Interference Suppression and Signal Detection for LTE and WLAN Signals in Cognitive Radio Applications

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***Abstract*—Cognitive radio spectrum is traditionally divided into two spaces. Black space is reserved to primary users transmissions and secondary users are able to transmit in white space. To get more capacity, black space has been divided into black and grey spaces. Grey space includes interfering signals coming from primary and other secondary users, so the need for interference suppression has grown. Novel applications like Internet of Things generate narrowband interfering signals. In this paper, the performance of the forward consecutive mean excision algorithm (FCME) method is studied in the presence of narrowband interfering signals. In addition, the extension of the FCME method called the localization algorithm based on double-thresholding (LAD) method that uses three thresholds is proposed to be used for both narrowband interference suppression and intended signal detection. Both Long Term Evolution (LTE) signal simulations and real-world LTE and Wireless Local Area Network (WLAN) signal measurements were used to verify the usability of the methods in future cognitive radio applications.**

Keywords–interference suppression; signal detection; grey zone; cognitive radio; measurements.

I. INTRODUCTION

Heavily used spectrum calls for new technologies and innovations. Novel applications and signals like Long Term Evolution (LTE) generate novel interfering environments like discussed in COCORA 2016 [1]. Cognitive radio (CR) [2][3][4][5][6][7] offers possibility to effective spectrum usage allowing secondary users (SU) to transmit at unreserved frequencies if they guarantee that primary users (PU) transmissions are not disturbed. Earlier, spectrum was divided into two zones (spaces): black and white zone. As black zone was fully reserved to PUs and off limits to secondary users, their transmission was allowed in white zones where there were no PU transmissions. The problem in this classification is that if the spectrum is not totally unused, secondary users are not able to transmit. Thus, the spectrum usage is not as efficient as it could be. Instead, spectra can be divided into three zones: white, grey (or gray) and black zone [8]. In this model, the SU transmission is allowed in white and grey spaces, as black spaces are reserved for PUs.

Cognitive radio has several novel applications. Long Term Evolution Advanced (LTE-A) is a 4G mobile communication technology [9]. LTE for M2M communication (LTE-M) exploits cognitive radio technology and utilizes flexible and intelligent spectrum usage. Its focus is on high capacity. LTE-A enables one of the newest topics called Wide Area Internet of Things (IoT) [10], where sensors, systems and other smart devices are connected to Internet. Therein, long-range communication, long battery life and minimal amount of data, as well as narrow bandwidth are key issues. IoT (or, widely thinking, Network of Things, NoT [11]) is already here. However, there are several problems and challenges. Many IoT devices use already overcrowded unlicensed bands. Another possibility is to use operated mobile communication networks but it wastes financial/frequency resources and technologies like 3G and LTE do not support IoT directly. Secondly, radio networks come more and more complex. Self-organized networks (SON) [12] form a key to manage complex IoT networks. One of the existing SON solutions is LTE standard. However, SON has no intelligent learning aka cognitivity. Cognitive IoT (CIoT) term has been proposed to highlight required intelligence [13][14]. CIoT can be considered to be a technological revolution that brings a new era of communication, connectivity and computing. It has been predicted that by 2020, there are billions of connected devices in the world [15]. Thus, cognitivity is really needed.

As cognitive radio technology offers more efficient spectrum use, there are many challenges. One of those is that the cognitive world is an interference-intensive environment. Especially in-band interfering signals cause problems. There are three main types of interference in CR: from SU to PU (SU-PU interference), from PU to SU (PU-SU interference), and interference among SUs (SU-SU interference) [16][17]. The basic idea in CR is that SU must not interfere PUs, so there should not be SU-PU interference. Instead, SU may be interfered by PUs or other SUs. When there are multiple PUs and SUs with different applications and technologies, cumulative interference is a problematic task [18]. In grey spaces, there is interference from PU (and possible other SU) transmissions. It is efficient to mitigate unknown interference in order to achieve higher capacity. Therefore, interference suppression (IS) methods are needed.

It is crystal clear that when operating in real-world with mobile devices and varying environment, computational complexity is one of the key issues. Fast and reliable as well as cost-effective, powersave and adaptive methods are needed. Thus, it is beneficial if one method does several operations. In this paper, a transform domain IS method called the forward consecutive mean excision (FCME) algorithm [19][20] is used for interfering signal suppression (IS) in cognitive radio applications [1]. Its extension called the localization algorithm based on double-thresholding (LAD) method [21][22] can be used for intended signal detection. Both the methods detect all kind of signals regardless of their modulation types. The difference is that the LAD method is more accurate and, thus, suitable for detection. Thus, the extended LAD method that uses three thresholds is proposed to be used for both interference suppression and intended signal detection. The FCME algorithm and the LAD method are blind constant false alarm rate (CFAR) -type methods that are able to find all kind of relatively narrowband (RNB) signals in all kind of environments and in all kind of frequency areas. Here, RNB means that the suppressed signal is narrowband with respect to the studied bandwidth. The wider the studied band is the wider the suppressed signal can be.

First, future cognitive radio applications and interference environment in cognitive radios are considered. Focus is on IS in SU receiver interfered by PUs and other SUs. A scenario that clarifies the interference environment is presented and IS methods are discussed. The FCME algorithm and LAD methods are presented and those feasibilities are considered. Simulations for LTE-signals are used to verify the performance of the extended LAD method that uses three thresholds. Measurement results for LTE and Wireless Local Area Network (WLAN) signals are used to verify the performance of the FCME IS method.

This paper is organized as follows. The state of art is discussed in Section II. Section III focuses on interference environment in cognitive radios as Section IV considers interference suppression. The FCME algorithm and the LAD method are presented and their feasibility is considered in Section V. Simulation and measurement results are presented in Section VI. Conclusions are drawn in Section VII.

II. State of the Art

Future applications that use cognitive approach include, for example, LTE-A and cognitive IoT [23][24]. LTE-A is an advanced version of LTE. Therein, orthogonal Frequency Division Multiplex (OFDM) signal is used. In OFDM systems, data is divided between several closely spaced carriers. LTE downlink uses OFDM signal as uplink uses Single Carrier Frequency Division Multiple Access (SC-FDMA). Downlink signal has more power than uplink signal. Thus, its interference distance is larger than uplink signals. OFDM offers high data bandwidths and tolerance to interference. As LTE uses 6 bandwidths up to 20 MHz, LTE-A may offer even 100 MHz bandwidth. LTE-A offers about three times greater spectrum efficiency when compared to LTE. In addition, some kind of cognitive characteristics are expected [25][26][27]. RNB interfering signals exist especially at grey zones. This calls for IS.

In the network ecosystem, it is expected that cognitive IoT [28][29] will be the next 'big' thing to focus on. Wide-area IoT is a network of nodes like sensors and it offers connections between/to/from systems and smart devices (i.e., objects) [10][30]. Cognitive IoT enables objects to learn, think and understand both the physical and social world. Connected objects are intelligent and autonomous and they are able to interact with environment and networks so that the amount of human intervention is minimized. Basically, a human cognition process is integrated into IoT system design. Technically, CIoT operates as a transparent bridge between the social and physical world. The radio platform in CIoT devices should be efficient, simple, agile and have low power. CIoT has several advantages, including time, money and effort saving while resource efficiency is increased. It offers adaptable and simple automated systems. CIoT will consist of numerous heterogeneous, interconnected, embedded and intelligent devices that will generate a huge amount of data. The long-range (even tens of kilometers) connection of nodes via cellular connections is expected. Data sent by nodes is minimal and transmissions may seldom occur. Thus, there is no need to use wide bandwidths for a transmission. This saves power consumption but also spectrum resources.

Proposed technologies include, e.g., LoRa ('long range') [31], Neul ('cloud' in English) [32], Global System for Mobile (GSM), SigFox [33], and LTE-M [34]. As Neul is able to operate in bands below 1 GHz and LoRa as well as SigFox operate in ISM band, LTE-M operates in LTE frequencies. In SigFox, messages are 100 Hz wide. In Neul, 180 kHz band is needed. A common thing is that the ultra-narrowband (UNB) signals are proposed to be used. For example, LTE-M (BW 1.4 MHz) and narrowband IoT (NB-IoT) in LTE bands (BW 200 kHz) are studied. In LTE-M, maximum transmit power is of the order of 20 dBm. In the Third-Generation Partnership Project's (3GPP) Radio Access Network Plenary Meeting 69, it was decided to standardize narrowband IoT [35][36]. Most of those technologies are on the phase of development. In any case, it is expected that the amount of narrowband signals is growing. Thus, IS is required, especially when it is operated in mobile bands.

III. Interference Environment in CR

The received discrete-time signal is assumed to be of form

$$r(n) = \sum_{i=1}^{m} s_i(n) + \sum_{j=1}^{p} i_j(n) + \eta, n \in \mathbb{Z}, \tag{1}$$

where $s_i(n)$ is the ith intended (relatively) narrowband signal, $i_j(n)$ is the jth unknown (relatively) narrowband interfering signal, m is the number of intended signals, p is the number of interfering signals, and η is a complex additive white Gaussian noise (AWGN) with variance σ_η^2. Here, relatively narrowband signal means that the joint bandwidth of the intended and interfering signal(s) is less than 80% of the total bandwidth, so the FCME method is able to operate [19].

In modern CR, the spectrum is divided into three zones - white, grey and black. In Figure 1, zone classification is presented. It is assumed that PU-SU distance is >y km in the white zone, <x km in the black zone, and in the grey zone it holds that x km <PU-SU-distance <y km [37]. It means that if SU is more than y km from the PU, SU is allowed to transmit. If SU is closer than y km but further than x km from the PU, SU may be able to transmit with low power. Spectrum sensing

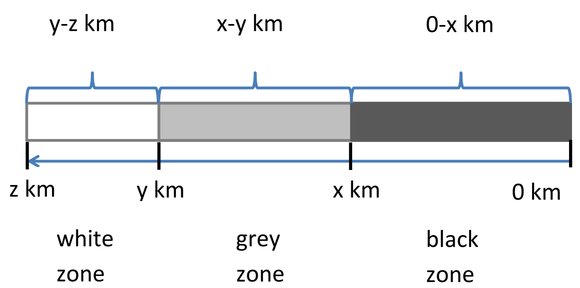

Figure 1: White, grey and black zones.

is required before transmission and there are interfering signals so IS is needed to ensure SU transmissions. If PU-SU distance is less than x km, SU transmission is not allowed.

Interference environment differs between the zones. White space contains only noise. Therein, the noise is most commonly additive white Gaussian (AWGN) noise at the receiver's front-end, and man-made noise. This is related to the used frequency band. Grey space contains interfering signals within the noise, which causes challenges. Grey space is occupied by PU (and possible other SU) signals with low to medium power that means interference with low to medium power. IS is required especially is this zone. Black space includes communications signals, possible interfering signals, and noise. In black space, there are PU signals with high power and SUs have no access.

There must be some rules that enable SUs to transmit in grey zone without causing any harm to PUs. According to [38], SU can transmit at the same time as PU if the limit of interference temperature at the desired receiver is not reached. In [3], it is considered the maximum amount of interference that a receiver is able to tolerate, i.e., an interference temperature model. This can be used when studying interference from SU to PU network. In [39], primary radio network (PRN) defines some interference margin. This can be done based on channel conditions and target performance metric. Interference margin is broadcasted to the cognitive radio network. In any case, the maximum transmit power of SUs is limited.

In our scenario presented in Figure 2, it is assumed that we have one PU base station (BS), several PU mobile stations and several SUs. SU terminals form microcells. Part or all of SUs are mobile and part of SUs may be intelligent devices or sensors (i.e., IoT). Between SUs, weak signal powers are needed for a transmission. One microcell can consist of, for example, devices in an office room. They can use the same or different signal types than PU. For example, in the office room case, WLAN can be used. Between the intelligent devices (IoT), UNB signals are used. It is assumed that SUs operate at grey zone, so IS is required to ensure the quality of SU transmissions.

SUs measure signals transmitted by PU base stations and estimate relative distance to them. Using this information, SUs know whether their short range communication will cause harmful interference to the PU base station. To enable secondary transmissions under continuous interference caused by the PU base station this interference is attenuated by IS.

The secondary access point knows the locations of PU terminals or SUs measure the power levels of the signals

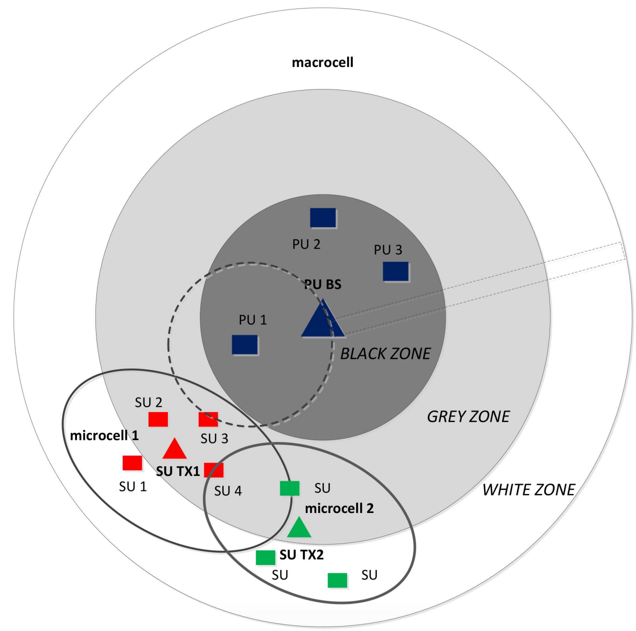

Figure 2: Scenario with one macrocell and two microcells.

coming from PU mobile terminals in the uplink. If it is assumed that SUs know the locations of PUs, SUs do not interfere with PUs. If SUs do not know PUs locations, their transmission is allowed when received PU signal power is below some predetermined threshold. If the level of the power coming from a certain primary terminal is small, it is assumed that secondary transmission generates negligible interference towards primary terminal. However, it may happen that SUs don't sense closely spaced silent PUs.

Let us consider microcell 1 in Figure 2. There are one SU transmitter SU TX1 and four terminals SU $i, i = 1, \cdots, 4$. In addition to the intended signal from SU TX1, SU 1 receives the noise η, SU 2 receives PU downlink (PU BS) signal and the noise η, SU 3 receives PU downlink (PU BS) and PU uplink (PU 1) signals and the noise η, and SU 4 receives PU downlink (PU BS) signal, signal from other microcell's SU, and the noise η. That is, we get from (1) that

$$r_1(n) = s(n) + \eta, \tag{2}$$

$$r_2(n) = s(n) + i_2(n) + \eta, \tag{3}$$

$$r_3(n) = s(n) + \sum_{j=1}^{2} i_j(n) + \eta, \tag{4}$$

$$r_4(n) = s(n) + \sum_{j=2}^{3} i_j(n) + \eta, \tag{5}$$

where $i_1(n)$ is PU 1, $i_2(n)$ is PU BS and $i_3(n)$ is other SU. For example, if it is assumed that PUs are in the LTE-A network and SUs use WLAN signals, receiver SU 2 has to suppress OFDM signal, receiver SU 3 has to suppress OFDM and SC-FDMA signals, and receiver SU 4 has to suppress OFDM and WLAN signals.

In addition, interfering and communication (intended) signals have to be separated from each other. The receiver has to know what signals are interfering signals to be suppressed and what signals are of interest. In an ideal situation, detected and interfering signals have distinct characteristics. However, this is not always the situation. An easy way to separate an interfering signal from the intended signal is to use different bandwidths. For example, in LTE networks, it is known that there are 6 different signal bandwidths between 1.4 and 20 MHz that are used [9]. Especially if a different signal type is used, it is easy to separate interfering signals from our information signal. It can also be assumed that interfering signal has higher power than the desired signal. However, this consideration is out of the scope of this paper.

IV. Interference Suppression

Interference suppression exploits the characteristics of desired/interfering signal by filtering the received signal [40]. After 1970, IS techniques have been widely studied. IS techniques include, for example, filters, cyclostationarity, transform-domain methods like wavelets and short-time Fourier transform (STFT), high order statistics, spatial processing like beamforming and joint detection/multiuser detection [41]. Filter-based IS is performed in the time domain. Those can be further divided into linear and nonlinear methods. Optimal filter (Wiener filter) can be defined only if the interference and signal of interest are known by their Power Spectral Densities (PSDs), which is only possible when they are stationary. Usually, the signal, the interference or both are nonstationary, so adaptive filtering is the alternative capable of tracking their characteristics. Linear predictive filters can be made adaptive using, for example, the least mean square (LMS) algorithm. In filter-based IS, both computational complexity and hardware costs are low but co-channel interference cannot be suppressed, and no interference with similar waveforms to signals can be suppressed. Cyclostationarity based IS has low hardware complexity but medium computational complexity. This may cause challenges in real-time low-power applications.

In transform domain IS [42], signal is suppressed in frequency or in some other transform domain (like fractional Fourier transform). Usually, frequency domain is used, so signal is transformed using the Fourier transform. Computational complexity is medium, but transform domain IS cannot be used when interference and signal-of-interest have the same kind of waveforms and spectral power concentration. However, waveform design may be used. Transform domain IS has low hardware complexity. High-order statistics based IS is computationally complex, and multiple antennas/samplers are needed, so its hardware cost is high and computational complexity too. In beamforming, co-channel interference as well as interference with similar waveforms to the signal of interest can be suppressed, but because of multiple antennas, the hardware cost is high. Its computational complexity is medium.

The less about the interfering signal characteristics is known, the more demanding the IS task will be. As most of the IS methods need some information about the suppressed signals and/or noise, there are some methods that are able to operate blindly [19]. Blind IS methods do not need any *a priori* information about the interfering signals, their modulations or other characteristics. Also, the noise level can be unknown, so it has to be estimated. Blind IS methods are well suited for demanding and varying environments.

V. The FCME and the LAD methods

The adaptively operating FCME method [19] was originally proposed for impulsive IS in the time domain. It was noticed later that the method is practical also in the frequency domain [20]. Earlier, the FCME method has mainly been studied against sinusoidal and impulsive signals that are narrowband ones. The computational complexity of the FCME method is $N\log_2(N)$ due to the sorting [20]. Analysis of the FCME method has been presented in [20].

The FCME method adapts according to the noise level, so no information about the noise level is required. Because the noise is used as a basis of calculation, there is no need for information about the suppressed signals. Even though it is assumed in the calculation that the noise is Gaussian, the FCME method operates even if the noise is not purely Gaussian [20]. In fact, it is sufficient that the noise differs from the signal. When it is assumed that the noise is Gaussian, $\overline{x^2}$ (=the energy of samples) has a chi-squared distribution with two degrees of freedom. Thus, the used IS threshold is calculated using [19]

$$T_h = -\ln(P_{FA,DES})\overline{x^2} = T_{CME}\overline{x^2}, \qquad (6)$$

where $T_{CME} = -\ln(P_{FA,DES})$ is the used pre-determined threshold parameter [20], $P_{FA,DES}$ is the desired false alarm rate used in constant false alarm rate (CFAR) methods,

$$\overline{x^2} = \frac{1}{Q}\sum_{i=1}^{Q}|x_i|^2 \qquad (7)$$

denotes the average sample mean, and Q is the size of the set. For example, when it is selected that $P_{FA,DES} = 0.1$ (=10% of the samples are above the threshold in the noise-only case), the threshold parameter $T_{CME} = -\ln(0.1) = 2.3$. In cognitive radio related applications, controlling $P_{FA,DES}$ is important, because $P_{FA,DES}$ is directly related to the loss of spectral opportunities and caused interference [20]. Selection of proper $P_{FA,DES}$ values is discussed more detailed in [20]. The FCME method rearranges the frequency-domain samples in an ascending order according to the sample energy, selects 10% of the smallest samples to form the set Q, and calculates the mean of Q. After that, (6) is used to calculate the first threshold. Then, Q is updated to include all the samples below the threshold, a new mean is calculated, and a new threshold is computed. This is continued until there are no new samples below the threshold. Finally, samples above the threshold are from interfering signal(s) and suppressed.

The FCME algorithm is blind and it is independent of modulation methods, signal types and amounts of signals. It can be used in all frequency areas, from kHz to GHz. The only requirements are that (1) the signal(s) can not cover the whole bandwidth under consideration, and (2) the signal(s) are above the noise level. The first requirement means that the FCME method can be used against RNB signals. For example, 10 MHz signal is wideband when the studied bandwidth is that 10 MHz, but RNB when the studied bandwidth is, e.g., 100 MHz. In fact, it is enough that the interfering signal does not cover more than 80% of the studied bandwidth. However, the narrower the interference is, the better the FCME method operates [43].

The LAD method [21] uses two FCME-thresholds in order to enhance the detection capability of the FCME method

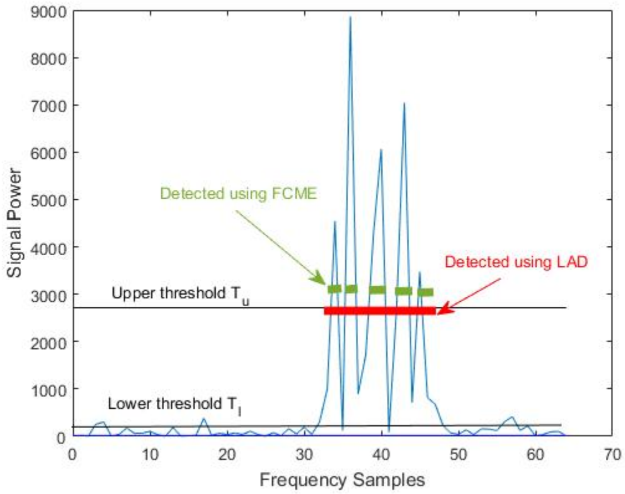

Figure 3: Detection difference between the FCME and LAD methods. The LAD method finds one signal, as FCME finds five.

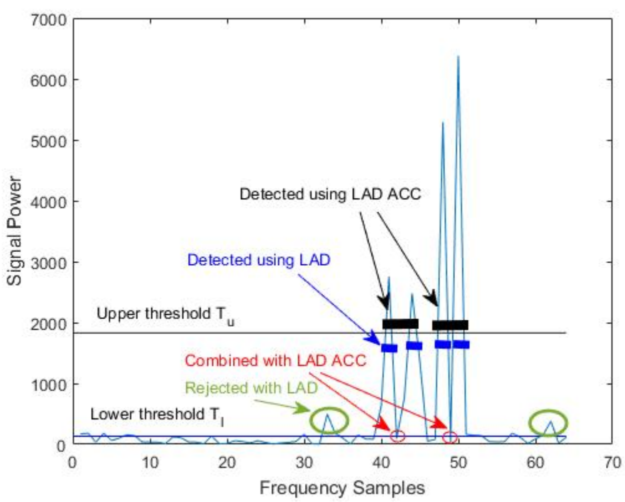

Figure 4: The LAD and LAD ACC methods.

[20]. One threshold is enough for interference suppressing, but causes problems in intended signal detection. If the threshold is too low, too much are detected. Instead, if the threshold is too high, not all the intended signals are detected. In the LAD method, the FCME algorithm is run twice with two different threshold parameters

$$T_{CME1} = -\ln(P_{FA,DES1}) \tag{8}$$

and

$$T_{CME2} = -\ln(P_{FA,DES2}) \tag{9}$$

in order to get two thresholds,

$$T_u = T_{CME1}\overline{x_j^2} \tag{10}$$

and

$$T_l = T_{CME2}\overline{x_l^2}. \tag{11}$$

Selection of proper values of $P_{FA,DES1}$ and $P_{FA,DES2}$ is presented in [20] and in references therein. Usually, $T_{CME1} = 13.81$ ($P_{FA,DES1} = 10^{-4}$) and $T_{CME2} = 2.66$ ($P_{FA,DES2} = 0.07$) are used [20].

After having two thresholds, a clustering is performed. Therein, adjacent samples above the lower threshold are grouped to form a cluster. If the largest element of that cluster exceeds the upper threshold, the cluster is accepted and decided to correspond a signal. Otherwise the cluster is rejected and decided to contain only noise samples. The detection difference between the FCME and LAD methods is illustrated in Figure 3. There is one raised cosine binary phase shift keying (RC-BPSK) signal whose bandwidth is 20% of the total bandwidth and signal-to-noise ratio (SNR) is 10 dB. The LAD method is able to find one signal. Instead, the FCME algorithm finds 5 signals if the upper threshold is used. If the FCME algorithm uses some other lower threshold, it still finds at least 5 signals because of the fluctuation of the signal.

The LAD method with adjacent cluster combining (ACC) [44] enhances the performance of the LAD method. Therein, if two or more accepted clusters are separated by at most p samples below the lower threshold, the accepted clusters are combined together to form one signal. The value of p is, for example, 1, 2 or 3 [20]. This enhances the correctly detected number of signals as well as bandwidth estimation accuracy of the LAD method [22]. In Figure 4, there are two RC-BPSK signals whose bandwidths are 5 and 8% of the total bandwidth. SNRs are 5 and 4 dB. The LAD method finds four signals, as the LAD ACC method finds two signals.

When considering IS, the LAD lower threshold may be too low thus suppressing too much. In addition, the LAD upper threshold may be too high thus suppressing too less. This problem can be solved when extending the LAD method include three thresholds instead of two. Then, the FCME algorithm is run three times with three values of $P_{FA,DES}$ to get three thresholds: the lowest one is the LAD lower threshold T_l, the highest one is the LAD upper threshold T_u, and the threshold in the middle T_m is the threshold used in the IS. Note, that the LAD method corresponds the FCME algorithm when $P_{FA,DES1} = P_{FA,DES2} (= P_{FA,DES3})$.

When both IS and detection are performed, it is possible to perform
(a) both IS and detection at the same time,
(b) first IS and then detection, or
(c) use IS only for detecting interfering signal(s).
Case (a) saves some time because the algorithm is run only once. IS part can be done using only one (T_u, T_m or T_l) or both the thresholds (T_u and T_l). In case (b), IS uses only one threshold (T_u, T_m or T_l) as detection uses both the thresholds (T_u and T_l). Case (c) can be used when the interference situation is mapped, so only one (T_u, T_m or T_l) or both the thresholds (T_u or T_l) can be used. In the latter case, interfering signal characteristics can also be estimated.

VI. Simulations and Measurements

In this paper, both simulations and real-life measurements are considered.

A. Simulations

The IS and signal detection ability of the extended LAD method that uses three thresholds was studied using MATLAB

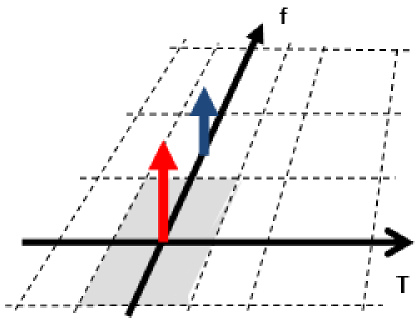

Figure 5: Received signals at receiver. Intended signal and PU-SU interference, T=time and f=frequency.

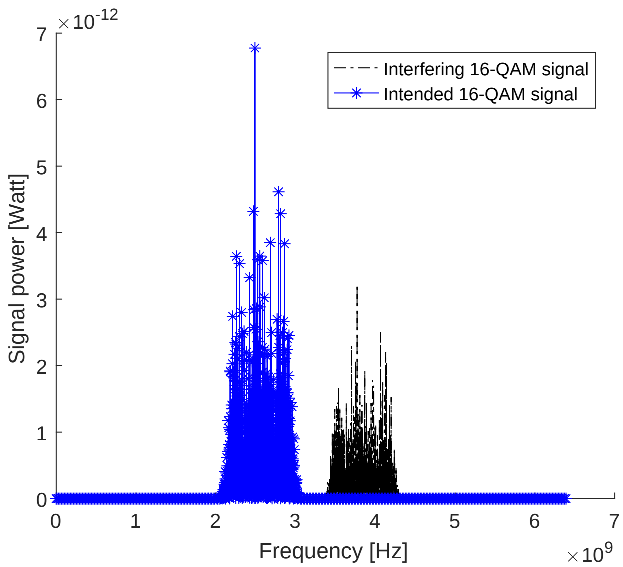

Figure 6: One intended 16-QAM signal and one interfering 16-QAM signal. SNR=15 dB, SIR=12 dB.

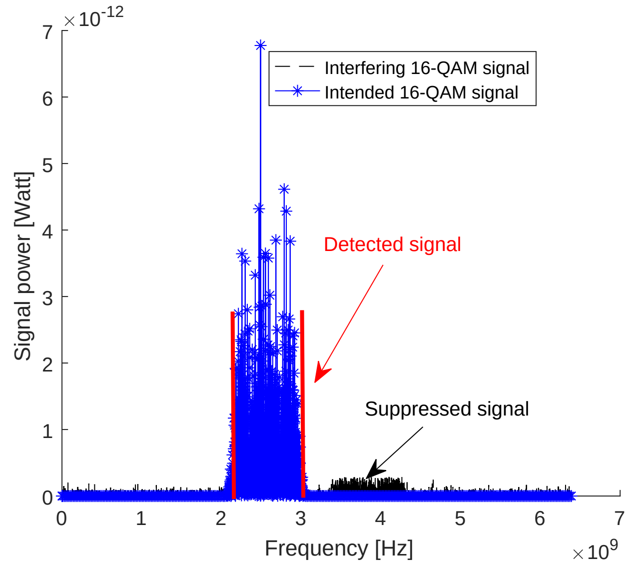

Figure 7: One intended 16-QAM signal and one interfering 16-QAM signal. After interference suppression and detection. SNR=15 dB, SIR=12 dB.

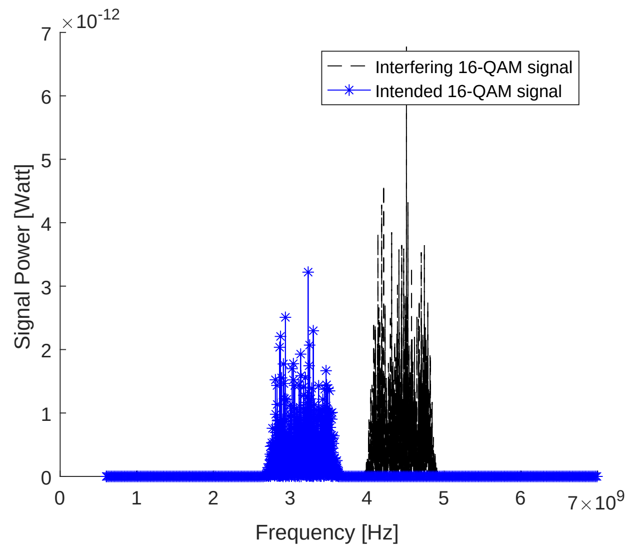

Figure 8: One intended 16-QAM signal and one interfering 16-QAM signal. SNR=12 dB, SIR=15 dB.

simulations. In the simulations the focus was on the last 100 meters at IoT network. There was a total of N devices, which were uniformly and independently deployed in a 2-dimensional circular plane with plane radius R. This deployment results in a 2-D Poisson point distribution of devices. After the network was formed the devices were assumed to be static. The noise was additive white Gaussian noise (AWGN). The signals and the noise were assumed to be uncorrelated. Here, 16-quadrature amplitude modulation (QAM) signal that transmits 4 bits per symbol was used. It is one of the modulation types used in LTE. There were 1024 samples and fast Fourier transformation (FFT) was used. In the simulations, IS and detection were performed at the same time. IS was performed using one threshold $T_m = 6.9$, as detection was performed using two LAD thresholds $T_u = 9.21$ and $T_l = 2.3$. SNR is the ratio of intended signal energy to noise power, as signal-to-interference ratio (SIR) is the ratio of intended signal energy to interfering signal energy.

The first situation is like (3), i.e., there is PU-SU interference (Figure 5). Thus, the received signal is of form $r_2(n) = s(n) + i_2(n) + \eta$, where $s(n)$ and $i_2(n)$ are both 16-QAM signals. Now, $s(n)$ is intended signal (red arrow) as $i_2(n)$ is interfering signal from PU (blue arrow). Their bandwidth covers about 30% of the total bandwidth. In Figure 6, SNR=15 dB and SIR=12 dB, so intended signal is stronger than interfering signal. Figure 7 shows the situation after interference suppression and signal detection. In Figure 8, SNR=12 dB and SIR=15 dB more, so intended signal is weaker than interfering signal. The situation after signal detection and IS is illustrated in Figure 9. It can be said that both the methods perform well.

Next, $r_4(n) = s(n) + \sum_{j=2}^{3} i_j(n) + \eta$ like in (5). Now

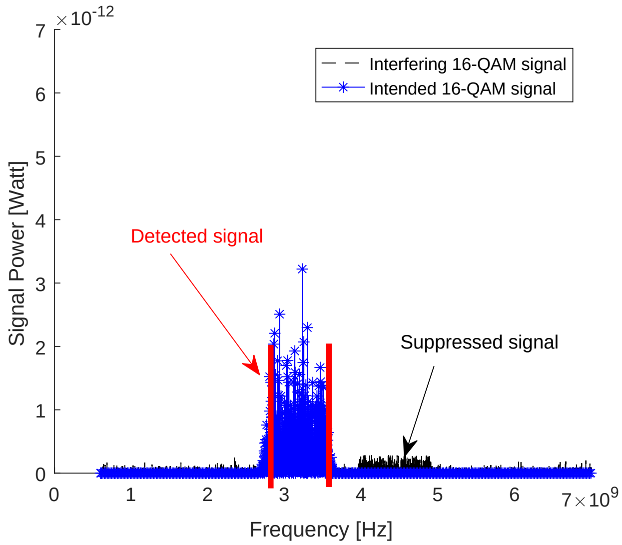

Figure 9: One intended 16-QAM signal and one interfering 16-QAM signal. After interference suppression and detection. SNR=12 dB, SIR=15 dB.

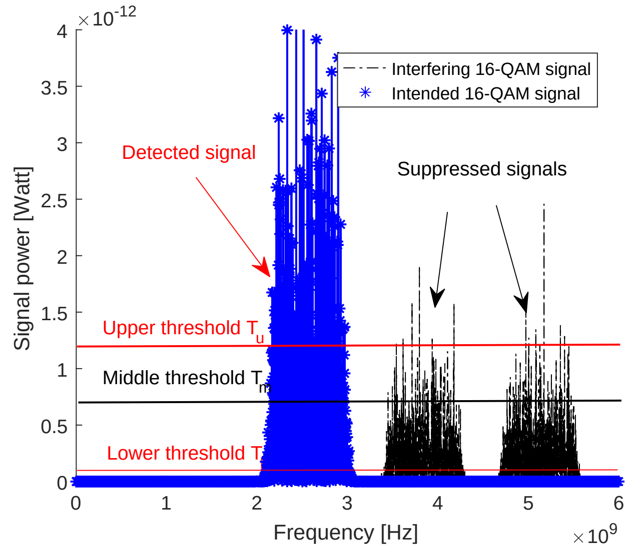

Figure 11: One intended 16-QAM signal and two interfering 16-QAM signals. Interference suppression (T_m) and detection (T_u and T_l) thresholds. SNR=15 dB, SIR=12 dB.

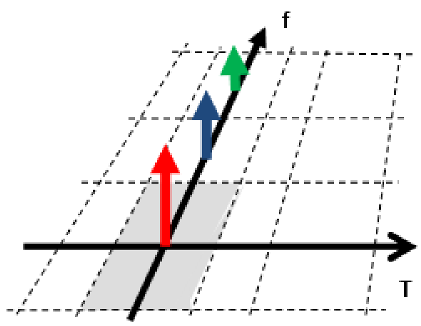

Figure 10: Received signals at receiver. Intended signal, PU-SU and SU-SU interference, T=time and f=frequency.

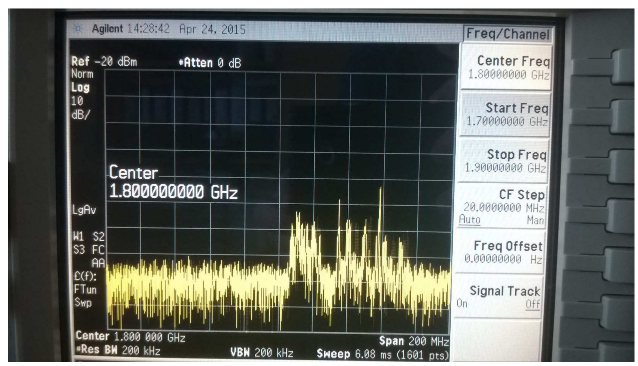

Figure 12: Agilent E4446. LTE1800 network downlink signals.

there are two suppressed signals: one is from PU and one is from other SU so there is both PU-SU and SU-SU interference (Figure 10). Now, $s(n)$ is intended signal (red arrow), $i_2(n)$ is interfering signal from PU (blue arrow), and $i_3(n)$ is interfering signal from other SU (green arrow). Their bandwidth covers about 45% of the total bandwidth. In Figure 11, all the thresholds T_u, T_l and T_m are presented. As the intended signal is detected using theresholds T_u and T_l, the IS is performed using threshold T_m. As can be seen, all the signals are found and both the interfering signals are suppressed.

B. Measurements

The IS performance of the FCME method against RNB signals was studied using real-world wireless data. The results are based on real-life measurements. Measurements were performed using spectrum analyzer Agilent E4446 [45] (Figure 12). Three types of signals were studied, namely the LTE uplink, LTE downlink, and WLAN signals. All those signals are commonly used wireless signals. Both LTE1800 network frequencies and WLAN signals were measured at the University of Oulu, Finland. IS was performed using the FCME method with threshold parameter 4.6, i.e., desired false alarm rate $P_{FA,DES} = 1\% = 0.01$ [20].

LTE1800 network operates at 2×75 MHz band so that uplink is on $1.710 - 1.785$ GHz and downlink is on $1.805 - 1.880$ GHz [46]. LTE downlink uses OFDM signal as uplink uses SC-FDMA. LTE assumes a small nominal guard band (10% of the band, excluding 1.4 MHz case).

One measurement at $1.7 - 1.9$ GHz containing 1000 time domain sweeps and 1601 frequency domain points is seen in Figure 13. Therein, yellow means strong signal power (=signal) as green means weaker signal power (=noise). Therein, only downlink signaling is present. Downlink signals have larger interference distance than uplink signals. Interfering signals cover about 30% of the studied bandwidth. In Figure 14, situation after the FCME IS is presented. Therein, yellow means strong signal power as white means no signal power. It can be seen that the signals (white) have been suppressed and the noise is now dominant (yellow). On uplink signal frequencies where no signals are present (600 first frequency

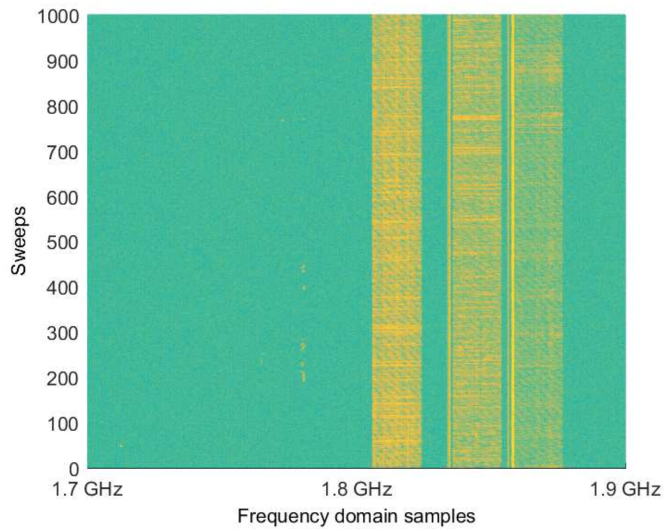

Figure 13: LTE1800 network frequencies. Spectrogram of downlink signals present.

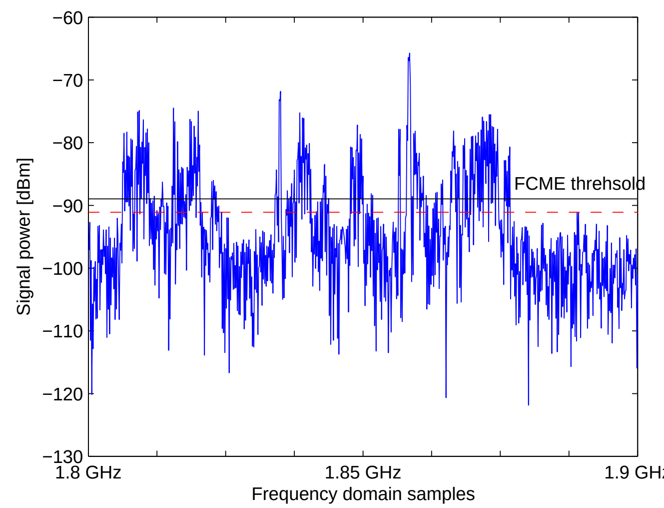

Figure 15: IS using the FCME method for LTE downlink signals. Upper threshold when the FCME calculated on $1.8 - 1.9$ GHz, lower threshold (dashed line) when the FCME calculated on $1.7 - 1.9$ GHz.

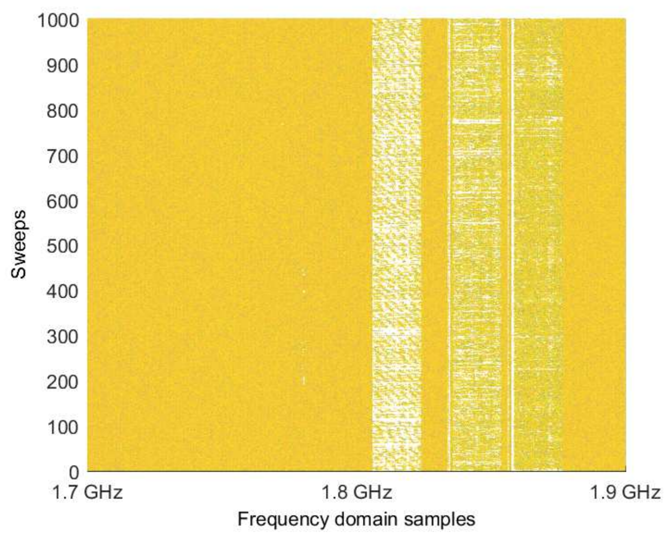

Figure 14: LTE1800 network frequencies. Spectrogram of suppressed downlink signals. The FCME method was used.

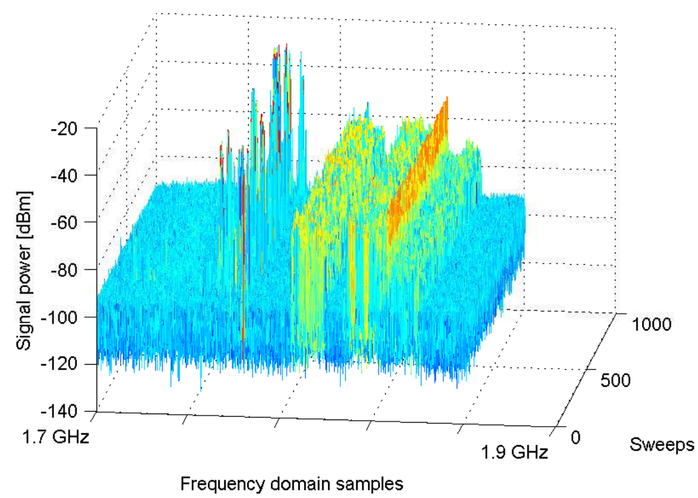

Figure 16: LTE1800 network frequencies. Uplink and downlink signals present.

domain samples), average noise value is -99 dBm before and after IS.

In Figure 15, first line (sweep) of the previous case is presented more closely. The FCME thresholds after two cases are presented. In the first case, the FCME is calculated using frequencies $1.8 - 1.9$ GHz (downlink). Interfering signals cover about 60% of the studied bandwidth. The threshold is -89 dBm (upper line). In the second case, the threshold is calculated using both uplink and downlink frequencies $1.7-1.9$ GHz when there is no uplink signals (like case in Figure 13), i.e., SU is so far away from PU that only downlink signals are present. Interfering signals cover about 30% of the studied bandwidth. In that case, the threshold is -91 dBm (lower dashed threshold). It can be noticed that when the studied bandwidth is doubled and this extra band contains only noise, we get 2 dB gain.

Next, both uplink and downlink signals are present. There were 2001 frequency domain points and 1000 time sweeps. Figure 16 presents one measurement at $1.7 - 1.9$ GHz. Both uplink and downlink signals are present. In Figure 17, one snapshot when both uplink and downlink signals are present is presented. Therein, both signals are suppressed.

In the WLAN measurements, $2.4-2.5$ GHz frequency area was used. There were 1000 sweeps and 1201 frequency domain data points. In Figure 18, one snapshot is presented when there is a WLAN signal present and the FCME algorithm is used to perform IS. As can be seen, the WLAN signal is found.

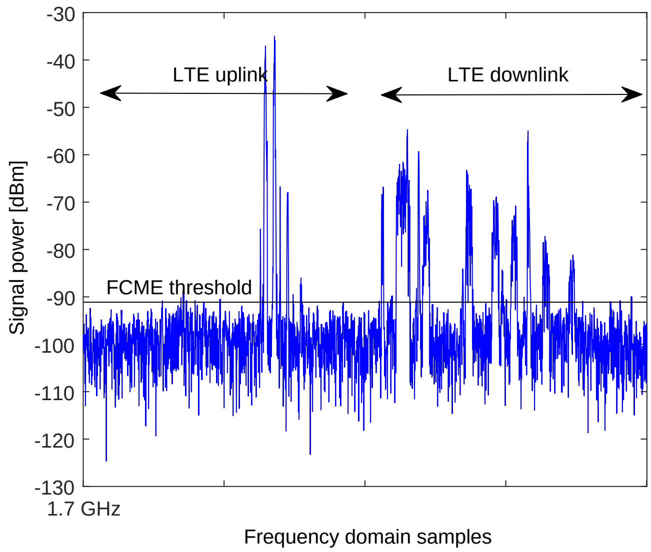

Figure 17: LTE1800 network frequencies. Uplink and downlink signals present. IS using the FCME method.

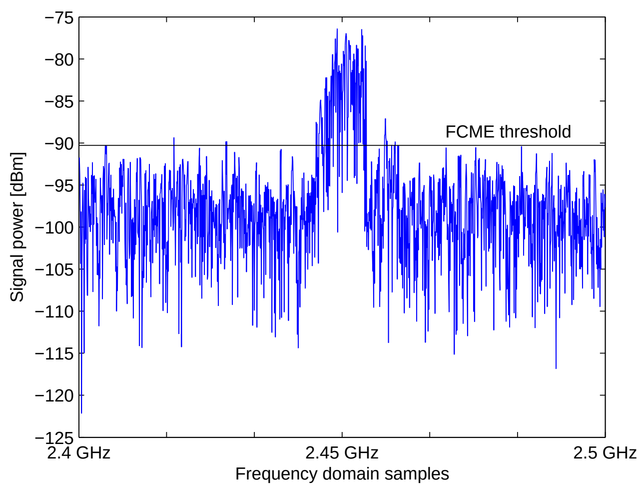

Figure 18: IS using the FCME method at frequencies $2.4-2.5$ GHz where WLAN signals exist. Threshold is -90 dBm.

Next, the desired false alarm rate ($P_{FA,DES}$) values are compared to the achieved false alarm rate (P_{FA}) values in the noise-only case. Figure 19 presents one situation when there is only noise present. According to the definition of the FCME method, threshold parameter 4.6 means that 1% of the samples is above the threshold when there is only noise present. Here, there are 1201 samples so $P_{FA,DES} = 1\% = 12$ samples. In Figure 19, 12 samples are over the threshold, so $P_{FA,DES} = P_{FA}$. We had 896 measurement sweeps in the noise-only case at WLAN frequencies. Therein, minimum 1 sample and maximum 19 samples were over the threshold as the mean was 10 samples and median value was 9 samples. Those were close of required 12 samples. Note that the definition has been made for pure AWGN noise.

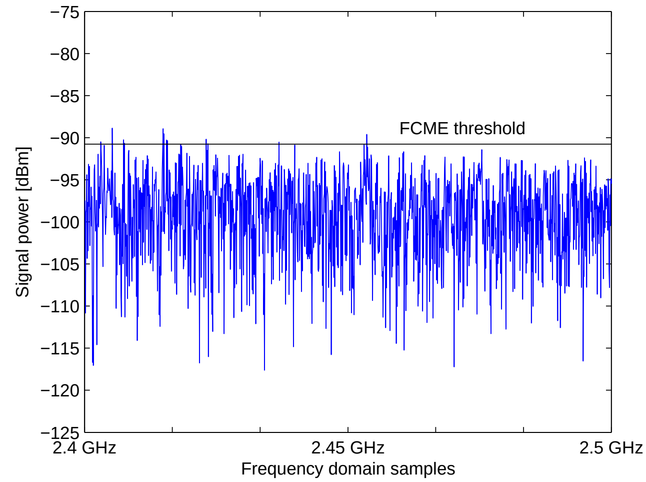

Figure 19: IS using the FCME method at frequencies $2.4-2.5$ GHz where are no signals present. Threshold is -91 dBm. $1\% = 12$ samples are above the threshold, as expected.

VII. Conclusion

In this paper, the performance of the forward consecutive mean excision (FCME) interference suppression method was studied against relatively narrowband interfering signals existing in the novel cognitive radio networks. The focus was on interference suppression in secondary user receiver suffering interfering signals caused by primary and other secondary users. In addition, the extension of the FCME method called the localization algorithm based on double-thresholding (LAD) method that uses three thresholds was proposed to be used for both interference suppression and intended signal detection. LTE simulations confirmed the performance of the extended LAD method that uses three thresholds. Real-world LTE and WLAN measurements were performed in order to verify the performance of the FCME method. It was noted that the extended LAD method that uses three thresholds can be used for detecting and suppressing LTE signals, and the FCME method is able to suppress LTE OFDM and SC-FDMA signals as well as WLAN signals. Our future work includes statistical analysis, more detected and suppressed signals, as well as comparisons to other methods.

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