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A Comparative Study on the Two Popular Cognitive Radio Spectrum Sensing Methods: Matched Filter Versus Energy Detector

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Abstract

In this paper, two well-known cognitive radio spectrum sensing (CR-SS) methods, energy detection (ED) and matched filter (MF), are numerically realized in time domain (TD) as well as frequency domain (FD). Simulations for both ED and MF methods demonstrate the similar results (probability of detection) in the similar conditions for TD and FD versions of each method. In contrast, the required processing time (or equally computational complexity) for TD realization of each method is higher than that for FD realization. In addition, the running time of MF is higher than that for the ED. Furthermore, in similar conditions, the false alarm rate for MF method is less than that for the ED which means higher accuracy for the MF method compared to the ED. Moreover, it is observed that the ED is more sensitive to threshold and in a small range of threshold, detection values will be changed, sharply. Finally, simulation results demonstrate that signal to noise ratio (SNR) has direct effect on the receiver operating characteristic (ROC), especially for the ED method.

Keywords

Cognitive Radio (CR), Spectrum Sensing (SS), Energy Detection (ED), Matched Filter (MF), False Alarm, Miss Detection, Time Domain, Frequency Domain

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1. Introduction

The radio frequency (RF) spectrum is a limited resource managed by government regulators, such as the office of communications (Of Com) in the United Kingdom, and the federal communications commission (FCC) in the United States. Under current policy, all frequency bands are exclusively allocated to wireless networks on a long term basis for large geographical regions, and each system has to operate within a particular band. With the increasing necessity of new wireless services and the explosive development of mobile internet applications, demands on RF spectrum have been sharply increased [1, 2].

In recent years, it has become evident that there will not be enough spectrums exclusively available for all wireless systems. Interestingly, the spectrum policy task force (SPTF) within the FCC has reported that localized geographical and temporal spectrum utilization efficiency ranges from 15% to 85% [1, 3]. In another experiment, as shown in Figure 1, the maximum usage of 30 MHz to 3 GHz frequency spectrum was reported to be only 13.1%, with average usage of 5.2% [4].

Cognitive radio (CR) is a new technique which helps users to efficiently use the available radio spectrum. It is able to find the holes in the wireless spectrum and activate some users to work in these unoccupied frequencies which can dramatically increase the spectral efficiency. In this way, spectrum sensing in CR is more important as the activation key.

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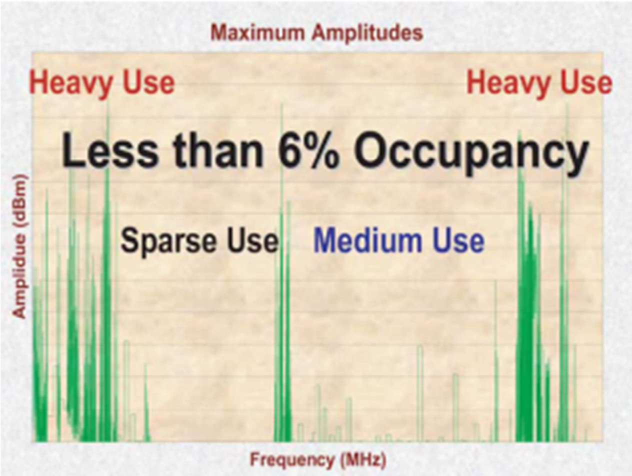


Fig. 1. Spectrum measurements averaged over six locations [4].

Spectral underutilization can be improved by allowing a secondary user (SU) to access to a licensed band when it is not used by a primary user (PU) [5]. As an innovative technology, CR system is designed to exploit spectrum opportunities by means of spectrum sensing and adaptation to the environment. An important necessity for cognitive radios is that secondary users are allowed to use spectrum holes without any harmful interference on the PUs. This task is dependent upon spectrum sensing process, which is one of the key functions in a cognitive radio system. Therefore, wideband spectrum sensing is of prime importance to ensure appropriate operation of both the primary and the secondary networks. Many extensive studies have been carried out to develop effective and reliable spectrum sensing methods. Despite numerous spectrum sensing algorithms being reported in the literature [1, 2], energy detection (ED) and matched filter (MF) methods are basic ones. In this research, these spectrum sensing methods are simulated in both time domain (TD) and frequency domain (FD).

The next section of this paper is organized as follows. Section 2 has a look at the cognitive radio. In addition, spectrum sensing is described with more details. Sections 3 and 4 represent the ED and MF methods with more details for time and frequency domains realizations. Performance analysis based on simulation results is addressed in Section 5. Finally, Section 6 concludes this paper.

2. Cognitive Radio and Spectrum Sensing

CR is known as a technique for improving the utilizations of radio spectrum [4, 6]. For the purpose of improving the spectrum utilization and providing high bandwidth to mobile users, the next generation (xG) communication networks program was developed to implement spectrum policy intelligent radios, also known as cognitive radios [4], by dynamic spectrum access techniques as shown in Figure 2. Furthermore, the IEEE has organized a new working group, known as the wireless regional area network (WRAN), IEEE 802.22 [4], for using cognitive radio techniques to allow sharing of geographically unused television spectrum on a non-interfering basis [4].

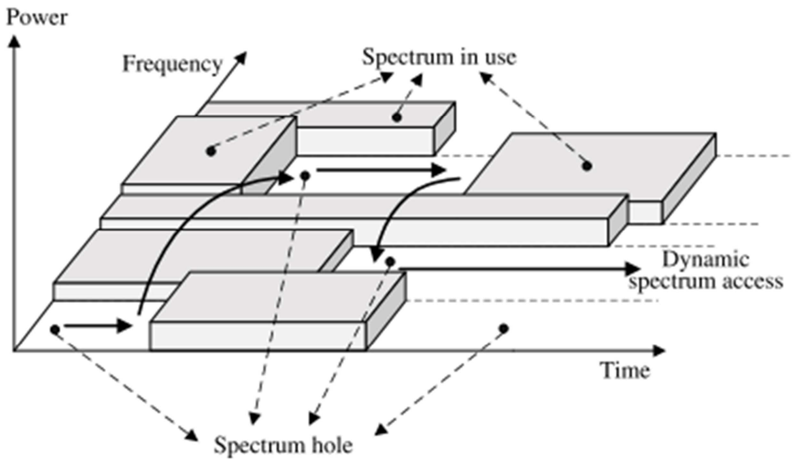


Fig. 2. Spectrum holes and the concept of dynamic spectrum access [4].

The term "cognitive radio" was first proposed by Mitola in [7] which has the following definition as:

Cognitive radio is an intelligent wireless communication system that is aware of its surrounding environment, and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters in real-time, with two primary objectives in mind:

- *Highly reliable communications whenever and wherever needed;*
- *Efficient use of the radio spectrum [7].*

As PUs have higher priority than SUs to access to the allocated frequencies, cognitive radios should either avoid interference to PUs, or keep the interference level lower than a predetermined threshold. In order to exploit spectrum opportunities, cognitive radio must detect spectrum holes. Most of the functions in the cognitive radio rely on spectrum sensing for implementing its environmental awareness.

Narrowband spectrum sensing algorithms are classified as cooperative and non-cooperative. The most effective way to sense spectrum holes is to detect active primary transceivers in the vicinity of the cognitive radios [4]. However, as some primary receivers are passive, such as TVs, some of them cannot be detected in practice. Due to the effects of multipath and shadowing, a cognitive radio user cannot decide between a deeply faded and an idle band. Hence, to overcome these effects, cognitive radio users cooperate with each other for efficient spectrum sensing in a fusion center which make a decision based on non-cooperative spectrum sensing results.

Three commonly used techniques for detecting the primary transmitters are the ED, MF and cyclostationary detection methods. The third one is appropriate for detect the cyclostationary signals [8]. In this research, the ED and MF methods are investigated with more details in time as well as frequency domains.

3. Energy Detection Spectrum Sensing in Time and Frequency Domains

Due to low computational and implementation complexities, energy detection approach known as radiometry or periodogram, is a popular technique for spectrum sensing. A commonly used method for detecting the PUs is energy detection, if the information about the PU in the cognitive radio is unknown [8]. Energy detection is a non-coherent detection method that avoids the need for complicated receivers required by other methods such as matched filter. An energy detector can be implemented in both time and frequency domains but it has some drawbacks. Major drawbacks for ED method are as follows:

1. Poor detection performance under low SNR scenarios.

2. It cannot separate the signal from a PU and the interference from other cognitive radios. Thus, it cannot take the advantage of adaptive signal processing, such as interference cancellation.

3. Noise level uncertainty can lead to further performance loss.

These disadvantages can be overcome by using two-stage spectrum sensing technique, i.e., coarse and fine spectrum sensing steps [8, 9]. Coarse spectrum sensing can be implemented by energy detection or wideband spectrum analyzing techniques. The aim of coarse spectrum sensing is to quickly scan the wideband spectrum and identify some possible spectrum holes in a short observation time. In contrast, fine spectrum sensing further investigates and analyses these suspected frequencies [10].

Limited number of samples entered in the energy detector, noise ambiguity and some unwanted fluctuations such as interference and multipath as well as shadowing introduce two types of errors:

1. The primary user is not present, but the average energy intake is greater than the threshold level. It is known as false alarm and its probability is denoted as P_f.

2. Primary user is present, but detected energy is lower than threshold level. It is known as missing case and its probability is denoted as P_m.

The received signal in the receiver of secondary user is given as equation (1) [11]:

$$x(t) = \begin{cases} n(t) & H_0 \\ s(t)+n(t) & H_1 \end{cases} \quad (1)$$

where $s(t)$ is the primary signal, $n(t)$ is additive noise, H_0 and H_1 are the hypotheses that demonstrate the absence or presence of primary user, respectively. In the TD-ED method, the decision should be based on the total energy of received signal using equation (2) [11]:

$$E_X = \sum_{n=1}^{N} |x(n)|^2 \quad (2)$$

In the equation (2), $x(n)$ is the nth sample of the received signal, E_X is total energy in N samples received in detector, N is the total number of samples of the received signal which is equal to $N = t\, f_s$ where t is the time of spectrum and f_s is the sampling frequency.

According to ED method, P_d, probability of correct detection and P_f can be determined as follows:

$$\begin{cases} P_d(\lambda) = P_r[E_X > \lambda | H_1] \\ P_f(\lambda) = P_r[E_X > \lambda | H_0] \end{cases} \quad (3)$$

Assuming S_u^2 as signal energy, S_n^2 as noise energy, the signal to noise ratio (SNR) defined as $g = \frac{S_u^2}{S_n^2}$ and λ as the decision threshold for energy detector, detection and false alarm probabilities can be derived as (4) and (5), respectively:

$$P_d = Q\left(\frac{\lambda}{S_M^2} - 1 - g\sqrt{\frac{t\, f_s}{1+2g}}\right) = 1 - P_m \quad (4)$$

$$P_{fa} = Q\left(\frac{\lambda}{S_M^2} - 1\sqrt{t\, f_s}\right) \quad (5)$$

If $\overline{P_{fa}}$ and $\overline{P_d}$ respectively represent the maximum and minimum allowable false alarm and detection probabilities, we have:

$$P_d = Q(\frac{Q^{-1}(\overline{P_{fa}})-g\sqrt{t\,f_s}}{\sqrt{1+2g}}) \quad (6)$$

And so if $\overline{P_d} = P_d$:

$$P_{fa} = Q(Q^{-1}(\overline{P_{fa}})\sqrt{1+2g} + g\sqrt{t\,f_s}) \quad (7)$$

Considering the $b = Q^{-1}(\overline{P_{fa}})\sqrt{1+2g}$:

$$P_{fa} = Q(b + g\sqrt{t\,f_s}) \quad (8)$$

Increasing the sensing time (the number of received samples) is the reason for increasing detection probability (or equivalently decreasing miss detection probability) as well as decreasing false alarm probability.

If γ is the receiver SNR, we have [11]:

$$P_d = Q(\sqrt{2\gamma+1}Q^{-1}(1-P_d) + \sqrt{xf_s\gamma}) \quad (9)$$

Above mentioned method is the same for TD and FD energy detection realizations, considering the following equation for calculating the energy in frequency domain:

$$E_X = \int_{-\infty}^{\infty} |X(f)|^2 df \quad (10)$$

Briefly, numerical realizations of TD-ED and FD-ED spectrum sensing methods involve the following steps:

Step 1: Receiving a noisy signal consisting of the primary user signal.

Step 2: Calculating the energy (based on Eq. 2 for time domain and Eq. 10 for frequency domain).

Step 3: Extracting the optimal threshold.

Step 4: Comparing the received energy with the threshold level.

Step 5: Decision-making about presence or absence of primary user based on the result of step 4.

4. Matched Filter Spectrum Sensing in Time and Frequency Domains

The matched filter method is an optimal approach for spectrum sensing in the sense that it maximizes the SNR in the presence of additive noise [4]. As another advantage of the MF method, it needs less observation time since the high processing gain can be achieved by coherent detection. For example, just O (1/SNR) samples are required to have a given probability of detection [4, 12]. This advantage is achieved by correlating the received signal with a template to detect the presence of a known signal in the received signal. However, it is a coherent method which needs prior knowledge about PUs, such as modulation type, and packet format, and requires the cognitive radio to be equipped with carrier synchronization and timing devices. With more types of PUs, the implementation complexity grows making the matched filter impractical [4].

A matched filter is a linear filter designed to maximize the output signal compared to noise signal for a given input signal. By using matched filter detection method, decision about primary user signal can be made when SU has a priori knowledge about PU signal. This method is equivalent to correlation in which the unknown signal is convolved with the filter whose impulse response is a version of the reference signal which is folded and shifted in time. Supposing the equation (1), the matched filter detection is based on the following equations, respectively for TD and FD versions:

$$y(t) = x(t) * h(t) \quad (11)$$

$$Y(f) = X(f).H(f) \quad (12)$$

where $x(t)$ and $X(f)$ are the time and frequency versions of the received signal in the receiver of secondary user, and $h(t)$ and $H(f)$ are the impulse and frequency responses of the matched filter, respectively. Frequency response of the matched filter should be adapted to the reference signal ($s(t)$) for maximizing the SNR [4, 13].

Briefly, numerical realizations of TD-MF and FD-MF spectrum sensing methods involve the following steps:

Step 1: Receiving a noisy signal consisting of the primary user signal.

Step 2: Considering the previous received signal as reference

Step 3: Finding $h(t)$ based on reference signal

Step 4: Calculating $y(t)$, based on Eq. (11) for TD-MF and Eq. (12) for FD-MF.

Step 5: Extracting the optimum threshold.

Step 6: Comparing the output signal, $y(t)$, to the threshold level.

Step 7: Deciding about presence or absence of primary user signal based on the result of step 6.

5. Simulation Results

In order to analyze the performcance and evaluate the complexity of ED and MF spectrum sensing methods, these methods are numerically simulated in both time and frequency domains which are reported in the next subsections. Simulations are run in MATLAB 7.11 software. A PC with an Intel Core i5-2400, 1.6 GHz CPU, and 2 GB

RAM is used to run the MATLAB codes. Signal bandwidth (BW) is assumed to be 100 kHz, smapling time (t_s) is 10ms and the number of samples (N) to do the spectrum sensing algorithm is 2000, based on the following equation.

$$N = 2 \times t_s \times \mathrm{BW} \tag{13}$$

Experiment 1: P_d of ED and MF Methods in Different Values of SNR and Threshold Level

As shown in Fig. 3, for both spectrum sensing methods, ED as well as MF (in both time and frequency domains), probabilities of detection are close to each other for different SNRs. In this experiment, noise variance is assumed to be known and proper threshold value is selected for ED method. In contrast, the channel (or reference signal) is fully known for MF detector.

In order to analyze the effect of threshold level on the performance of ED and MF methods, an experiment is investigated. As shown in Figure 4, ED method is more sensitive to the threshold value compared to MF.

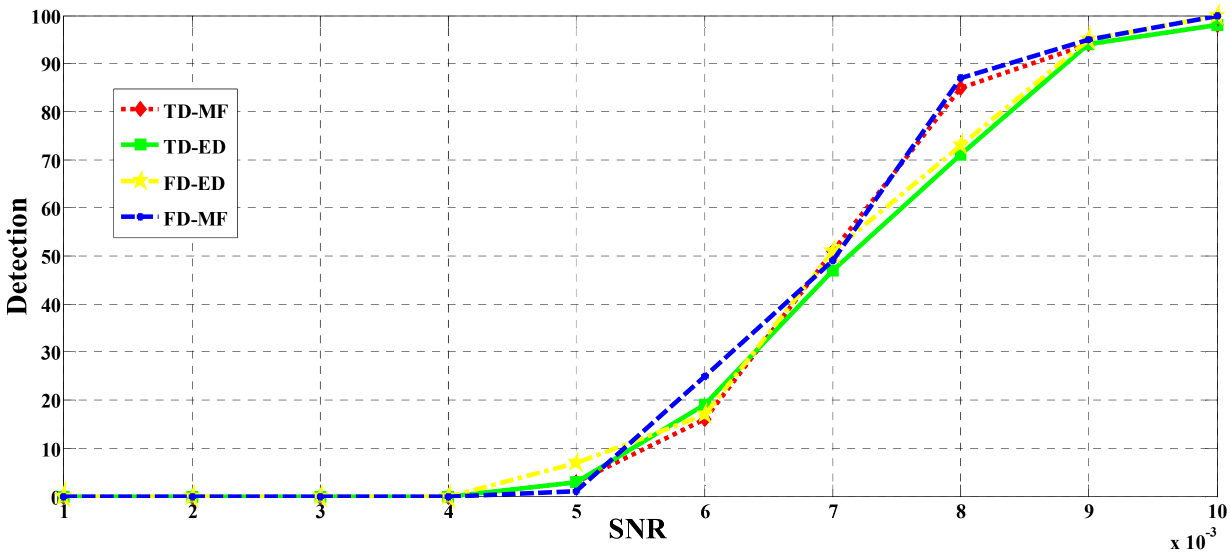


Fig. 3. Probability of detection versus SNR for both time and frequency domain realizations of ED and MF spectrum sensing methods.

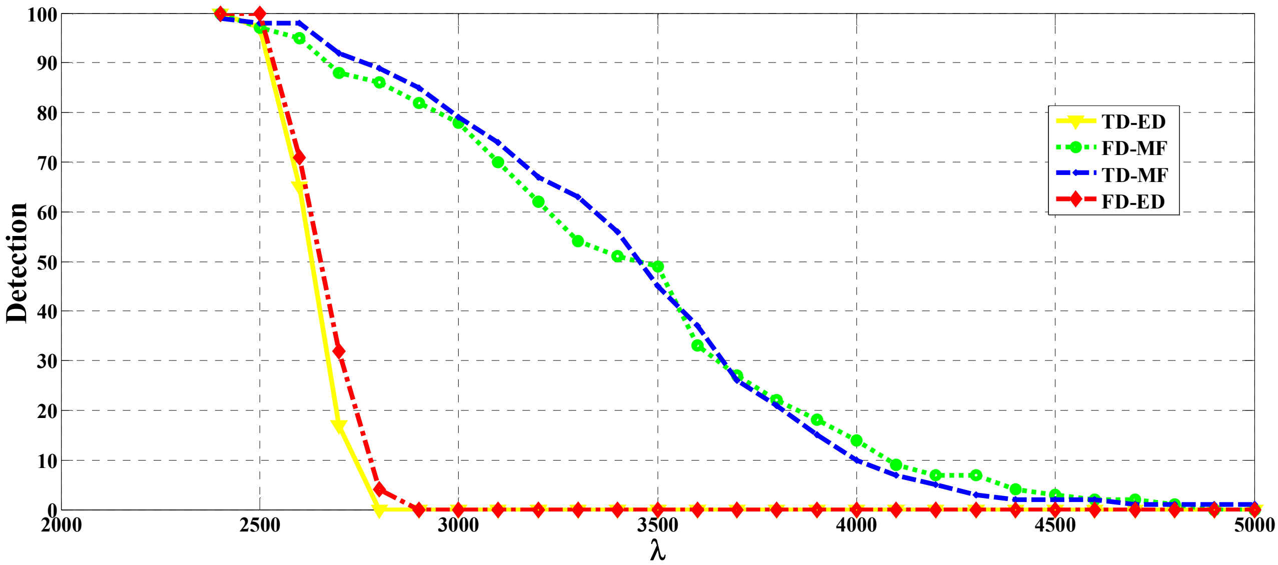


Fig. 4. Probability of detection versus threshold level (λ) for both time and frequency domain realizations of ED and MF spectrum sensing methods.

Experiment 2: Performance Evaluation of ED and MF Methods in Different Values of SNR and Threshold Level

Fig. 5 depicts the effect of the threshold value on the performance of ED and MF methods. Althogh threshold level has neglected effect on MF spectrum sensisng method in both time and frequency domains, selecting the proper threshold value is very important in ED method. As shown in this figure, increasing the threshold level in both TD-ED and FD-ED methods is a reason for increasing probabilities of false alarm and miss detection.

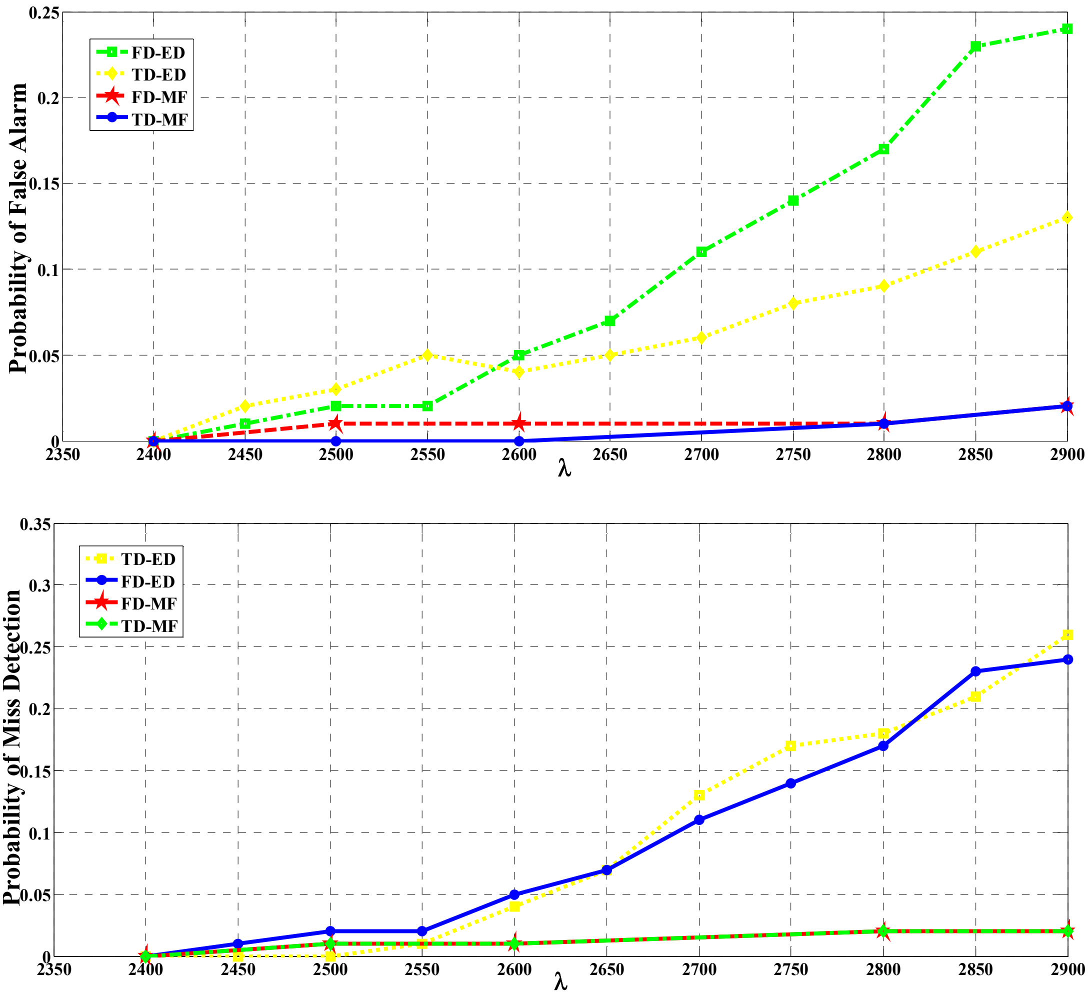
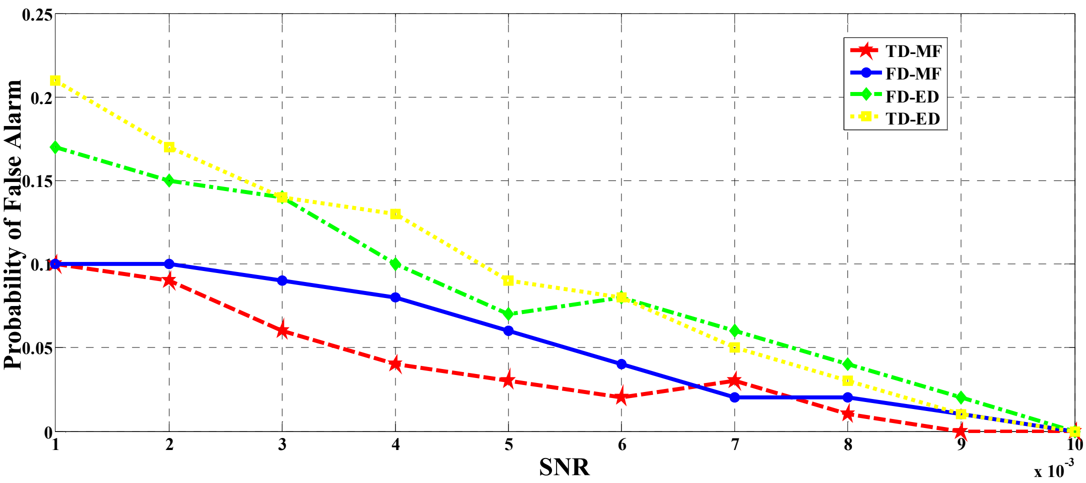


Fig. 5. Probabilities of false alarm and miss detection versus threshold value in both time and frequency domain realizations of ED and MF spectrum sensing methods.

The impact of SNR on the performance of ED and MF methods is investigated. As depicted in Fig. 6, increasing SNR causes decreasing P_f and P_m in a joint state, for both time and frequency domains realizations of ED and MF spectrum sensing methods. It is clear that changing SNR has more effect on P_f of ED and lower effect on P_m of ED compared to that for MF method. It means that ED method experiences more improper receiver operating characteristic (ROC), jointly higher P_f and lower P_d, than MF, by decreasing the level of SNR.



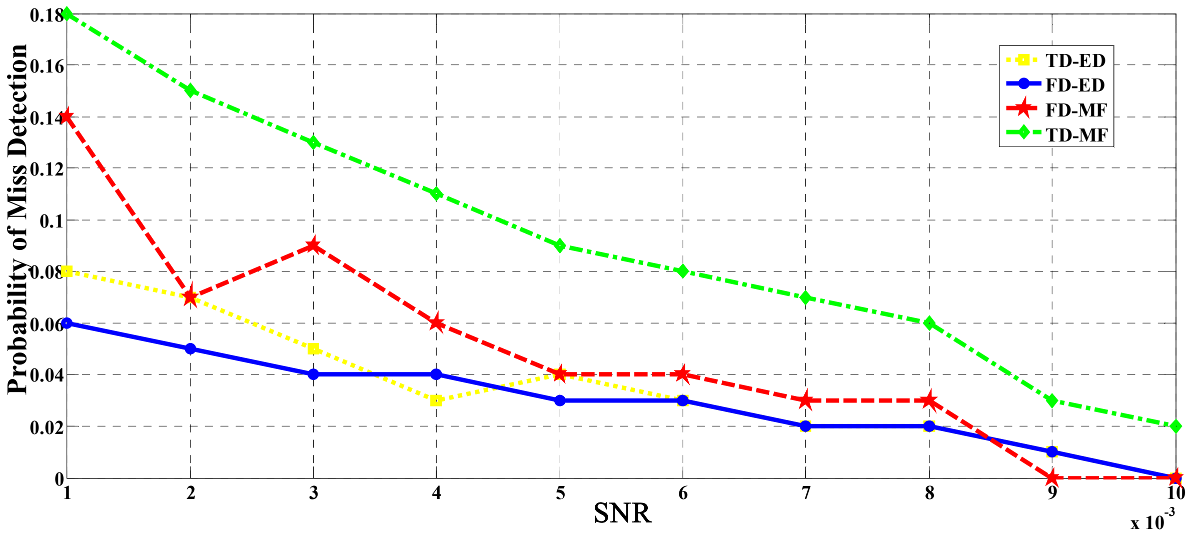


Fig. 6. Probabilities of false alarm and miss detection versus SNR in both time and frequency domain realizations of ED and MF spectrum sensing methods.

Experiment 3: Running Time Evaluation for ED and MF Realizations in Time and Frequency Domains

As shown in Table 1, the lowest running time belongs to TD-ED and the highest one belongs to FD-MF. In this experiment, it is assumed that the number of samples is the same for different methods. It is clear that frequency domain version needs more processing time compared to associated time domain realization.

Table 1. Relative running time for ED and MF spectrum sensing methods.

Spectrum sensing method	Relative running time (respect to reference one)
TD-ED	5%
FD-ED	6.15%
TD-MF	89%
FD-MF	100% (ref.)

6. Conclusion

Nowadays, appropriate usage of radio frequency spectrum resources in wireless communication systems is major research topic. Cognitive radio technique uses white spaces of radio spectrum by enabling spectrum sensing for opportunistic spectrum usage. Hence, proper spectrum sensing methods are needed to achieve efficient use of available spectrum and limited interference to PUs.

The main objective of this investigation was the performance evaluation of two popular spectrum sensing methods, ED and MF, in an AWGN channel by simulating them in both time and frequency domains. The effect of SNR and threshold level was evaluated on the performance of these methods. By comparing the running time of different realizations for spectrum sensing, simulation results show that TD-ED needs lower time compared to the others.

As summarized in Table 2, energy detection spectrum sensing is a non-coherent method which is sensitive to the knowledge about noise variance. Therefore, ED performance depends on selecting threshold level. In contrast, matched filter spectrum sensing is a coherent method which means that just in the case that the PU data is known for SUs is feasible. Therefore, it is optimum detection method if the prior knowledge about PU is accessible for secondary users in the presence of additive white Gaussian noise (AWGN). The major problem with this approach is that it requires different receivers for different type of primary users [14].

Table 2. Comparison of ED and MF spectrum sensing methods.

Method	Type of Detection	Advantages	Disadvantages
ED	Non-coherent: Calculating the energy of the received signal samples	1. Easy to implement 2. No knowledge about PUs	1. Improper ROC due to noise uncertainty 2. Unreliable in low SNRs 3. No difference between noise and signal
MF	Coherent: Projecting the received signal in the direction of the known PU signal	1. Robust against noise uncertainty 2. Proper detection in low SNRs 3. Less samples for detection	1. Prior knowledge about PUs 2. More running time 3. Different receivers for different signals

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