A New Dynamic Max-to-Mean Ratio Energy Spectrum Sensing Model for 5G Cognitive Radio System

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Abstract: Spectrum utilization is the most recent issue in the area of wireless communication. It became more important with the high traffic demand and increasing number of applications in 4G/5G communication systems. Cognitive Radio (CR) technology provides new capabilities that support dynamic spectrum access and spectrum sharing by allowing a secondary user to opportunistically access the available spectrum of a primary user without causing the interference. Spectrum sensing is considered as the first step and most important part in CR implementation. The current challenges issues of the CR spectrum sensing to solve the underutilization problem are sensing time, implementation complexity, background noise, and power consumption. An improved energy detection method for any signals in Gaussian noise is proposed in this study to replace the traditional energy detection method, which is based on different characteristics of the noise and the signal waveforms. This is due to the fact that most of the noise has a flat power density spectrum, which totally differ from the transmitted signals. Those different characteristics can be exploited to perform a very efficient detection. The results of the probability of detection are obtained and then compared with the conventional energy detection method. The results show a significant improvement in terms of achieving higher probability of detection with lower level of SNR.

Keywords: Optimization, Cognitive Radio, Spectrum Sensing, 5G, Energy detection, Max-to-Mean Ratio.

1. Introduction

The exponentially growing demand for high-speed mobile broadband is putting extreme pressure on better utilization of the available radio resources and is driving research activities for 5G networks. CR is a key enabler technique to dynamically access the underutilized spectral resources. According to the 5G vision, future wireless systems should fulfill the requirements of huge capacity, massive connectivity, high reliability and low latency. Hence, a cognitive cellular network is a promising paradigm for the 5G systems [1-5].

CR is expected to play an essential protagonist in 5G communication systems by enabling access to broader pools of the spectrum and more efficient utilization of current wireless resources. However, there is a challenge pertaining spectrum sensing in CRs due to the dense Heterogeneous Networks (HetNets) deployment, multi-radio technologies and the need for interworking with different technologies [6-7].

Efficient and fast spectrum sensing is the key enabler of CRs. There are different techniques for spectrum sensing each one has a trade-off between complexity, accuracy and speed. However, when there is no information available about the transmitted signal, energy detector is optimum, since it does not need any prior knowledge about the Primary User’s (PU) signal characteristics [8-11]. It is commonly used for its low computational cost, speed, simple implementation in hardware, and low power consumptions, thus can justify the essential need of energy detection in spectrum sensing [12]. For 5G HetNets, we recommend the researcher to focus on energy detection method due to the existence various types of wireless access technology.

In this paper, a new approach in energy detection has been suggested to overcome the limitations of the traditional energy detection method. The suggested approach is an intelligent energy detection method that utilizes different characteristics of the man-made signal and noise. The new method is able to differentiate between PU signal and noise (but not between different types of user yet), performs well under lower Signal-to-Noise Ratio (SNR) environment comparing to the conventional method and also, it overcomes the problem of setting threshold by providing dynamic threshold setting embedded in the method itself. The rest of the paper is organized as follows: In Section 2, the traditional energy detection method is briefly explained with the aid of some simulation for the probability of detection using approximation, theoretical approach, and Monte-Carlo simulation. The proposed method is introduced and explained in Section 3. In Section 4, the results of the simulation are given with a detailed analysis. Finally, Section 5 provides some concluding remarks.
2. Conventional Energy Model

The conventional energy detection is a binary detection method and the purpose is to find the presence or absence of the signal, which is the simplest detection problem that we want to decide between two possible hypotheses, hence, it is termed as Binary Hypothesis Testing (BHT) [11]. The energy detection is optimum when the signal details are unknown and there is no prior knowledge about the signal. In this case, the received signal is treated as a function of a random process with random amplitude. The conventional energy detection can be performed in both frequency and time domain. In the time domain, the signal passes through bandpass filter; the signal is then squared and integrated in a period of time. The integrated value is compared with the threshold to be used for the test statistic. Figure 1 illustrates the construction of the energy detector in the time domain. In the frequency domain, the Analog-to-Digital (A/D) Converter is used to sample the signal. The signal is $N$ point FFT (Fast Fourier Transform), is applied to the samples to convert the signal into the frequency domain, after that, the FFT is squared and averaged over $M$ bins to be compared with the threshold for the decision making. The schematic diagram of the energy detector in the frequency domain can be presented as in Figure 2.

![Figure 1. Energy detector in time domain.](image)

![Figure 2. Energy detector in frequency domain.](image)

As in [12], it is assumed that the noise is Additive White Gaussian Noise (AWGN) and has a flat band-limited power density spectrum and the processed signal is pre-filtered by a bandpass filter to limit the average power of the noise coupled with the signal. In this model, the power of the processed signal ($E_s$) is compared to the certain level of power, called the detection threshold $V_{th}$, which in turn depends on the probability of the false alarm, the presence of the transmitted signal or the presence of the PU is represented by $H_1$; on the other hand, the absence of the PU is represented by $H_0$. The scenario can be formulated by using the BHT problem as shown in (1).

$$
\begin{align*}
H_0 &: E_s = W_n \quad \text{Primary User is Absent} \\
H_1 &: E_s = W_n + S \quad \text{Primary User is Present}
\end{align*}
$$

where $E_s$ is the power of the received signal, $S$ is the power of the transmitted signal only, and $W_n$ is the power of the noise coupled with the signal, which is assumed to be AWGN. The $H_0$ and $H_1$ are null hypotheses and alternative hypotheses, respectively, used in the BHT.

The detector compares the observed value with the threshold and consequently, two types of error occur. The first one is deciding $H_1$ given that $H_0$ is true, this is called the probability of the false alarm ($P_f$), the other type of error is deciding $H_0$ provided that $H_1$ is true, which is called the probability of miss or misdetection probability ($P_m$). The probability of detection ($P_d$) would be the probability of deciding $H_1$ and $H_1$ is true.

According to [14], the theoretical values of the probability of the false alarm, the detection probability, and the probability of miss can be given as:

$$
\begin{align*}
P_f &= P_f[E_s > V_{th} \mid H_0] = \frac{\Gamma(u, V_{th} / 2)}{\Gamma(u)} \\
P_m &= P_f[E_s < V_{th} \mid H_1] = 1 - P_d \\
P_m &= P_f[E_s < V_{th} \mid H_1] = 1 - P_d
\end{align*}
$$

where $\gamma$ is the SNR, $V_{th}$ is the energy threshold, $\Gamma()$ and $\Gamma(_{\cdot})$ are the complete and incomplete gamma functions, respectively, and $Q(\cdot)$ is the generalized Marcum Q-function with $u$ degree of freedom, which is the Time-Bandwidth product (TW) in this case, can be defined as:

$$
Q_\mu(a, b) = 1/\alpha^{\mu-1} \int_b^\infty x^\mu \exp\left(-\frac{x^2 + \alpha^2}{2}\right) I_{\mu-1}(ax)dx
$$

where $I_{m,\mu}$ is the modified Bessel function of the first kind of order $m$.

Concurrently, when the noise (statistically independent random variables) is alone in the transmitted channel, the sum of its squares has a chi-square distribution under $H_0$. In the presence of a deterministic signal, the output signal of the energy receiver has a non-central chi-square distribution under $H_1$ [12, 15]. Hence, the decision statistic of the energy collected in the frequency domain $E_s$ can be formulated in the following:

$$
E_s \sim \begin{cases} 
\chi^2_{2u}, & \text{under } H_0 \\
\chi^2_{2u}(2\gamma), & \text{under } H_1
\end{cases}
$$

where the symbol $\sim$ means “distributed according to”, $\chi^2_{2u}$ is the central chi-distribution with $2u$ degree of freedom, and
\( \chi^2_n(2\gamma) \) is the non-central chi-distribution with 2\( \gamma \) degree of freedom and non-centrality parameter 2\( \gamma \). The \( \gamma \) refers to the SNR of the signal and \( \mu = TW \) (the Time-Bandwidth product), where \( T \) is the observation time of the signal and \( W \) is the bandwidth of the bandpass filter.

In [11] and [16], a \( \chi^2_n \) random variable can be approximated by a Gaussian random variable when \( N \) is large (\( N > 100 \)) and the performance of energy detector or the probability of detection can be approximated by:

\[
P_d = Q \left( \frac{Q^{-1}(P_f) - \frac{N}{2} \frac{SNR}{SNR + 1}}{SNR + 1} \right)
\]

\( (6) \)

Figure 3. Approximated probability of detection.

Figures 3 and 4 show a computer based simulation for both approximated and theoretical approaches, respectively, based on (3) and (6), correspondingly.

Figure 4. Theoretical probability of detection.

For more close-to-practical results of the energy detector, Monte-Carlo simulation is used. Figure 5 illustrates the resulting probability of detection using Monte-Carlo simulation versus SNR for different values of false alarm compared to the theoretical probability.

Figure 5. Theoretical and Monte-Carlo simulated probability of detection.

3. Proposed Energy detection Model

The idea of this novel approach for the energy detection is the efficient detection of the signals in low SNR. It could be to differentiate between the energy of the signal and the energy of the noise in a particular band based on different signal and noise characteristics. This makes it possible to be exploited and used for the spectrum sensing with high efficiency. In this study, it is assumed that the noise coupled with the signal or captured alone by the sensing antenna is characterized by its flat band-limited power density spectrum. In other words, it is termed as AWGN as mentioned earlier.

Figure 6 represents the spectral density of the received signal without any noise. It is clear that the noise-free modulated signals have a peak component value in the frequency domain much greater than the average of the total spectrum components over the total number of bins. On the other hand, in the presence of noise, which is assumed in this study to have a flat spectrum, the average is relatively larger compared to the maximum values/peaks that results in smaller peaks-to-average values, which is the key idea of this new method. The spectrum of the AWGN noise and its mean is shown in Figure 7.
The proposed algorithm used in this study is explained here. The conventional energy detection in the frequency domain is adopted as the underlying structure of the proposed method. This implies that the FFT is used due to the easiness of implementation, the ability to improve the estimation of the signal energy by changing the number of FFT points, and the empowerment of the future integration with other algorithms.

Figure 7. The power spectral density of white noise.

In the case of a noisy signal, Figure 8 shows that the average value will significantly differ from that of the noise-free signal. More specifically, the mean value will increase as the noise component attached to the signal will increase, that is, when the SNR becomes smaller. The demonstration of the scheme is shown in Figure 9, which illustrates the change of the average value with the change of SNR. The change of the average value is due to the characteristics of the added noise, since it tends to be more flat spectrum with smaller peaks-average difference and having smaller standard deviation from its mean value.

Figure 8. Power spectral density for noisy signals.

Figure 9. Spectrum components: mean value vs. SNR (dB).

This process is repeated for \( N \) times to find the value of the largest component in each portion, the sum of the bins and the maximum-to-sum ratios. To examine the nature of the noise-free signal and noisy signal with a small SNR, it is noticeable from Figures 6, 7, and 8 that \( \text{Max}_{\text{Bins}}(i) \) is relatively larger compared to noise only; consequently, the values of \( V_b \) will be larger for the sup-band occupied with a signal. Averaging the total values of \( \text{Max}_{\text{Bins}} \) and divide it over the average of (Bins) after deducting the sum of the maximum values \( \text{Max}_{\text{Bins}} \) is carried out and the result is stored in the threshold voltage \( V_{th} \) for taking the decision as shown in (7).

\[
V_b(i) = \frac{\text{Max}_{\text{Bins}}(i)}{\text{Bins}(i) - \text{Max}_{\text{Bins}}(i)} \tag{7}
\]

The final process before taking the decision is the calculation of the overall average \( V_{av} \), which can be easily and efficiently done by dividing the average of (Bins) over \( M \) (this is the idea of dynamic threshold voltage) as follows.

\[
V_{th} = \frac{\text{mean}(\text{Max}_{\text{Bins}})}{\text{mean}(\text{Bins}) - \text{Max}_{\text{Bins}}} = \frac{\text{mean}(\text{Max}_{\text{Bins}})}{\text{mean}(\text{Bins}) - \text{mean}(\text{Max}_{\text{Bins}})} \tag{8}
\]
\[ V_{av} = \frac{\sum_{i=1}^{N} \sum_{j=1}^{M} Bins(i)}{M \times N} = \frac{\sum_{i=1}^{N} Bins}{M \times N} \]

Since we have, \( \frac{\sum_{i=1}^{N} Bins}{N} \) = mean(Bins) and \( V_{av} = \frac{\text{mean(Bins)}}{M} \)

Taking the decision is an independent block with its own algorithm. In this proposed model, decision algorithm is separated to enable future development and integration with other methods in spectrum sensing. The decision box takes three parameters \( V_b \), \( V_{th} \), and \( V_{av} \) as shown in Figure 11 and gives the final decision whether the PU exists or not.

![Figure 11. Diagram of decision algorithm.](image)

The parameters \( (V_b \text{ and } V_{th}) \) are different for each of the noise-free signal, noisy signal, and pure noise. In case of low SNR, \( V_b \) decreases as the noise increases and also \( V_{th} \) decreases, but in a rate higher that the decrease rate of \( V_b \) implies that \( V_b \) is greater than \( a*V_{th} \) as the signal exists. On the other hand, when the signal is coupled with a small component of noise or it is noise-free, \( V_{th} \) will increase and \( V_b \) might be less than \( V_{th} \) in some sup-bands, but still greater than the constant value \( c \), which is set to 2 in our simulation. In case of the presence of noise only or extremely high noise attached to the signal, both conditions will be not valid and the absence of the signal will be reported even if we have a very high-power noise, which is usually reported as a signal in the conventional energy detection method.

From Figure 11, it is obvious that the decision box uses \( V_b \) and \( V_{th} \) only and overall average \( V_{av} \) is presented for future development and integration with other methods. Also, with different communication systems, different modulation techniques and/or different transmission schemes, the signal spectrum component is slightly different from each other that would require further adjustment and adoption of the model for accurate decision making.

Similar to the conventional energy detection method, the BHT is used in the proposed method to decide the presence or absence of the signal. Similarly, \( H_0 \) and \( H_1 \) are the null hypotheses and the alternative hypotheses, respectively, used in the BHT. The probability of detection (\( P_d \)) is one of the interests in this study and would be the probability of deciding \( H_1 \) and \( H_1 \) is true. The scenario of the proposed method can be formulated using the BHT problem as shown in (10).

\[
\begin{align*}
H_1: V_b > a*V_{th} \text{ or } V_b > c & \quad \text{Primary User is Present} \\
H_0: \text{otherwise} & \quad \text{Primary User is Absent}
\end{align*}
\]

where \( a \) and \( c \) are constant that are to be determined with an intelligent algorithm to suit with different types of signal.

### 4. Results and discussion

In this section, the proposed method is verified through the simulated results analysis. The signal of interest is the same as the sum of the signals shown earlier in Figure 6 with AWGN ranging from -50 dB to 20 dB. The signals under the test are QPSK modulated signal with the band ranging from 100 MHz to 500 MHz. In this analysis, the major concentration is on the probability of detection as the probability of false alarm is assumed to be extremely small and can be approximated to zero, especially in case of relatively higher SNR. The parameters of \( c \) and \( a \) shown in Figure 11 (in the decision box diagram) are chosen to be 2 and 3, respectively (those values are determined with trial and error procedure). In this analysis, the main concentration is on the probability of detection rather than the probability of false alarm.

![Figure 12. The proposed method versus traditional approach.](image)

In Figure 12, the probability of false alarm is plotted against SNR using Monte-Carlo simulation method and compared with the approximated traditional detection method [13, 14]. It is observed from the graph that the proposed method can work under a very low SNR compared to the traditional approach. The simulated version of the proposed method is taken with averaging number \( M \) of 1000, 5000, and 10000 and it can detect with the probability of detection of 90% signal with SNR as low as -32.3 dB and -34.5 dB, respectively, when \( M \) equals to 5000 and 1000 while the traditional approach can detect with the probability of detection of 90% when the SNR is -6.7 dB and -9.3 dB, respectively (as the probability of false alarm is \( 10^{-8} \) and \( 10^{-3} \)). From the obtained results, it can be seen that, the proposed method significantly improves the range of detection in terms of SNR with a value of 21 dB to 27.8 dB.
Increasing the observation time of the signal to be detected increases the probability of detection and makes the system slightly more reliable with additional complexity to the detector, since memory needed for storing the samples becomes larger, also the number of FFT point required to perform similar transformation will increase. Another point is that the required power will be doubled due to the large number of FFT, which is the main source of the power consumption. Figure 13 shows the probability of detection with both T and 2T observation time by averaging number M of 5000. The T is taken as 20000000 samples in the time domain, which is obtained in the stage of Analog-to-Digital Conversion (ADC). Similarly, the period of 2T is obtained by taking 40000000 samples with the similar sampling rate in both cases. The T is chosen so that 2 complete symbols of the source observed signal is obtained, which is QPSK with sampling frequency of (2 * 500 MHz) in our simulation. The M can be varied, however, it cannot be either very large or very small.

![Figure 13](image_url)

**Figure 13.** The effect of increasing the observation time.

The obtained results justify the significance of the proposed model. It can be observed that the proposed method is able to differentiate between the power of the noise and the power of the transmitted signal even though the noise has a very large power. The detection time for the proposed method is very small as compared to other spectrum sensing techniques. Moreover, it has a low computational cost with a very little complexity added to the system. Another advantage is that information about the SNR can be extracted from the nature of the spectrum and the average values.

5. Conclusion

In this paper, a new method is proposed to optimize the conventional energy detection algorithm (in spectrum sensing) that suffers from a few drawbacks, such as susceptibility of changing the level of noise and inability to work under low SNR. Unlike the traditional method, the proposed method utilizes the spectrum features of the PUs to differentiate between the power of the signal and the power of the noise to an acceptable degree. The obtained results show that the proposed method outperforms the existing energy traditional detector. The proposed model achieves higher probability of detection and it can be further observed that the proposed approach significantly improves the range of detection in terms of SNR with a value of 21 dB to 27.8 dB with the minimal computational cost and complexity equal to that of the conventional method. However, dynamically setting the values of c and a, further enhancement of the proposed method, and the experimental results to address the practical CRs are to be considered in our future work.
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