An Investigation into a Novel Multi Slot Spectrum Sensing for Cognitive Radio

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Abstract - In cognitive radio, unlicensed users are allowed to opportunistically use a licensed band under the condition of harmless interference to licensed users. To ensure such condition, the key function of cognitive radio, spectrum sensing, needs to be reliable and fast. A new scheme of spectrum sensing where the sensing period is divided into multiple mini-slots is proposed to improve the performance of existing spectrum sensing techniques. Under the concept of multi mini-slots spectrum sensing the Primary User, PU, detection is performed for each mini-slot and the existence of PU is summarized by a fusion rule. In this paper, the multiple mini-slot concept is investigated and a comprehensive study is presented. The simulation results show that the more slots each sensing period is divided into, the higher the accuracy of detection becomes. The computational time is slightly increased as well, but it has no significant effect on the overall performance. The paper evaluates its performance against other conventional techniques. The results show our technique performs the best with the highest probability of detection. The computational time is kept short, similar to Energy Detection, ED.

Keywords - Cognitive radio, Spectrum sensing, Mini-slots

I. INTRODUCTION

Recently, the number of wireless communication services has been noticeably increasing with a huge demand on spectrum resources, but these resources are limited. In a static spectrum allocation policy, which is in current use, a licensed band is assigned to specific holder who has licensed of spectrum usage, primary users (PUs). Any unlicensed user, secondary users (SU), is not allowed to operate the licensed band, although the licensed band is not being utilized. The underutilization is reported in licensed band, where PU’s may not fully utilize the licensed band. To address the issue of underutilization, cognitive radio (CR) [1-7] is proposed where it allows SU to exploit the licensed bands dynamically when they are available. Moreover, the SUs are not allow to cause harmful interference to PU when they utilize the licensed band. Once the available licensed bands become more utilized, the usage of limited spectrum resources is more efficient.

To ensure causing harmless interference to PU, the behaviour of the PU in the licensed band must be checked by using the function of the cognitive radio which is called “spectrum sensing” [8-10]. The SU needs to monitor the spectrum band continually to monitor the spectrum usage of the PU. If the PU stops its activity on the licensed band, the SU can utilize the band opportunistically. As soon as the PU needs to reclaim the spectrum usage rights, the licensed band needs to be vacated immediately. Therefore, the spectrum sensing needs to be reliable and fast.

Once a PU operates on the spectrum band, a reliable detection refers to a correct declaration about the PU’s status that can be shown by the probability of detection ($P_d$). To ensure causing harmless interference to the PU caused by the SU, $P_d$ needs to be maximized. On the other hand, a false detection when the PU does not operate on the spectrum band can be shown by the probability of false alarm ($P_{fa}$). The probability of false alarm ($P_{fa}$) needs to be minimized to increase an opportunity of spectrum utilization of the SU. Moreover, an average sensing time is a parameter that affects the performance of spectrum utilization of the SU. If the spectrum sensing performs sensing within short period of time, the achievable throughput increases and also decreases an opportunity of a causing interference to the PU. The objective performance of the spectrum sensing technique, which is stated by IEEE 802.22 spectrum sensing requirement document [12], are high $P_d$ as 0.9, less $P_{fa}$ as 0.1 and short sensing time as 2 seconds.

In practice, the spectrum sensing technique which performs sensing with any knowledge about a waveform of a PU is more appropriate to be implemented in CR device. This kind of spectrum sensing is categorized into two types: semi-blind and blind spectrum sensing. For the semi-blind technique, the noise power is required to be known to perform spectrum sensing. The two well-known techniques of this type are energy detection (ED) [12-13] and maximum eigenvalue detection (MED) [14-15]. On the other hand, the second type does not require any knowledge about the waveform and noise power to perform spectrum sensing. The two well-known techniques for blind technique are energy to minimum eigenvalue detection (EME) [16], maximum to minimum eigenvalue detection (MME) [17] and covariance absolute detection (CAV) [18-19].

By comparing the characteristic of these techniques, ED is the most applicable technique to be implemented in CR device in practice since it performs spectrum sensing with low computational complexity and short time consuming. Nevertheless, the performance of ED degrades on the quality of a received signal determined by the signal-to-noise ratio.
(SNR). In general, EME, MME and CAV are proposed to perform spectrum sensing under noise uncertainty environment. Therefore, their performance are robust to the noise uncertainty. However, we focus on the environment that the quality of signal degrades on the additive white Gaussian noise (AWGN) only. By measuring statistical covariance of the received signal, CAV and MME outperform the detection performance of ED since the statistical covariance has less effect of noise than energy. Once MED determines the PU existence using statistical covariance of the received signal and noise power, it gives the best detection performance among these techniques. However, the demerit of detection performance based on the statistical theorem is a high computational complexity and long time consuming.

There are two alternative solutions are proposed to improve the performance of ED including adaptive threshold and a multi-slot scheme. In this paper, we focus on three alternative techniques. An adaptive energy detection (AED) [20-21] adapts its system threshold by combining two spectrum sensing metrics — constant false alarm rate (CFAR) and constant detection rate (CDR). The system threshold of AED is weighted between CFAR and CDR thresholds by using an adaptive weight. Although the $R_b$ is improved, AED cannot outperform a trade-off between $R_b$ and $R_0$. Therefore, $R_b$ is high at low SNRs. To outperform the trade-off between $R_b$ and $R_0$, double constraints adaptive energy detection (DCAED) [22] is proposed. The system threshold of DCAED is generated on the estimated SNR controlled $R_b$ and $R_0$. Multi-slot double constraints adaptive energy detection (MDCAED) [23] detects the PU by combining the merits of a multi-slotted technique and adaptive scheme, therefore it improves the performance of the existing techniques.

In general, spectrum sensing performance normally increases on an increasing of a number of samples. However, the increasing of sample comes at a cost of computational complexity and sensing time. Generally, conventional technique performs spectrum sensing by using a gathered signal from a sensing slot. On the other hand, MDCAED splits the sensing slot into multiple mini-slots and the PU status is declared by using a decision fusion rule. In this paper, we give a comprehensive investigation of multi-slot double constraints adaptive energy detection (MDCAED) [23] to determine the optimal parameters for the technique. Therefore, the performance of MDCAED can be maintained while consumes less computational complexity and sensing time.

The remainder of this paper is organized as follows. Section 2 gives brief introduction to conventional spectrum sensing techniques. In section 3, a model of MDCAED is described in details. In section 4, the simulation results are shown and discussed. Finally, conclusions are presented in Section 5.

II. SPECTRUM SENSING

In this section, we briefly introduce the spectrum sensing techniques — ED, AED, DCAED, MDCAED, MED, EME, MME and CAV — and described their merits/demersits. To perform a spectrum sensing, two hypotheses of received signal can be expressed as:

$$x = \begin{cases} \eta & \text{when PU absents } \{H_0\} \\ s + \eta & \text{when PU presents } \{H_1\} \end{cases}$$

where $x$ is received signal at the SU receiver, $\eta$ is additive white Gaussian noise and $s$ is the transmitted PU signal.

A. Energy Detection

Energy detection (ED) [12-13] is the most interested spectrum sensing technique due to its merits such as simplicity, low computational complexity and short sensing time. To perform a spectrum sensing, ED requires to know a noise power in order to generate a decision threshold. After the energy of the received signal is calculated, it is compared to the threshold. If the energy is greater than the threshold, the status of spectrum band is declared as available (PU presents). Otherwise, the status of spectrum band is declared as unavailable (PU absents). The demerit of ED is an unreliable detection at low SNR environment.

B. Adaptive Energy Detection

An adaptive energy detection (AED) [20-21] is a spectrum sensing technique based on energy measuring. AED improves the detection performance of ED by adapting the decision threshold using the combination between CFAR and CDR thresholds. By combining these two thresholds, AED improves the detection performance of ED. However, the false alarm rate of AED is high at low SNR environment. This is caused by a trade-off between $R_b$ and $R_0$ corresponding to the threshold setting. To set a CDR threshold, a SNR must be estimated by the SU.

C. Double Constraints Adaptive Energy Detection

Double constraints adaptive energy detection (DCAED) [22] is a kind of adaptive energy detection that improves the detection performance of ED and AED on both $R_b$ and $R_0$. After the signal is received, a SNR is estimated then the decision threshold is generated controlled by both $R_b$ and $R_0$ at the same time. Therefore, DCAED gives higher correct detection rate ($R_b$) than AED and gives less false alarm rate ($R_0$) than AED. To reduce a wasted threshold adapting at high SNR, DCAED switches the used the CFAR threshold by using its adaptive factor when the threshold adapting is not necessary. Then, the performance of DCAED slightly
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D. Maximum Eigenvalue Detection

Among the spectrum sensing that does not require a PU signal waveform as a prior knowledge, maximum eigenvalue detection (MED) [14-15] gives the best detection performance. After the signal is received, the maximum eigenvalue is obtained. Then, the value is compared to the decision threshold which needs to know noise power to be generated. However, its demerits are long sensing time consuming and high computational complexity.

E. Energy-Minimum Eigenvalue Detection

A blind spectrum sensing, energy to minimum eigenvalue detection (EME) [16], performs spectrum sensing by measuring a signal energy and the minimum eigenvalue. By obtaining a minimum eigenvalue to calculate the decision statistic, EME does not need a noise power to generate a decision threshold. The merits of EME is a robustness to noise uncertainty, which is not concerned in this paper. However, it has to compute both energy and minimum eigenvalue, therefore it consumes long sensing time.

F. Maximum-Minimum Eigenvalue Detection

A maximum to minimum eigenvalue detection (MME) [17] outperforms a detection performance of EME by obtaining both minimum and maximum eigenvalue from the received signal. Then, the ratio of maximum to minimum eigenvalue is used to determine the status of the PU. As mentioned earlier, once the minimum eigenvalue is a part of the decision, MME also does not need a noise power to generate the decision threshold. Then, MME is robust to noise uncertainty. Similar to EME, the demerits of MME are long sensing time consuming and high computational complexity.

G. Covariance Absolute Value Detection

Covariance absolute value detection (CAV) [18-19] is the most accurate spectrum sensing among blind techniques: EME and MME. The decision threshold of CAV is based on statistical covariance of the received signal. By using this theorem, CAV does not need a noise power to calculate the decision threshold. A sensing time consuming of CAV is nearly to EME, MME and MED. The demerits of CAV is that it gives $P_a$ higher than the spectrum sensing requirement.

III. MULTI-SLOT DOUBLE CONSTRAINTS ADAPTIVE ENERGY DETECTION

In this section, we describe an operation of a multi-slot double constraints adaptive energy detection (MDCAED) [23]. MDCAED consists of two important elements, i.e., DCAED and decision fusion rule. As shown in fig.1, a sensing slot is separated into $M$ mini-slots where the number of sample of each mini-slot ($N_m$) is $M/M$. Each mini-slot is determined the existence of PU individually. After the existence of PU in each mini-slot is determined, the final decision about the PU status is made by decision fusion rule. As described in [24-26], a K-of-N rule is the most appropriate fusion rule to be used as a decision fusion of MDCAED.

![Fig. 1. The system model of MDCAED](image)

An energy of a mini-slot is measured and used as a decision statistic ($T_m^DCAED$) which is given by:

$$T_DCAED = \frac{1}{N_m} \sum_{k=1}^{N_m} |x_k|^2, \quad j = 1, 2, \ldots, M. \quad (2)$$

![Fig. 2: The system model of DCAED for mini-slot](image)

To determine the existence of the PU of each mini-slot, a DCAED for mini-slot is utilized (as shown in fig.2). Firstly a noise variance ($\sigma^2$) of each slot is estimated by an SNR estimator and the estimated SNR ($\hat{\gamma}_m^DCAED$) is computed. Then, this information is gathered by a threshold setter. The
threshold setter compares the estimated SNR ($\gamma_{est}$) to the critical SNR ($\gamma_c$) where the critical SNR ($\gamma_c$) is considered as an SNR that spectrum sensing meets the target performance metrics on both values, i.e., $F_1$ and $F_1$. Then, $\gamma_c$ can be expressed as:

$$\gamma_c = \frac{\xi^2}{\xi^2 - 1}$$

where $\xi$ is standard Gauss complementary cumulative distribution function.

After the estimated SNR ($\gamma_{est}$) is compared to the critical SNR ($\gamma_c$), the adaptive factor ($\beta_{MDCAED}$) is generated. Then, it is given as:

$$\beta_{MDCAED} = \frac{\gamma_{est} \gamma_c - \gamma_c}{\gamma_c \gamma_c - \gamma_c}$$

(4)

and

$$\gamma_{est} = \gamma_c$$

(5)

where $\gamma_{est}$ is the CFAR threshold for mini-slot and $\gamma_c$ is a noise variance.

Then, the decision threshold can be expressed as:

$$\lambda_{MDCAED} = \beta_{MDCAED} \lambda_{MIN} \frac{(\gamma_{MIN}^2 - 1)}{\gamma_{MIN}^2} + \lambda_{MIN}^2$$

(6)

If the $\lambda_{MDCAED}$ is greater than the $\lambda_{MIN}$, a binary “1” of decision statistic is generated and sent to decision fusion process. Otherwise, a binary “0” is sent to decision fusion process. As mentioned earlier, K-of-N rule is used as the decision fusion rule. The hypotheses of K of N rule are given as:

$$H_0: \sum_{i=1}^{K} A_{c_i} + \sum_{i=1}^{K} A_{n_i} = K$$

$$H_1: \sum_{i=1}^{K} A_{c_i} = K$$

(8)

(9)

Thus, the PU status will be declared as presents when the binary decision statistic of at least $K$ is “1”. Otherwise, the PU status will be declared as absents.

IV. SIMULATION RESULTS

In this section, we firstly investigate a performance of MDCAED under different size of samples ($N$) and number of mini-slots ($M$). Three parameters: $F_1$, $F_2$, and sensing time, are used to evaluate the spectrum sensing performance. In general, a value of $F_1$ should be maximized while $F_2$ and sensing time should be minimized. A PU can be secured from an interference caused by a SU when $F_1$ is high. When $F_2$ is small, opportunity of spectrum utilization by the SU increases. On the other hand, the system throughput and the number of sensing spectrum band increase when the average sensing time is short. In addition, we also investigate the performance of 7 sensing techniques — ED, AED, DCAED, MED, EME, MME and CAV — under different size of samples. Once the optimal parameters of MDCAED are found, the performance of MDCAED is compared to the other techniques. All of the results are averaged on 10,000 Monte-Carlo realizations. A primary user (PU) signal is considered as a random occurring waveform of wireless microphone signal [27] where the simulated parameters are shown in table 1. The communication channel is determined as an additive white Gaussian noise (AWGN) channel whose SNR is between -24 to 0 dB. Other related parameters are as follows: $F_3 = 0.5$ and $F_4 = 0.1$. It should be noted that the received SNR and noise power are:

The wireless microphone signal can be derived as:

$$s(t) = A_c \cos(2\pi f_c t + 2\pi k_l \int_0^t m(\gamma) d\gamma)$$

(10)

and

$$m(\gamma) = \sin(\gamma t)$$

(11)

where $A_c$ is amplitude of carrier signal, $m(\gamma)$ is the modulating signal, $\xi$ is information frequency, $f_c$ is carrier frequency of transmitted signal and $k_l$ is frequency modulation (FM) deviation factor.

<table>
<thead>
<tr>
<th>TABLE 1: MODEL OF WIRELESS MICROPHONE SIGNAL [27]</th>
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<tbody>
<tr>
<td>Silent</td>
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<tr>
<td>FM deviation factor ($F_3$)</td>
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<tr>
<td>m(\gamma) frequency (kHz)</td>
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</tbody>
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Firstly, we investigate the effect of a number of samples ($N$) and a number of mini-slots ($M$) to the performance of MDCAED when a SNR is fixed as -24 dB. As shown in fig.3, an increasing in a number of samples ($N$) does not affect an improving or decreasing for all number of mini-slots ($M$). However, a number of mini-slots ($M$) has a great impact on the performance of MDCAED. As mentioned earlier, the objective of spectrum sensing performance is to minimize $F_3$ and maximize $F_4$. Then, we find that MDCAED maintains the performance on both perspective when $N$ is 10. The other factor that should be concerned is an average sensing time. The average sensing time increases when $M$ increases as shown in fig.4. However, the MDCAED meets the spectrum sensing requirement of sensing time for all number of mini-slots.

As described in a spectrum sensing requirement based on IEEE 802.22, a prime concern of spectrum sensing performance are $F_3$ and $F_4$, while the average sensing time is the lower priority. As depicted in fig.5, MDCAED maintains a performance on both parameters when $M$ is 10,
where it gives high $P_d$ and low $P_f$ for the shown SNR levels. Therefore the optimal parameters for MDCAED as follows: $N = 5000$ and $M = 10$.

Secondly, the performance of 7 spectrum sensing techniques: ED, AED, DCAED, MED, EME, MME and CAV, are investigated under different size of samples ($N$). As shown in fig. 6 and fig. 7, an increasing in the number of sample ($N$) affects the detection performance of MED, MME and CAV. The performance of these techniques improve on the increasing of the number of sample ($N$). On the other hand, the performance of spectrum sensing technique based on energy of received signal: ED, AED, DCAED and EME, slightly increases when number of sample ($N$) increases. However, these improvement also come at a cost of average sensing time.
In fig. 8, the performance of MDCAED is compared to the other techniques - ED, DCAED, MED, EME, MME and CAV - under different size of samples \(N\) when SNR is -24 dB. As a result, a performance of MED approaches to MDCAED when the size of samples of MED is 40000. At this point, an average sensing time of MED is much more than MDCAED (approximately 41 times of MDCAED), where the size of samples of MED is 5000 (as shown in fig. 9). Noted that, the performance of AED is ignored in this comparison because its gives high rate of both \(P_d\) and \(P_f\), then AED is not appropriate to be implemented in practice.

Finally, the performance of optimal MDCAED is compared to ED, DCAED, MED, EME, MME and CAV. As shown in fig. 10, MDCAED gives the highest \(P_d\) for all SNRs and meets the spectrum sensing requirement, where \(P_d\) should be equal to or higher than 0.9, when SNR is greater than -20 dB. On the other hand, MDCAED gives low rate of \(P_f\) as nearly to zero when the SNR is greater than -16 dB (as shown in fig. 11). Since the
SNR decreases, it is difficult to separate a PU signal from noise by using an energy measuring, then the computational complexity increases. In perspective of sensing time, MDCAED benefits from a merit of spectrum sensing based on energy measuring, therefore it consumes much less sensing time than a spectrum sensing based on statistical theorem while gives better detection performance (as shown in fig. 12).

From the simulation results, once a sensing slot is split into 10 mini-slots (\( n = 10 \)), MDCAED benefits from different noise effect on each mini-slot because a noise variance distributes on the time varying. Then, MDCAED determines the status of the PU from mini-slots that have less noise effect. Therefore, MDCAED improves the spectrum performance of the existing techniques.

V. CONCLUSION

In our research project reported in this paper, we investigated the optimal parameters for a multi-slot double constraints adaptive energy detection (MDCAED) and compared its performance to the existing spectrum sensing techniques. Once the number of samples reaches a level where it does not affect the performance of MDCAED, the computational complexity can be reduced. Then, a high system throughput and a large number of sensing spectrum bands can be achieved. On the other hand, MDCAED gives an accurate PU detection, then the PU is secured from harmful interference caused by the SU. Moreover, MDCAED gives low rate of false detection, the SU has more opportunities to utilize an available spectrum band.

REFERENCES