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Research Article

GSM-RF Channel Characterization Using a Wideband Subspace Sensing Mechanism for Cognitive Radio Networks

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In this paper, we examine a spectrum sharing opportunities over the existing Global System of Mobile Communication (GSM) networks, by identifying the unused channels at a specific time and location. For this purpose, we propose a wideband spectrum sensing mechanism to analyze the status of 51 channels at once, belonging to the 10 MHz bandwidth centered at the frequency 945 MHz, in four different areas. We propose a subspace based spectral estimation mechanism, adapted to deal with real measurements. The process begins with data collection using Secondary User (SU) device enabled with Software Defined Radio (SDR) technology, configured to operate in the GSM band. Obtained samples are used then to feed the sensing mechanism. Spectral analysis is delivered to estimate power density peaks and corresponding frequencies. Decision making phase brings together power thresholding technique and GSM control channel decoding to identify idle and busy channels. Experiments are evaluated using detection and false alarm probabilities emulated via Receiver Operating Characteristic (ROC) curves. Obtained performances show better detection accuracy and robustness against variant noise/fading effects, when using our mechanism compared to Energy Detection (ED) based ones as Welch method, and Beamforming based ones as Minimum Variance Distortionless Response (MVDR) method. Occupancy results exhibit considerable potential of secondary use in GSM based primary network.

1. Introduction

Nowadays, the Internet of Things (IoT) paradigm is known as being the trend that defines the global orientation of information technology actors. The early stage idea behind this paradigm consists of deploying smart devices mainly conceived for physical phenomena monitoring and control. It is expanding gradually to reach a point-to-point interaction between humans and devices leading to a smart and connected ecosystem. Billions of things already proliferate in the IoT ecosystem, yielding to novel application domains such as Smart Cities [1, 2] as an all-embracing perspective including variant sub-applications, Industry 4.0, e-government, among others. This vision appears highly promising, although it divulges new types of challenges requiring low latency, low energy consumption and cost, and easy operation of massive number of embedded-systems. Those small size devices need to coexist with high level mobile devices such as Smartphones, Tablets, and similar accessories and share the available telecommunication bandwidth to ensure their connectivity. IoT designed-devices operate mainly in the unlicensed and limited industrial, scientific, and medical (ISM) bands. With the proliferation of IoT devices, ISM band is congested and there is a need to explore utilizing other bands. In this direction, important research on 5G futuristic telecommunication standard has investigated the possibility of exploiting millimeter wave range of 30 − 300 GHz to enhance the availability [3]. However, millimeter waves are very susceptible to penetration and are still being investigated in terms of energy efficiency and hardware suitability for IoT application [4].

In this paper, we explore the underused spectrum in GSM band to alleviate the spectrum congestion problem in IoT application. Our interest to use GSM infrastructure is mainly motivated by the extensive demands for using the $800 - 900$ MHz bands by NarrowBand IoT (NB-IoT) devices [5], and the under-utilization of this band [6]. In fact, deploying NB-IoT in such frequency bands is a great choice because they provide an already large and established ecosystem and extensive coverage capabilities. They also have excellent propagation characteristics which generally improves the indoor penetration [7]. In particular we focus at considering Cognitive Radio (CR) technology as the key technology to overcome the spectrum efficiency challenges [8]. We aim at allowing unlicensed or "secondary users (SUs)" to access the unused spectrum bands of GSM. To intelligently access and leave the bands of interest, without interfering with the primary devices, CR user needs to have the ability to perform (1) spectrum sensing, (2) decides whether the channel is available for use, (3) shares the spectrum, and then (4) decides whether to stay or leave the channel (spectrum mobility) [9]. In our work, we will focus on the spectrum sensing functionality [10], which is indispensable to identify where the unused portions of the GSM spectrum, commonly called "white spaces," are located.

Few research contributions have already explored CR opportunities over GSM networks. Chowdhury and al. [11] have combined the FDD (Frequency Division Duplex) and TDMA (Time Division Multiple Access) features of GSM standard to model PUs (Primary Users) behavior and performed dynamic spectrum access. An opportunistic access to the 850 MHz GSM uplink frequency channel has been investigated by Gao [12]. However, spectrum sensing has not concretely been addressed in both papers. Authors have adopted many assumptions to meet spectrum sensing constraints in GSM bands, which question the validity of the model for real case scenarios. Other works in the literature [13, 14] have addressed spectrum sensing using Energy Detection (ED) based techniques in GSM, though they are significantly vulnerable in noisy environments. Furthermore, such techniques are limited to narrow band sensing problems, which make them unable to detect more than one frequency channel per time. Thus, performing a "Wideband" spectrum sensing for GSM networks will significantly enhance opportunistic access possibilities.

In this paper, we propose a subspace-based wideband spectrum sensing mechanism for GSM downlink channels characterization. The proposed technique outperforms the existing approaches in several aspects; it is adaptable to realistic scenarios, robust against fading and noise effects, capable of sensing multiple channels at once. Subspace techniques are known to be used in multiple sources multiple antennas architectures since they rely on eigen-decomposition of the autocorrelation matrix of the received signals [15]. In our approach, we adapt the mathematical basics of subspace algorithm to suite the received data while using SDR-enabled devices equipped with single antenna to reduce the sensing cost. Data collection was done in four different areas to experience different attenuation/noise effects. The SDR was configured to operate in the GSM band between 940 and 950 MHz, which contains 51 channels of 200 kHz bandwidth. We then use the received samples as inputs to our sensing mechanism modeled in Matlab simulation tools to study its performance. We obtain the PSD (Power Spectrum Density) distribution all over the band and its corresponding frequency estimates using Multiple Signal Classification (MUSIC) algorithm. We retrieve then the power content in each 200 kHz channel and compare it to specific predetermined threshold to decide whether it is busy or idle. To evaluate the efficiency of the proposed mechanism, we opted for an analytical study of GSM control channels. We decoded them to obtain the ARFCN (Absolute Radio-Frequency Channel Number) parameters that correspond to active channels in advance. This study allows us to obtain correct detection and false alarm probabilities to evaluate detection accuracy of our technique versus Welch ED-based approach and MVDR (Minimum Variance Distortionless Response) beamforming-based one. The results prove the efficiency of the presented mechanism in different radio environments and its suitability to characterize accurately GSM channels activity.

The remainder of this paper is organized as follows. In Section 2, we review some of the related works in the literature. Section 3 lays out the mathematical model of the presented sensing mechanism. Section 4 outlines the experimental scenario and reports the results obtained from our experiments. In Section 5, we conclude our work and discuss potential improvements.

2. Related Works

Cognitive Radio is essentially based upon resources sharing and coexistence between primary networks and secondary ones. Thus, enabling SUs with dynamic RF-spectrum access protocols requires accurate spectrum sensing mechanisms to avoid interference with PUs. In this sense, several sensing approaches have been proposed in the literature including ED, cyclostationarity features detection [16], matched filtering [17], among others [18]. The commonly used within GSM-based primary networks is the ED, mainly because of its low computational load and minimum dependency to a priori information [19]. It was implemented in a primitive way, in [13] using a spectrum analyzer to retrieve spectrum occupancy statistics of GSM band at Jaipur city, India. However, ED is vulnerable to noise uncertainty and needs to have an accurate knowledge of the noise floor, which interrogates the accuracy of signal detection in the presence of injurious shadowing and multipath fading effects. Another relevant paper [14] has portrayed CR opportunities over GSM by examining captured samples in real time, based upon Fast Fourier Transform (FFT) algorithm to do spectrum sensing. Nonetheless, the FFT analysis is marked by tradeoffs in windowing, time domain averaging, and frequency domain averaging of sampled data obtained from random processes in order to balance the need to reduce side lobes and to ensure adequate spectral resolution [20]. The authors in

[21] have come up with the idea of a spectrum pooling scenario to enable dynamic access to the GSM unused bands by an OFDM (Orthogonal Frequency-Division Multiplexing) based secondary system. The sensing technique was built upon cyclostationnarity features extraction of GMSK (Gaussian Minimum-Shift Keying) based modulation and OFDM-based one coupled with frequency domain and time domain ED tests to enhance the performance under specific constraints. Similarly in [22] the couple GSM and OFDM were, respectively, examined as primary and secondary systems by adopting an interference elimination mechanism through the insertion of a ZFBF (Zero Forcing Beamforming) precoding and postcoding, respectively, at the secondary system transmitter and receiver. The approaches in [21, 22] are far to be investigated for a generalized detection mechanism, since they are uniquely adequate to detect OFDM modulated signals, which is not the case in heterogeneous radio environments as for IoT paradigm, where secondary devices are enabled with different multiplexing and access technologies. Besides, the aforementioned spectrum sensing policies are narrowband, which means that they make single binary decision for the whole spectrum [23]. This is a real bottleneck since they cannot identify individual spectral opportunities that lie within the considered spectrum [24]. For this reason, adopting wideband sensing that consists in a joint observation of multiple subchannels at a stroke and joint decision on the occupancy in each sub-band makes the sensing more efficient, especially in GSM based primary network where all targeted 200 kHz subbands need to be investigated at once. Several research studies have been used in this sense, such as multi-band joint detection algorithm and filter-bank detection [25]. Such methods treat the problem as a narrowband sensing one, since they rely on dividing the wideband spectrum into narrower subbands for processing. The main drawback of these methods is that they require prefixed bandwidth locations which may cause detection errors in realistic scenarios when signals exceed frequency bins boundaries. Wavelet methods were adopted to solve this problem by detecting edges in the PSD of wideband channel [26, 27]. Unlike the above mentioned methods, subspace based techniques are highly promising for wideband spectrum sensing since they can sense multiple channels in one go [15, 28] which makes them the most convenient tools for GSM channels detection. In addition, they do not need a priori information of the PUs signal characteristics as in [21, 22] since they are not restricted to specific modulations. Furthermore, subspace techniques are significantly robust against noise as shown in [29], unlike the methods used in [13, 14, 19], because they rely on the eigen-decomposition of the autocorrelation matrix which allows to remove the uncertain background noise in advance. This was the main motivation behind the recent study held in [30] that used subspace filtering to sense multiple PU signals corrupted with AWGN (Additive White Guassian Noise) and Rayleigh fading. The probabilistic analysis seems to be the main contribution of this work, which was already addressed in several previous studies [31, 32]. Rao and al. in [15] have addressed wideband sensing problem by proposing a cooperative subspace detection scheme. They considered received samples over all cognitive SUs, where each of them is equipped with multiple antennas, and by default, they all participate in sensing. This may be neither efficient nor necessary owing to the cost associated with sensing in realistic scenarios. Furthermore, in such model, one PU signal can be detected by more than one SU, which creates estimates association problem that needed data fusion procedure to keep the correct estimates. In our paper, we make the following contributions:

(1) Different from the works in [11, 13, 14], we are proposing realistic testbed using SUs devices enabled with SDR, configured to act independently and collect periodically the signal samples emitted by GSM PUs to lower the sensing cost that usually accompanies subspace techniques in multiple antennas system design as in [15].

(2) We have adapted the mathematical basics of the subspace method to suit data inputs retrieved by sampling GSM channels.

(3) Our model eliminates data fusion problem, since it does not involve multiple antennas architecture, and the PSDs are evaluated with respect to each 200 kHz subband within the 10 MHz without worrying about the number of users.

(4) Performing an analytical study besides the blind detection one as subspace leads to better threshold selection and accurate decision making process.

3. Subspace Based Technique for Spectrum Sensing

Spectrum sensing mechanism is primordial in CR communication cycle, since it defines the occupancy or the availability of the band of interest, so as to figure out how to best take advantage of unused spectrum. To meet the sensing requirements of a GSM based primary network, a wideband sensing mechanism is investigated to identify where the white spaces reside in a wide portion of the spectrum, characterized byspecific number of GSM downlink channels. The bandwidth of each one is fixed to 200 kHz according to the standardized properties of the GSM network.

3.1. Formulation of the Signal Model. Let us assume that there are L secondary users attempting to access the GSM spectrum in an opportunistic manner. Let D be the maximum number of signals that may occupy the band of interest which corresponds to the number of primary users active at a specific time, each with a carrier frequency f_d for $d \in [1, D]$. Equation (1) indicates the mathematical representation of the primary signal, while $\alpha_d(n)$ and $\beta_d(n)$ represent, respectively, the amplitude and the phase of the signal sample n with $n \in [1, N]$.

$$S_d(n) = \alpha_d(n) \cos\left(2\pi f_d n + \beta_d(n)\right) \quad (1)$$

Considering the complex envelope of the signal, we obtain the analytical expression in equation (2):

$$S_d^{env}(n) = \alpha_d(n) \cdot e^{j\beta_d(n)}$$
$$\text{where } S_d(n) = \Re\left\{S_e^{env}(n) \cdot e^{j2\pi f_d n}\right\} \quad (2)$$

The mathematical processing is developed for one secondary user in different nonoverlapped signal bursts I_t for $t \in [1, \tau]$, where τ refers to the whole observation time in the present use case scenario. During each burst I_t, the secondary user SU_l receives a vector $\overrightarrow{v}_{I_t}(n)$ containing K samples as expressed in equation (3).

$$\overrightarrow{v}_{I_t}(n) = \left[v_{I_t}(n), v_{I_t}(n+1), \ldots, v_{I_t}(n+k-1)\right]^T \quad (3)$$

In the present use case scenario, and inspired by [15], K is selected to be enough small to respect the condition $D < K << N$, and to ensure the slow variation property of the process $S_d(n)$ with respect to the sampling rate F_s of the SDR chosen in the experimental phase. Thus, we assume that $S_d(n) \approx S_n(n+k)$ for $k \in [1, K-1]$. The generalized model of the complete signal received during the observation time τ by SU_l is delivered in equation (4).

$$\mathbf{V}_l(n) = \left[\overrightarrow{v}_{I_1}(n), \overrightarrow{v}_{I_2}(n), \ldots, \overrightarrow{v}_{I_\tau}(n)\right]$$
$$\mathbf{V}_l(n) = \mathbf{AS}(n) + \mathbf{Z}_l(n) \quad (4)$$

with $\mathbf{A} = [\overrightarrow{A}_1, \overrightarrow{A}_2, \ldots, \overrightarrow{A}_D]$ where each column $\overrightarrow{A}_d = [1, e^{-j2\pi f_d}, \ldots, e^{-j2\pi(K-1)f_d}]^T$ for $d \in [1, D]$. $\mathbf{S} = [\overrightarrow{S}_1, \overrightarrow{S}_2, \ldots, \overrightarrow{S}_{I_\tau}]$ where each column $\overrightarrow{S}_{I_\tau} = [S_{(I_t,1)}, S_{(I_t,2)}, \ldots, S_{(I_t,D)}]^T$ contains the complex signal received from the d-th PU signal at the antenna in the block I_t. $\mathbf{Z}_l(n) = [\overrightarrow{Z}_{I_1}(n), \overrightarrow{Z}_{I_2}(n), \ldots, \overrightarrow{Z}_{I_\tau}(n)]$ is a zero mean Gaussian white noise matrix with variance σ^2, where the column $\overrightarrow{z}_{I_t} = [z_{I_t}(n), z_{I_t}(n+1), \ldots, z_{I_t}(n+K-1)]^T$. The autocorrelation matrix of the complete signal is given in equation (5).

$$\mathbf{R}_{vv} = E\left\{\mathbf{V}_l(n)\mathbf{V}_l^H(n)\right\} \quad (5)$$

where $E\{\cdot\}$ denotes the expectation operator. Substituting the equation (4) in equation (5), we obtain

$$\mathbf{R}_{vv} = \mathbf{AR}_{ss}\mathbf{A}^H + \sigma^2\mathbf{I}_{no} \quad (6)$$

where $\mathbf{R}_{ss} = E\{\mathbf{S}(n)\mathbf{S}^H(n)\}$ is the autocorrelation matrix of signals. The quantity $\sigma^2\mathbf{I}_{no}$ corresponds to the noise autocorrelation matrix with variance σ^2 and $\mathbf{I}_{no}$ the identity matrix. The matrix $\mathbf{R}_{ss}$ holds in its diagonal the average power received from D signal sources by the secondary user l, during the whole observation period τ divided into time intervals I_t. Thus, it can be expressed according to equation (7)

$$\operatorname{diag}(\mathbf{R}_{ss}) = \left[\sum_{n=1}^{\tau}\left|S_{I_{n,1}}(n)\right|^2, \sum_{n=1}^{\tau}\left|S_{I_{n,2}}(n)\right|^2, \ldots, \sum_{n=1}^{\tau}\left|S_{I_{n,D}}(n)\right|^2\right] \quad (7)$$

As a matter of fact, the exact value of the autocorrelation matrix analytically obtained in equation (6) cannot be accurately attained. For this reason, we adopt the following approximation in equation (8).

$$\mathbf{R}_{vv} \approx \frac{1}{N-K+1}\sum_{n=1}^{N-K+1}\mathbf{V}_l(n)\mathbf{V}_l^H(n) \quad (8)$$

As soon as we get to define the data model, the estimation methods can be used to estimate the spectral content in the received data set.

3.2. Eigen-Decomposition of the Autocorrelation Matrix. The eigen-decomposition phase allows to separate the space of observations in two orthogonal vector subspaces, the signal subspace, and its complement, the noise subspace. The autocorrelation matrix obtained by equation (6) can be written as a decomposition of K eigenvectors $\{\overrightarrow{\Phi}_i\}_{i=1,\ldots,K}$ and K associated eigenvalues $\{\lambda\}_{i=1,\ldots,K}$, arranged in the descending order, as shown in equation (9).

$$\mathbf{R}_{vv} = \sum_{i=1}^{K}\lambda_i\overrightarrow{\Phi}_i\overrightarrow{\Phi}_i^H = \overrightarrow{\Phi}_i\overrightarrow{\Lambda}\overrightarrow{\Phi}_i^H \quad (9)$$

where $\overrightarrow{\Lambda} = \operatorname{diag}\{\lambda_1, \lambda_2, \ldots, \lambda_K\}$. Since there are D signal sources and the noise is an AWGN (Additive White Gaussian Noise), we have $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_D \geq \lambda_{D+1} = \cdots = \sigma_N^2$ [33]. In fact, the eigenvector $\overrightarrow{\Phi}_i$ associated with its particular eigenvalue λ_i satisfies the following equation (10):

$$\left(\mathbf{R}_{vv} - \lambda_i\mathbf{I}_{no}\right)\overrightarrow{\Phi}_i = 0 \quad (10)$$

Considering the eigenvectors corresponding to the (K-D) smallest eigenvalues, we obtain

$$\begin{aligned}\left(\mathbf{R}_{vv} - \sigma_i^2\mathbf{I}_{no}\right)\overrightarrow{\Phi}_i &= \mathbf{AR}_{ss}\mathbf{A}^H\overrightarrow{\Phi}_i + \sigma_i^2\mathbf{I}_{no}\overrightarrow{\Phi}_i - \sigma_i^2\mathbf{I}_{no}\overrightarrow{\Phi}_i \\ &= \mathbf{AR}_{ss}\mathbf{A}^H\overrightarrow{\Phi}_i = 0 \\ &\quad \text{for } i = D, D+1, \ldots, K\end{aligned} \quad (11)$$

Since matrix $\mathbf{A}$ is full rank and $\mathbf{R}_{ss}$ is nonsingular, we conclude that $\mathbf{A}^H\overrightarrow{\Phi}_i = 0$. Thus, the eigenvectors associated with the $(K-D)$ smallest eigenvalues are orthogonal to D directional vectors that make up as written in equation (12).

$$\left\{\overrightarrow{A}_1, \overrightarrow{A}_2, \ldots, \overrightarrow{A}_D\right\} \perp \left\{\overrightarrow{\Phi}_{D+1}, \overrightarrow{\Phi}_{D+2}, \ldots, \overrightarrow{\Phi}_K\right\} \quad (12)$$

This analysis shows that the eigenvectors composing the autocorrelation matrix $\mathbf{R}_{vv}$ belong to one of the two orthogonal subspaces. We define the signal subspace $\mathbf{U}_{sig} = [\overrightarrow{\Phi}_1, \ldots, \overrightarrow{\Phi}_D]$ and the noise subspace $\mathbf{U}_{no} = [\overrightarrow{\Phi}_{D+1}, \ldots, \overrightarrow{\Phi}_K]$. Thus, the information relative to the signal space is held in D eigenvectors that correspond to the highest eigenvalues. The remaining $(K-D)$ eigenvectors compose the noise subspace that does not contain any information referring to the spectral content of the signal.

3.3. Frequencies Estimation with Multiple Signal Classification (MUSIC) Algorithm. The estimation of the frequency values from the autocorrelation matrix of the signal cannot be achieved without the prior knowledge of the number of sources D in the communication environment. Otherwise, the parameter D needs to be also estimated [15]. In the present use case scenario where the primary network is based on GSM standard, the number of signals can be identified since it corresponds to the slots of 200 kHz channels present in the band under study. At this stage, following the computation of the eigenstructure of the received waveforms and the number of signals, the Multiple Signal Classification (MUSIC) algorithm [34] is used to obtain the estimates of frequencies $\{f_d\}$ for $d \in [1, D]$. The idea of the algorithm is based upon the property of orthogonality between the signal space and the noise space. The MUSIC spectrum is evaluated as the inverse of the squared Euclidean distance between the vectors in the matrix and the noise space. Thus, the power peaks expression is given by equation (13).

$$P = \frac{1}{\mathbf{A}^H \mathbf{U}_{no} \mathbf{U}_{no}^H \mathbf{A}} \tag{13}$$

3.4. Channels Occupancy Analysis. After the spectral estimation step using the subspace technique, we opt for evaluating the average power of received signals in each GSM channel with 200 kHz bandwidth. We resort to this technique in order to build our decision making procedure which is based upon the threshold selection. Thus, equation (14) is applied to sweep the detected power peaks in each channel independently for $c \in [1, N_c]$ with N_c denoting the number of channels and N_p denoting the number of bins in each channel.

$$P_{ch}(c) = \frac{1}{N_p} \sum_{m=(c-1)\cdot N_p}^{c\cdot N_p - 1} P(m) \tag{14}$$

In the present use case scenario, we are using real measurements taken from the received signal samples for detection, and no information on the transmitted signal and channel is needed. Such methods belong to the so called blind detection methods. In the simple case of ED based methods, accurate knowledge on the noise power is therefore the key to the success of the method. Unfortunately, in practice, the noise uncertainty is always present; thus, the estimated noise power may be different from the actual noise power [32]. To this purpose, in our use case scenario based upon subspace based mechanism, we set the decision threshold γ that guarantees the best compromise between the false alarm and misdetection probabilities. We then classify the channels as idle or busy as follows:

$$\begin{aligned} &\text{if } P_{ch}(c) \geq \gamma \Longrightarrow \text{channel is busy} \\ &\text{if } P_{ch}(c) < \gamma \Longrightarrow \text{channel is idle} \end{aligned} \tag{15}$$

4. Experimental Scenario

4.1. The Experimental Setup. The experimental prototype used to monitor the GSM downlink radio channels is based on a SDR platform. It is composed of GNU-Radio which is an open source toolkit radio applications prototyping [35], run on a Linux-based Desktop, connected to the Universal Software Radio Peripheral (USRP) transceiver board, model B200, from Ettus Research company [36]. The testbed is illustrated in Figure 1(a). Experiments have been enrolled in an urban area in four different locations, which are the GPS coordinates, respectively, 37 35′ 3, 46″ North/15 2′ 22, 51″ East, 37 35′ 4, 72″ North/15 2′ 21, 20″ East, 37 35′ 2, 76″ North/15 2′ 23, 14″ East and 37 35′ 3, 65″ North/15 2′ 23, 02″ East, in the province of Catania, Italy. Positions one and three are in the same sea level where positions two and four are in another same sea level. Figure 1(b) illustrates the four positions where the SDR prototype was located to receive the GSM complex samples, marked with the red color. The SDR equipment was tuned to scan the GSM base station downlink transmission in the frequency band from 940 to 950 MHz that corresponds to the ARFCN (Absolute Radio-Frequency Channel Number) codes from 25 to 75, using a sample rate of 10 $MSamples/s$. Data analysis is made considering different windows of samples; each one contains $N = 1024$ discrete points. A block of 512 points between each two consecutive observation vectors was discarded to avoid the overlapping. Each window is spread over a resolution bandwidth of 10 MHz centered in 945 MHz, engendering a frequency spacing of 9.76 kHz between each two points, obtained every 10μs.

In parallel to our sensing approach we have made an analytical study using the open source project "gr-gsm" [37], that allows us to have a priori information about the occupied ARFCNs in the considered area, so that we can evaluate false alarm and misdetection probabilities of our approach. Specifically the gr-gsm project provides the "grsgm_scanner" tool which gives information about ARFCNs used in the sensed area by decoding GSM control channels. We consider the active ARFCNs in both, the cell covering the current receiver position, and its neighbor ones, all obtained while decoding the control channels. Table 1 contains the active ARFCNs and their corresponding central frequencies in the 940 – 950 MHz band.

Figure 2 shows the estimated PSDs obtained in each acquisition point using Welch method applied on a long sequence of 4096 non overlapped windows of 1024 received samples weighted by means of Hanning window. The vertical-red lines correspond to the central frequencies of each active GSM channel. PSD distribution reveals tiny idle bands referring to the inactive channels at 940.2 MHz and 941.2 MHz, and a 4 MHz idle band referring to the inactive channels from 945.6 MHz to 949.6 MHz.

4.2. Simulation Results and Discussion. The first step of our GSM downlink channels characterization mechanism consists in implementing the spectrum sensing mechanism described in Section 3. We used complex samples acquired by means of the USRP device as input to our subspace based algorithm. The acquisition system was installed in four different positions as specified in the previous Section 4.1 to

Table 1: Occupied ARFCNs in the data collection area.

ARFCN	25	27	28	29	30	32	33	34	35	36	37	38	39	40
f_o MHz	940.0	940.4	940.6	940.8	941.0	941.4	941.6	941.8	942.0	942.2	942.4	942.6	942.8	943.0
ARFCN	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**	**74**	**75**
f_o MHz	943.2	943.4	943.6	943.8	944.0	944.2	944.4	944.6	944.8	945.0	945.2	945.4	949.8	950.0

(a) (b)

Figure 1: (a) Experimental Testbed; (b) Data collection area.

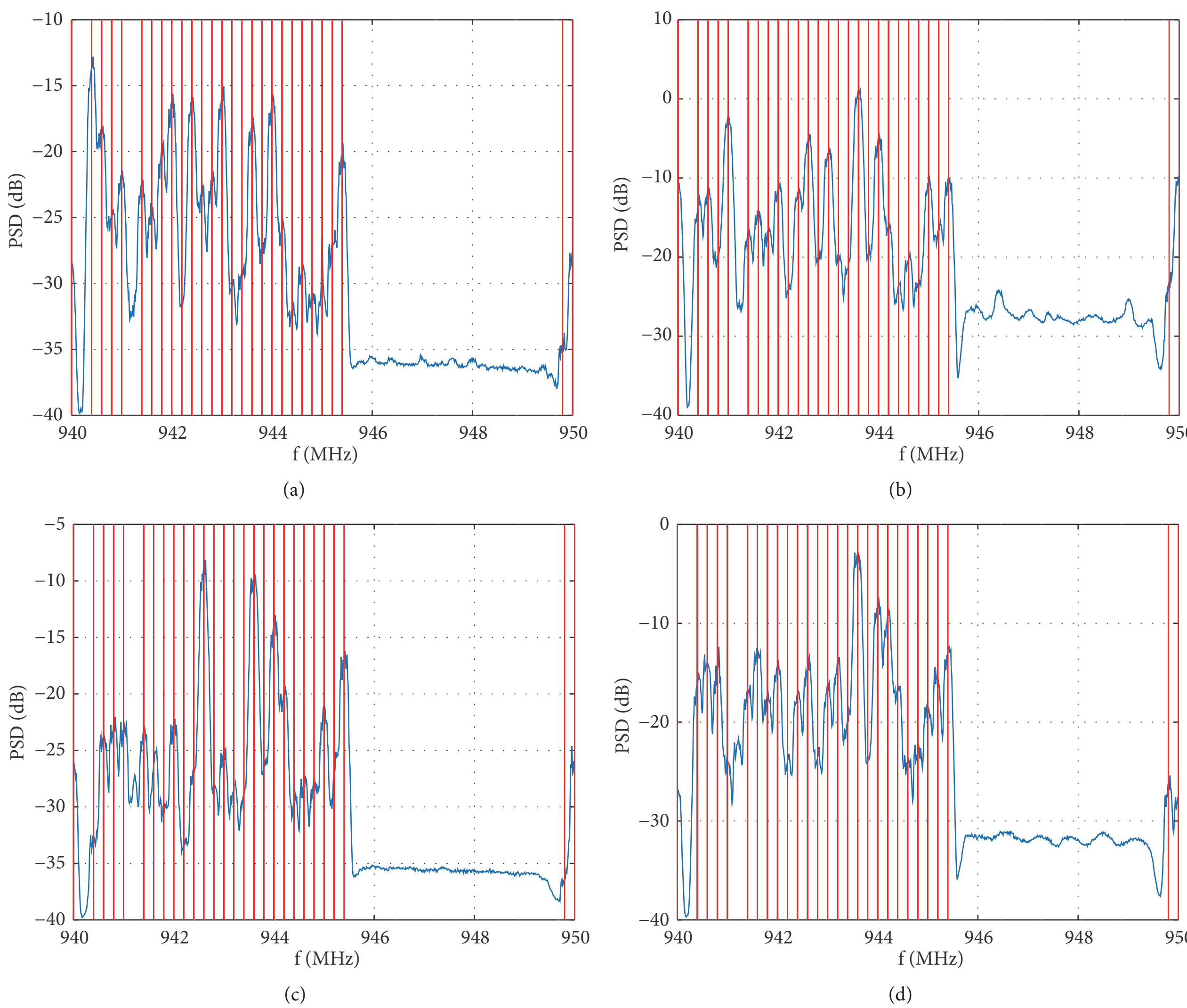

Figure 2: Estimated PSDs obtained in each acquisition point: (a) position 1, (b) position 2, (c) position 3, and (d) position 4. The vertical red lines mark the active ARFCNs.

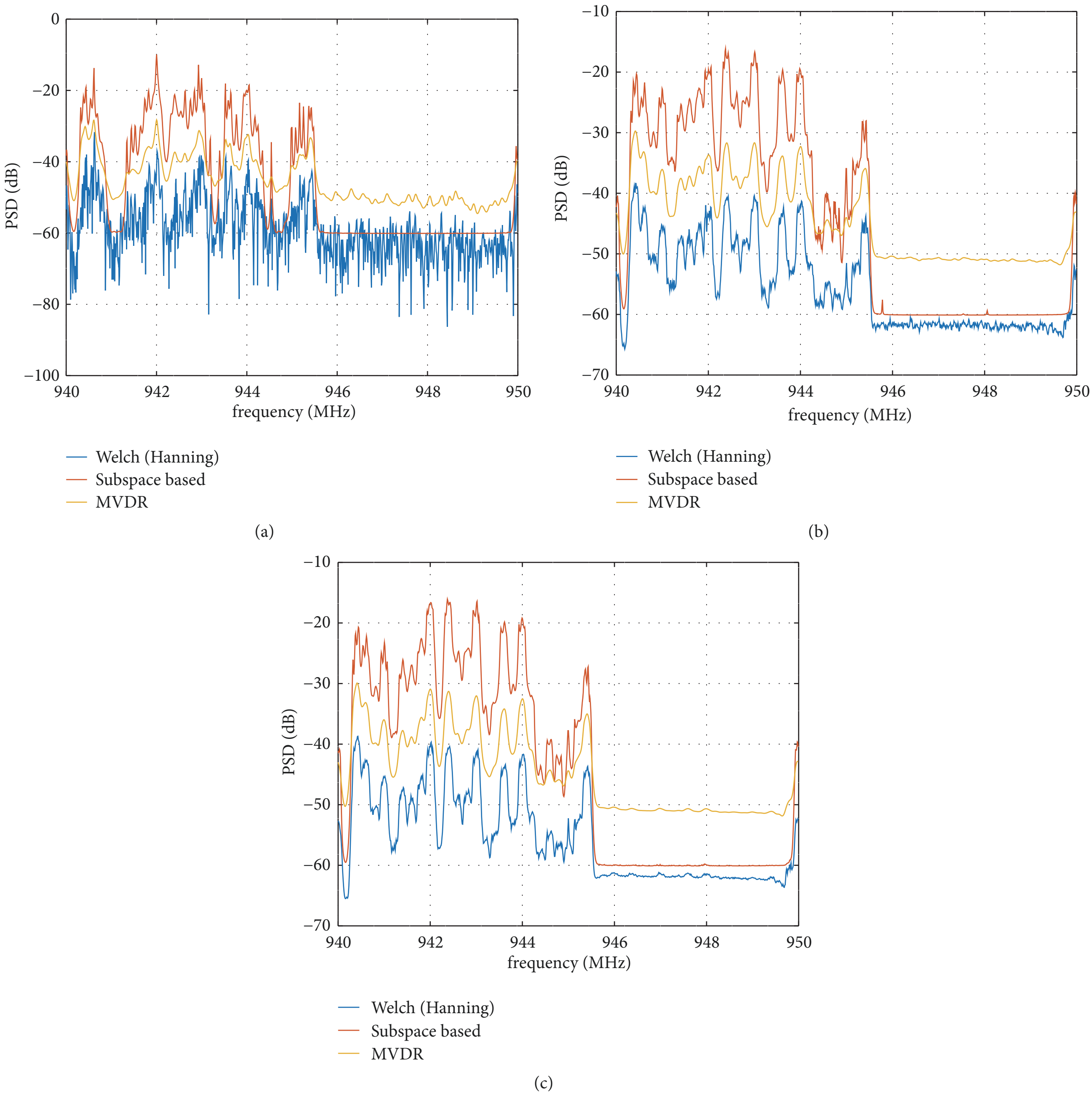

Figure 3: Spectral estimation results obtained in the first position using: (a) 1 window, (b) 128 windows, and (c) 4096 windows.

experience the effects of PUs distance variations (the GSM BTSs in the cell and in the neighbor cells), surrounding buildings, and vegetation on threshold selection and detection accuracy. In parallel, we have implemented two other spectral estimation techniques, the traditional Welch method with Hanning windowing and the MVDR method [38]. The latter belongs to the beamforming techniques for processing spatiotemporal samples to estimate incoming signals and the directions of arrival (DOA). We opt for those approaches since they rely on other computational basics different than the subspace one.

The three approaches are evaluated using different amounts of samples acquired in each area of the four considered locations. Firstly, we processed only one window containing 1024 samples. Secondly, we used 128 windows of 1024 samples, and thirdly we dealt with 4096 windows of 1024 samples. The PSD distributions show the same behavior in different locations. Figure 3 illustrates the obtained PSDs in the first position. Spectral analysis results exhibit a tremendous impact of the number of windows using Welch and MVDR methods. The subspace based one appears insensitive to the number of windows used. In fact, the variance of the PSD estimates is significantly high using Welch and MVDR while processing one window of 1024 samples, particularly in low power density areas. Subsequently, it starts decreasing with higher number of windows (128 windows of 1024

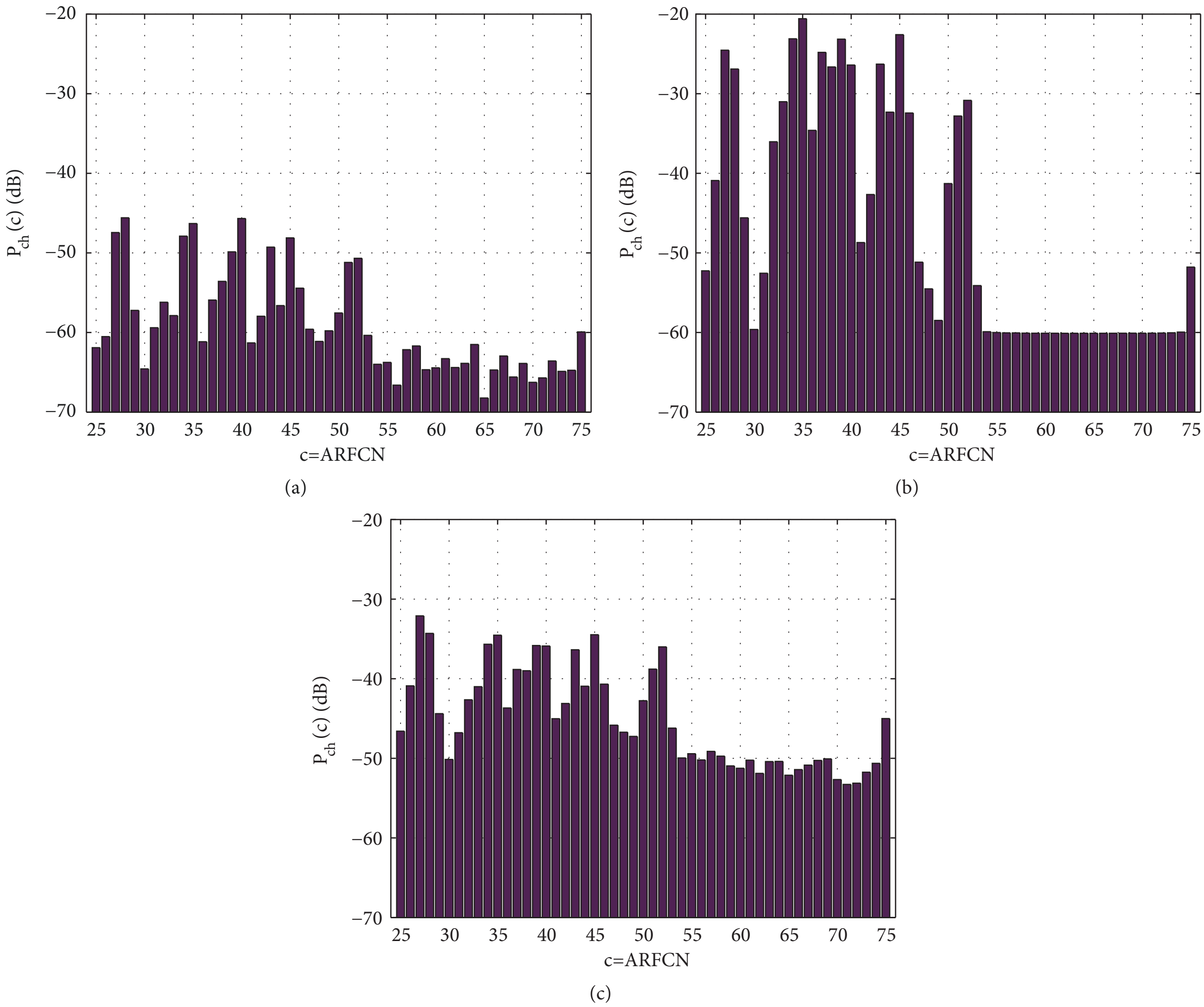

Figure 4: Averaged power density over each 200 *kHz* channel evaluated using 1 window in the first position: (a) Welch method, (b) Subspace based, and (c) MVDR.

samples) until it reaches stable values when a thousand of windows (4096) of samples are used. In such case, the execution time will be a real bottleneck even though the computational complexity of the algorithm itself is practically low as in the case of Welch method. On the other hand, the subspace-based technique gives better performances with less number of samples with significant improvement in terms of power peaks resolution and dB levels.

In step two, we proceed by evaluating independently and consecutively the averaged power content obtained using the considered mechanisms in each 200 *kHz* GSM channel in the 10 *MHz* bandwidth using equation (14). The maximum number of channels to be processed by our subspace sensing mechanism is fixed to $N_c = 51$. Figure 4 shows the obtained results in the first position using the three considered spectral estimation methods.

To evaluate the performance of the proposed mechanism versus the other considered techniques in this paper, we used ROC (Receiver Operating Characteristic) curves analysis in each position. The classification of each single channel as busy or idle is performed using equation (15). We evaluate correct detection P_d and false alarm probabilities P_{FA} based upon GSM control channels information obtained by “grsgm scanner” tool that decodes active channels as listed in Table 1. As the reader can deduce from the analysis performed in Figure 5, the subspace based method outperforms in each position both Welch and MVDR with correct detection probability that reaches 100%. Threshold values that maximize the probability of correct detection P_d and its corresponding P_{FA} in our use case scenario, for the four positions, are gathered in Table 2. The optimal values are also indicated on the ROC curves (Figure 5) with red circles. Obtained results prove the efficiency of the proposed mechanism in the presence of variant fading/noise effects in each area, since threshold values and corresponding probabilities do not mark relevant variations when we change the experiments location. Except position four, we are able to obtain 100% correct detection, while keeping the false alarms less than 22% in the worst

Table 2: Threshold values vs probabilities.

	Position 1	Position 2	Position 3	Position 4
Threshold γ (dB)	−59.977	−59.974	−60.015	−60.061
P_D	100%	100%	100%	99.714%
P_{FA}	13.000%	13.565%	17.739%	21.435%

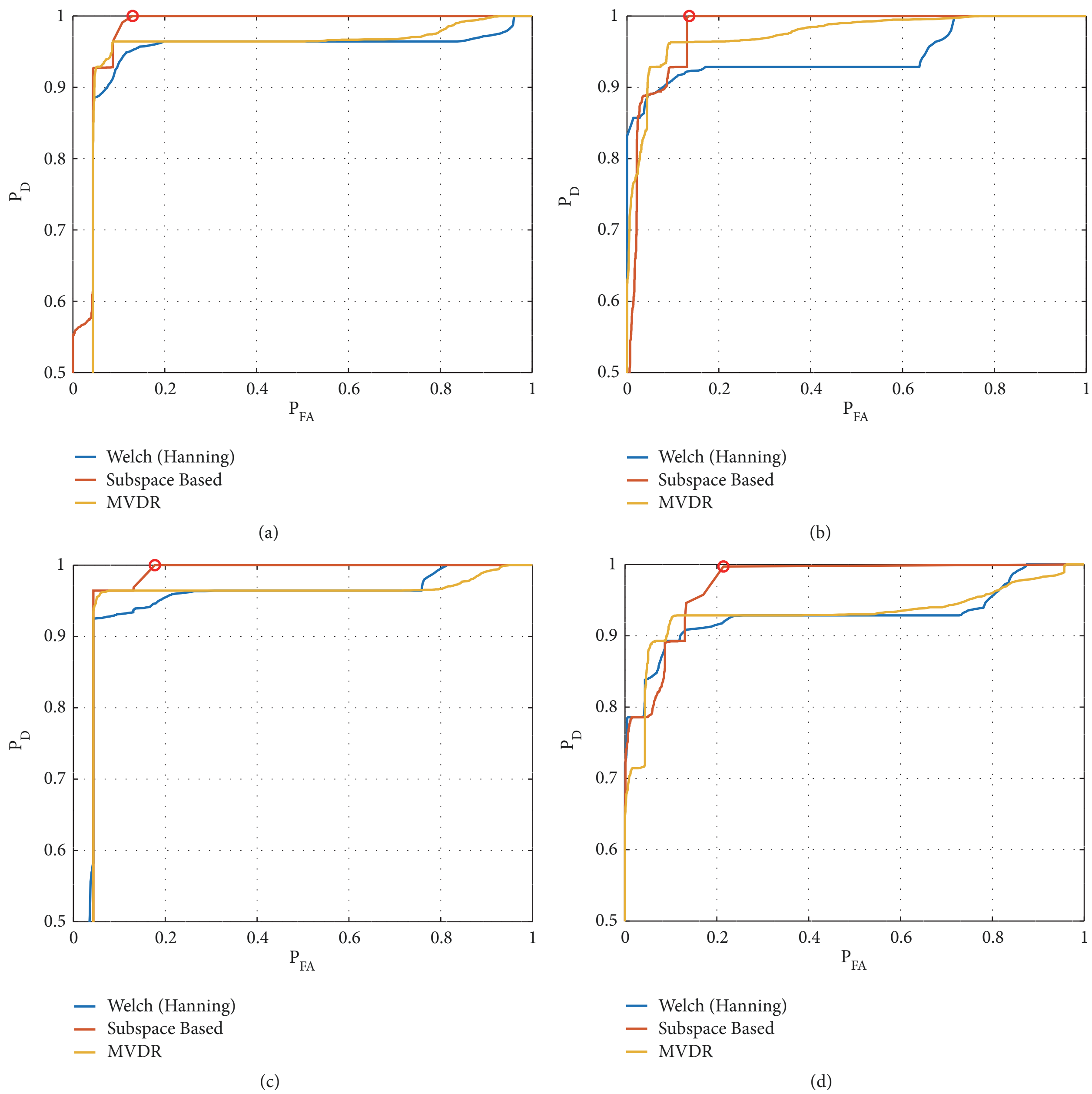

Figure 5: ROC curves evaluated in each position: (a) position 1, (b) position 2, (c), position 3, and (d) position 4.

case. Even being in such case, the probability that a SU correctly classifies an idle channel reaches 88%. Thus, the presented sensing mechanism provides us with a powerful tool to characterize the radio spectrum. On average, in the studied area, a SU can approximately access 39% *MHz* over 10 *MHz* of the considered band without interfering with PUs.

5. Conclusions

Enabling CR users with wideband and accurate spectrum sensing mechanism is primordial to ensure efficient spectral resources sharing. Thus, a subspace technique based on the eigen-decomposition of signals autocorrelation matrix has been proposed to perform wideband spectrum sensing over the GSM system network. The Average of power density peaks obtained using MUSIC algorithm is evaluated in each channel to be then compared to a decision threshold. The aforementioned processing was applied on real measurements collected and sampled using a SDR platform in four locations. The obtained probabilities prove the efficiency of the proposed sensing approach and a considerable potential of opportunistic access to GSM band, allowing devices with CR capabilities to coexist with GSM based primary networks. In the future work, we opt for investigating an opportunistic use of the active channels too in the free time slots, taking advantages of the Time Division Multiple Access (TDMA) method implemented within GSM standard that allows several users to share the same frequency channel during a specific time slot.

Data Availability

The MATLAB data used to support the findings of this study are included within the supplementary information file(s) (available here).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Supplementary Materials

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