AUTONOMOUS DETECTION OF VACANT FREQUENCY BANDS FOR COGNITIVE RADIO

Inna Valieva, Mats Björkman, Johan Åkerberg, Mikael Ekström
School of Innovation, Design, and Engineering
Mälardalen University
Vasterås, Sweden
inna.valieva@mdh.se

Bharath Shashidhar,

Iurii Voitenko
Electronics Development
Wireless P2P Technologies
Falun, Sweden
iurii.voitenko@wp2p.org

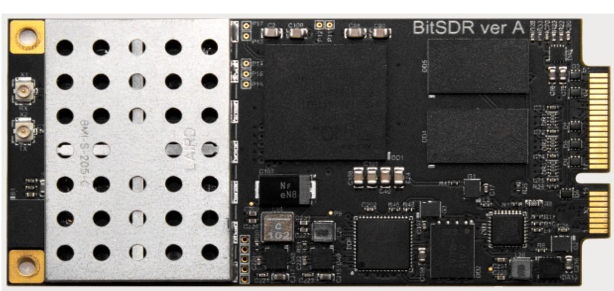
Abstract — **This This paper is focused on the autonomous detection of the vacant frequency channels in the wide observation band of 60MHz. Vacant channel detection has been modeled as a binary hypothesis testing problem. Three signal detection algorithms including energy detection, wavelets, and cyclostationary have been tested and evaluated in terms of accuracy. Testing has been performed offline on the data samples collected during the controlled experiment. Data samples consisting of AWGN noise and FSK, BPSK, QPSK modulated signals have been generated using the hardware signal generator and received on our target application's receiver (AD9364) front end as a time-domain complex signal. The optimal threshold value has been determined as an optimal value between the hit rate and the false positive rate. The highest accuracy of 91.0% has been reached the wavelet transform feature extraction, energy detection has shown 86.4% accuracy. Cyclostationary detection has shown no distinguishable difference in the spectrum correlation values calculated for the AWGN noise sample and samples containing BPSK and 2FSK modulated signals captured with -20 dB power.**

Keywords— wavelet transform, energy detection, vacant frequency channels, cognitive radio

I. INTRODUCTION

The number of mobile devices and gadgets actively using the radio frequency (RF) spectrum is constantly growing worldwide. The traditional spectrum utilization policies based on rigid licensed bands allocation over large, geographically defined regions have been reformed in recent years to cope with the growing data traffic demand, with the objective to allow the unlicensed secondary users to access licensed bands without causing interference to the licensed primary users.[1] Cognitive Radio is a highly agile, environmentally aware communication paradigm that has a potential to improve spectrum occupancy by opportunistically identifying and reusing the available spectrum resources without causing harmful interference. The most common example of the dynamic spectrum access (DSA) is the reuse of the TV white spaces: the spectrum allocated to TV broadcasters is reused for other wireless communication applications, eliminating harmful interference to the incumbent TV receivers [1], [2]. Since the fundamental requirement for spectrum reuse, is to avoid interference to potential primary users in their vicinity, one of the challenges in a cognitive radio system is the detection of vacant frequency channels. From the spectrum reuse perspective RF spectrum could be classified into black spaces, gray spaces, and white spaces [3], [4]. Black spaces are occupied by high power local interfere and unlicensed users should avoid those spaces at that time. Gray spaces are partially occupied by low power interference, but they are still candidates for secondary use. White spaces are free from the RF interference except for the ambient noise made up of natural and artificial noise including the thermal noise, transient reflection, and impulsive noise [3],[4]. White spaces are obvious candidates for secondary reuse.

This paper is focused on autonomous, also referred to as non-cooperative or blind methods for vacant frequency channels detection suitable for the reuse. Autonomous methods are defined as methods that do not require any prior knowledge about primary users and transmitted signals. The main motivation for this work is the performance evaluation of the wavelet feature extractor, energy detection and cyclostationary feature extraction algorithms for vacant channels detection in our target application BitSDR: a software-defined radio-based network consisting of the digital cognitive radio nodes. The radio part is based on Analog Devices AD9364 transceiver. It has Zynq 7020 FPGA and dual-core ARM Cortex A9 CPU with embedded Linux OS. Figure 1 presents the photo of our target application and its schematics. Nodes are operating in the noncooperative communication environment within the



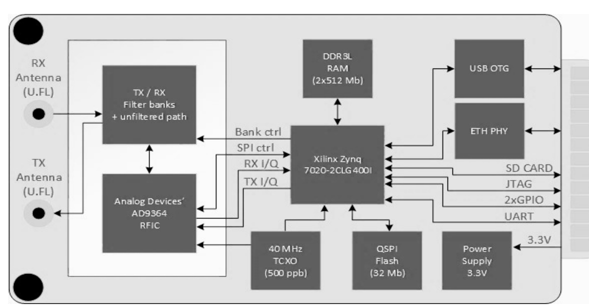


Figure1.Target application BitSDR and its schematics.

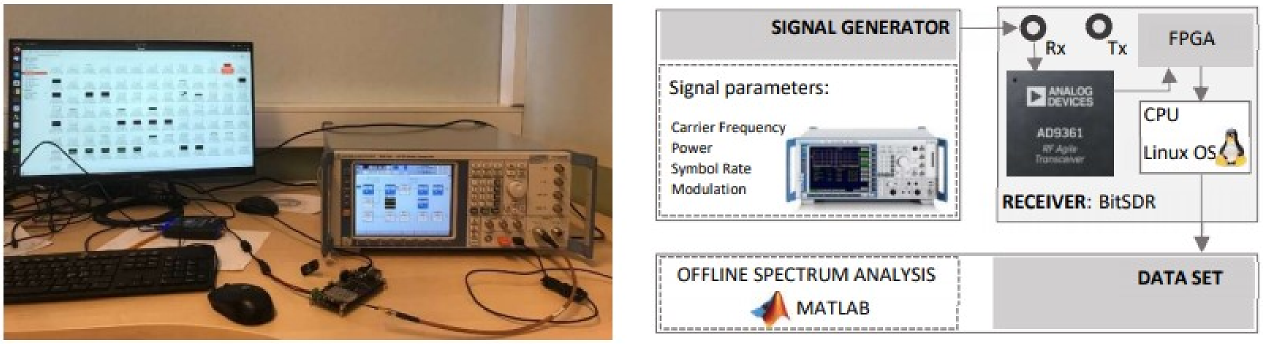


Figure 2. Experiment set up for data set generation. Flow chart of data collection and processing.

spectrum band of 70 MHz-6GHz. Cognitive waveforms are generated by supporting multiple modulations including both linear: QPSK, BPSK, QAM, and non-linear: FSK and three symbol rates: 10, 100, and 1000 KSymbol/second. To meet the real-time operation requirements the observation of the radio scene must be performed within 500 microseconds or less. The experimental data set consists of signal samples generated using the signal generator and collected as a received signal by our target application hardware. The radio scene observation band has been performed in the wide band of 60 MHz, where 56MHz is usable, due to the maximum receiver sensitivity limit. The observation band has been divided into 60 channels: 1 MHz each. The processing of the data samples and classification itself has been performed off-line in Matlab environment using energy detection, wavelet transform and cylostationary.

II. Literature Review

In the literature, the signal detection problem is often modeled as a binary hypothesis testing problem [2]. There are two possible hypotheses: H0 and H1:

$$H_0: \quad x(t) = n(t)$$
$$H_1: \quad x(t) = s(t) + n(t) \qquad (1)$$

Where H0 is used to describe a frequency channel as vacant [2], [3] if the filtered radio signal within this channel is only composed of noise. In the occupied channel H1, this signal consists of an unknown nonzero number of telecommunication signals in addition to the noise. Prior to the hypothesis testing the received signal is processed to extract the significant features. This literature study is focused mainly on the feature extraction algorithms that do not require demodulation, such as energy detection, wavelets, and cyclostationary.

Digital communication signals are associated with sine wave carriers, pulse trains, repeating spreading, hopping sequences, or cyclic prefixes that contain built-in periodicity. Even though the data is a stationary random process since statistics of these modulated signals exhibit periodicity they are characterized as cyclostationary. If the mean of a signal shows periodicity, it is said to show the **first-order periodicity**. Other first-order periodicity statistical characteristics include variance, standard deviation, skewness, kurtosis, root mean square, entropy, and median. If the autocorrelation of a signal is periodic, the signal is **second-order cyclostationary**. This periodicity is typically introduced intentionally in the signal format so that a receiver can exploit it for parameter estimation such as carrier phase, pulse timing, or direction of arrival. Signal analysis in the cyclic spectrum domain preserves phase and frequency information related to the timing parameters in modulated signals [5]. Therefore, features overlapping in the power spectrum density are non-overlapping features in the cyclic spectrum and therefore different types of modulated signals that have identical power spectral density functions can have highly distinct spectral correlation functions. Furthermore, stationary noise and interference exhibit no spectral correlation. The key advantage of the cyclostationary feature detection techniques is their compatible performance in low SNR. Main disadvantages are: 1. they perform worse than the energy detectors in conditions of the stationary noise; 2. they may be completely lost due to channel fading [6], [7]; 3. They are known to be vulnerable to sampling clock offsets [8] [3]; 4.They are more computationally complex compared to energy detection methods.

Energy detection. The received signal is integrated over a

Table 1. Data samples

Data Sample	Fc, MHz	Signal 1			Signal 2			Signal 3		
		Modulation	Power, dB	Symbol Rate, kSymbol/s	Modulation	Power, dB	Symbol Rate, kSymbol/s	Modulation	Power, dB	Symbol Rate, kSymbol/s
1	160	AWGN								
2	156	BPSK	-20	100	2FSK	-20	100	BPSK	-20	1000
3	156	BPSK	10	1000	2FSK	-10	10	BPSK	-5	100
4	156	BPSK	-20	10	2FSK	-20	100	-	-	-
5	156	BPSK	-20	100	2FSK	-20	10	-	-	-
6	40	QPSK	20	1000	BPSK	40	100	2FSK	30	10
7	140	QPSK	30	1000	BPSK	45	100	2FSK	50	100

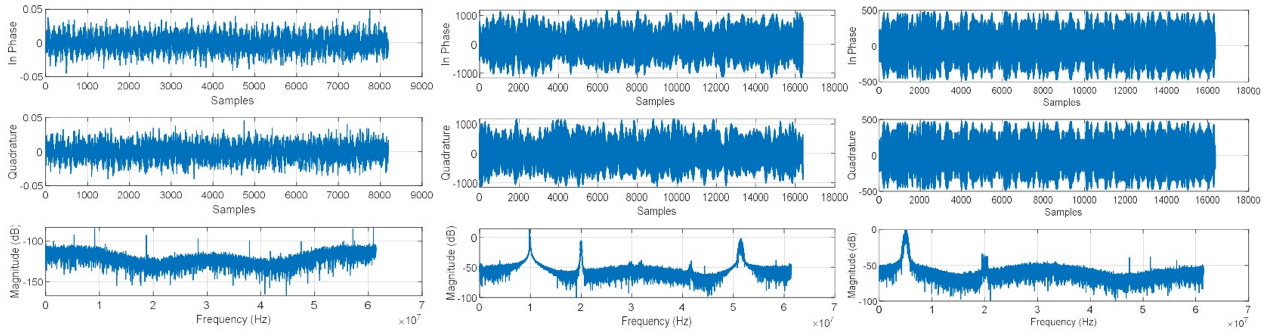


Figure 3. Data samples: a) Data sample 1: white noise; b) Data sample 3: Three signals BPSK,2FSK, BPSK; c) Data sample 7: Three signals QPSK, BPSK and 2FSK.

certain time period to obtain the average power at the filter's center frequency. The signals can be detected based on a decision threshold. i.e. power levels above this threshold are identified as signals. J. Zheng et al [5] have summarized multiple ways to determine the decision threshold 1. Empirical analysis of data [9], [10]; 2. Computation from system properties such as noise floor [11], [9]; 3. Using a priori knowledge of statistics of noise [12], [13], and 4. Estimation of threshold directly from the data [5].

T. Yucek and H. Arslan in [3] have classified energy detection as the least computationally demanding and at the same time worst in terms of classification accuracy compare to cyclostationary, waveform-based, matched filtering and radio identification methods. The main disadvantages of threshold estimation techniques are as follows: 1. The threshold estimated is specific to the receiver, and hence they fail to detect the presence of signals that occur below the receiver's noise floor; 2. They require a priori knowledge of the noise statistics, and they show significant performance deterioration in the presence of noise power that varies throughout the frequency band of interest [8], [3]; 4. poor performance under low SNR conditions because at low SNR noise variance is not accurately known [14]; 5. Cannot Distinguish Users Sharing the Same Channel; 6. baseband filter effects and spurious tones [15].

Wavelet Detection. By employing a wavelet transform of the power spectral density (PSD) of the observed signal, the frequency bands can be found. The main advantage of wavelet-based signal detection listed in the literature is their good performance for the wideband signals. The main disadvantages: 1. does not work for spread spectrum signals; 2. relatively high computational cost; 3. high sampling rates characterizing larger bandwidths. Based on this literature study of the spectrum sensing three algorithms including energy detection, cyclostationary and wavelet transform have been applied to identify the vacant bands in the data samples received by our proprietary hardware. Some of these algorithms could be potentially used complementary to each other in different noise conditions, for example. cyclostationary are performing well when the noise is non-stationary, while energy-based are starting to fail in the presence of noise power that varies stochastically throughout the frequency. The limitation also has been made regarding the use of these methods at low SNRs.

III. Data Set

The testing data set have been generated by the signal generator and received by proprietary SDR hardware's transceiver. Generated data samples contain both digital signals, modulated into FSK, BPSK and QPSK with various carrier frequencies, power, symbol rate, and AWGN noise. Experimental setup photo and schematics are presented in Figure 2. Each data sample has been observed and recorded during 500 microseconds or less.

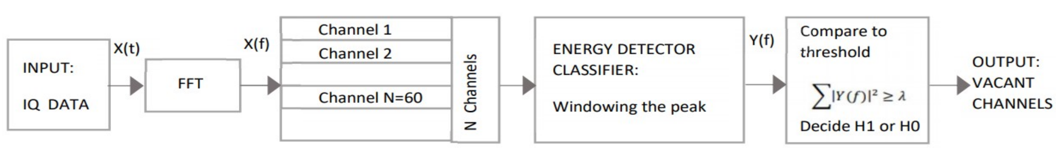


Figure 4. Energy detection-based vacant channels detection.

Figure 5. Wavelet transform-based vacant channels detection.

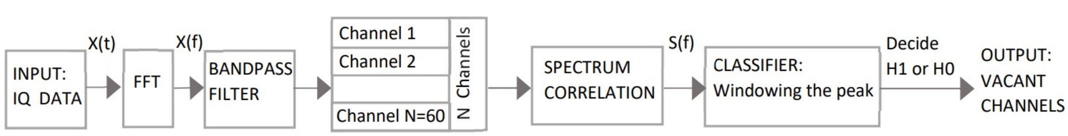


Figure 6. Cylostationary-based vacant channels detection.

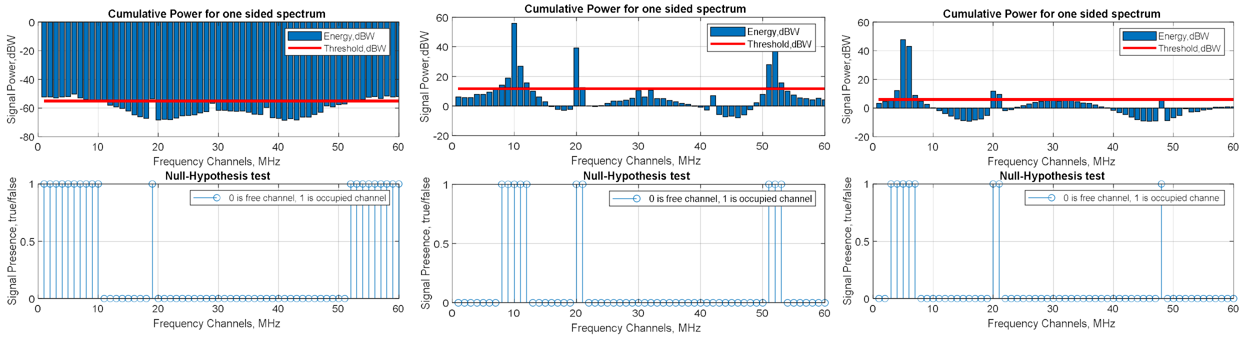


Figure 7.Signal energy calculated for every channel and null hypothesis test: a) Data sample 1: white noise; b) Data sample 3: Three signals BPSK, 2FSK, BPSK; c) Data sample 7: Three signals QPSK, BPSK and 2FSK.

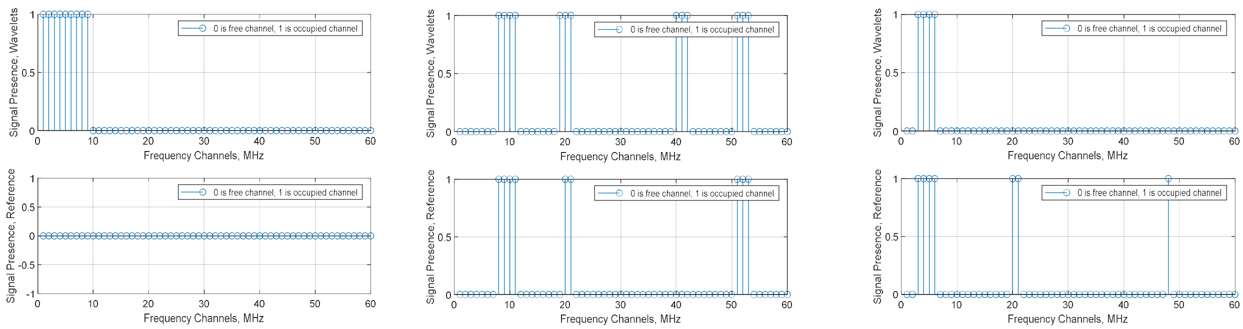


Figure 8. null hypothesis test for wavelet transform Data samples: a) Data sample 1: white noise; b) Data sample 3: Three signals BPSK,2FSK, BPSK; c) Data sample 7: Three signals QPSK, BPSK and 2FSK.

Figure 3 presents examples of the data samples consisting of the in-phase and quadrature components of the complex received signal and their power spectrum density (PSD) plots. The main characteristics of the data samples are summarized in Table 1. Data sample 1 contains AWGN with no modulated signal, captured on the receiver front end. The captured noise data follows the Gaussian distribution: it has the mean value of -7.5×10^{-5} and the standard deviation of 0.0116, what lies within the 95% confidence interval. This allows us to conclude that the noise in the studied frequency band is AWGN noise.

IV. Energy Detection

Vacant frequency channels detection using energy detection feature extraction is performed by comparing the integrated energy value over each channel to the threshold value. Figure 4 describes the energy detection workflow.

The input data samples collected as a complex time domain signal in the form of in-phase and quadrature components are converted to the frequency domain using fast Fourier transform. The 60 MHz observation band has been divided into 60 channels, 1 MHz each. The frequency domain signal has been integrated, to obtain the average power for every channel and compare it to the threshold value. The threshold has been determined empirically to achieve the optimal detection performance, defined as the highest hit rate for the smallest number of false positives. Three values of the threshold calculated as the mean value of the energy calculated for all 60 channels plus minimum signal power: 2, 3 and 4dB have been compared.The optimal detection has been observed for the mean value of the energy calculated for all 60 channels plus minimum signal power 3 dB. The calculated energy value in the channel above this threshold has been identified as signals; below the threshold - as vacant channels.

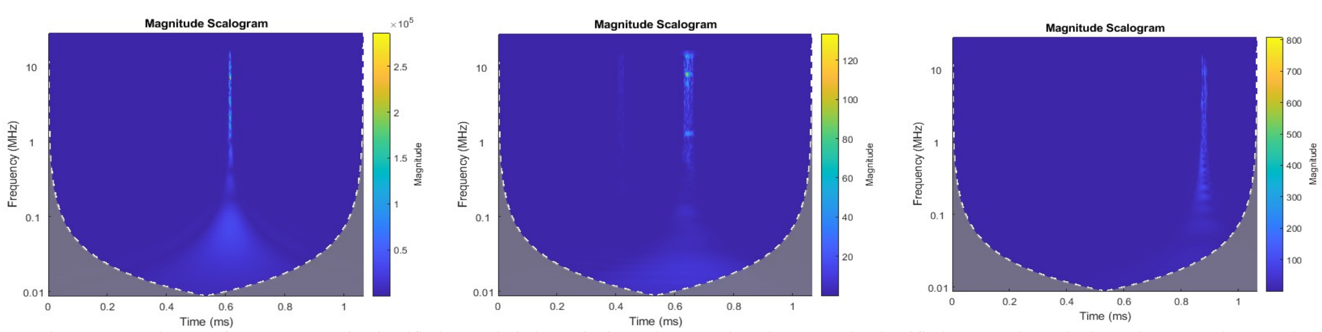


Figure 9.Wavelet transform: a)Correctly classified occupied channel, channel 5, sample 7; b) Correctly classified vacant channel, channel 15, sample 7; c)missed detection, channel, sample 7.

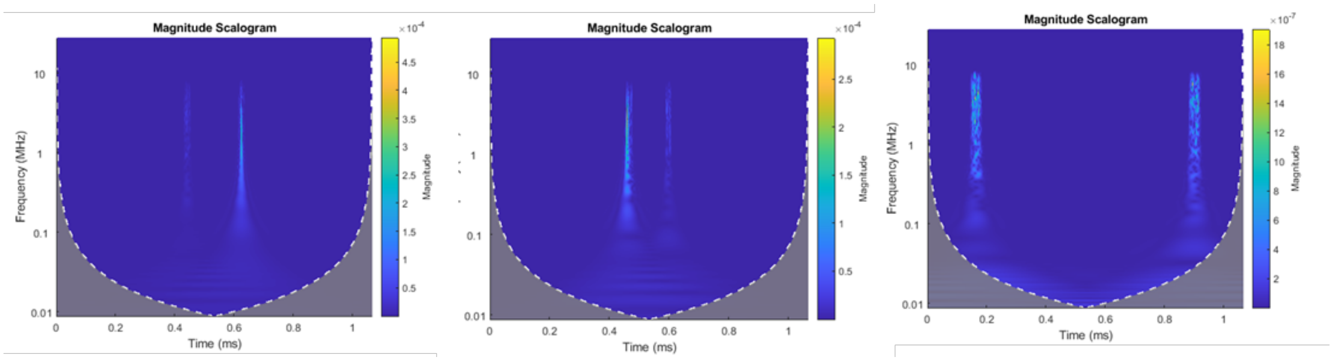


Figure 10.Wavelet transform: a)False positive detection, channel 1, sample 1; b) False positive detection, channel 5, sample 1; c) Correctly classified vacant channel, channel 15, sample 1.

Relative cumulative energy plots for three signal samples described are described in Figure 7. The red line indicates the threshold value calculated as the mean value of energy for 60 channels plus 3dB. This method is showing some false positives since the threshold is calculated as a relative value based on the mean value of the energy in the studied frequency band. Figure 7a presents the data sample 1, containing AWGN noise with false positive detections for 18 channels.

V. CYCLOSTATIONARY

The second order periodicity is defined as the presence of the non-zero correlation between some spectral components in the time series. Spectral correlation is a measure of the second order periodicity in the time-series[16]. Figure 12 describes the spectrum correlation plots and its mean value for the data sample 1 containing the AWGN noise and data sample 4 containing two signals BPSK and 2FSK. The maximum values of the spectrum correlation and the maximum value of the mean spectrum correlation for the channels containing the signal have shown no distinguishable difference. This could be due to the cyclostationary activity in the studied noise sample. Therefore, the cyclostationary based detectors have not been further studied and tested in scope of this work.

VI. WAVELET TRANSFORM

Wavelet transform of the PSD signal allows to detect the local maximums of the PSD, thus the vacant frequency bands can be also found. Figure 5 describes the workflow used for the detection of vacant channels using wavelet transform feature extraction. To identify the vacant channelsin the wide band 60 MHz band has been divided into 60 channels, 1 MHz each. The bandpass filter has been applied. Then the wavelet transform using Morse wavelet has been applied to every channel. The local maximum has been calculated for every channel and compared to the average value calculated for all channels in the band. Figures 9 and 10 describe the local maximum detection. The threshold for the vacant channel has been set to the average value of the local maximum calculated for 60 channels plus 25% of the average.

VII. TESTING RESULTS

The performance of both wavelet transform and energy detector has been evaluated in terms of classification accuracy, false positive rate, and missed detection rate. The accuracy has been calculated as the percentage of correctly classified channels in relation to the total number of tested channels.

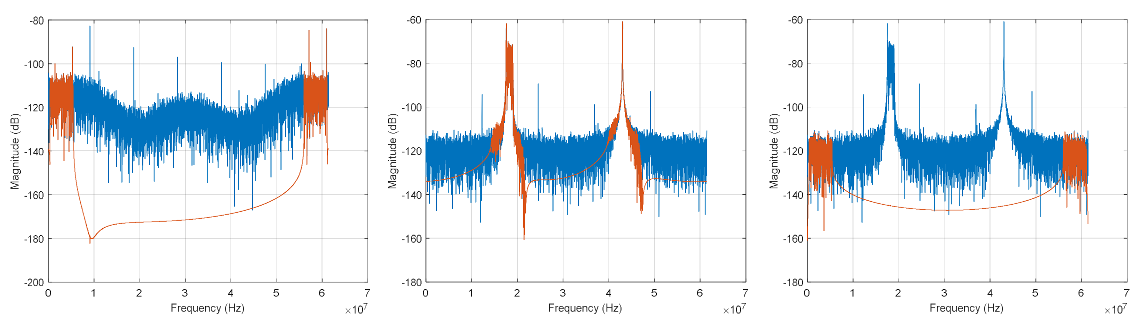


Figure 11. Fourier transform with 5 MHz bandpass filter: a) Sample 1 AWGN, b) two signals BPSK and 2FSK signals, band pass filtered 15 -20 MHz; c) two signals BPSK and 2FSK signals, band pass filtered 0 -5 MHz.

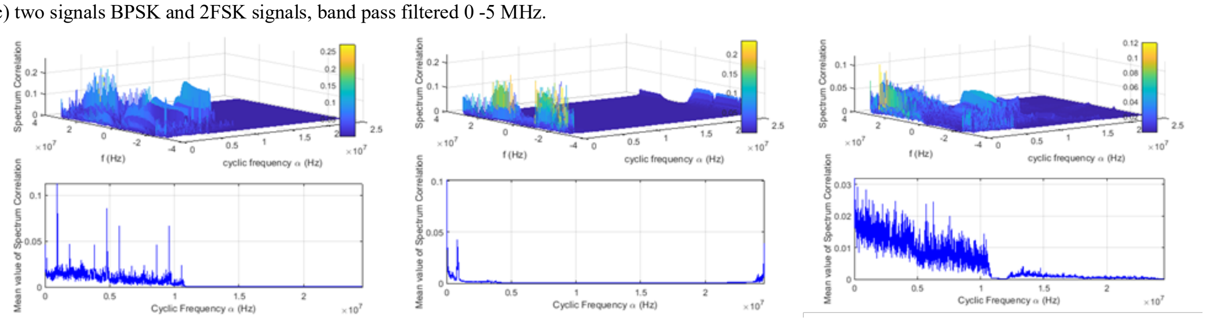


Figure 12. Spectrum correlation and mean value of spectrum correlation for the bandpass filtered signal samples: a) Sample 1 AWGN band pass filtered 0 -5 MHz; b) two signals BPSK and 2FSK signals, band pass filtered 15 -20 MHz; b) two signals BPSK and 2FSK signals, band pass filtered 0 -5 MHz.

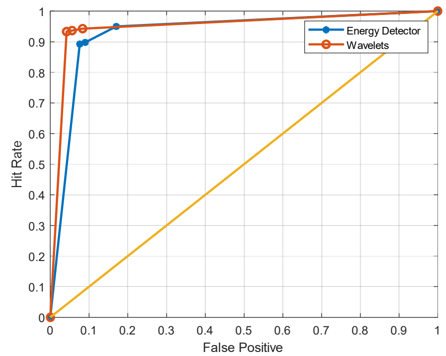


Figure 13. ROC for energy detection and wavelets

False positive detection is described as the vacant channel being classified as occupied. Missed detection vice versa: an occupied channel described as vacant. Wavelet transform-based detection of vacant bands has shown the accuracy of 91.0% for the studied signal samples what is higher than the accuracy of 86.4% observed for the energy detection method for the optimal value of the threshold. Also, wavelet transform based detection has shown a lower false positive rate of 5.5% compared to 8.2% demonstrated by energy detection. Wavelet transform has demonstrated also lower missed detection rate of 3.5% vs. 5.2% demonstrated by energy detection. The threshold values for both algorithms have been varied to identify the optimal value of the threshold. Figure 13 presents the ROC (receiver operational characteristics) curve describing the hit rate vs false positive rate for both energy detector and wavelet transform. Hit rate has been calculated as the ratio of the number of hits to the number of hits plus missed.

The optimal performance of the energy detection has been observed for the threshold value set to mean energy in the 60 MHz band plus 3 dB. Lower and higher threshold values have been studied, however lower threshold corresponding to mean energy in the 60 MHz band plus 2 dB resulted in significantly higher 0.17, i.e 17% false positive detections, and higher threshold, calculated as mean plus 4 dB resulted in a higher rate of missed detections. The optimal performance for the wavelet-based detection has been observed for the threshold value set to mean value of the local maximum calculated for 60 channels plus 25% of this mean value.

Also, lower and higher values of the threshold have been studied: increase in threshold up to mean plus 30% resulted in an increase in the hit rate and in number of false positives, while decrease to mean plus 20% resulted in decreased hit rate and increased number of missed detections. Thresholding approach and null hypothesis testing, however, will always show some false positives even in the vacant channels, since the threshold is relative and based on the mean value of the energy in the band. Figures 7 and 8 present null hypothesis test for data sample 1 containing the AWGN captured on the receiver front end, however, 18 out of 60 channels have been misclassified as not vacant using energy detection and 9 channels misclassified as non-vacant using wavelets.

VIII. CONCLUSIONS

In the scope of this work, three algorithms: energy detector, wavelets, and cyclostationary have been tested for vacant frequency channels detection. Test data samples have been generated during the controlled experiment by the hardware signal generator and received by proprietary hardware based on AD9461 Analog Devices transceiver. The highest accuracy of 91% has been demonstrated by the wavelet transform detector. Energy detection has shown 86.4% accuracy. The maximum values of the spectrum correlation and the maximum value of the mean spectrum correlation for the channels containing the signal have shown no distinguishable difference from the channels containing AWGN noise, therefore the cyclostationary based detection has not been further studied and tested in scope of this work.

IX. DISCUSSION

Both methods have demonstrated the lowest accuracy and highest false positive detection rate for the data sample 6. Figures 14 and 15 present the null hypothesis testing together with wavelet transform and energy detection. False positive detections in this sample are caused by the relatively high level of noise for the channels 1-20. The thresholding approach and null hypothesis testing, however, will always show some false positives even in the vacant channels, since the threshold is relative and based on the mean value of the energy in the channel or the local maximum value.

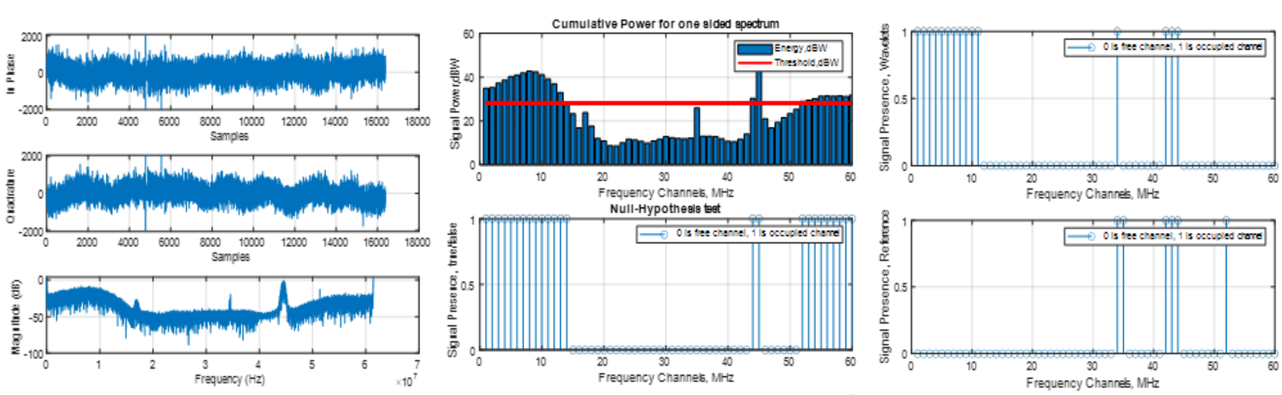


Figure 14. Data samples 6, its FFT Energy detection and wavelet transform null hypothesis test

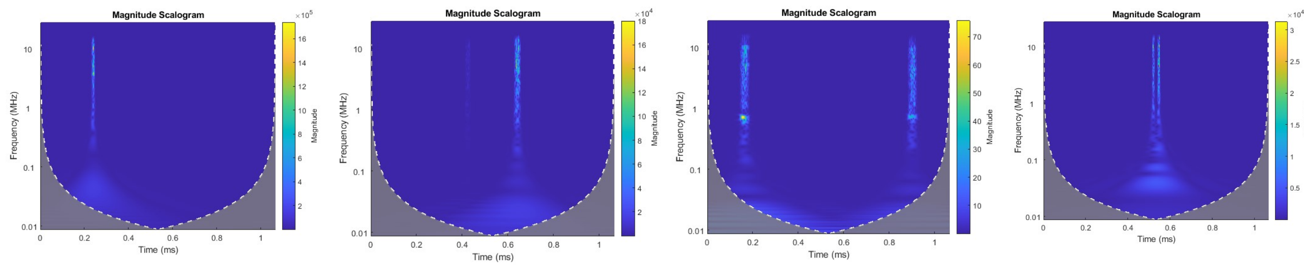


Figure 15. Wavelet transform, data sample 6: a)Channel 44, correctly classified; b) channel 34 correctly classified as occupied; c)channel 50, correctly classified as vacant; d) Channel 2, empty false positive detection.

In this case, 18 channels containing data samples with AWGN noise have been misclassified as not vacant using energy detection. For the bands with high occupancy, there could be a risk of misclassification of occupied channels as vacant when the decision is based on relative threshold values. There could be potential to improve the detection accuracy by testing other wavelet families. In the scope of this work only Morse wavelets have been tested. The testing results in study are also limited to the radio hardware used for the data set collection: transceiver AD9364.

X. References

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