples are captured for a time slot of $\tau = 0.1$ ms. The number of these samples is found as $N = \lceil \tau f_s \rceil = \lceil 0.1 \text{ ms} \times 56 \text{ MS/s} \rceil = 5600$ samples. Based on which, the energy of each sensing event can be calculated and plotted instantaneously as shown in Fig. 5 (top-left), which shows the real-time energy detection of the idle/busy periods in the frequency channel 2.462 GHz. Comparing the energy values with a predefined threshold $\lambda = 0.05$ (selected to be in the middle for PSS operation), binary decisions can be made about the state of the channel (idle $\mathcal{H}_0$ or busy $\mathcal{H}_1$). Based on these decisions, the idle/busy periods durations can be estimated, which in turn will provide an estimation for the channel activity statistics such as mean period as shown in Fig. 5 (top-right), duty cycle (bottom-left) and distribution (bottom-right). These statistics are shown for busy periods, however, similar tendency can also be observed for the idle periods.

As it can be appreciated from Fig. 5, the larger the number of periods (sample size) used to estimate the statistics the closer the estimation approaches the original statistics. This can help to determine how many periods are required to provide an accurate estimation for channel activity statistics, which can therefore validate the analysis conducted in [12], [24]. Notice that the statistics shown in Fig. 5 are recalculated and updated in real-time every time a new period is observed.

The prototype can also be configured to operate under ISS by selecting a threshold value that satisfies a predefined P_{fa}. This threshold can be found by first running the receiver to save a large number of (noise-only) sensing energies (i.e., when the transmitter is off), then selecting the point where the Cumulative Distribution Function (CDF) of these energies is equal to $1 - P_{fa}$, i.e., $\lambda = F_{E_x}^{-1}(1 - P_{fa})$. As shown in Fig. 6, the CDF of the energy values fits well with the Gaussian CDF, from which a threshold $\lambda = 0.0081$ J is found to run the prototype under ISS with $P_{fa} = 0.1$.

In order to show how this prototype can serve as a proof-of-concept for the ongoing research on the channel activity statistics, we consider the theoretical estimation methods proposed in [16] to be validated experimentally under realistic conditions of wireless channel and hardware limitations. The work in [16] finds mathematical expressions to accurately estimate the original statistics (mean and duty cycle) based on the statistics observed under ISS. Therefore, we run the prototype under ISS using $P_{fa} = 0.1$ (as explained above) to detect the idle/busy periods and estimate their statistics (which will be inaccurate due to the sensing errors). Then we apply [16] expressions to correct the estimation of these statistics observed experimentally in order to compare their performance with respect to the theoretical results. As shown in Fig. 7, there is an evident agreement between the obtained experimental results (for the mean of busy periods under ISS) and the theoretical expressions proposed in [16] for different

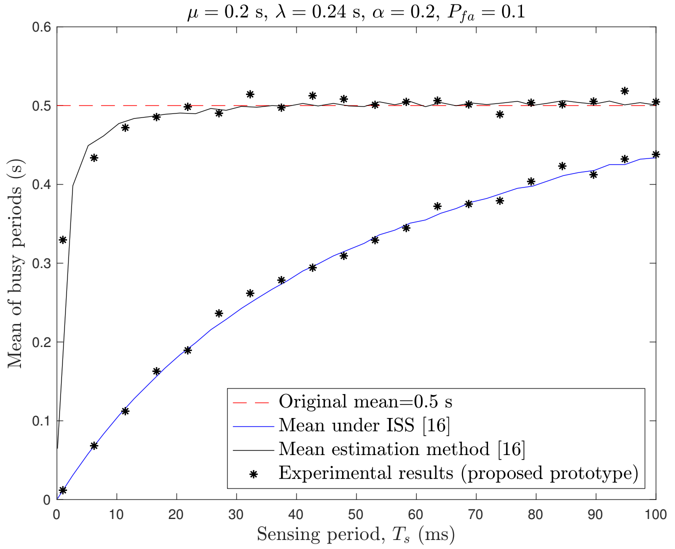


Fig. 7: Experimental validation of the mean period estimator proposed in [16].

sensing period T_s, thus providing an experimental validation for the work conducted in [16].

VI. Conclusion

Due to the importance of the channel activity statistics on the performance of smart spectrum sharing systems, it is essential to have a sophisticated platform where a wide range of research-related experiments can be carried out under actual degrading effects of wireless channel and other practical limitations of the transmitter and receiver hardware. In this context, this work has proposed a new USRP-based prototype for real-time estimation of channel activity statistics. The proposed prototype outperforms the platform used in the literature in terms of functionality, wide applicability and utilisation facility. In addition, this prototype provides an important capability of estimating and illustrating the statistical parameters of the channel activity in real-time, which helps examining the accuracy of estimation while detecting channel's idle/busy periods in real-time. Moreover, it has been shown, with an illustrative experiment, how the proposed prototype can serve as a proof-of-concept for the ongoing research on the channel activity statistics.

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