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Spectrum Sensing Based Cyclostationary Detection in Cognitive Radio Networks

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Abstract: Spectrum usage has become more requisite due to new technologies that are enhanced. It has become more congested though Federal Communication Commission (FCC) has extended some band of frequency for unlicensed users. To prevail over the congested spectrum, cognitive radio has invented sensing techniques to sense the spectrum and use the licensed band in an unlicensed manner by secondary users when primary users are not present without interference. In spectrum sensing techniques Energy detection cannot discriminate between the primary signal and noise especially at low SNR & Matched filter detection requires a prior knowledge of the primary user whereas in cyclostationary detection no need of prior knowledge and it discriminate between primary signal and noise.

Thus, we are going to use Cyclostationary feature detection under BPSK modulation scheme to detect the primary users at very low SNR. We are going to enhance Cyclostationary feature detection with peak detection algorithm and spectral autocorrelation function technique to analyze the spectrum. For better efficiency the noise peaks in Cyclostationary output are reduced using three techniques namely absolute threshold, standard deviation, Filtfilt to identify peak signal at low SNR.

Keywords: Cyclostationary, BPSK modulation, spectral correlation function, autocorrelation, Filtfilt, absolute threshold, standard deviation.

1. Introduction

Cognitive radio is one of the modern techniques for wireless communication systems to utilize the unused spread spectrum effectively in an unlicensed manner. The motivation for Cognitive radio is a concept of utilizing licensed spectrum in an unlicensed manner without causing interference. Cognitive radio can sense the available spectrum for the secondary users when primary user is not using the allotted frequency spectrum, so that spectrum utilization can be improved. Consequently, spectrum sensing performed by CR cannot be restricted to simply monitor the power in some frequency bands of interest but must include detection and identification in order to avoid interference. The main challenges with cognitive radios are that it should not interfere with the licensed users and should vacate the band when required. For this it should sense the signals faster.

Spectrum sensing plays an important role in cognitive radio (CR) systems; to implement without Interference to the primary signal, the cognitive radio needs to sense the availability of the spectrum before accessing the channel [1]. So the ability of sensing an idle spectrum and the ability to temporarily utilize a spectrum without interfering with Primary Users are two essential components required for the success of cognitive radios [2]. Cognitive radio can sense the available spectrum for the secondary users when primary user is not using the allotted frequency spectrum, so that spectrum utilization can be improved. Cognitive radios are fully programmable wireless devices that can sense their environment and dynamically adapt their transmission waveform, channel access method, spectrum use, and networking protocols as needed for good network and application performance.

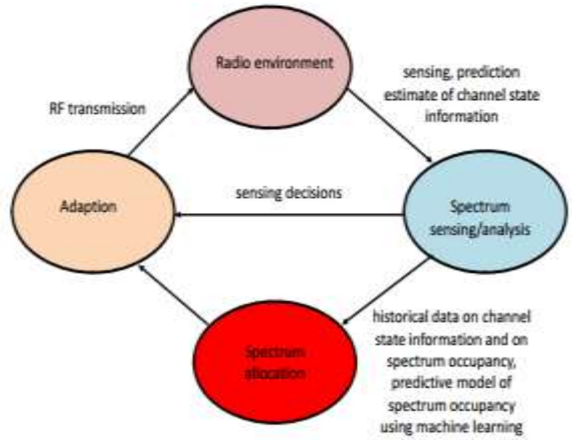

Fig 1: Cognitive radio

Cognitive radios are regarded as Transceivers that automatically detect available channels in a wireless spectrum and accordingly, change their transmission or reception parameters [2, 3]. This work focuses on the spectrum sensing techniques that are based on primary transmitter detection. An important aspect of a cognitive radio is spectrum sensing, which involves two main tasks: signal detection and modulation classification. Signal detection refers to detection of unused spectrum [3] (spectrum holes). This task is important so that the unlicensed users do not cause interference to licensed users.

2. Literature Survey

Cognitive radio was first introduced officially in an article by Joseph Mitola III and Gerald Q. Maguire, Jr in 1999. Communication systems techniques that are used in broadband mobile telecommunication, marine communication; defense and emergency services utilize the radio spectrum. Due to the growth of communication users in this generation the spectrum has become more congested even though federal communication commission (FCC) has expanded some unlicensed spectrum bands for users. This overcrowded spectrum will reduce overall quality of service for users in that allotment. To overcome this spectrum scarcity a potential solution to this problem is COGNITIVE RADIOS. “Cognitive radio: A radio or system that senses its operational electromagnetic environment and can dynamically and autonomously adjust its radio operating parameters to modify system operation, such as maximize throughput, interference, facilitate interoperability, access secondary markets.” [4]. In a cognitive radio system a primary system operated in the licensed band has the highest priority to use that frequency band (e.g. 3G/4G cellular, digital TV broadcast). Other unlicensed users/systems can neither interfere with the primary system in an Intolerable way nor occupy the license band .

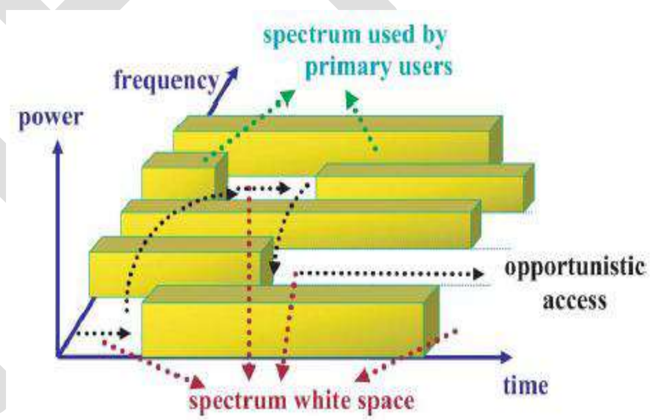

Fig 2: Representation of spectrum holes

The fundamental problem of spectrum sensing is to discriminate an observation that contains only noise from an observation that contains a very weak signal embedded in noise. It is difficult to find vacant bands to deploy new services and enhance existing ones. To overcome this situation, we need an improved utilization of the spectrum which will create opportunities for Dynamic Spectrum Access (DSA). Here we can sense the spectrum using different spectrum sensing techniques such as energy detection, matched filter detection & cyclostationary detection to utilize unused bands by secondary users. thus in this paper we use cyclostationary spectrum sensing to check whether the primary users are utilizing the spectrum band or not, even at low SNR to allocate for secondary users in their absence. And it can also easily discriminate between the primary signal and noise. Where as in energy detection it cannot discriminate between the primary signal and noise especially at low SNR & in Matched filter the problem is that it requires a prior knowledge of the primary user. Cyclostationary detector is based on the spectral redundancy present in almost every manmade signal. It is called a cyclic feature detector. The second order cyclostationary is used to extract sine-wave from the signal is introduced by Gardner in [5–6]. Cyclic Domain Profile refers to the cyclic repetition of frequency [7].

3. Cyclostationary Principle

In Cyclostationary signals, the mean value and autocorrelation function have periodicity. In this paper a signal is taken which can be called as primary signal.

X (t) = s (t) + w (t)

- x(t) is the input transmitted signal
- w(t) is the noise signal (AWGN) and
- s(t) is the primary user signal

Cyclic spectral analysis deals with second order transformations of a function and its spectral representation. A function x (t) is said to exhibit second order periodicity if spectral components of x (t) exhibit temporal correlation.

A. Temporal Redundancy:

A wide-sense Cyclostationary signal $x(t)$ exhibits a periodic autocorrelation function [6, 8]. It has periodic components that can be found by CR to eliminate it from noise. A cyclostationary process is a signal having statistical properties that vary cyclically with time. A cyclostationary process can be viewed as multiple interleaved stationary processes. These processes are not periodic function of time but their statistical features indicate periodicities. The following conditions are essential to be filled by a process for it to be wide sense cyclostationary. The periodicity of the mean and autocorrelation functions are expressed by the equations are as follows:

$$R_x(t,\tau) = E[x(t)x^*(t-\tau)]$$

Where,

$R_x(t,\tau) \rightarrow$ Autocorrelation function

$x(t) \rightarrow$ Random signal

$x(t-\tau) \rightarrow$ Signal with shift `τ`

Mean function is expressed as

$$m_a = E\{x(t)\} = 0$$

Since autocorrelation function is periodic, it can be expressed by applying Fourier series which is decomposed as

$$R_x(t,\tau) = \sum_{\alpha} R_x^{\alpha}(\tau) e^{j2\pi\alpha t}$$

$R_x^{\alpha}(\tau) \rightarrow$ Cyclic autocorrelation function, and represents the Fourier coefficient of the series given by

$$R_x^{\alpha}(\tau) = \frac{1}{T_0} \int_{t=-T_0/2}^{T_0/2} R_x(t,\tau) e^{-j2\pi\alpha t} dt$$

Where $T_0 \rightarrow$ Time period

The autocorrelation function is replaced by its time average which is represented as

$$R_x^{\alpha}(\tau) = \lim_{T\to\infty} \frac{1}{T} \int_{t=-T_0/2}^{T_0/2} x(t)x^*(t-\tau) e^{-j2\pi\alpha t} dt$$

The cyclic autocorrelation is therefore intuitively obtained by extracting the frequency α sine- wave from the time-delay product $x(t)x^*(t-\tau)$. The Spectral correlation density (SCD) is defined as the Fourier transform of $R_x^\alpha(\tau)$ over τ.

B. Spectral Redundancy:

The Fourier transform of *x* (*t*) is *X (f)*. The SCD measures the degree of spectral redundancy between the frequencies $f - \alpha/2$ and $f + \alpha/2$ (α is the cyclic frequency). The Fourier transform of autocorrelation function is defined as Spectral Correlation Function (SCF) [12] and is expressed as

$$s_x^\alpha(f) = \int_{-\infty}^{\infty} R_x^\alpha(\tau) e^{-j2\pi f t} d\tau$$

$s_x^\alpha(f)$ → Spectral correlation density (SCD)

It can be mathematically expressed as the correlation between two frequency bins centered on $f - \alpha/2$ and $f + \alpha/2$ when their width tends toward zero [6, 8].

$$S_x^\alpha(f) = \lim_{T\to\infty} \lim_{\Delta t\to\infty} \frac{1}{T\Delta t} \int_{t=-\Delta t/2}^{\Delta t/2} X_T\left(t, \frac{f+\alpha}{2}\right) X_T^*\left(t, \frac{f-\alpha}{2}\right) dt$$

In practice there are only a limited number of samples available and hence SCF needs to be estimated from these samples. Let us define the cyclic periodogram as [9][10].

$$S_{xT}^\alpha(t, f) = \frac{1}{T} X_T\left(t, \frac{f-\alpha}{2}\right) X_T^*\left(t, \frac{f-\alpha}{2}\right)$$

Where X_T (*t*, *f*) is the short-time Fourier transform of signal

$$X_T(t, f) = \int_{t-T/2}^{t+T/2} x(u) e^{-j2\pi f u} du$$

SCF can be obtained by increasing the observation length *T* and decreasing Δt.

$$s_x^\alpha(f) = \lim_{T\to\infty} \lim_{\Delta t\to 0} S_{xT}^\alpha(t, f)$$

Δt → time index

C. Spectral Coherence and α-Profile:

SCF is a correlation of frequency components shifted by $f - \frac{\alpha}{2}$ and $f + \frac{\alpha}{2}$. It is intuitive to define Spectral Coherence (SC) [11] as

$$C_x^\alpha = \frac{S_x^\alpha(f)}{[S(f+\frac{\alpha}{2})S(f-\frac{\alpha}{2})]^{1/2}}$$

$C_x^\alpha \rightarrow$ Spectral coherence

$\alpha \rightarrow$ Cyclic frequency

The magnitude of SC is always between 0 and 1. In order to reduce the computational complexity, one just uses the Cyclic Domain Profile (CDP) or α-profile, which is defined as

$$I(\alpha) = \max_f \left| C_x^\alpha(f) \right|$$

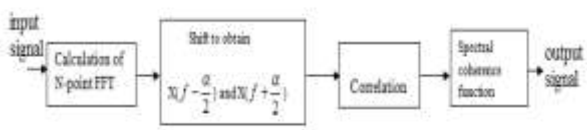

Fig 3: Extraction of spectral coherence function

4. Signal Detection

Modulated signals exhibit second order cyclostationary. Two random signals are considered and correlated each other produces a peak at certain frequency with some noise peaks if we again correlate the received output peak the centre peak increases and noise peaks gets diminished.

Fig. 4 shows the representation of the correlated signal using BPSK modulation technique. From the CDP of the signal, important information about the signal like modulation type, keying rate, pulse shape, and carrier frequency can be obtained, [13]. When SCF is plot, the occupancy status of the spectrum can identified easily.

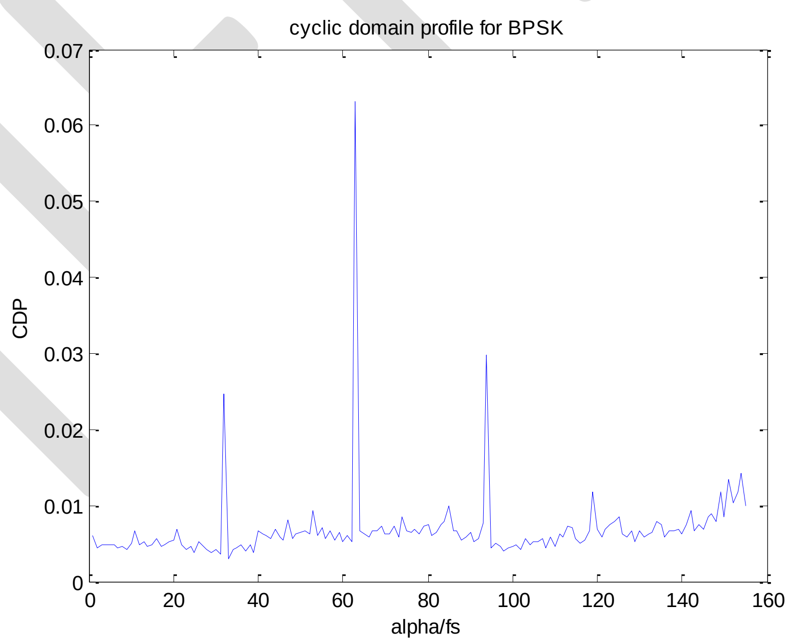

Fig 4: Cyclic domain profile for BPSK

If a primary user signal is present in the operating frequency range, the SCF gives a peak at its centre. The peak will not be present in the case when there is no primary user signal present in the concerned frequency range. If we have a 3peak output in the spectrum analyzer, it is a BPSK modulation. Based on the peak output the modulation technique is identified.

Spectrum sensing is utilized to determine the presence or absence of primary users so we need to distinguish between these two hypotheses [14];

$$H_0 : x(t) = n(t)$$
$$H_1 : x(t) = s(t) + n(t)$$

First, we need to determine threshold C_{TH} for signal detection and when signal is absent, i.e. x (t) = n (t), C_{TH} will use the relationship as [15];

$$C_{TH} = \max[I(\alpha) / \sqrt{(\sum_{\alpha=0}^{N} I^2(\alpha)) / N}]$$

N $\longrightarrow$ length of observation data

We can distinguish signal from noise by analyzing the SCD function. Furthermore, it is possible to distinguish the signal type because different signals may have different nonzero cyclic frequencies [17]. Cyclostationary detection block contains a FFT, AWGN, correlate, average over threshold and a feature detection block as follows

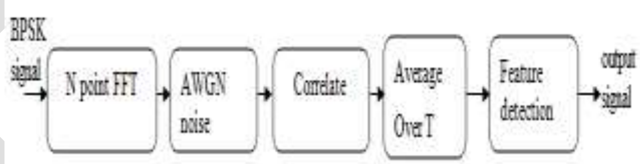

Fig 5: cyclostationary detection

A random discrete signal is charmed and modulated using different modulation schemes. The CFD contains filters, ADC, encoder, and fft blocks. In this paper, we use fast Fourier transform (FFT) and a Noise is included by AWGN block. Cyclostationary feature detection method deals with the inherent cyclostationary properties or features of the signal. Such features have a periodic statistics and spectral correlation that cannot be found in any interference signal or stationary noise. It exploits this periodicity in the received primary signal to identify the presence of primary users, and that is why the cyclostationary feature detection possesses higher noise immunity than any other spectrum sensing method. The output is charmed using spectrum analyzer, which displays the output in a graphical form, which can be easily understandable. The output plot thus obtained is the cyclic SCF. Peak detection algorithm is used for the Cyclostationary output. The plot between probability of detection and SNR is termed as the receiver operating characteristics; using sensing algorithm the cyclostationary detection method, shows that the primary signal is present, and probability of detection increases with Different SNR values[16].

5. TECHNIQUES APPLIED

1. Cyclostationary output:

By applying cyclostationary method to the BPSK modulated signal the output is displayed in the spectral analyzer which is represented as cyclic domain profile the peak output contains more number of noise signals to reduce that we use three techniques to reduce it bit by bit for better efficiency i.e. absolute threshold, standard deviation, Filtfilt. The output can be seen in the fig 6 in graphical representation combined with all techniques.

2. *Absolute Threshold:*

In some applications we do not need to know the exact peak amplitudes and locations, rather we need to know the number or general location of peaks, in this case, we use an absolute threshold function. The absolute threshold is obsolete by several different factors such as motivations, expectations, and cognitive processes, that whether the subject is adapted to the stimulus or not. The absolute threshold is vied to the difference threshold, which is the measure of how two different stimuli must be for the subject to notice that they are not the same.

If we consider two random variables Correlation between two random signals gives rise to centre higher peak along with the noise peaks, if again the correlation is made for repeating times the centre peak gives rise to maximum higher peak whereas, noise peaks gets eliminated this observation can be seen in the fig 6 shows reduction of noise peaks at different frequencies, and a centre peak indicates the probability of detection. For the cyclostationary output, the absolute threshold is rigid and the noise peaks are not esteem when it is below the threshold value and hence the signal is recognized by using threshold. Moreover, the amplitude of the absolute threshold is increased due to the repetition of correlation between the outputs peaks produced. Hence in cyclostationary output by correlating the signal repeating times, the amplitude of the CDP increases in the output of absolute threshold.

3. *Standard deviation:*

Standard deviation is a measure of amount of variations in the signal for different sample N-values. For a sine wave, the Standard deviation is zero and hence by increasing the number of samples the noise peaks are diminished as shown in the Fig 6. The standard deviation diminishes the noise peaks more than the absolute threshold based on the increased number of samples. Sample standard deviation is represented as

$$S = \left[\frac{1}{N-1} \sum_{i=1}^{N} \left(x_i - \bar{x} \right)^2 \right]^{1/2}$$

Where,

N = Number of samples.

S = Sample Standard Deviation.

x_i = Individual x-values.

$\bar{x}$ = sample mean.

$\left(x_i - \bar{x} \right)^2$ = subtracting the mean with the Individual values and squaring the result.

$$\text{Mean } \bar{x} = \left[\frac{1}{N} \sum_{i=1}^{N} x_i \right]$$

Instead of taking whole spectrum the sample, set of frequency range is consider to estimate the signal where the calculation becomes easier but while considering a sample values we lose some accuracy. In normal standard deviation, N-1 is replaced instead of N, which estimates only the sample set of data. Hence, by calculating its mean and Standard deviation the produced output peak is used to indicate whether the signal is present or not.

3. Filtfilt

Filtfilt is a zero phase forward and reverse filtering, after filtering in the forward direction; the filtered sequence is then reversed and run back through the filter. The Filtfilt is compute by the difference equation:

y(n) = b(1)*x(n) + b(2)*x(n-1) + ... + b(nb+1)*x(n-nb)- a(2)*y(n-1) - ... - a(na+1)*y(n-na).

Where**,** `y´ is the time reverse of the output of the second filtering operation.

In general filters there will be a phase shift of 90° due to filtering of noise signals whereas in Filtfilt technique phase is zero because of forward and backward filter, in forward filter phase shift of 90° occurs and again the signal is filtered in backward which shifts to 0° phase shift and thus we get accurate peak signal. The result has precisely zero phase distortion and magnitude modified by the square of the filter's magnitude response. The length of the input x must be more than three times the filter order, defined as max(length(b)-1, length(a)-1). FILTFILT is not be used with differentiator and Hilbert FIR filters, since the operation of these filters depends heavily on their phase response. Fig 6 shows the output of the Filtfilt command where the noise is completely diminished by using the difference equation. By comparing with the other two techniques, Filtfilt is the best method for reducing the noise by filtering and has a good efficiency.

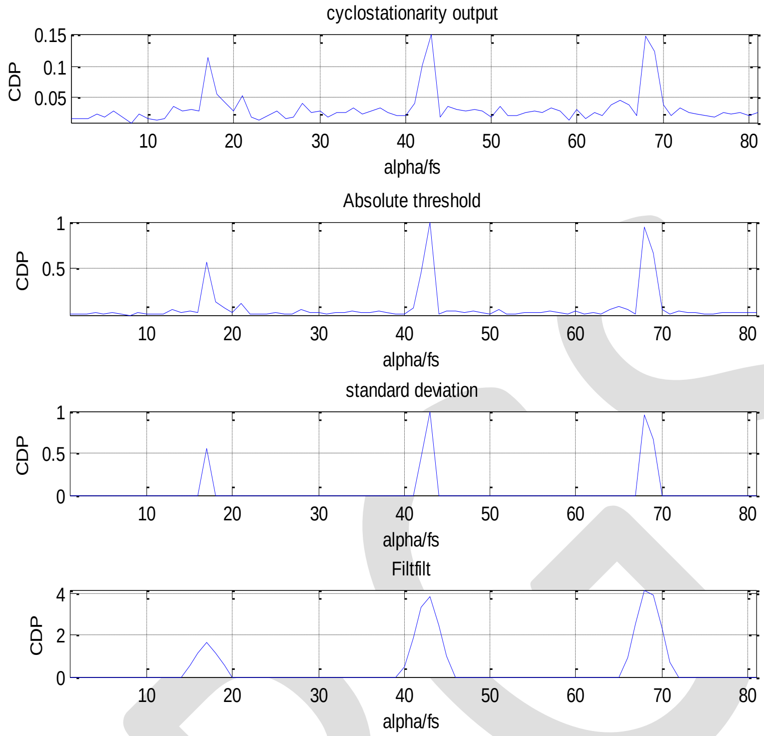

Fig 6: simulation output applying various Techniques

Thus by comparing all the results obtained after reducing the noise peaks using different techniques Filtfilt is the best approach for eliminating the complete noise in the observed output. The signal efficiency is estimated by considering Pd vs. SNR plot. Fig 7 shows the efficient output at low SNR value by considering the plot we can identify that at SNR= -5 the efficiency is 0.92 and till SNR= -10 we can estimate the peak signal.

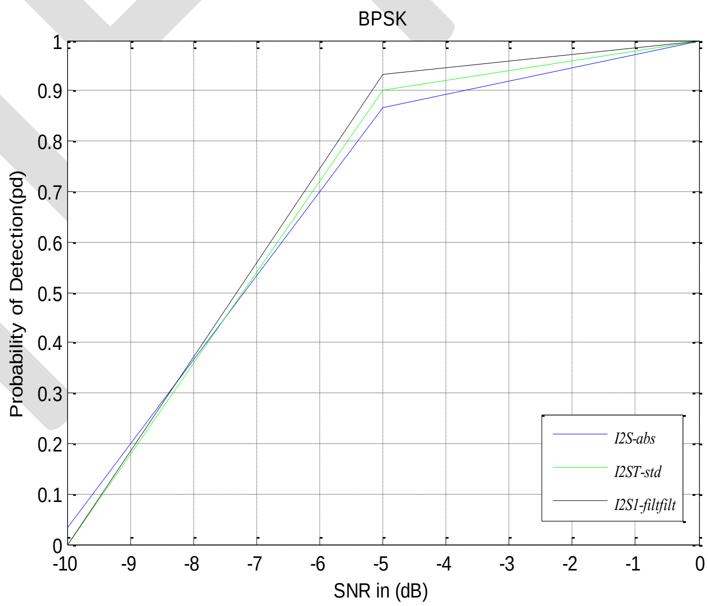

Fig 7: Simulation output for Pd vs. SNR plot

Table 1: efficiency comparison of three techniques

Technique used	**Efficiency (%)**
Absolute threshold	0.88
Standard deviation	0.90
Filtfilt	0.92

CONCLUSION

In this paper, we have presented the peak detection algorithm for estimation and detection of the primary signal to analyze the spectrum. Fig 7 shows the simulation analysis and suggests that cyclostationary spectrum detection is optimal for signal detection at low signal-to-noise (SNR) values. And if the peak signal is present at the centre of the SCF then it is said to be that primary user is present, if not the primary user is absent then the secondary user can occupy the spectrum band. Among the entire three techniques absolute threshold, standard deviation, and Filtfilt the best approach is Filtfilt for reducing noise peaks where we can identify the signal accurately as shown in fig 6.

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