Adaptive Two-stage Spectrum Sensing under Noise Uncertainty in Cognitive Radio Networks

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ABSTRACT

To utilize licensed spectrum bands efficiently, spectrum sensing needs to be accurate and fast. The occurrence of noise uncertainty and the lower in received PU signal power due to the distance between the transmitter and the receiver, path loss, are the main challenges that has a great impact on the accuracy of spectrum sensing.

In this paper, we propose a new scheme of two-stage spectrum sensing, "Adaptive Two-stage Spectrum Sensing (ATSS)", under noise uncertainty environment. ATSS is a modified of a conventional two-stage spectrum sensing where the decision threshold of both stages are adapted on the distance, estimated noise variance and calculated noise uncertainty interval. Therefore, ATSS improves the detection performance of the existing spectrum sensing and is robust to noise uncertainty.

The contribution of this paper is three-fold. First, an unreliable detection and wasted stage activation of a conventional two-stage spectrum sensing are reduced. Second, noise uncertainty is addressed. Third, a new parameter, critical distance (d_c), is proposed in order to reduce computational burden and sensing time of the first-stage.

Keywords: Cognitive radio, Spectrum sensing, Adaptive, Noise uncertainty, Path loss.

1. INTRODUCTION

Cognitive radio (CR) technology [1]-[4] is considered a new solution to improve an underutilization of existing spectrum resources. The licensed band becomes more utilized when a secondary user (SU) is allowed to dynamically use a licensed spectrum band provided the licensed band is not in used. The first standard for CR technology operates in TV White Spaces (TVWS) which is referred to IEEE 802.22 wireless regional area networks (WRAN) [5]. In IEEE 802.22, there are two types of licensed users including TV services and wireless microphone (WM) devices. The WM devices are considered as the lower priority licensed user (secondary licensed user) of the TV band. To achieve an efficient spectrum utilization, the SU is allowed to use a licensed band with harmless interference to licensed user (or primary user: PU). As soon as the licensed band is reclaimed by PU, the SU must stop its activity and vacates the band immediately. Thus, the SU needs to have a function to continually monitor the spectrum band. This function is called "spectrum sensing" [6]-[7].

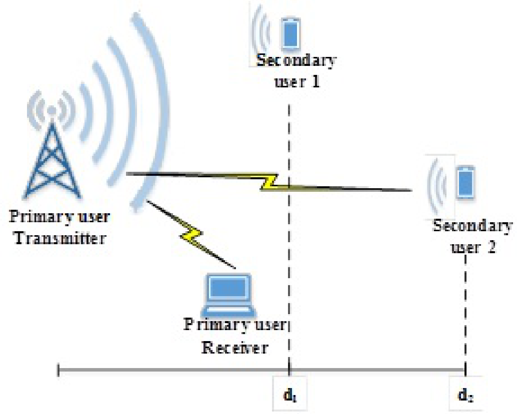

Fig.1: *Spectrum sensing problem.*

In a practical network, there are a PU transmitter and a PU receiver as depicted in Fig.1. Two secondary users, SU_1 and SU_2, are sensing the spectrum band at the same time. Assume that the distances between a PU transmitter and SU_1 and SU_2 are d_1 and d_2. If d_1 is less than d_2, chances are that SU_1 might be able to detect a primary user, while SU_2 cannot, because SNR at SU_2 is much lower than the SNR at SU_1. Therefore, SU_2 will cause harmful interference to the PU receiver.

Three critical parameters associated with the performance of spectrum sensing are probability of detection (P_d), probability of false alarm (P_{fa}) and sensing time (τ_s). P_d which is treated at the highest priority among these critical parameters, is the

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correct declaration of the PU's activities whether it absents or presents. P_d should be maximized to prevent interference to the PU. The second parameter, P_{fa} , is the declaration of PU's activities when it actually absents. P_{fa} should be minimized to increase the opportunity to utilize the unused licensed band. The third parameter, sensing time ($_s$), is the time duration consumed by spectrum sensing function to determine the existence of PU. τ_s has a great impact on the accuracy of spectrum sensing. Decreasing in τ_s increases the opportunity to search an available spectrum band. On the other hand, as the higher accuracy is needed, the longer τ_s is also required. In IEEE 802.22 standard [8], the SU is specified to perform spectrum sensing with P_d of higher than 0.9 and P_{fa} of less than 0.1 within 2 seconds of τ_s .

The two main challenges which have a great impact on the accuracy of spectrum sensing including low signal-to-noise ratio (SNR) and noise uncertainty. In practical environment, the received PU signal power at the receiver decreases due to the distance between the transmitter and the receiver which is referred to path loss effect [9]-[10]. Therefore, the SNR at the receiver decreases, e.g., a WM device operates in TV channel with low transmit power (typically 10-50 mW within 100 m coverage area). As the WM device is 100 meters away from an SU the received WM signal power may drop to -95 dBm [11]-[13]. The noise power in a 6 MHz DTV (Digital Television) channel is -96 dBm. Thus, the SNR at the receiver may greatly drop to -23.46 dB at 500 m. On the other hand, noise in practical system occurs from various sources. The noise variance may change over the time that is referred to noise uncertainty. An occurrence of noise uncertainty dramatically degrades the accuracy of spectrum sensing.

Conventional single-stage spectrum sensing techniques [14]-[23] have been widely studied and the results show that their performance do not sufficient for all conditions of practical communication channel. For example, a low complexity spectrum sensing - energy detection [14]-[16] - gives reliable detection within short sensing time when the SNR is high but it gives unreliable detection when the SNR is low. On the other hand, higher complexity techniques âĂŤ maximum eigenvalue detection (MED) [17]-[18] and covariance absolute value detection (CAV) [20]-[21] - improve the detection performance of ED but they consume longer sensing time. Since there is no single-stage spectrum sensing technique that is perfect enough to be implemented in practical CR device, two-stage technique which combines the merits of single-stage technique is proposed to improve the overall detection performance.

Two-stage spectrum sensing performs spectrum sensing by separating its operation into 2 stages including coarse sensing stage (first-stage) and fine sensing stage (second-stage). The coarse sensing stage firstly determines an existence of a PU. If the coarse sensing stage cannot ensure that the PU exists or not, the fine sensing stage is activated. Normally, ED is exploited as a coarse sensing stage because it consumes the least time in sensing period. In fine sensing stage, MED and cyclostationary detection (CS) [19] were utilized since they outperform the detection performance of ED at low SNR levels. However, CS is very difficult to be implemented in practical CR network because the cyclic frequency of PU's signal is required as a prior knowledge. Hence, ED-MED [24]-[27] is considered in this paper. The demerit of ED and MED is that they require an exactly noise power to generate decision threshold. Moreover, the detection performance of ED and MED dramatically degrades when noise uncertainty, which always present in practical networks, occurs. To perform spectrum sensing under noise uncertainty, the combination between ED and CAV as a two-stage spectrum sensing (ED-CAV) [31] is proposed. Since CAV [20]-[21] performs spectrum sensing from a received signal directly and does not require any prior knowledge to set the decision threshold, then it is known to be robust to noise uncertainty. Then the combination between ED and CAV - ED-CAV - outperforms the detection performance among existing spectrum sensing techniques. In addition, maximum-minimum eigenvalue detection (MME) [22] is another blind spectrum sensing techniques that is robust to a noise uncertainty. However, it gives worst detection performance than CAV.

Adapting the decision threshold is an alternative solution to improve detection performance of spectrum sensing. An adaptive energy detection (AED) [30] was proposed to improve the detection performance of an ED at low SNR levels. Although the P_d of AED increases, it cannot maintain the P_{fa} at low levels as required in IEEE 802.22 document. In [28], we proposed a new scheme to adapt the decision threshold known as double constraints adaptive energy detection (DCAED). DCAED improved the detection performance of AED on both P_d and P_{fa} . However, these two adaptive techniques did not take the factor of noise uncertainty in the account.

In this paper, we propose a new scheme of two-stage spectrum sensing, "Adaptive Two-stage Spectrum Sensing (ATSS)", under noise uncertainty environment. The ATSS composes of four main modules including noise estimator, stage activator, the first-stage spectrum sensing and the second-stage spectrum sensing. The noise estimator estimates noise variance and calculates noise uncertainty interval. The stage activator selects the appropriate stage of spectrum sensing to the status of received signal. For the first-stage spectrum sensing, we propose a modified-DCAED (Mo-DCAED) which improves the detection performance of DCAED [28] under noise uncertainty environment. In the second-stage, we introduce an adaptive maximum eigenvalue detection (AMED) to improve the detection performance of a conventional MED under noise uncertainty environment.

The contribution of this paper is three-fold. First, an unreliable detection and wasted stage activation of a conventional two-stage spectrum sensing are reduced. The unreliable detection of a conventional two-stage spectrum sensing is addressed by adapting the decision threshold of both stages. This is a main difference from other two-stage techniques because other two-stage techniques only perform spectrum sensing twice from a fixed decision threshold of each stage. Moreover, to reduce an unnecessary adapting process and to decrease a false alarm detection, we use a stage activator to activate the appropriate spectrum sensing technique to the status of received signal, e.g., low SNR of received signal together with noise uncertainty environment. Second, noise uncertainty is addressed by using a double constraints adaptive concept. The double constraints adaptive scheme of ATSS adapts the decision threshold on the changing in on the distance, estimated noise variance and calculated noise uncertainty interval. Third, a new parameter, critical distance (d_c), is proposed to be used as a first-stage adaptive selection. Therefore, computational burden and sensing time of the first-stage can be reduced since the first-stage threshold is not necessary to be always adapted.

To adapt the AMED threshold, the double constraints adaptive concept cannot be used directly since the maximum eigenvalue of PU's signal is required to be known by the SU. The maximum eigenvalue of PU's signal is used to generate the adaptive factor. However, the maximum eigenvalue of PU's signal is not practical in network operation. Therefore, we introduce a new solution to generate the adaptive factor by using an equality in boundary of spectrum sensing. Then, we exploit an equality of $P_{fa(ED)}$ and $P_{d(ED)}$ to generate the second-stage adaptive factor. By using this equality in boundary, we can reduce computational complexity of adapting the second-stage threshold since we does not compute the maximum eigenvalue of PU's signal.

As shown in the simulation results, by adapting the decision threshold on the changing in distance and estimated noise power and noise uncertainty interval, ATSS improved the detection performance of the existing single spectrum sensing techniques - ED, MED, CAV, MME, AED, ED-MED and ED-CAV. ATSS is also robust to the occurrence of an uncertainty behaviour of noise. In perspective of sensing time, ATSS highly achieves the spectrum sensing requirement which is much less than 2 seconds.

The remainder of this paper is organized as follows. Section 2 gives brief introduction to conventional spectrum sensing techniques. In section 3, two challenges of spectrum sensing are described. Section 4, performance of conventional spectrum sensing techniques are investigated. In section 6, the model of ATSS is explained in details with its mathematical models. The simulation results are shown in Section 6. Finally, conclusions are presented in Section 7.

2. SPECTRUM SENSING TECHNIQUE

In this section, spectrum sensing techniques - ED, MED, CAV, MME and two-stage spectrum sensing - are briefly introduced together with their own operational requirement and merits/demerits. Moreover, a preliminary study of the effect of noise uncertainty to the spectrum sensing's performance is also shown. To determine the received signal under noise uncertainty and path loss effect, the hypothesis models of received signal are given by

$$\mathbf{x} = \begin{cases} \alpha\eta & \text{whenPUabsents}\,[H_0] \\ PL \cdot s + \alpha\eta & \text{whenPUpresents}\,[H_1] \end{cases} \tag{1}$$

where $\mathbf{x}$ is received signal by SU, η is additive white Gaussian noise, $\mathbf{s}$ is the transmitted signal by PU and PL is path loss and α is a noise uncertainty interval.

2.1 Energy detection

ED [14]-[16] is popularly utilized in practical CR network because it is the simplest spectrum sensing technique. ED can be utilized without any prior knowledge about PU's signal. In addition, ED performs spectrum sensing with the least complexity and time consuming. The existence of PU is determined by comparing an average energy of a received signal to a predetermined threshold. If the average energy is greater than the threshold, the SU declares that the PU presents. On the other hand, the spectrum band is declared as vacant if the average energy is less than the threshold. However, ED requires to know noise power to generate the threshold. ED gives an unreliable at low SNRs. Under environment as noise uncertainty, the detection performance of ED significantly degrades.

2.2 Maximum Eigenvalue Detection

MED [17]-[18] utilizes statistical theory and eigendecomposition to perform spectrum sensing. Similar to ED, noise power is required as a prior knowledge for this technique. MED outperforms detection performance of ED at low SNRs. MED compares the maximum eigenvalue to its predetermined threshold. The communication channel is empty when the maximum eigenvalue of the received signal is less than the threshold. However, the detection performance of MED under noise uncertainty is unreliable. MED relies on a pre-assumed noise power in order to generate its decision threshold. In practice, when noise power uncertainty occurs, the noise power is different from pre-assumed value, then the performance of MED degrades.

2.3 Covariance Absolute Value Detection

By comparing the auto-correlation of the received signal to the CAV [20]-[21] threshold, the existence of a PU is determined from the received signal. The knowledge of PU's signal and noise power are not required. Since CAV performs spectrum sensing by exploiting only the statistical covariance of received signal, CAV offers better detection performance under noise uncertainty than MED. However, CAV will perform poorly when the auto-correlation of the received signal is low.

2.4 Maximum-Minimum Eigenvalue Detection

MME [22]-[23] uses ratio between maximum and minimum eigenvalue of the received signal to determine the existence of the PU. Similar to CAV, MME does not require any knowledge of PU's signal and noise power. MME outperforms detection performance of ED and MED under noise uncertainty environment. However, MME will perform poorly when the auto-correlation of the received signal is low.

2.5 Adaptive energy detection

In order to improve the detection performance of ED, an alternative solution, adaptive scheme, was introduced. From [30], an adaptive energy detection technique (AED) adapts its decision threshold using an AED adaptive factor (β_{AED}) to vary the threshold depending on the SNR at the receiver. The decision threshold (λ_{AED}) is given by

$$\lambda_{\mathrm{AED}} = \lambda_{\mathrm{CFAR}} + \beta_{\mathrm{AED}} * \left(\lambda_{\mathrm{CDR}} - \lambda_{\mathrm{CFAR}}\right), 0 \leq \beta_{\mathrm{AED}} \leq 1 \quad (2)$$

where λ_{CFAR} is a threshold that fixes the P_{fa} as a target detection performance where P_{fa} is 0.1 and the λ_{CDR} is a threshold that fixes the P_d as a target detection performance where P_d is 0.9. Denote the CFAR stands for constant false alarm rate and CDR stands for constant false alarm rate.

Since the AED decision threshold (λ_{AED}) is vary between λ_{CDR} and λ_{CFAR} , AED improves the detection performance of AED at low SNR levels. Although AED gives higher rate of P_d than ED, AED cannot overcomes a tradeoff in setting λ_{AED} using λ_{CDR} . Therefore, AED gives high rate of P_{fa} which P_{fa} should be minimized.

2.6 Double constraints adaptive energy detection

In our previous work, we proposed an alternative adapting scheme for energy detection, double constraints adaptive energy detection (DCAED) [28], by adapting its decision threshold controlling by P_d and P_{fa} at the same time while other techniques control their decision threshold by fixing only P_d or P_{fa} at a time. An adaptive factor of DCAED (β_{DCADE}) is used to adapt the decision threshold on the estimated SNR at the receiver (γ_{est}) where γ_{est} is compared to the critical SNR (γ_c,).γ_c is the SNR that the first-stage gives reliable detection without adapting the decision threshold. The adaptive factor of DCAED (β_{DCADE}) can be expressed as Maximize $X_s(i)$ Subject to

$$\beta_{\mathrm{DCAED}} = \begin{cases} \dfrac{\lambda_{\mathrm{CFAR}} - \sigma_{\mathbf{est}}^2}{\left(\frac{\lambda_{\mathrm{CFAR}}}{\sigma_\eta^2} - 1\right)\sigma_{\mathbf{est}}^2}, \gamma_{\mathrm{est}} \geq \gamma_{\mathrm{c}} & (3) \\ \dfrac{\gamma_{\mathrm{est}}\sqrt{N/2}}{\left(Q^{-1}\left(\mathrm{P_{fa}}\right) - Q^{-1}\left(\mathrm{P_d}\right)\left(\gamma_{\mathrm{est}}+1\right)\right)}, \gamma_{\mathrm{est}} < \gamma_{\mathrm{c}} & (4) \end{cases}$$

$$\gamma_{\mathrm{c}} = \frac{Q^{-1}\left(\mathrm{P_{fa}}\right) - Q^{-1}\left(\mathrm{P_d}\right)}{Q^{-1}\left(P_{\mathrm{d}}\right) - \sqrt{\frac{N}{2}}} \quad (5)$$

where σ_{est}^2 is an estimated noise variance, Q(.) is standard Gauss complementary cumulative distribution function, σ_η^2 is a noise variance and N is a sample.

The decision threshold of DCAED is given by

$$\lambda_{\mathrm{DCAED}} = \beta_{\mathrm{DCAED}}\sigma_{\mathrm{est}}^2\left(\frac{\lambda_{\mathrm{CFAR}}}{\sigma_\eta^2} - 1\right) + \sigma_{\mathrm{est}}^2 \quad (6)$$

As mentioned earlier, our previous work - DCAED - was not proposed to address a noise uncertainty environment. Therefore, the parameters - λ_{DCAED} , β_{DCAED} and γ_c - have to be re-derived and can be derived from (6) and the following equations:

$$\mathrm{P_{fa}} = Q\left(\left(\frac{\lambda_{\mathrm{CFAR}}}{\sigma_\eta^2} - 1\right)\sqrt{\frac{N}{2}}\right) \quad (7)$$

$$\mathrm{P_d} = Q\left(\frac{1}{\left(\gamma_{\mathrm{est}}+1\right)}\left(Q^{-1}\left(\mathrm{P_{fa}}\right) - \gamma_{\mathrm{est}}\sqrt{\frac{N}{2}}\right)\right) \quad (8)$$

$$\mathrm{P_{fa}} = Q\left(Q^{-1}\left(\mathrm{P_d}\right)\left(\gamma_{\mathrm{est}}+1\right) + \gamma\sqrt{\frac{N}{2}}\right) \quad (9)$$

$$N_c = \frac{2}{\gamma_{\mathrm{est}}^2}\left[Q^{-1}\left(\mathrm{P_{fa}}\right) - Q^{-1}\left(\mathrm{P_d}\right)\left(\gamma_{\mathrm{est}}+1\right)\right]^2 \quad (10)$$

It should be noted that DCAED is the technique that adapts the decision threshold of a conventional energy detection (ED), therefore λ_{DCAED} is derived from a target detection performance of ED - P_{fa} and P_d.

2.7 Two-stage spectrum sensing techniques

Two-stage spectrum sensing [24]-[27], [31] exploits merits of the single-stage techniques and performs sensing by separating its operation into 2 stages including coarse sensing stage and fine sensing stage. Once the PU's signal is received, the coarse stage firstly determines an existence of a PU by comparing a decision statistic of coarse stage to the predetermined coarse stage threshold. As no PU is detected, the fine stage is activated to perform another spectrum sensing. The mathematical models of P_{fa} and P_d for two-stage technique can be expressed as

$$P_{\mathrm{fa}} = P_{\mathrm{fa},1^{\mathrm{st}}} + \left(1 - P_{\mathrm{fa},1^{\mathrm{st}}}\right)P_{\mathrm{fa},2^{\mathrm{nd}}} \quad (11)$$

$$P_{\mathrm{d}} = P_{\mathrm{d,1^{st}}} + \left(1 - P_{\mathrm{d,1^{st}}}\right) P_{\mathrm{d,2^{nd}}} \tag{12}$$

where P_{fa} is an overall probability of false alarm, P_d is an overall probability of detection, $P_{fa,1^{st}}$ is the probability of false alarm of the first-stage, $P_{fa,2^{nd}}$ is the probability of false alarm of the second-stage, $P_{d,1^{st}}$ is the probability of detection of the first-stage and $P_{d,2^{nd}}$ is the probability of detection of the second-stage.

3. PROBLEM STATEMENT

In this section, we give a brief overview of two main issues that will cause a degradation in detection performance of spectrum sensing including path loss and noise uncertainty.

3.1 Noise uncertainty

In practical communication system, noise may occur from more than one source. Then the variance of noise is difficult to be exactly estimated. Once noise occurs from various sources, the disturbance of noise is undesirable that is referred to an "uncertain behaviour" or "noise uncertainty" [16]. The noise uncertainty may occur from the time-varying of thermal noise in a receiver and the non-linearity of the receiver. In addition, the transmission of other users also cause the noise uncertainty. When the uncertainty of noise occurs, the variance of noise distributes within range of $\left[\alpha\sigma_\eta^2, \frac{1}{\alpha}\sigma_\eta^2\right]$. Then, an estimated noise power can be expressed as.

$$\hat{\sigma}_\eta^2 = \alpha\sigma_\eta^2 \tag{13}$$

where α is a noise uncertainty interval and σ_η^2 is a noise variance. Then, noise uncertainty factor (in dB) distributes within range [-B, B] when noise uncertainty factor (in dB) is given as.

$$\mathrm{B} = max\{10\log_{10}\alpha\} \tag{14}$$

3.2 Path loss

Path loss is described as an attenuation of signal strength (power) due to the propagation distance between PU and SU. Then the SNR at receiver becomes lower. The mathematical model of path loss is derived as

$$\mathrm{PL} \equiv \mathrm{C}\mathrm{d}^{-\aleph} \tag{15}$$

where PL is path loss, d is distance between PU and SU, C is loss constant and $\aleph$ is path loss exponent.

Then, the SNR at the receiver as a function of path loss can be expressed as

$$\tilde{\gamma}_{\mathrm{PL}} = \frac{\mathrm{PL}\cdot\sigma_{\mathrm{s}}^2}{\sigma_\eta^2} \tag{16}$$

where σ_s^2 is a signal variance.

Table 1: *Model of wireless microphone signal [36].*

	Silent	Soft speaker	Loud speaker
$m(\tau)$frequency (kHz)	32	3.9	13.4
FM deviation factor(kHz)(k_f)	±5	±15	±32.6

4. PRELIMINARY EXPERIMENTS

In this section, we simulate the performance of spectrum sensing techniques - ED, MED, CAV, MME, AED, DCAED, ED-MED and ED-CAV- under noise uncertainty environment where additive white Gaussian noise (AWGN) is considered as a communication channel. The WM (wireless microphone) [36] signal, which is used as PU signal, is random occurring pattern. The SNR at the receiver decreases due to the distance between PU and SU that is known as path loss effect. To simulate path loss effect, the WM device and SU are set with different distance (d) in the range of 10 to 500 meters. As stated in [11]-[13], the received signal power is -95 dBm at 100 m, then the loss constant (C) is set be 0.00031623. The uncertainty of noise is simulated by the noise uncertainty factor (B) in the range of 0 to 2 dB [16]. SU is set to be capable of estimating noise variance (σ_{est}^2) [34] and path loss. After noise variance is estimated, the noise uncertainty interval (α_{est}) is then calculated using (48) which will be described later. Other parameters are setting as follows: N=5000, L=8 , $\aleph$=2 , P_d=0.9 and P_{fa}=0.1.

The mathematical model of the WM signal is given by

$$s\left(t\right) = A_{\mathrm{c}}\cos\left(2\pi f_{\mathrm{c}}t + 2\pi k_{\mathrm{f}}\int_0^t m\left(\tau\right)\mathrm{d}\tau\right), \tag{17}$$

$$m\left(\tau\right) = \sin\left(f_{\mathrm{m}}t\right), \tag{18}$$

where A_c is amplitude of carrier signal, $m(\tau)$ is the modulating signal, f_m is message frequency, f_c is carrier frequency and k_f is frequency modulation (FM) deviation factor.

Based on IEEE 802.22, the parameter of silent, soft speaker and loud speaker of the WM signal are set as shown in Table 1.

To investigate the performance of ED, MED, CAV, MME, AED, DCAED, ED-MED and ED-CAV, two performance metrics P_d and P_{fa} are measured. All the experiments are done by using MATLAB and averaged on 10,000 Monte-Carlo realizations.

As shown in Fig.2, the detection performance of ED under different noise uncertainty factors are depicted. When noise uncertainty does not occur (α=0), $P_{d(ED)}$ begins to decrease when d is 220 m, while $P_{d(ED)}$ begins to decrease at 130 and 110 m when α is 1 and 2, respectively. This means that the

PU signal suffers from an uncertainty of noise and it is difficult to determine the PU existence by using the received signal energy. Therefore, the $P_{d(ED)}$ significantly decreases due to the increasing in the strength of noise uncertainty (α). To evaluate a false alarm of spectrum sensing, only noise occurs at the SU, i.e., the PU does not exist. As depicted in the figure, the $P_{fa(ED)}$ when uncertainty of noise does not exist is higher than $P_{fa(ED)}$ when uncertainty of noise exists.

A tradeoff between $P_{fa(MED)}$ and $P_{d(MED)}$ under different strength of noise uncertainty effect are shown in Fig 3. As a result, $P_{d(MED)}$ significantly decreases due to the occurrence of noise uncertainty. When noise uncertainty does not occur, $P_{d(MED)}$ begins to decrease when d is 300 m, while $P_{d(MED)}$ begins to decrease at 210 and 180 m when α is 1 and 2, respectively. Similar to ED, $P_{fa(MED)}$ when noise uncertainty exists is lower than $P_{fa(MED)}$ when uncertainty of noise does not exist. The effect of noise uncertainty causes noticeably decreasing in $P_{d(MED)}$ and $P_{d(ED)}$ because both techniques require an exactly noise variance to set their decision thresholds.

On the other hand, CAV and MME do not require any prior knowledge to set their decision thresholds then the occurrence of noise uncertainty slightly decrease $P_{d(CAV)}$ and $P_{d(MME)}$ as shown in Fig.4 and Fig.5, respectively. In perspective of P_{fa} , $P_{fa(CAV)}$ is higher than 0.1 which does not meet the spectrum sensing requirement while $P_{fa(MME)}$ is lower than 0.1. Since $P_{d(CAV)}$ and $P_{d(MME)}$ do not decrease due to the increasing in noise uncertainty effect, then CAV and MME are robust to noise uncertainty.

As shown in Fig.6, by adapting a decision threshold, the spectrum sensing based on energy detection, AED, gives higher rate of P_d than ED ($P_{d(AED)} > P_{d(ED)}$). However, AED adapts its decision threshold (λ_{AED}) by varying the threshold (λ_{AED}) between λ_{CDR} and λ_{CFAR} , then $P_{fa(AED)}$ is high since λ_{AED} cannot outperform a tradeoff between P_d and P_{fa} . Due to the nature of energy detection, the energy of the received signal suffers from the occurrence of noise uncertainty, then $P_{d(AED)}$ significantly decreases when noise uncertainty occurs.

On the other hand, the DCAED did not proposed to address the environment of noise uncertainty, the simulation results (as depicted in Fig. 7) show that although the DCAED gives high rate of P_d , the DCAED cannot maintain the rate of P_{fa} at low levels as required in the spectrum sensing requirement. From the results, we found that the critical distance is 247.71, 135.57 and 110.99 when the noise uncertainty interval (α) is 0, 1 and 2, respectively. When the distance is greater than the critical distance, the adaptive factor is select as (4). As depicted in the equation, the adaptive factor (β_{DCAED}) is set and the value is corresponding to the estimated SNR. Then, at distance greater than the critical distance, DCAED gives a good detection performance. However, when

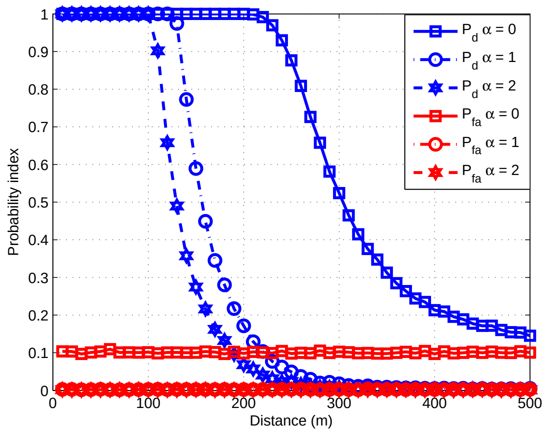

Fig.2: *Tradeoff in an accuracy of detection of ED as a function of distances.*

the distance is less than the critical distance, the adaptive factor is select as (3) that is used to generate the threshold as the conventional energy detection where noise uncertainty does not be concerned. Then, DCAED gives poor detection performance. Therefore, when we determine the overall performance, the parameter of DCAED should be modified.

As shown in Fig.8 and Fig.9, detection performance of two-stage techniques - ED-MED and ED-CAV - under different noise uncertainty interval (Îś) are evaluated. As described in section 3.7, the P_d and P_{fa} of two-stage technique is a summation between P_d and P_{fa} of each single-stage technique. $P_{d(ED-MED)}$ significantly decreases due to the occurrence of noise uncertainty because the decision threshold of each stage requires to know an exactly noise variance to set the threshold. $P_{fa(ED-MED)}$ is much lower than 0.1 when noise uncertainty occurs because $P_{fa(ED)}$ and $P_{fa(MED)}$ are also much lower than 0.1. Then, the summation of $P_{fa(ED)}$ and $P_{fa(MED)}$,when noise uncertainty occurs, is lower than 0.1. On the other hand, when noise uncertainty occurs, the summation of $P_{fa(ED)}$ and $P_{fa(MED)}$ is greater than 0.1. On the other hand, the effect of noise uncertainty does not degrade $P_{d(ED-CAV)}$ since the second-stage of ED-CAV is robust to noise uncertainty.

5. ADAPTIVE TWO-STAGE SPECTRUM SENSING

In this section, we propose a new two-stage spectrum sensing scheme - ATSS -, two new single-stage techniques - modified-double constraints adaptive energy detection (Mo-DCAED) and adaptive maximum eigenvalue detection (AMED) - and a new parameter - critical distance. The details and mathematical models are described in this section.

To determine the existence of a PU, the opera-

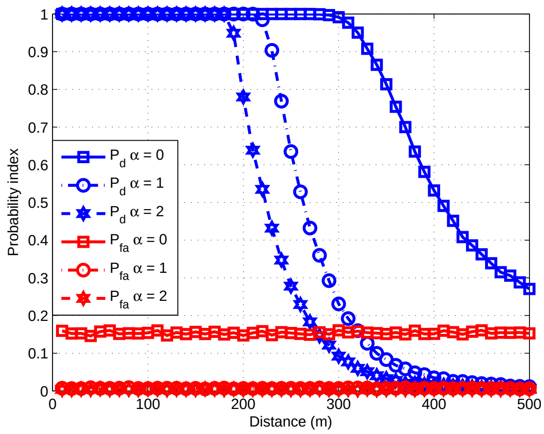

Fig.3: *Tradeoff in an accuracy of detection of MED as a function of distances.*

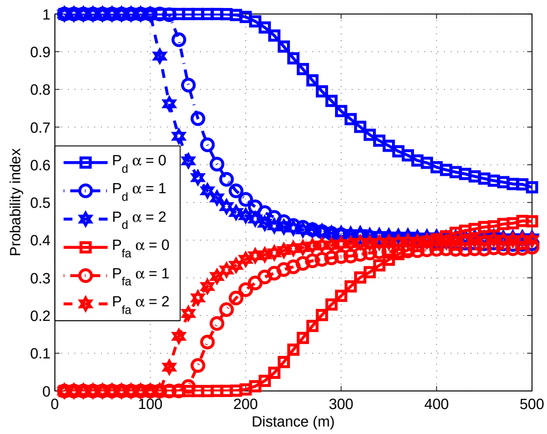

Fig.6: *Tradeoff in an accuracy of detection of AED as a function of distances.*

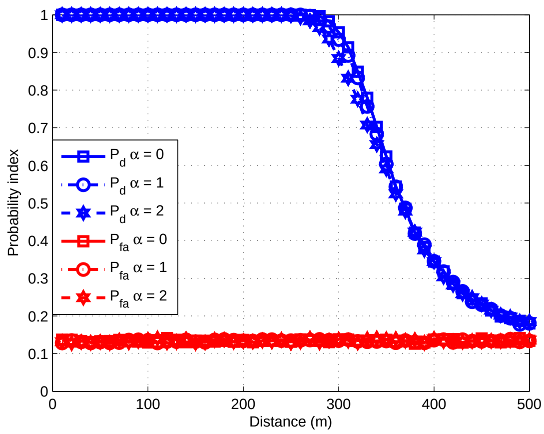

Fig.4: *Tradeoff in an accuracy of detection of CAV as a function of distances.*

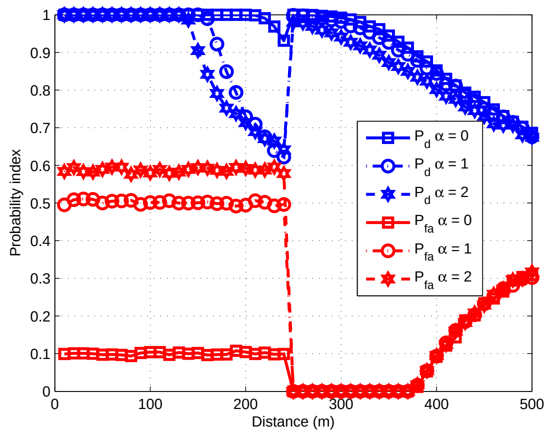

Fig.7: *Tradeoff in an accuracy of detection of DCAED as a function of distances.*

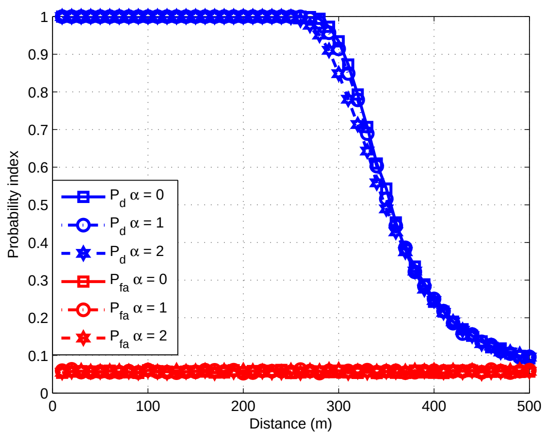

Fig.5: *Tradeoff in an accuracy of detection of MME as a function of distances.*

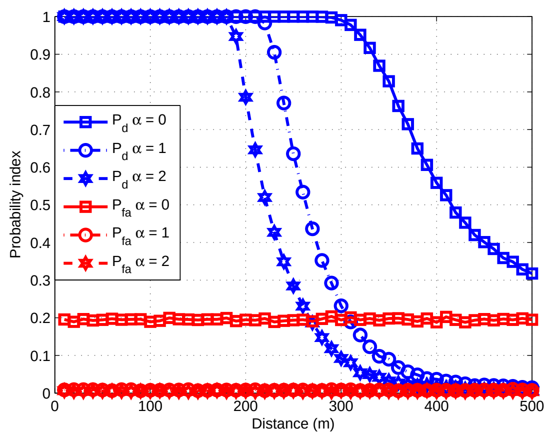

Fig.8: *Tradeoff in an accuracy of detection of ED-MED as a function of distances.*

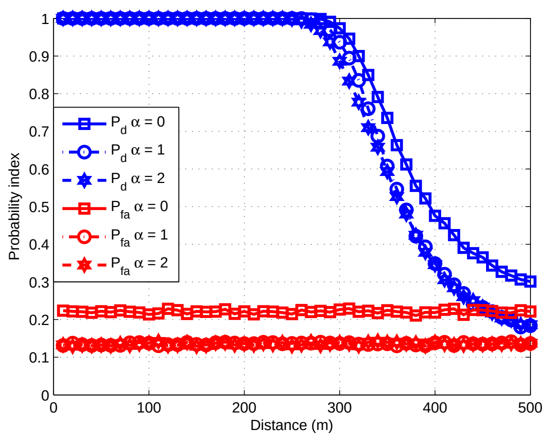

Fig.9: *Tradeoff in an accuracy of detection of ED-CAV as a function of distances.*

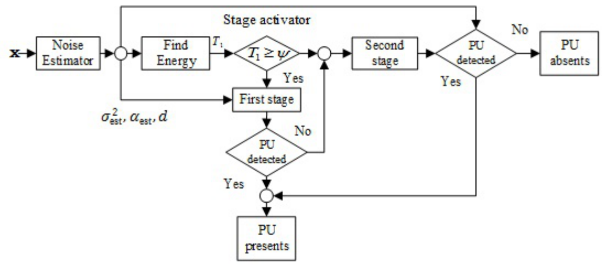

Fig.10: *Adaptive two-stage spectrum sensing model.*

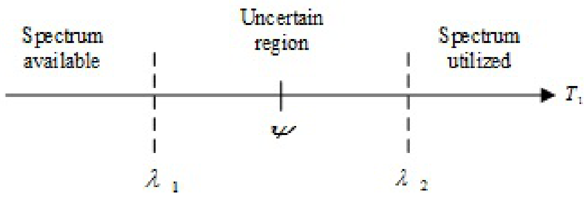

Fig.11: *Adaptive two-stage spectrum sensing model.*

tion of ATSS is separated into two stage including coarse sensing stage and fine sensing stage. The Mo-DCAED is used as a coarse sensing stage and the AMED is used as a fine sensing stage. The critical distance (d_c) is used to select the first-stage adaptive factor in order to reduce a computational burden and sensing time of the first-stage.

There are two main difference from other spectrum sensing techniques. The first difference is that the other two-stage techniques only perform spectrum sensing twice from a fixed decision threshold of each stage while ATSS adapts its decision threshold on both stage in order to perform spectrum sensing. Moreover, to reduce an unnecessary adapting process and to decrease a false alarm detection, we use a stage activator to activate the appropriate spectrum sensing technique to the status of received signal, e.g., the low SNR of received signal together with noise uncertainty environment. Secondly, our previous proposed adaptive scheme, double constraints adaptive scheme, adapts the decision threshold on the changing in an only estimated SNR which is not appropriate to perform spectrum sensing under noise uncertainty environment while ATSS adapts its decision thresholds on both stages on the changing on the strength of path loss effect due to the distance (d) between PU and SU. Moreover, the second-stage of ATSS, AMED, adapts the decision threshold using an equality in boundary of spectrum sensing to generate the adaptive factor. By using the equality in boundary of spectrum sensing and $P_{fa(ED)}$ and $P_{d(ED)}$ to generate the adaptive factor, we can reduce a computational complexity of adapting the second-stage threshold since we does not compute the maximum eigenvalue of PU's signal.

As shown in Fig.10, ATSS is composed of four main modules including noise estimator, stage activator, first-stage threshold setter and second-stage threshold setter. The noise estimator estimates the noise variance (σ^2_{est}) and calculates noise uncertainty interval (α_{est}). The noise variance can be estimated by the various known techniques [32]-[33]. It should be noted that distance (d) between PU and SU is required to be known at SU [34], therefore a spectrum sensing technique can gather the information about the distance (d) from SU's knowledge base. Then, σ^2_{est} , α_{est} and d are sent to the threshold setter of both stage to generate the decision threshold.

After SU gathers the signal from the spectrum band, the received signal is measured its energy (T_1) and then compared to a threshold of stage activator (ψ). To generate ψ, we find the average value of CFAR threshold (λ_{CFAR}) and CDR threshold (λ_{CDR}), where will be described in the section of Mo-DCAED.

$$T_1 = \frac{1}{N}\sum_{n=1}^{N}|x\left(n\right)|^2 \tag{19}$$

$$\psi = \frac{\lambda_1+\lambda_2}{2} \tag{20}$$

As shown in Fig. 11, the spectrum band, where determined by the received signal energy, can be ensured that the PU does not exist if the energy is less than λ_1 . On the other hand, the spectrum band can be said that PU exists when the energy is greater than λ_2" . If the energy is between λ_1 and λ_2 , the status of the PU cannot be reliably determined. Through this concept, we find the average value between λ_1 and λ_2 and use as a stage activator in order to choose the appropriate stage of ATSS to the status of PU. It should be noted that the λ_2 can be either λ_{CFAR} or λ_{CDR}, it is depends on the strength of PU signal. If T_1 is less than ψ, the second-stage is activated to perform spectrum sensing. Since the energy of the received signal is under the region that the status of PU signal cannot be reliably determined, then it is not necessary to first determined by the first-stage. On the other hand, if T_1 is greater than ψ, a normal two-stage operation is utilized where the first-stage is first determined the status of the PU. If the PU is not found, the second-stage is activated to ensure the PU's status.

5.1 Critical distance

In this subsection, we describe a critical distance (d_c) that will be used to evaluate the performance of spectrum sensing technique. Moreover, a critical distance for the energy detection ($d_{c,ED}$) is derived. It should be noted that $d_{c,ED}$ is used in the Mo-DCAED in order to select the first-stage adaptive factor (κ_1) where κ_1 is used to generate the first decision threshold (λ_1).

To derive $d_{c,ED}$, an interdependent between $P_{fa,ED}$ and $P_{d,ED}$ is exploited. As mention in section 3.1, the variance of noise distributes within range of $\left[\alpha\sigma_\eta^2, \frac{1}{\alpha}\sigma_\eta^2\right]$ when the uncertainty of noise occurs. Thus, the probability of detection (P_d) of ED can be derived into two ways by setting a noise variance at the receiver as $\alpha\sigma_\eta^2$ and $\frac{1}{\alpha}\sigma_\eta^2$[12]-[14].

$$P_{\mathrm{d\_lower}} = Q\left[\frac{\sqrt{N}}{\sqrt{2}\left(\gamma+\alpha\right)}\left(\frac{\lambda_{\mathrm{ED}}}{\alpha\sigma_\eta^2} - \left(\tilde{\gamma}_{\mathrm{PL}}\right) - \alpha\right)\right] \tag{21}$$

$$P_{\mathrm{d\_upper}} = Q\left[\frac{\sqrt{N}}{\sqrt{2}\left(\gamma+\frac{1}{\alpha}\right)}\left(\frac{\lambda_{\mathrm{ED}}}{\frac{1}{\alpha}\sigma_\eta^2} - \left(\tilde{\gamma}_{\mathrm{PL}}\right) - \frac{1}{\alpha}\right)\right] \tag{22}$$

where α is noise uncertainty interval and σ_η^2 is a noise variance.

The probability of false alarm can be derived by setting the noise variance at the receiver as $\alpha\sigma_\eta^2$ which can be expressed as

$$P_{\mathrm{fa}} = Q\left[\left(\frac{\lambda_{\mathrm{ED}}}{\alpha\sigma_\eta^2} - 1\right)\sqrt{\frac{N}{2}}\right] \tag{23}$$

From (23), the decision threshold of ED (λ or λ_{CFAR}) by fixing P_{fa} as a target performance metric can be written as

$$\lambda = \left(\sqrt{\frac{2}{N}}Q^{-1}\left(P_{\mathrm{fa}}\right)+1\right)\alpha\sigma_\eta^2 \tag{24}$$

Therefore, a the probability of detection for a by fixing P_{fa} is given by

$$\mathrm{P_d} = Q\left(\frac{1}{\left(\gamma+\frac{1}{\alpha}\right)}\left(\alpha Q^{-1}\left(\mathrm{P_{fa}}\right) - \left(\tilde{\gamma}_{\mathrm{PL}}\right) + \sqrt{\frac{N}{2}}\left(\alpha-\frac{1}{\alpha}\right)\right)\right). \tag{25}$$

From (3) and (4), $\tilde{\gamma}_{\mathrm{PL}}$ can be expressed as

$$\tilde{\gamma}_{\mathrm{PL}} = \gamma\cdot \mathrm{Cd}^{-\aleph} \tag{26}$$

where γ is the signal to noise ratio between transmits signal power and noise power d is distance between PU and SU, C is loss constant and $\aleph$ is path loss exponent.

Finally, by fixing two target probabilities ($P_{fa,ED}$ and $P_{d,ED}$), the maximum distance that ED achieves both target performance metrics, critical distance ($d_{c,ED}$), can be derived by (25) and (26).

$$Q^{-1}\left(\mathrm{P_d}\right) = \frac{1}{\left(\tilde{\gamma}_{\mathrm{PL}}+\frac{1}{\alpha}\right)}\left(\alpha Q^{-1}\left(\mathrm{P_{fa}}\right) - \left(\sqrt{\frac{N}{2}}\tilde{\gamma}_{\mathrm{PL}}\right) + \sqrt{\frac{N}{2}}\left(\alpha-\frac{1}{\alpha}\right)\right) \tag{27}$$

$$\mathrm{d}^{-\aleph} = \frac{\alpha Q^{-1}\left(\mathrm{P_{fa}}\right) + \sqrt{\frac{N}{2}}\left(\alpha-\frac{1}{\alpha}\right) - \frac{1}{\alpha}Q^{-1}\left(\mathrm{P_d}\right)}{\gamma\mathrm{C}\left(Q^{-1}\left(\mathrm{P_d}\right)+\sqrt{\frac{N}{2}}\right)} \tag{28}$$

For more convenience, we assume that

$$A = \frac{\alpha Q^{-1}\left(P_{\mathrm{fa}}\right) - \frac{1}{\alpha}Q^{-1}\left(P_{\mathrm{d}}\right) + \sqrt{\frac{N}{2}}\left(\alpha-\frac{1}{\alpha}\right)}{\gamma\mathrm{C}\left[Q^{-1}\left(P_{\mathrm{d}}\right)+\sqrt{\frac{N}{2}}\right]} \tag{29}$$

Hence,

$$-\aleph\ln\left(\mathrm{d}\right) = \ln\left(A\right) \tag{30}$$

Therefore, the critical distance ($d_{c,ED}$) is given as

$$d_{\mathrm{c}} = e^{\frac{-\ln A}{\aleph}} \tag{31}$$

5.2 Modified-Double constraints adaptive energy detection

After the Mo-DCAED is activated, the Mo-DCAED threshold setter gathers the σ_{est}^2 and α_{est} from noise estimator and gathers information about the distance (d) between the PU and SU from the SU database [34].

As shown in Fig.12, the information about the distance (d) between the PU and SU is firstly compared to the critical distance (d_c) to generate a first-stage adaptive factor (κ_1). Since the parameter - α_{est} and σ_{est}^2 - are gathered, then the critical distance (d_c) is calculated using (27) when replace α with α_{est} and $\gamma=\frac{\sigma_s^2}{\sigma_{\mathrm{est}}^2}$.

The decision threshold is then set using the first-stage adaptive factor (κ_1) and can be expressed as

$$\lambda_1 = \kappa_1\sigma_{\mathrm{est}}^2\left(\frac{\lambda_{\mathrm{CFAR}}}{\sigma_\eta^2} - 1\right) + \sigma_{\mathrm{est}}^2 \tag{32}$$

$$\lambda_{\mathrm{CFAR}} = \left(\sqrt{\frac{2}{N}}Q^{-1}\left(P_{\mathrm{fa}}\right)+1\right)\alpha\sigma_\eta^2 \tag{33}$$

where λ_{CFAR} is a decision threshold of ED, σ_η^2 is a noise variance and σ_{est}^2 is an estimated variance of noise.

It should be noted that by using (27), the λ_{CDR} is given by

$$\lambda_{\mathrm{CDR}} = \left(\sqrt{\frac{2}{N}}\left(\gamma+\frac{1}{\alpha}\right)Q^{-1}\left(P_{\mathrm{d\_upper}}\right)+\tilde{\gamma}_{\mathrm{PL}}+\frac{1}{\alpha}\right)\frac{1}{\alpha}\sigma_\eta^2. \tag{34}$$

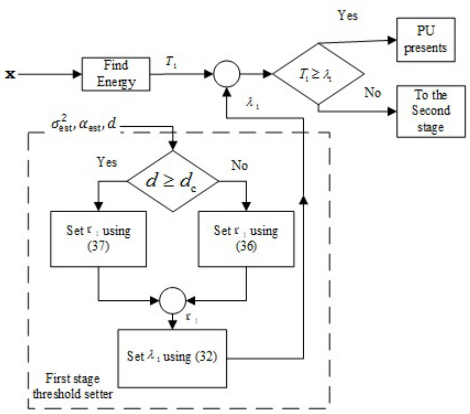

Fig.12: *System model of the DCAED.*

By utilizing double constraints adaptive scheme, the decision threshold is adapted by fixing P_{fa} and P_d at the same time. Therefore, the critical sample (N_c), where N_c is the minimum number of samples that is required to achieve the target accuracy performance metrics (P_{fa} and P_d), is adopted to generate the adaptive factor. The main difference from our previous work (DCAED), in this paper, the adaptive factor is changing on the strength of path loss effect due to the distance (d) between PU and SU. Thus, the critical sample (N_c) can be derived as

$$N_{\mathrm{c}} = \frac{2}{(\mathrm{PL}\gamma)^2}\left[\alpha Q^{-1}\left(P_{\mathrm{fa}}\right) - Q^{-1}\left(P_{\mathrm{d}}\right)(\mathrm{PL}\cdot\gamma+\alpha)\right]^2 \cdot \quad (35)$$

Thus, the first-stage adaptive factor (κ_1) is derived from (27), (29), (31), (32) and (35). Then, κ_1 can be expressed as

Maximize $\quad X_s(i)$

Subject to

$$\kappa_1 \begin{cases} \dfrac{\lambda_{\mathrm{CFAR}} - \sigma^2_{\mathrm{est}}}{\left(\frac{\lambda_{\mathrm{CFAR}}}{\alpha_{\mathrm{est}}\cdot\sigma^2_\eta} - 1\right)\sigma^2_{\mathrm{est}}}, d < d_{\mathrm{c}} & (36) \\ \dfrac{(\gamma\cdot PL)\sqrt{N/2}}{\left(\alpha_{\mathrm{est}}\cdot Q^{-1}\left(P_{\mathrm{fa}}\right) - Q^{-1}\left(P_{\mathrm{d}}\right)\left((\gamma\cdot PL)+\frac{1}{\alpha_{\mathrm{est}}}\right)\right)}, d \geq d_{\mathrm{c}} & (37) \end{cases}$$

To determine the existence of the PU, the decision statistic (T_1) is compared to the decision threshold (λ_1). If T_1 is greater than λ_1, the ATSS declares that PU exists. Otherwise, the second-stage is activated in order to make sure that the PU does not exists.

5.3 Adaptive maximum eigenvalue detection

If the PU is not detected by the first-stage or the status of PU is in the region that the status of PU signal cannot be reliably determined by the first-stage, the second-stage is activated in order to ensure that the spectrum band is available to utilize. Therefore, the PU is more protected from harmful interference caused by the transmission of the SU.

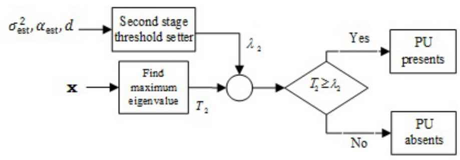

Fig.13: *System model of the AMED.*

As depicted in Fig.13, the operation of the AMED can be separated into two paths. The first path is to calculate the AMED decision threshold (λ_2). The other path is to calculate the AMED decision statistic (T_2). Then, these two path are combined at decision block and the existence of PU is considered by comparing the T_2 to λ_2 . If T_2 is greater than λ_2" , the ATSS declares that PU exists. Otherwise, ATSS declares that PU does not exists.

From (5), the consecutive samples of the received signal is given by

$$\mathbf{x} = \left[x(n)\, x(n-1)\ldots x(n-\mathrm{L}-1)\right]^{\mathrm{T}}, \quad (38)$$

$$\mathrm{s} = \left[\mathrm{s}(n)\, \mathrm{s}(n-1)\ldots \mathrm{s}(n-\mathrm{L}-1)\right]^{\mathrm{T}}, \quad (39)$$

$$\eta = \left[\eta(n)\, \eta(n-1)\ldots \eta(n-\mathrm{L}-1)\right]^{\mathrm{T}}, \quad (40)$$

where L is a smoothing factor.

The statistical covariance matrix is calculated by the following procedure:

The sample covariance matrix is given by

$$\mathbf{R_x}(N) = \begin{bmatrix} \varphi(0) & \varphi(1) & \cdots & \varphi(l-1) \\ \varphi(1) & \varphi(0) & & \varphi(l-2) \\ \vdots & & \ddots & \vdots \\ \varphi(l-1) & & \cdots & \varphi(0)) \end{bmatrix} \quad (41)$$

where φ is the sample auto-correlations of the received signal which can be shown as

$$\varphi(l) = \frac{1}{N}\sum_{m=0}^{N-1} x(m)\, x(m-l)\,, l = 0, 1, 2, \ldots, \mathrm{L}-1 \quad (42)$$

Then the maximum eigenvalue (e_{max}) can be obtained by exploiting eigen-decomposition and used as the second-stage decision statistic (T_2).

As mention in section 1, to adapt the decision threshold by fixing $P_{fa(MED)}$ and $P_{d(MED)}$ at the same time is difficult to be done in practical network operation. Thus, we proposed a new adaptive scheme for the second-stage by utilizing the equality in boundary of spectrum sensing between to generate the second-stage adaptive factor (κ_2). In this proposed, $P_{fa(ED)}$, $P_{d(ED)}$ and $P_{fa(MED)}$ are used. In addition, by using the equality in boundary of spectrum sensing and using $P_{fa(ED)}$ and $P_{d(ED)}$ to generate the adaptive factor, we can reduce a computational complexity of adapting the second-stage threshold since we does not compute the maximum eigenvalue of PU's signal.

Before adapting the second-stage threshold (λ_2) by using the second-stage adaptive factor (κ_2) which is derived from $P_{fa(ED)}$ and $P_{d(ED)}$, the threshold of conventional MED (λ_{MED}) has to be firstly calculated. Without prior knowledge about the maximum eigenvalue of PU's signal, threshold of conventional MED (λ_{MED}) is calculated from $P_{fa(MED)}$. Thus, the $P_{fa(MED)}$ can be expressed as

$$P_{\mathrm{fa(MED)}} \approx 1 - F\left[\left(\frac{\lambda_{\mathrm{MED}} N - \rho}{v}\right)\right], \tag{43}$$

$$\rho = \left(\sqrt{N-1} + \sqrt{\mathrm{L}}\right)^2, \tag{44}$$

$$v = \left(\sqrt{N-1} + \sqrt{\mathrm{L}}\right)\left(\frac{1}{\sqrt{N-1}} + \frac{1}{\sqrt{\mathrm{L}}}\right)^{1/3}, \tag{45}$$

By adapting the second-stage threshold (λ_2) through the equality in boundary of $P_{fa(ED)}$ and $P_{d(ED)}$, the second-stage adaptive factor (κ_2) can be derived by using (22), (23), (24) and (43). Then, the second-stage adaptive factor (κ_2) is derived as

$$\kappa_2 = Q\left[\frac{1}{\alpha_{\mathrm{est}}}\left(Q^{-1}\left(P_{\mathrm{d}}\right)\left(\mathrm{PL}\cdot\gamma + \alpha_{\mathrm{est}}\right) + \sqrt{\frac{N}{2}}\left(\mathrm{PL}\cdot\gamma\right)\right)\right] \tag{46}$$

Then, the second-stage decision threshold (λ_2) can be obtained as

$$\lambda_2 = \left(\frac{F^{-1}\left(1-\beta_{\mathrm{MED}}\right)v + \rho}{N}\right)\sigma_{\mathrm{est}}^2 \tag{47}$$

Then, the existence of PU is determined by comparing T_2 to λ_2 . Consequently, the PU presents when T_2 is greater than λ_2 .

6. SIMULATION RESULTS

In this section, we simulate the detection performance of ATSS and then compares to ED, MED, CAV, MME, AED, ED-MED and ED-CAV under noise uncertainty environment where noise uncertainty interval (α) is 1 to 2. Three performance metrics P_d, P_{fa} and sensing time (τ_s) are measured and averaged on 10,000 Monte-Carlo realizations. All parameters and environments are set as same as section 3.8. The ability of detection of each technique is summarized in table 2.

As mentioned earlier, it has to estimate the noise uncertainty interval (α_{est}) for generating the adaptive factor of Mo-DCAED (κ_1). In practice, it cannot be estimated α_{est} directly, then the value can be estimated by comparing a pre-assumed noise power to the estimated noise power. Therefore the estimate the noise uncertainty interval (α_{est}) is given by

$$\alpha_{\mathrm{est}} = \frac{\sigma_{\mathrm{est}}^2}{\sigma_\eta^2} \tag{48}$$

where σ_{est}^2 is an estimated noise power and σ_η^2 is pre-assumed noise power.

In practice, there are several techniques, such as received signal strength indicator (RSSI) [35], this evaluates the distance between nodes by using the received signal strength. Therefore, RSSI can be used to estimate the distance between the SU and PU. As by IEEE 802.22, the base station is required to know the distance (d) between the primary user (PU) and secondary user (SU) [34]. Then, the SU can gather the value of d from the base station. Therefore, in this paper, we assume that the distance is known by the SU.

Fig. 14, Fig. 15 and Fig.16 show the detection performance of spectrum sensing when noise uncertainty occurs with noise uncertainty interval (α) equals to 1. It should be noted that Mo-DCAED and AMED are the first-stage and second-stage of ATSS, respectively. As a result, although AED gives higher P_d than ATSS at d greater than 420m, AED does not achieve a spectrum sensing requirement on both P_d and P_{fa} since 180 m. As compares ATSS to other techniques - ED, MED, CAV, MME, Mo-DCAED, AMED, ED-MED and ED-CAV, ATSS and AMED give the highest P_d while maintain rate of P_d as 0.1.

Fig. 16, the sensing time of ATSS begins to decrease when d is 249 m. Since the status of the PU can be detected by a single-stage (Mo-DCAED or AMED). It should be noted that ATSS performs spectrum sensing twice when T_1 is less than ψ and PU is not detected by Mo-DCAED. On the other hand, both Mo-DCAED and AMED are activated to ensure the status of the PU, therefore the ATSS consumes more sensing time to perform spectrum sensing.

When compare ATSS to AMED in perspective of sensing time, ATSS consumes less sensing time than AMED. Then, ATSS reduces an unnecessary spectrum sensing performing by using a high complexity spectrum sensing technique under the concept of two-stage spectrum sensing. As compare ATSS to ED, MED, CAV, MME, AED, ED-MED and ED-CAV, although ATSS consumes longer sensing time than these techniques, it meets the spectrum sensing requirement which is less than 2s.

Fig. 17, Fig. 18 and Fig.19 show the detection performance of spectrum sensing when noise uncertainty occurs with noise uncertainty interval (α) equals to 2. As mentioned in section 3.8, the detection performance of spectrum sensing techniques- ED, MED, Mo-DCAED, AED and ED-MED - significantly decreases due to the increasing in the strength of noise uncertainty. As a result, ATSS still gives the highest rate of P_d among spectrum sensing techniques -ED, MED, Mo-DCAED, AED and ED-MED - while maintains P_{fa} as low as 0.1. Even though the strength increases, ATSS still consumes as less sensing time as required by spectrum sensing requirement.

As shown in Fig.20, although the detection performance of ATSS decreases due to the occurrence of noise uncertainty, its performance does not decrease

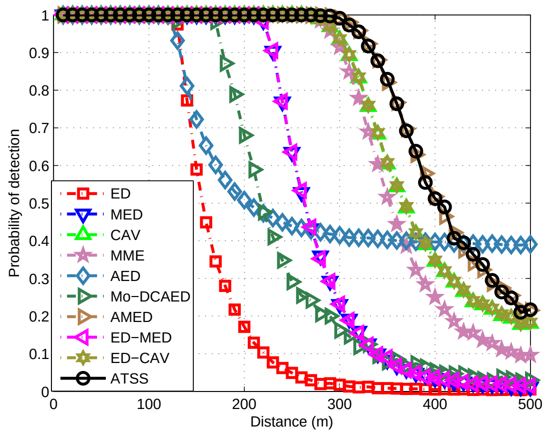

Fig.14: *Comparison of probability of detection with different distance of ATSS with other techniques when α is 1.*

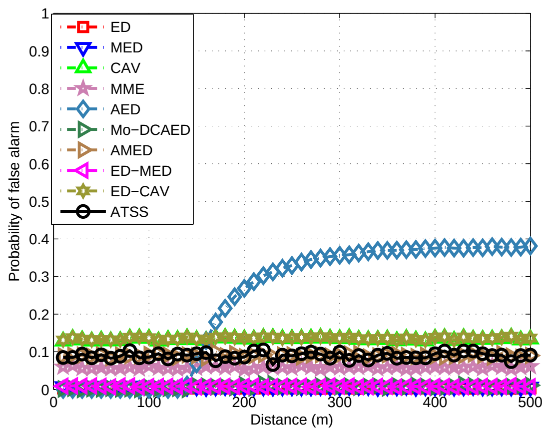

Fig.15: *Comparison of probability of false alarm with different distance of ATSS with other techniques when α is 1*

due to the increasing in the strength of noise uncertainty (or increasing in the noise uncertainty interval: α). Consequently, ATSS gives the best detection performance while preserves the rate of false alarm at low level for all distances and noise uncertainty interval. By adapting the decision threshold of ATSS on the changing in distance and estimated noise power and noise uncertainty interval, ATSS is robust to the increasing in the strength of noise uncertainty when the noise uncertainty occurs. In perspective of critical distance, the ATSS achieves the spectrum sensing requirement with the greatest critical distance for all distances and noise uncertainty factors.

7. CONCLUSION

In this paper, we propose a new scheme of two-stage spectrum sensing - "Adaptive Two-stage Spectrum Sensing (ATSS)" -, two new single-stage tech-

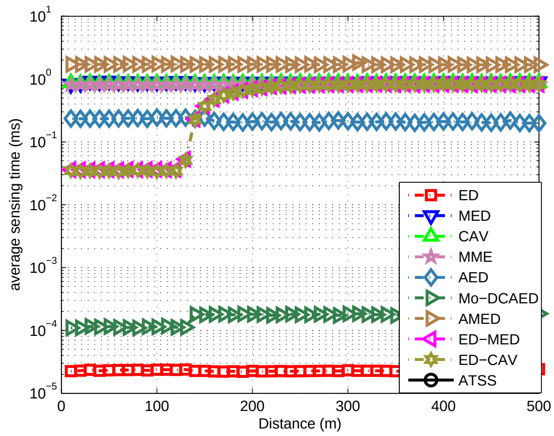

Fig.16: *Comparison of average sensing time with different distance of ATSS with other techniques when α is 1.*

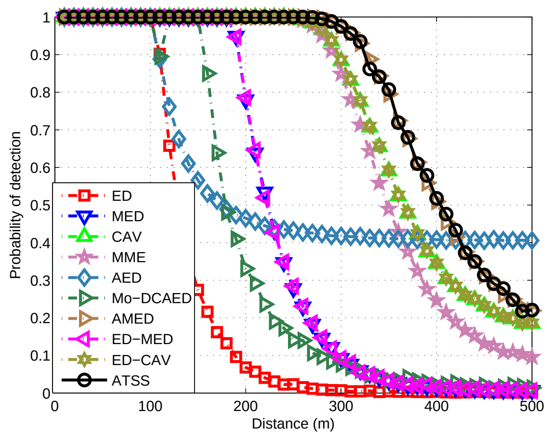

Fig.17: *Comparison of probability of detection with different distance of ATSS with other techniques when α is 2.*

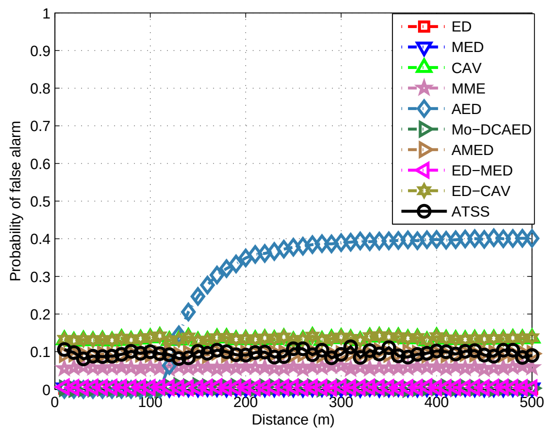

Fig.18: *Comparison of probability of false alarm with different distance of ATSS with other techniques when α is 2.*

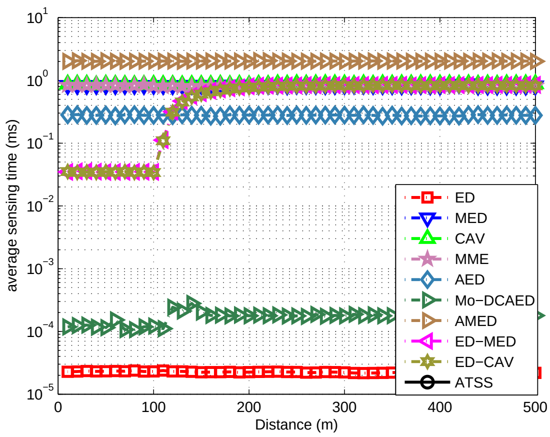

Fig.19: *Comparison of average sensing time with different distance of ATSS with other techniques when* α *is 2.*

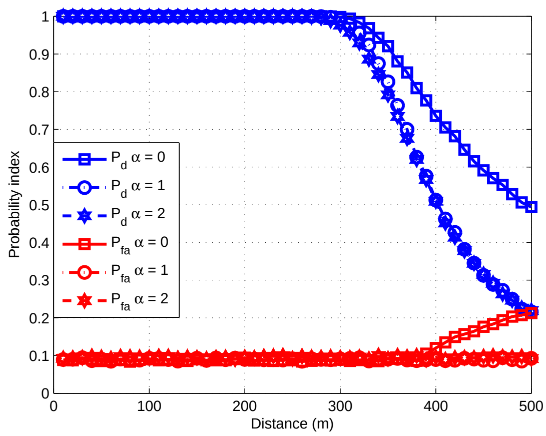

Fig.20: *Tradeoff in an accuracy of detection of ATSS as a function of distances.*

Table 2: *Model of wireless microphone signal [36].*

Spectrum sensing technique	Critical distance ($P_d \geq 0.9\&P_{fa} \geq 0.1$)	
	α=1	α=2
ED	130 m	110 m
MED	230 m	190 m
CAV	300 m	290 m
MME	300 m	290 m
AED	140 m	100 m
Mo-DCAED	170 m	150 m
AMED	330 m	320 m
ED-MED	230 m	190 m
ED-CAV	0 m	0 m
ATSS	330 m	320 m

niques - modified-double constraints adaptive energy detection (Mo-DCAED) and adaptive maximum eigenvalue detection (AMED) - and a new parameter - critical distance. To reduce a wasted computation of conventional two-stage spectrum sensing, we use a stage activator to activate the appropriate stage to the status of received signal. By using a double constraints adaptive scheme, ATSS improves the detection performance of the existing spectrum sensing techniques and is robust to the increasing in the strength of noise uncertainty. Not only achieves the spectrum sensing with the longest critical distance, ATSS highly achieves the requirement in perspective of sensing time. The main difference from other techniques is that ATSS adapts its decision threshold on both stage and ATSS using a function of distance to activate the threshold setter while other adaptive techniques use a critical SNR. Therefore, the ATSS can be effectively used for spectrum sensing, which PU signal is correlated signal, over long distances together with noise uncertainty. ATSS can individually perform spectrum sensing in practical communication system and does not require prior knowledge about the PU signal waveform.

8. ACKNOWLEDGEMENT

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