Micro-slotted Dual-stage Spectrum Sensing for Cognitive radio networks

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ABSTRACT

Spectrum sensing is used to determine an existence of a primary user in order to avoid harmful interference to the primary user caused by a secondary user in cognitive radio network. In general sensing, a PU is assumed to use the band since the beginning of the sensing period. In fact, a PU can be active at any time of the sensing period.

In this paper, we propose a novel technique – micro-slotted dual-stage spectrum sensing (MDMS) – to detect a PU no matter when it is active during the sensing period. The technique also addresses low SNR due to path loss effect in an adaptive fashion. The technique is more reliable compared to previous works of MDCAED and DCAED. MDMS is shown that it meets the spectrum sensing requirement (IEEE 802.22) of sensing time for all distances and gives the best detection performance among the other techniques. Not only the primary user can be ensured that its transmission will not be interfered by the secondary user, the number of detecting spectrum bands by the SU also increases because it consumes short sensing time. Thus, the efficiency of spectrum utilization can be improved.

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

1. INTRODUCTION

In recent years, the number of wireless application rapidly increases together with spectrum resource demand. Meanwhile, these spectrum resources are limited and getting crowded. By allowing only licensed users (or primary user: PU) to utilize a licensed spectrum band, the existing licensed band is not efficiently used because the PU does not use the spectrum band at all time. This behaviour refers to an underutilization of limited spectrum resources. As a result stated in [1], a spectrum of television broadcasting, TV White Spaces (TVWS), is being under-utilized. The Federal Communications Commission (FCC) selected the TV band for the unlicensed user to use in an opportunistic manner. Then, a cognitive radio technology was proposed to solve this underutilization by allowing an unlicensed user (or secondary user: SU) to utilize the licensed band dynamically without harming the PU.

The IEEE 802.22 standard [2], wireless regional area network (WRAN), is developed based on a cognitive radio [3-9]. Then, the SU is allowed to use the TV bands in an opportunistic manner. There are two types of primary users in the TV bands, i.e., TV broadcasting and wireless microphone (WM) devices. To avoid interfering PUfunctions, an SU must periodically monitor all PU's activities on the spectrum band. Once the PU is detected, the SU must vacate the band. This core function in cognitive radio is called "spectrum sensing" [10-40].

To evaluate the performance of spectrum sensing, two statistical parameters – probability of detection (P_d) and probability of false alarm (P_{fa}) – are considered. The probability of detection (P_d) determines as a correct declaration of the PU status either absents or presents. In general, P_d should be maximized to prevent interference to the PU. On the other hand, the probability of false alarm (P_{fa}) determines a false detection when the PU does not exist. Rate P_{fa} should be minimized to achieve a utilizing of an available spectrum band efficiently. Moreover, once the PU is detected, the SU must leave the spectrum band within a specific of time. Therefore, the average sensing time is the other parameter which is defined to evaluate the spectrum sensing performance. There is a document – spectrum sensing requirement [41] – that has stated the specific value of these parameters. Then, the spectrum sensing technique should perform spectrum sensing with P_d higher than 0.9, P_{fa} less than 0.1 and the average sensing time less than 2 seconds.

As shown in fig.1, a frame of the cognitive radio consists of a sensing slot and data transmission slot [42-44]. An SU can search for an available band only in the sensing slot. Provided a band is available, the SU can send its data in the data transmission slot.

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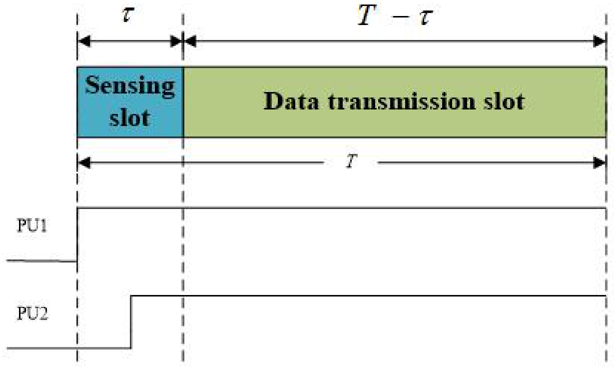

Fig.1: *Frame structure for cognitive radio networks with different PU occurrence in the sensing slot.*

In performance evaluation of all techniques, the PU is simulated to use the band only from the beginning of the sensing period [13-40]. The fact that a PU can be active at anytime is disregarded [45]. When a PU is active sometime after the beginning of the sensing slot, it is more likely that a miss detection will occur. Therefore, the SU will start its transmission that causes an interference to the PU.

A factor that degrades the spectrum sensing performance is a low signal-to-noise ratio (SNR) environment [46]. This condition occurs when the power of the PU signal is much less than a noise power. In practice, the PU signal received by an SU is attenuated due to a distance between the PU transmitter and the SU, which is called the path loss effect [47-49]. For example, a WM device operates in TV channel with low transmitting 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 [50-52]. 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.

In general, there are two types of spectrum sensing, i.e., knowledge based spectrum sensing [14-18] and blind spectrum sensing [19-26]. The knowledge based spectrum sensing requires both information about PU signal waveform and noise power. Once this information is known, the knowledge based techniques give better detection performance than blind techniques. Otherwise, the detection performance of knowledge based techniques significantly degrade. Moreover, knowledge based techniques perform spectrum sensing with higher computational complexity and more time consuming than blind techniques. It should be noted that to know a signal waveform of the primary user is not practical in cognitive radio network, therefore knowledge base spectrum sensing is not concerned in this paper.

Blind spectrum sensing can be categorized into two types including blind technique and semi-blind technique. Blind techniques, such as energy to minimum eigenvalue detection (EME) [19], maximum to minimum eigenvalue detection (MME) [20] and covariance absolute detection (CAV) [21-22], do not require any knowledge on both PU signal waveform and noise power. These techniques perform spectrum sensing based on an auto-correlation of the received signal, therefore it comes at a cost of a high computational complexity.

Semi-blind spectrum sensing, such as energy detection (ED) [23-24] and maximum eigenvalue detection (MED) [25-26], requires to know a noise power to perform spectrum sensing. ED is a widely studied technique because it performs spectrum sensing with low computational complexity and less sensing time. However, its detection performance significantly degrades under low SNRs.

Due to a simplicity and short sensing time consuming, energy detection (ED) is widely studied from researchers in order to improve its detection performance. Adapting the decision threshold is a solution to improve ED's performance. Adaptive energy detection (AED) [28-29] improves the detection performance of ED in perspective of P_d , however, there always be a tradeoff between P_d and P_{fa} due to the threshold adapting. Therefore, AED gives high rate of P_{fa} at low SNR levels. Double constraints adaptive energy detection (DCAED) [30] outperforms the detection performance of AED of both P_d and P_{fa} .

Moreover, multi-slotted spectrum sensing techniques – multi-slot energy detection [31] and multi-slot double constraints adaptive energy detection (MDCAED) [32] – are also proposed to improve the performance of conventional energy detection. Multi-slot energy detection and MDCAED split a sensing frame into a multiple slots and performs spectrum sensing separately and the status of PU is determined cooperatively using decision fusion rule [33-36]. It should be noted that decision fusion rule is normally used by cooperative spectrum sensing scheme in order to determine the existence of PU from a gathered information from a multiple SUs. The main difference between MDCAED and multi-slot energy detection is that MDCAED performs spectrum sensing by adapting its decision threshold for each mini-slot while a conventional multi-slot energy detection [31] uses a decision threshold of a convention energy detection. Nevertheless, these techniques did not proposed to perform spectrum sensing when the environment as a random existence of PU did not be taken in the account.

In this paper, we propose a novel multi-slotted spectrum sensing, micro-slotted dual-stage spectrum sensing (MDMS), that split a sensing slot into several micro-slots and performs spectrum sensing each micro-slot using a dual-stage technique. Then, the final decision is done by a micro-slotted decision fusion. The contribution of this paper is three-fold. First, an anytime of PU activation in a sensing period is addressed by using a micro-slotted spectrum sensing and micro-slotted decision fusion scheme. By determining a PU status from the multiple micro-slotted, MDMS improves the detection performance of existing spectrum sensing techniques on both perspective − P_d and P_{fa} . Second, the issue of low SNR due to path loss effect is addressed by using a double constraints adaptive fashion where the decision threshold is adapted on the distance between the PU and SU. Third, we improve the performance of our previous works − MDCAED and DCAED − to be more reliable by using dual-stage scheme.

The main difference between dual-stage spectrum sensing and two-stage spectrum sensing [37-40] is that DMS performs spectrum sensing by computing a decision statistic once, i.e., the energy of the received signal, while the two-stage spectrum sensing performs spectrum sensing by computing a decision statistic twice i.e., the decision statistic of the first-stage and second stage. It should be noted that the two-stage spectrum sensing uses different single-stage spectrum sensing on each stage. If the first-stage of DMS cannot ensure the status of PU, the decision threshold of DMS is adapted on the second-stage and PU status is determined again while the two-stage spectrum sensing has to calculate the second-stage decision threshold to perform spectrum sensing. Moreover, we also simulate the performance of these techniques under different point of PU existence as a function of distances. The simulation results show that the detection performance of both blind spectrum sensing − EME, MME and CAV − and semi- blind spectrum sensing − ED, MED, DCAED and MDCAED − degrade on both factors − point of PU existence and the distance between the PU and SU.

The remainder of this paper is organized as follows. Section 2 describes two important challenges of spectrum sensing including path loss and the existence of a PU in the sensing period. The conventional spectrum sensing techniques and fusion rules are introduced in section 3. A preliminary experiment is shown in section 4. In section 5, the model of MDMS is explained in details with the mathematical models. The simulation results are shown in section 6. Finally, conclusions are presented in Section 7.

2. PROBLEM STATEMENT

In this section, two spectrum sensing challenges − path loss and occurrence of the PU on the sensing slot − are described. These challenges have a great impact on the accuracy of spectrum sensing.

2.1 Path loss

An attenuation of signal power due to the transmission distance between a transmitter and receiver can be described by path loss model [47-49]. Then, the path loss can be expressed as

$$\mathrm{PL} \equiv \mathrm{Cd}^{-\aleph} \tag{1}$$

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

Once the path loss is taken to the account, the SNR at the receiver is given as

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

where ${\sigma_{\mathrm{s}}}^2$ is a signal variance and ${\sigma_\eta}^2$ is a noise variance.

2.2 The occurrence of the PU in the sensing period

Another factor that degrades the spectrum sensing performance is the occurrence of the PU in the sensing period. As shown in Fig.1, a frame structure of the cognitive radio consists of a sensing slot and a data transmission slot. In general, the performance of spectrum sensing techniques is simulated when the occurrence of PU is at the beginning of the sensing slot (PU1). However, in practical, the PU may not exists at the beginning of the sensing slot (PU2). Once the PU2 occurs in the middle of the sensing slot, the received signal power may be lower than to be detected although the distance between the PU2 and SU is not that far. Therefore, the transmission of PU2 may not be detected by the SU. Then, the SU will begins its transmission and will cause an interference to the PU2.

3. SPECTRUM SENSING TECHNIQUE

In this section, spectrum sensing techniques − ED, MED, CAV, MME and two-stage spectrum sensing − and fusion rules − AND, OR and K-of-N − are described with merits/demerits and spectrum sensing requirements.

To determine the received signal under noise uncertainty and path loss effect, the hypothesis models of received signal are given by

$$\mathbf{x} = \begin{cases} \eta & \mathrm{whenPUabsents}\,[H_0] \\ \mathrm{PL} \cdot \mathrm{s} + \eta & \mathrm{whenPUpresents}\,[H_1] \end{cases} \tag{3}$$

where X is received signal by SU, η is additive white Gaussian noise, s is the transmitted signal by PU and PL is path loss.

3.1 Energy detection

Among the existing spectrum sensing techniques, energy detection (ED) [23-24] is the most widely used technique. ED performs spectrum sensing with the shortest sensing time, the least computational complexity and without prior knowledge about the PU signal waveform. Only a noise power is required in order to generate the decision threshold.

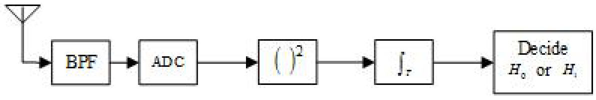

Fig.2: *Model of energy detection.*

Therefore, it is the simplest spectrum sensing. In the sensing period, ED measures the received signal energy in the sensing slot and compared to decision threshold. The performance of ED noticeably degrades due to the distance between the PU and SU.

3.2 Maximum Eigenvalue Detection

Once ED gives an unreliable detection when the SU is far away from the PU (low SNR level), maximum eigenvalue detection (MED) [25-26] improves the detection of ED in such environment. As shown in fig.3, MED performs spectrum sensing based on statistical theorem. Only noise power is required to generate the decision threshold. In the sensing period, the maximum eigenvalue of the received signal is calculated and compared to the decision threshold. To measure the maximum eigenvalue of the received signal, the maximum eigenvalue is described as an energy of the PU signal. But it is more robust to effect of noise by measuring the energy signal from eigen-decomposition.

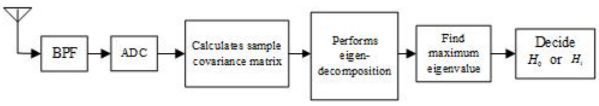

Fig.3: *Model of maximum eigenvalue detection.*

3.3 Energy-minimum eigenvalue detection

An energy to minimum eigenvalue detection (EME) [19] is a kind of blind spectrum sensing technique. As mention earlier, the maximum eigenvalue is described as an energy of the PU signal. On the other hand, the minimum eigenvalue of the received signal is determined as a variance of noise.

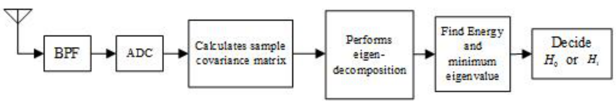

Fig.4: *Model of energy to minimum eigenvalue detection.*

As shown if fig.4, once the EME determines the status of the PU by using the ratio between a measured energy and the minimum eigenvalue, EME does not require a noise power as a prior knowledge.

3.4 Maximum-Minimum Eigenvalue Detection

A maximum to minimum eigenvalue detection (MME) [20], whose framework is illustrated in fig.5, is a type of blind spectrum sensing technique. The ratio between maximum and minimum eigenvalue of the received signal is used as a decision statistic which is compared to the decision threshold in order to determine the existence of the PU. As mention earlier, the energy of signal which is obtained from the maximum eigenvalue takes less effect from noise than obtain from a measuring the energy directly. Therefore, MME outperforms the detection performance of EME.

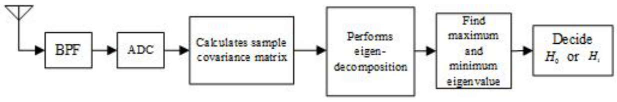

Fig.5: *Model of maximum to minimum eigenvalue detection.*

3.5 Covariance absolute value detection

Covariance absolute value detection (CAV) [21-22] is a blind spectrum sensing technique based on statistical theorem. A statistical covariance of received signal is calculated and compared to the decision threshold. By exploiting the statistical covariance of received signal, CAV also does not require any prior knowledge about PU signal waveform and noise power.

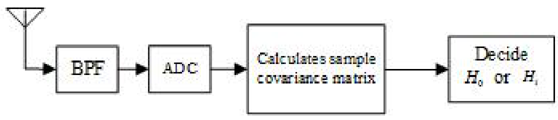

Fig.6: *Model of covariance absolute value detection.*

3.6 Double constraints adaptive energy detection

A double constraints adaptive energy detection (DCAED) [30] is an alternative technique of the energy detection which is based on the adaptive algorithm. Normally, an adaptive algorithm for energy detection, such as AED [28-29], adapts the decision threshold controlled by target performance metrics (P_d and P_{fa}) separately. A DCAED adapts its decision threshold by controlling by P_d and P_{fa} at the same time. However, there is always be a tradeoff between P_d and P_{fa} when the adaptive concept is used. DCAED gives high rate of P_{fa} at low SNR levels (or when the SU is far away from the PU).

3.7 Multi-slot double constraints adaptive energy detection

A multi-slot double constraints adaptive energy detection (MDCAED) [32] was proposed to improve the detection performance of DCAED by exploiting a multi-slot concept. MDCAED separates a sensing slot into several mini-slot. As shown in fig.7, each mini-slot is perform spectrum sensing separately and the status of PU is decided by a decision fusing rule, where majority rule is exploited. MDCAED benefits from a mini-slot detection since the received SNR increases due to the diversity reception effect. Therefore, MDCAED gives lower P_{fa} than DCAED and little improves the rate of P_d of DCAED.

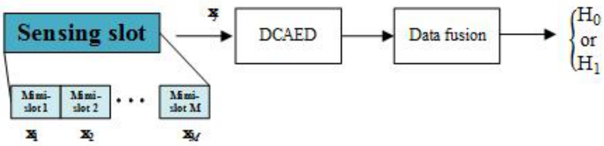

Fig.7: *Model of multi-slot double constraints adaptive energy detection.*

3.8 Decision fusion rule

There are three well-known of decision fusing rule, i.e., AND rule, OR rule, AND rule and majority rule. Normally, these fusion rule are used in cooperative spectrum sensing where the existence of the PU is determined cooperatively using the decision statistic from several SUs. It should be noted that $\triangle_m$ is an individual decision statistics from SU where $\triangle_m$ =0,1.

3.8.1 For AND rule, the PU is declared as exists when the PU is detected by all SUs. The AND rule can be formulated as follows:

$$H_1 : \sum_{m=1}^{M} \Delta_m = M \tag{4}$$

$$H_0 : \text{otherwise} \tag{5}$$

3.8.2 For OR rule, the PU is declared as exists when the PU is detected by at least one SU. The OR rule can be formulated as follows:

$$H_1 : \sum_{m=1}^{M} \Delta_m \geq 1 \tag{6}$$

$$H_0 : \sum_{m=1}^{M} \Delta_m = 0 \tag{7}$$

3.8.3 For majority rule, the PU is declared as exists when the PU is detected by at least K SUs. The majority rule can be formulated as follows:

$$H_1 : \sum_{m=1}^{M} \Delta_m \geq K \tag{8}$$

$$H_0 : \sum_{m=1}^{M} \Delta_m < K \tag{9}$$

4. PRELIMINARY EXPERIMENTS

In this section, we investigate the performance of spectrum sensing techniques – ED, MED, EME, MME, CAV, DCAED and MDCAED – under path loss effect and different PU occurrence where the communication channel is additive white Gaussian noise (AWGN). A random occurring waveform of WM signal is considered as a primary user (PU) signal. It should be noted that there are three types of WM waveforms – silent, soft speaker and loud speaker – which operate in the same carrier frequency. In such environment, the SNR at the receiver decreases due to path loss effect. At 100 meter (m), the transmitted PU signal power decreases to -95 dBm [50-52], therefore, the parameter of path loss model are set as the following : loss constant (C) is 0.00031623 and path loss exponent ($\aleph$) is 2. In the simulation, the distance (d) is set between 10 to 500 m and the occurrence of PU is 0 to $\frac{4}{5}N$ where N is number of samples. It should be noted that existing time of PU (τ) is 0 when PU exists at the beginning of sensing period. A noise variance (σ^2_{est}) is set to be estimated by the SU [53-54]. Other parameters are setting as follows: $N = 5000$, $L = 8$, $\aleph = 2$, $P_d = 0.9$ and $P_{fa} = 0.1$. It should be noted that L is a smoothing factor.The simulation results are averaged on 10,000 Monte-Carlo realizations using MATLAB. All of simulation parameters are summarized in table.1.

Table 1: *Simulation parameters*

Parameter	Value
Loss constant (C)	0.00031623
distance (d)	10 to 500 m.
Samples (N)	5000
Smoothing factor (L)	8
Probability of detection (P_d)	0.9
Probability of false alarm (P_{fa})	0.1

The mathematical model of the WM signal can be expressed as

$$s(t) = A_{\mathrm{c}} \cos\left(2\pi f_{\mathrm{c}} t + 2\pi k_{\mathrm{f}} \int_0^t m(\tau)\,\mathrm{d}\tau\right), \tag{10}$$

$$m(\tau) = \sin(f_{\mathrm{m}} t), \tag{11}$$

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

The parameters for different WM waveforms [55], silent, soft speaker and loud speaker, are shown in table 2.

Table 2: *Model of wireless microphone signal*

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

Fig.8 shows the trade-off between $P_{d(ED)}$ and $P_{fa(ED)}$ under different PU occurrence as a function of distances. As a result, rate of $P_{d(ED)}$ decreases due to an increasing of distance and point of PU occurrence. The reason is that when the distance increases, then the transmitted signal power is attenuated and less than to be detected. Moreover, when the sensing period has already begun and the PU accesses to the spectrum band, the measured PU signal power drop as compared to measured PU signal power when the PU accesses the spectrum band at the beginning of sensing period. Therefore, the received signal power is less than to be detected even though the SU is not far away from the PU.

Fig.9 shows the trade-off between $P_{d(MED)}$ and $P_{fa(MED)}$ under different PU occurrence as a function of distances. As mention earlier, MED performs spectrum sensing using the maximum eigenvalue which is more robust to the effect of noise than the energy. Therefore, MED gives better detection performance than ED.

Fig.10 shows the trade-off between $P_{d(EME)}$ and $P_{fa(EME)}$ under different PU occurrence as a function of distances. As mention in the previous section, the minimum eigenvalue is described as a variance of noise. Therefore, by dividing the received signal energy by the minimum eigenvalue, the effect of noise is reduced. Then, EME gives better detection performance than ED and also gives less P_{fa} than 0.1.

Fig.11 shows the trade-off between $P_{d(MME)}$ and $P_{fa(MME)}$ under different PU occurrence as a function of distances. Once a received signal energy, which is described by the maximum eigenvalue, takes less effect from noise than measures the energy directly. MME outperforms detection performance of EME for all distances. However, its performance still drops due to the point of occurrence of the PU.

Fig.12 shows the trade-off between $P_{d(CAV)}$ and $P_{fa(CAV)}$ under different PU occurrence as a function of distances. By performing spectrum sensing through statistical theorem, CAV gives high rate of P_d . However, $P_{fa(CAV)}$ is greater than 0.1, which is the spectrum sensing requirement.

Fig.13 shows the trade-off between $P_{d(DCAED)}$ and $P_{fa(DCAED)}$ under different PU occurrence as a function of distances. DCAED adapts its decision threshold on the changing in an SNR which can be calculated when the distance between PU and SU is known [36]. At the distance where the critical SNR is occurred, i.e., d is 247.73 m, a trend of performance improvement of DCAED is suspended. This is because, at critical SNR, DCAED is decided to re-calculate the adaptive factor B in a less computational complexity formula (Fig. 8), but with acceptable accuracy ratio. As a simulation results, DCAED gives high rates of P_d , however, it gives high rate of P_{fa} when the distance is greater than 300 m. When the PU existence is not at the beginning, it causes an error of SNR estimation from whole received signal in the sensing slot. Therefore, the performance of DCAED drops.

Fig.14 shows the trade-off between $P_{d(MDCAED)}$ and $P_{fa(MDCAED)}$ under different PU occurrences as a function of distances. MDCAED exploits a double constraints adaptive scheme and multi-slot technique to perform spectrum sensing. The sensing slot is separated into M mini-slots and N_m is a sample size of each mini-slot. As a result, the performance of MDCAED significantly drops due to the issue of anytime activation of the PU. This is because a requirement of a number of PU detected mini-slots, which is used to make a decision about PU status (K), is fixed. When a number of mini-slots that contain PU signal is less than the requirement, MDCAED gives poor detection performance.

As shown in these simulation results, the occurrence of PU has a great impact on the spectrum performance of all techniques. When the point of PU existence is not at the beginning, a sample of sensing slot that PU active (N_a) decreases. Then, it is difficult to detect the existence of PU by from a received signal of a whole sensing slot. Even though a multi-slot technique, MDCAED, outperforms detection performance of the others, its performance significantly drops when its detection criterion is not appropriate to the occurrence of the PU. Moreover, the adaptive scheme of DCAED and MDCAED are activated inappropriately in such environment. Therefore, a new multi-slot spectrum sensing and a new decision fusing rule for mini-slot spectrum sensing are proposed in the next section.

5. MICRO-SLOTTED DUAL-STAGE SPECTRUM SENSING

In this section, a micro-slotted dual-stage spectrum sensing (MDMS) is described in details together with mathematical models. As shown in Fig. 15, MDMS consists of two important modules, i.e., dual-stage spectrum sensing (DMS) and micro-slotted de-

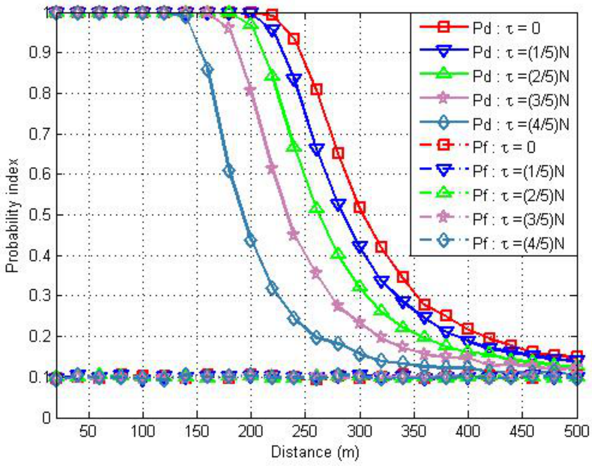

Fig.8: *Tradeoff in an accuracy of detection of ED under different PU occurrence as a function of distances.*

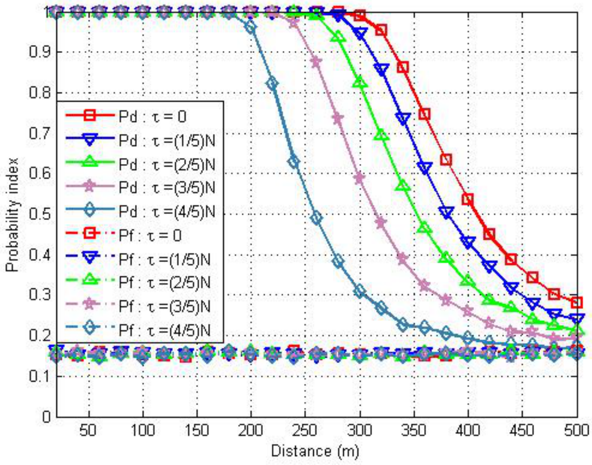

Fig.9: *Tradeoff in an accuracy of detection of MED under different PU occurrence as a function of distances.*

cision fusion (MDF). Firstly, DMS performs spectrum sensing for each micro-slot and reports its results to MDF sequentially. When the PU signal is found for the micro-slot, “1” is reported. Otherwise, “0” is reported. MDF makes a final decision about the PU status.

5.1 Critical distance

A dual-stage spectrum sensing improves a concept of two-stage spectrum in order to perform spectrum sensing of each micro-slot. The main difference to other two-stage technique is that the dual-stage spectrum sensing calculates the decision statistic once, while the others need to calculate the decision statistic twice.

As shown in Fig.16, the operation of DMS can be

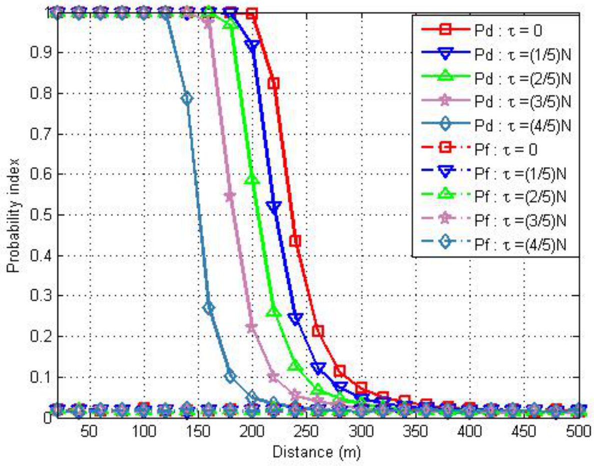

Fig.10: *Tradeoff in an accuracy of detection of EME under different PU occurrence as a function of distances.*

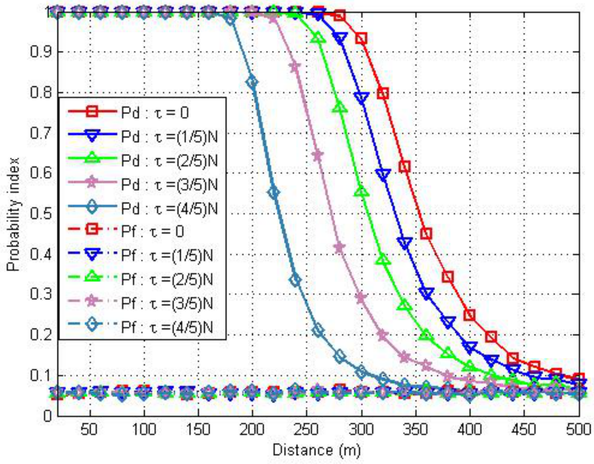

Fig.11: *Tradeoff in an accuracy of detection of MME under different PU occurrence as a function of distances.*

separated into two phases. Firstly, the energy of a micro-slot, which is used as a decision statistic (T_j), is measured and then compared to the first stage threshold ($\lambda_{CFAR,mini}$). If the measured energy is greater than the first-stage threshold ($\lambda_{CFAR,mini}$), the status of PU for the micro-slot is reported as active. Otherwise, the second phase is activated. Since the second phase is activated, a noise estimator estimates a noise variance (σ^2_{est}) of the micro-slot and the SNR is then calculated (γ_{est}) using the estimated noise variance and the knowledge of the distance (d) between PU and SU [35].

Normally, there are several well-known noise variance estimation [53-54]. Then, the threshold setter gathers σ^2_{est} and γ_{est} and generates the second-stage decision threshold (λ_2). To make a final decision

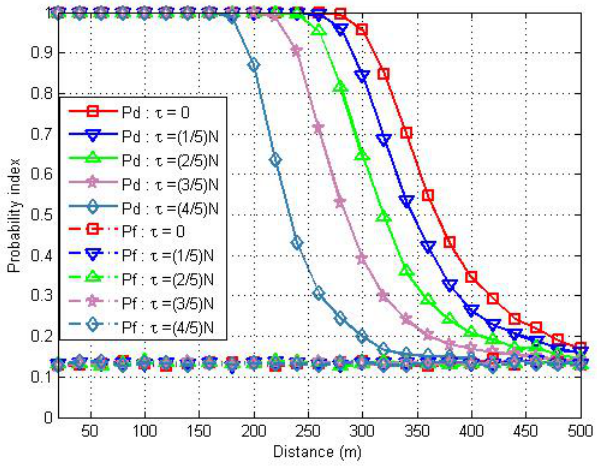

Fig.12: *Tradeoff in an accuracy of detection of CAV under different PU occurrence as a function of distances.*

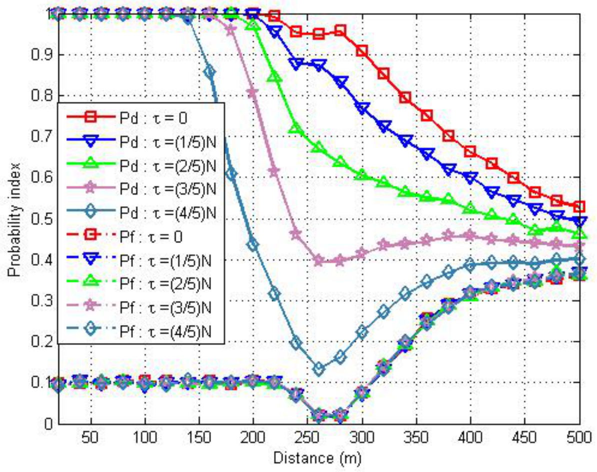

Fig.13: *Tradeoff in an accuracy of detection of DCAED under different PU occurrence as a function of distances.*

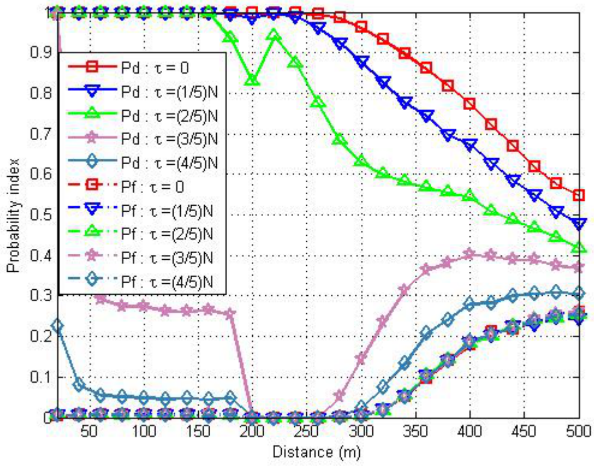

Fig.14: *Tradeoff in an accuracy of detection of MD-CAED under different PU occurrence as a function of distances.*

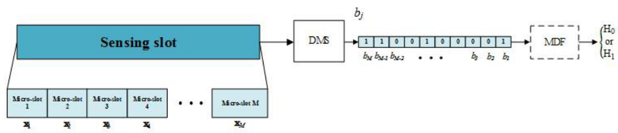

Fig.15: *Micro-slotted dual-stage spectrum sensing model.*

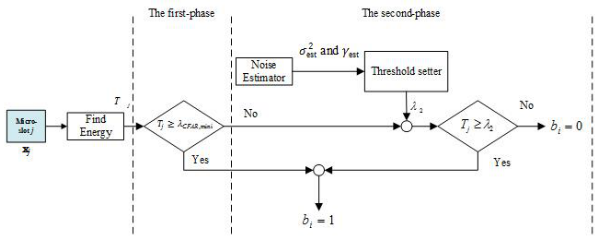

Fig.16: *Dual-stage multi-slot spectrum sensing.*

about status of PU for the micro-slot, the measured energy (T_j) is compared to the second-stage decision threshold (λ_2). If T_j is greater than λ_2, the status is reported as active. Otherwise, the status is reported as inactive.

For each micro-slot, the decision statistic (T_j) is given as

$$\mathrm{T_j} = \frac{1}{N_\mathrm{m}} \sum\nolimits_{n=1}^{Nm} \left|\mathbf{x}_\mathrm{j}\left(\mathrm{n}\right)\right|^2, j = 1, 2, \ldots, \mathrm{M} \qquad (12)$$

$$\mathrm{N_m} = \frac{\mathrm{N}}{\mathrm{M}} \qquad (13)$$

where j is the j^{th} micro-slot, N is the sample size of a sensing slot, N_m is a sample size of each micro-slot and M is a number of micro-slot.

To determine the status of the PU in each micro-slot, the decision statistic of DMS is computed once. Firstly, the decision statistic (T_j) is compared to a decision threshold of micro-slot energy detection $(\lambda_{CFAR,mini})$ which is given by

$$\lambda_{\mathrm{CFAR,mini}} = \left(Q^{-1}\left(\mathrm{P_{fa}}\right) \sqrt{\frac{2}{N_\mathrm{m}}} + 1 \right) {\sigma_\eta}^2 \qquad (14)$$

where $Q(\cdot)$ is standard Gauss complementary cumulative distribution function.

The $\lambda_{CFAR,mini}$ is generated once and before the first time of spectrum sensing performing. If T_j is greater than $\lambda_{CFAR,mini}$, the status of PU for the micro-slot is determined as active and the decision result "1" is reported to the MDF. Otherwise, the next stage is activated.

After the second-stage is activated, a noise estimator estimates a noise variance $({\sigma_{\mathrm{est}}}^2)$ and calculates the SNR (γ_{est}). The second-stage decision threshold (λ_2) is generated by using a double constrained adaptive concept where the threshold is controlled by fixing P_{fa} and P_d at the same time. The threshold setting can be done by exploiting an interdependent between P_{fa} and P_d and the threshold based on conventional energy detection. The P_{fa} and P_d of micro-slot energy detection can be derived as

$$P_{\mathrm{d}} = Q\left[\sqrt{\frac{N_{\mathrm{m}}}{2}}\left(\frac{\lambda_{\mathrm{ED,mini}}}{{\sigma_\eta}^2} - (\tilde{\gamma}_{\mathrm{PL}}) - 1\right)\right] \tag{15}$$

$$P_{\mathrm{fa}} = Q\left[\left(\frac{\lambda_{\mathrm{ED,mini}}}{{\sigma_\eta}^2} - 1\right)\sqrt{\frac{N_{\mathrm{m}}}{2}}\right] \tag{16}$$

where ${\sigma_\eta}^2$ is a noise variance.

Using (14), (15) and (16), the second-stage decision threshold (λ_2) can be expressed as

$$\lambda_2 = \left(\frac{(\gamma_{\mathrm{est}})\left(\frac{\lambda_{\mathrm{ED,mini}}}{{\sigma_\eta}^2} - 1\right)\sqrt{N_{\mathrm{m}}}}{\left(\cdot Q^{-1}\left(P_{\mathrm{fa}}\right) - Q^{-1}\left(P_{\mathrm{d}}\right)(\gamma_{\mathrm{est}})\right)} + 1\right){\sigma_{\mathrm{est}}}^2 \tag{17}$$

$$\gamma_{\mathrm{est}} = \frac{\mathrm{Cd}^{-\aleph}\cdot{\sigma_{\mathrm{s}}}^2}{{\sigma_{\mathrm{est}}}^2} \tag{18}$$

Then, the status of PU for the micro-slot is determined by compare T_j to λ_2 . If T_j is greater than λ_2 , the status of PU for the micro-slot is determined as active and the decision result "1" is reported to the MDF. Otherwise, the status of PU for the micro-slot is determined as inactive and the decision result "0" is reported. Then, the reported results are combined and MDF makes a final decision for the PU status.

5.2 Micro-slotted decision fusion

In this section, we introduce a decision fusion for micro-slotted spectrum sensing, micro-slotted decision fusion. A micro-slotted decision fusion determines the status of PU by changing its fusion threshold adaptively, i.e., a number of adjacent micro-slots (K_{AC}). A flow chart of micro-slotted decision fusion is depicted in Fig. 17. A decision result is gathered by MDF sequentially.

After decision results are generated from a dual-stage spectrum sensing, the results are sent to micro-slotted decision fusion sequentially. Firstly, a decision result "1" is checked in order to generate a number of adjacent micro-slots (K_{AC}) where the K_{AC} is given by

$$K_{\mathrm{AC}} = max\left\{2, \frac{M - j_{\mathrm{d}} + 1}{2}\right\} \tag{19}$$

where M is a number of micro-slot and j_d is the sequence of micro-slot when "1" is detected.

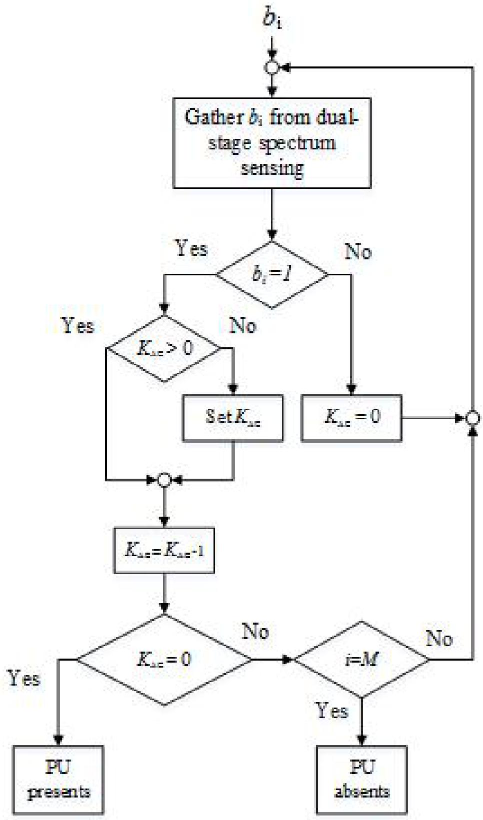

Fig.17: *Micro-slotted decision fusion.*

After the K_{AC} is set, the decision results of K_{AC} adjacent micro-slots are checked. If all of K_{AC} adjacent micro-slots are equal to 1, the PU status is declared as present. Otherwise, the algorithm continue its process until the last slot or the other decision result "1" is found. The status of PU is declared as absent when the decision results of two last micro-slots are [0,0] or [1,0] or [0,1]. In order to prevent a fault declaration from a false alarm of dual-stage spectrum sensing, the decision result at least two last micro-slots should be [1,1] and then the status of the PU is declared as present.

An example for the micro-slotted decision fusion is shown in Fig. 18. As depicted in Fig. 18 (a), a PU is detected since the first micro-slot. Then, a number of adjacent micro-slots (K_{AC}) is set using (19).In order to declare that the PU presents, the decision results of K_{AC} adjacent micro-slots (b_1 to $\mathrm{b}_{K_{\mathrm{AC}}}$)) must equal to 1. Otherwise, the algorithm continues detecting a "1" decision result in order to set a new K_{AC} and check the K_{AC} adjacent micro-slots. In Fig. 18 (b), the decision result "1" is found at b_6 , then K_{AC} is set and K_{AC} adjacent micro-slots starts checking again. Once the decision result of K_{AC} adjacent micro-slots do not equal to 1, the algorithm continues its detection until the last micro-slot (b_M). In Fig. 18 (c), a decision result "1" is found at b_{M-1} , then K_{AC} is set to be 2. Therefore, the decision result of 2 adjacent micro-slots (b_{M-1} and b_M) are checked. Since these results are equal to 1, the PU status is declared as present. It can be seen that K_{AC} is changed depending on the remained detecting micro-slots. Therefore, an issue of anytime PU activation in the sensing period can be solved.

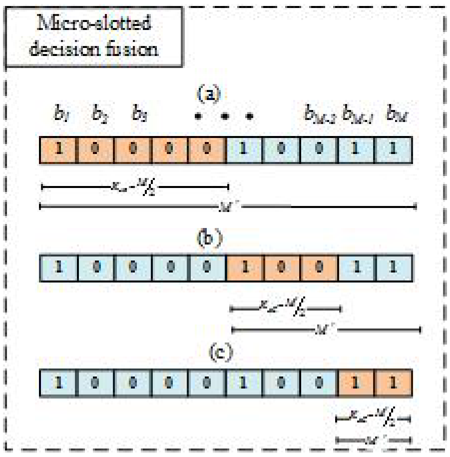

Fig.18: *An example of micro-slotted decision fusion.*

As described above, MDMS determines the PU existence by separating the received signal into multiple micro-slots. Each of micro-slot is performed spectrum sensing and the detection result is sent to decision fusion section in order to decide the PU status. By splitting the received signal into multiple micro-slots, the PU status can be reliably determined even if the operation of the PU does not start at the beginning of sensing slot. Moreover, the decision fusion is used to ensure the detection results from micro-slotted spectrum sensing since the detection result from only a micro-slot may be a false alarm.

6. SIMULATION RESULTS

In this section, we simulate the performance of our proposed algorithm, micro-slotted dual-stage spectrum sensing (MDMS), under different PU occurrence as a function of distances and then compares to other seven spectrum sensing techniques âĂŤ ED, MED, EME, MME, CAV, DCAED, and MDCAED. The parameters that are used to simulate the performance of these spectrum sensing techniques are the same as section 4. As stated in [32], MDCAED splits a sensing slot into 5 mini-slots.

Firstly, we evaluate the performance of the MDMS in order to determine an appropriate number of micro-slot (M) that should be split to perform spectrum sensing. Fig. 19, Fig 20, Fig, 21 and Fig, 22 show the performance of the MDMS when the number of micro-slot is 4, 5, 8 and 10, respectively. From the results, the performance of the MDMS improves when the number of micro-slot increases. As shown in Fig.18, since the sensing slot is split roughly, 2 micro-slots, the performance of the MDMS gives high rate on both P_d and P_{fa} which does not meet our objective to improve the detection performance on both metrics. As mentioned in section 4, the performance of multi-spectrum sensing decreases when a number of micro-slot does not appropriate to the existence of the PU. When a sample of sensing slot that is PU active, N_a, is less than a sample size of micro-slot, the performance of micro-slot spectrum sensing degrade. It should be noted that the size of micro-slot (N_m) decreases when the number of micro-slot (M) increases. When M is 10, the MDMS gives the best detection performance and also robust to the existence of the PU. Therefore, we set M to be 10 in this paper. It should be noted that existing time of PU (τ) is 0 when PU exists at the beginning of sensing period.

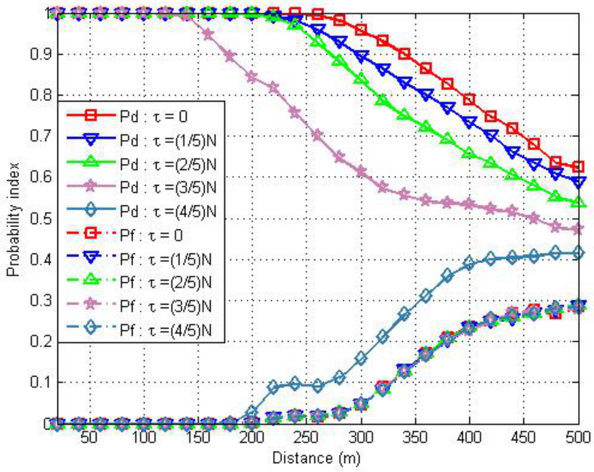

Fig.19: *Tradeoff in an accuracy of MDMS under different PU occurrence as a function of distances when N_m is $\frac{N}{4}$.*

After the number of micro-slot (M) for the MDMS is selected, then the performance of the MDMS is compared to ED, MED, EME, MME, CAV, DCAED, and MDCAED. As mentioned earlier, the performance of the spectrum sensing technique – ED, MED, EME, MME, CAV, DCAED, and MDCAED – decreases due to the point of PU existence. As shown in Fig. 23, although the MDMS may not give the highest P_d when the PU exists at the beginning of sensing period, it gives higher P_d than other six spectrum sensing – ED, MED, EME, MME, CAV and DCAED. As mentioned earlier, it is difficult to detect the existence of PU from the received signal of a whole sensing slot. Then, the performance of spectrum sensing techniques – ED, MED, EME, MME, CAV and DCAED – drop when the PU does not activate at the beginning of the sensing slot. Moreover, the performance of MDCAED drop when a number of mini-slots that contain PU signal is less than the detection requirement.

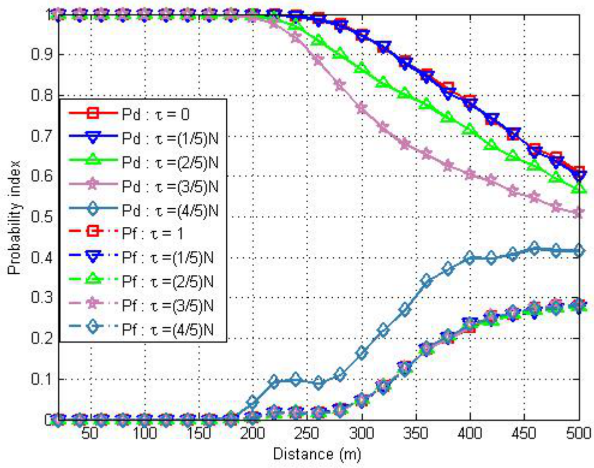

Fig.20: *Tradeoff in an accuracy of MDMS under different PU occurrence as a function of distances when* N_m *is* $\frac{N}{5}$.

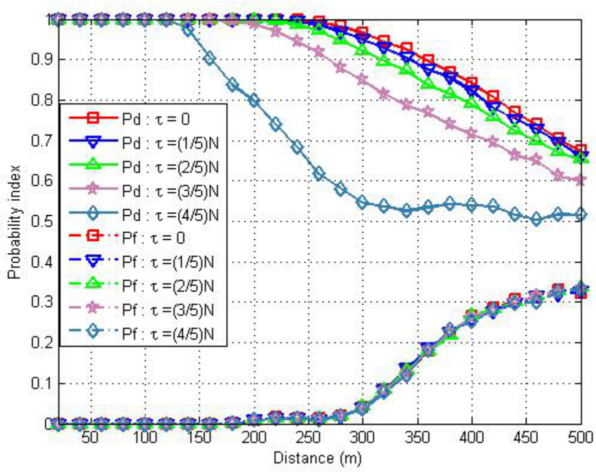

Fig.21: *Tradeoff in an accuracy of MDMS under different PU occurrence as a function of distances when* N_m *is* $\frac{N}{8}$.

As shown in Fig. 24 to Fig. 27, the performance other techniques – ED, MED, EME, MME, CAV, DCAED, and MDCAED – decreases while the MDMS maintains its performance nearly the same. The reason is that MDMS divides a sensing slot into multiple micro-slots where the effect of noise of each micro-slot is different. The micro-slots that take less noise effect than the others are used to determine the existence of the PU. As shown in Fig. 26, the proposed algorithm gives P_{fa} nearly to zero when the distance is lower than 300 m. At the distance greater than 300 m, although the P_{fa} of the proposed algorithm increases, it is still less than $P_{fa(DCAED)}$.

Finally, the average sensing time of to ED, MED, EME, MME, CAV, DCAED, MDCAED and the

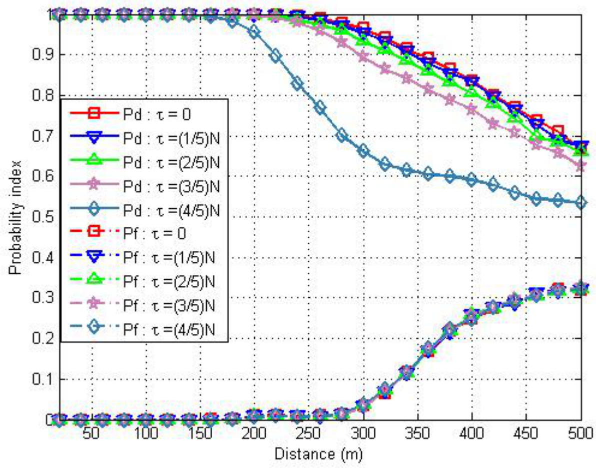

Fig.22: *Tradeoff in an accuracy of MDMS under different PU occurrence as a function of distances when* N_m *is* $\frac{N}{10}$.

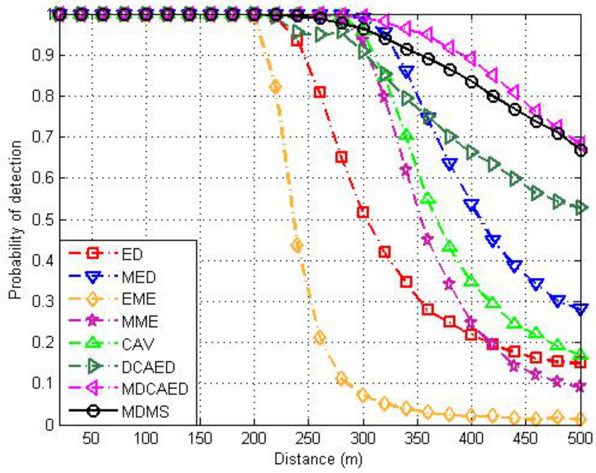

Fig.23: *Comparison of probability of detection with different distance of MDMS with other techniques when* τ *is 0.*

MDMS are compared in Fig.29. As a result, MDMS consumes less sensing time much than spectrum sensing based on statistical covaraince such as MED, EME, MME and CAV. This is because MDMS measures an energy of the received signal where the computational complexity is much less than a measure of statistical covaraince of the received signal. When the SU is not far away from the PU, i.e., distance is less than 200m, the sensing time of the MDMS is less than the time consuming when distance is greater than 200m.

Generally, spectrum sensing techniques determine the status of a PU from an average value of the noise distribution where the variance of noise distributes on the time varying and under the assumption that a PU exists for the whole sensing slot. To address

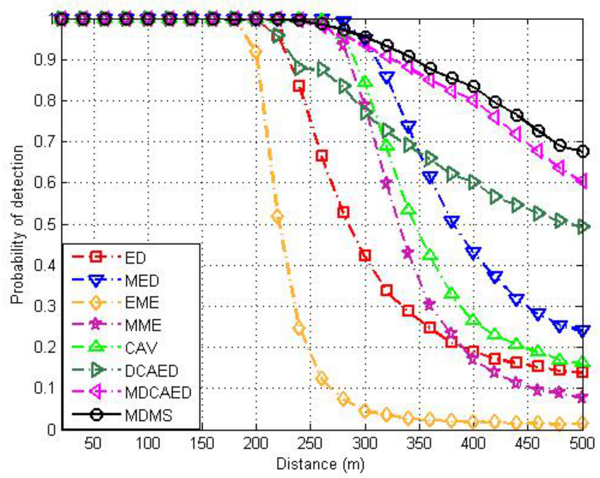

Fig.24: *Comparison of probability of detection with different distance of MDMS with other techniques when* τ *is* $\frac{1}{5}N$.

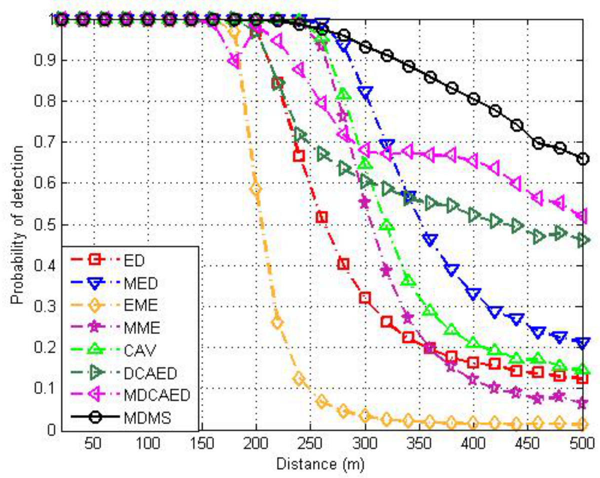

Fig.25: *Comparison of probability of detection with different distance of MDMS with other techniques when* τ *is* $\frac{2}{5}N$.

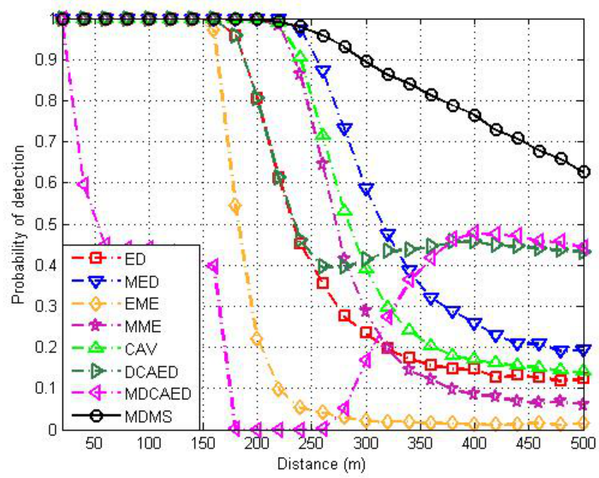

Fig.26: *Comparison of probability of detection with different distance of MDMS with other techniques when* τ *is* $\frac{3}{5}N$.

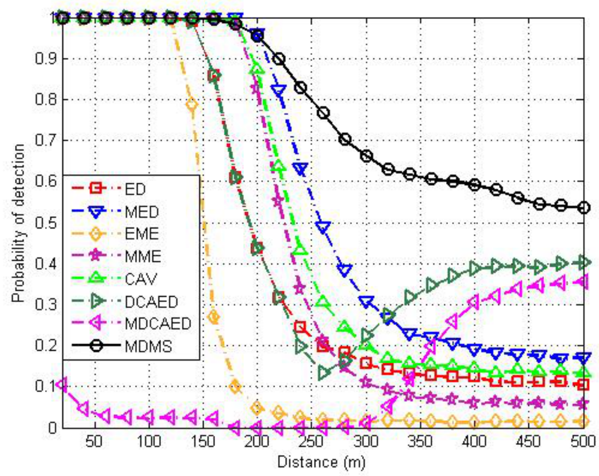

Fig.27: *Comparison of probability of detection with different distance of MDMS with other techniques when* τ *is* $\frac{4}{5}N$.

an issue of noise distribution and anytime PU activation, our technique divides a sensing slot into multiple micro-slots. As the effect of noise to each micro-slot is different, MDMS benefits from the spectrum sensing from micro-slots that have less noise effects. As a result, MDMS gives higher P_d than other spectrum sensing which performs spectrum sensing from a single slot. Moreover, with micro-slotted decision fusion, MDMS can avoid false alarm detection occurrences. It is found that, at 10 micro-slots (M=10), the technique is the most tolerant to anytime PU activation.

7. CONCLUSION

In this paper, we propose a micro-slotted dual-stage spectrum sensing (MDMS) which exploits a multi-slot concept, adaptive technique and two-stage spectrum sensing scheme. By splitting a sensing slot into multiple micro-slots, an issue of the anytime activation of PU in the sensing slot can be solved. MDMS also addresses low SNR due to path loss effect since a double constraints adaptive scheme is adopted. Moreover, MDMS greatly achieves the IEEE 802.22 spectrum sensing requirement in perspective of sensing time for all distances. Therefore, the primary user can be ensured that its transmission will not be interfered by the secondary user and the number of detecting spectrum bands by the SU increases. MDMS can be used as a spectrum sensing in practical CR system where the noise variance and the distance between a PU and SU can be estimated.

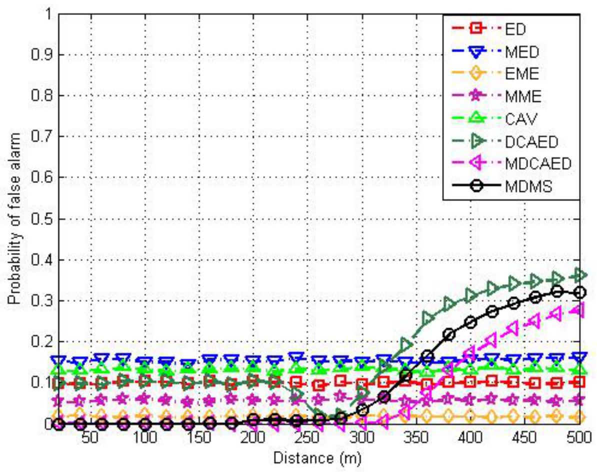

Fig.28: *Comparison of probability of detection with different distance of MDMS with other techniques.*

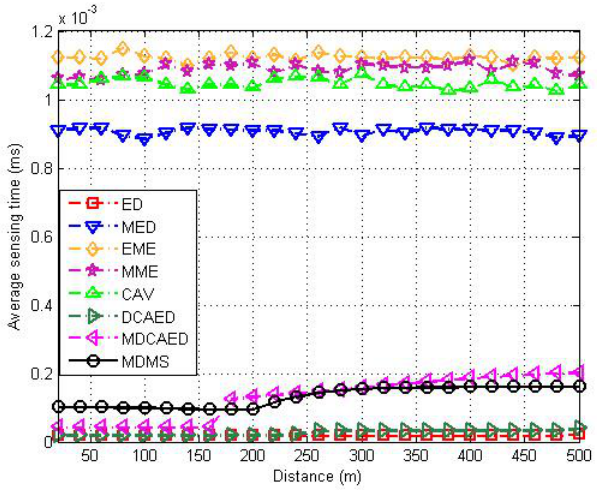

Fig.29: *Comparison of average sensing time with different distance of MDMS with other technique.*

8. ACKNOWLEDGEMENT

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