Spectrum Sensing Techniques in Cognitive Radio Technology: A Review Paper

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Abstract—Over the past decade, Rapid growth in the field of wireless communication has increased demand for spectrum resources and created a shortage of available radio spectrum. The cognitive radio technology is one of the promising technology to address the scarcity of spectrum resources, from the introduction of cognitive technology there is a lot of research is going on its spectrum sensing techniques, this paper aimed to provide an in-depth review on recent advances in spectrum sensing techniques and thoroughly presents the merit, demerits, and scope of further research of each spectrum sensing techniques. Finally, this review paper is presented to help new researchers and to make them familiar with concepts of spectrum sensing.

Index Terms—Narrowband sensing, wideband sensing

I. INTRODUCTION

Over the past decade, there is a dramatic growth in wireless communication technology has increased the number of internet users alongside the fixed allocation of the radio spectrum has created the shortage of spectrum resources. In fact, for the most part of the existing spectrum resources are not effectively utilized, which may create unwanted rejection of service events. So the scarcity of spectrum resources is the one of the major issue that has yet to be addressed.

One solution to address the shortage of radio spectrum is Cognitive radio technology, which allows the wireless devices to sense the radio spectrum to decide whether a particular frequency band is occupied or not. The devices can use the licensed frequency band when the primary is not active.

Over the past decade, a number of techniques are used for spectrum sensing; majorly spectrum sensing is classified into two types namely Narrowband spectrum sensing and Wideband spectrum sensing. In the former case, one frequency band is scanned at a time in the later case number of frequency channels are scanned at a time. This paper provides an in-depth review of recent progress in spectrum sensing and it also highlights the merits and demerits of each technique.

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II. CLASSIFICATION OF SPECTRUM SENSING

Spectrum sensing techniques are classified into two categories as Narrowband spectrum sensing and Wideband spectrum sensing, further, they are classified as illustrated in Fig. 1.

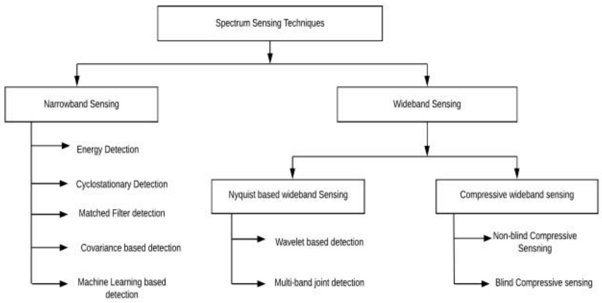

Fig. 1. Classification of Spectrum sensing techniques.

A. Narrowband Spectrum Sensing

Narrowband spectrum sensing is used to find out the status of primary user i.e whether the user is present or absent so that the secondary user can access that particular frequency channel. Narrowband sensing uses the following techniques for sensing they are

- Energy detection
- Cyclosationary detection
- Matched filter detection
- Covariance based detection
- Machine learning based sensing.

The above methods are used to find out the probability of false alarm and probability of detection.

Probability of Detection: It is used to find out the activity of a primary user i.e whether it is present or not.

Probability of false alarm: It indicates that the sensing technique detects the activity of a primary user wrongly. It detects the primary user as present actually when it is absent. The increase of probability of false alarm indicates that secondary user transmits in an occupied channel thereby interrupting the primary user communication.

Energy Detection: In the case of energy detection sensing technique, each received sample energy is calculated and it is compared with the predefined threshold value.

If the energy of a sample exceeds the threshold value, then it detects the presence of a primary user, if the energy of a sample falls below the threshold value, then it detects the absence of the primary user. The energy of a sample can calculated as

$$E_{ed} = \frac{1}{N}\sum_{n=1}^{N}\left(Y\left[n\right]\right)^2 \tag{1}$$

where $Y\left[n\right]$ = nth received sample

N= Total number of received samples

Let γ_{ed} is a threshold value then

If $E_{ed} > \gamma_{ed}$ primary user is present

$E_{ed} < \gamma_{ed}$ Primary user is absent.

The selection of threshold value $\left(\gamma_{ed}\right)$ will depend on the noise level presented, and the value $\left(\gamma_{ed}\right)$ will affect the performance of the detection.

The energy detection method is shown in Fig. 2.

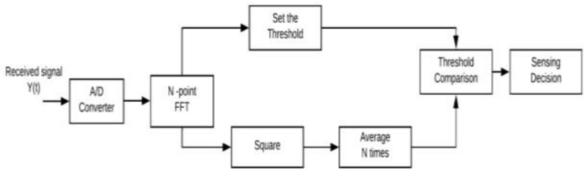

Fig. 2. Energy detection method of spectrum sensing

The energy detection method is simple and easy to implement, but it has some disadvantages i.e it cannot identify the actual sample and noise sample particularly in the case of low signal to noise ratio the performance of this method is very low.

However, the performance of this method can be improved by dynamic selection of threshold [1]-[4]. The author proposed a constant false alarm method [1] for dynamic selection of threshold, where the threshold value is continuously updated to maximize the probability of detection. The author suggested an adaptive threshold detection method [2] that uses the previous decision and number samples into account for dynamic selection of the threshold. The author used a double-threshold method [3] for dynamic selection of threshold which decreases the collision probability, but the performance is not acceptable for low signal to noise ratios. The author used DFT filter bank method [4] for dynamic selection of threshold in the presence of noise with minimum sensing error.

Cyclostationary detection: The Cyclostationary method is used to detect the activity of a primary user in the presence of noise. In this method, it uses the spectral correlation of signals to distinguish signal and noise.

Let $y(t)$ is a received signal

The mean value of the received signal is given as

$$\mu_y(t) = \mathrm{E}\left[y(t)\right] = \int_{-\infty}^{\infty} y(t)f(t)dt \tag{2}$$

The auto-correlation function of the received signal is given as

$$R_{yy}(\tau) = \int_{-\infty}^{\infty} y(t)y(t-\tau)dt \tag{3}$$

If the mean and autocorrelation functions of the received signal are periodic then it is known as Cyclostationary.

$$\mu_y(t) = \mathrm{E}\left[y(t)\right] = \mu_y(t+\mathrm{T}_0) \tag{4}$$

$$R_{yy}(\tau) = R_{yy}(\tau+\mathrm{T}_0) \tag{5}$$

where T_0 is the period of the received signal. The cyclostationary detection is shown in Fig. 3.

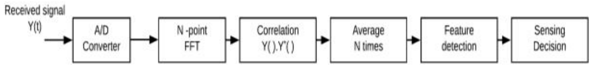

Fig. 3. Cyclostationary detection

Matched filter detection: In this method, received samples values are compared with the stored pilot samples of the transmitter to compute test statics.

The test static of matched filter is given by

$$T_{mfd} = \frac{1}{N}\sum_{n=1}^{N} y(n)x_p^{*}(n) \tag{6}$$

where $x_p^{*}(n)$ are the pilot samples of transmitter. The matched filter detection is shown in Fig. 4.

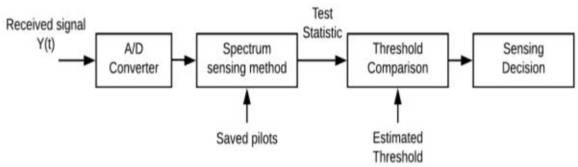

Fig. 4. Matched filter detection

Let γ_{mfd} is a threshold value then

If $T_{mfd} > \gamma_{mfd}$ primary user is present

$T_{mfd} < \gamma_{mfd}$ Primary user is absent.

***Covariance based detection*:** In this method of detection, first, it computes the sample covariance matrix of a received signal after that it uses the singular value decomposition techniques to compute Eigen values from the sample covariance matrix. Once the Eigen values are computed, then the ratios of maximum and minimum Eigen values are taken, later this ratio is used to compare with a threshold value to decide the status of the primary user. The sample covariance matrix of a received signal is given by

$$C_y(N) = \frac{1}{N}\sum_{n=L-1}^{L-2+N_s} \hat{y}(n)\hat{y}^{+}(n) \tag{7}$$

Machine learning based sensing: In the cognitive radio technology, in order to sense the spectrum accurately, the cognitive user has to learn from the environment, to enable a cognitive user to learn from the environment several authors are considered machine learning algorithms for spectrum sensing [5]-[7]. Complex mathematical calculations, interpretation, and analysis of patterns, decision-making abilities of machine learning are used to sense the spectrum in a dynamically changing environment.

In machine learning-based spectrum sensing, it extracts the feature vector from the pattern and classifies them into hypothesis classes of the presence/absence of a primary user.

Machine learning algorithms are classified into two types

i) Supervised learning
ii) Unsupervised learning

From existing work, machine learning-based spectrum sensing is classified into two categories as two step and one step process.

TABLE I: MACHINE LEARNING BASED SPECTRUM SENSING RELATED WORK

Related work	Feature extracted	ML Algorithm	Evaluation parameter
H.A.Shah [8]	Quantized Energy vector	• K-nearest neighbor	• Detection probability • Spectral hole exploitation
GC.Sobabe [9]	Eigen vectors	• K-means clustering • Gaussian mixture model	• False alarm rate • Detection probability
Lu.Y [10]	Probability vector	• K-means clustering • Support vector machine	• Training duration • Classification delay • Detection probability
Kumar. V [11]	Spectrum occupancy	• K-means clustering	• Channel fading coefficients
Wang, Z [12]	Frame Energy statics	• Decision tree • Naïve Bayes • Support vector machine • K-nearest neighbor	• Detection probability
Thilina, K.M [13]	Energy levels	• K-means clustering • Gaussian mixture model • Support vector machine • Weighted K-nearest neighbor	• Average training duration • Detection probability
Awe, O.P. [14]	Eigen vectors	• Support vector machine	• False alarm probability • Detection probability

In the first category, spectrum sensing is a two-step process; in the first step unsupervised learning is used to identify the pattern of a primary user. In the second step, supervised algorithms are applied to train the model. In the first step, k-means algorithms are used to identify the patterns, in the second step support vector machines are used to train the model.

The second category is a one-step process, it uses supervised machine learning algorithms like KNN (K-nearest neighbor), support vector machine to recognize patterns and to classify the data [15].

The related work of machine learning based sensing is shown in Table I.

Summary of Narrowband spectrum sensing techniques:

- The energy detection method of spectrum sensing is very easy to implement, but it gives a poor performance at low SNR. However the performance of energy detection can be improved by dynamic selection of threshold [16] and the increasing number of samples, but it increases the cost of implementation, sensing time and it is very susceptible to noise.
- Cyclostationary spectrum sensing gives better performance in the presence of noise, but it requires an increasing number of samples which results in high sensing time.
- Matched filter based sensing technique gives good detection performance with few numbers of samples, but it requires the prior knowledge signal characteristics, which is not always possible in the dynamically changing environment [17].
- The sample covariance matrix gives good detection performance, but computational complexity is very high in this method.
- Machine learning-based spectrum sensing will give better performance than other narrowband sensing techniques, but training a model in the fast-changing environment is a difficult task in this method.

B. Wideband Spectrum Sensing

In order to cope up with increasing data rates, higher bandwidths are needed which means that secondary users as to sense a wide frequency range of a radio spectrum to find the best available frequency channel [18].

In most cases of wideband spectrum sensing the available spectrum is divided into several narrow bands and spectrum sensing is performed by using either sequential sensing or parallel sensing.

In the case of sequential sensing at any given time only one narrowband is scanned. In parallel sensing, several bands are scanned parallel by using multiple sensors.

Wideband spectrum sensing is of two types they are

i) Nyquist based spectrum sensing
ii) Compressive based spectrum sensing

In Nyquist based wideband spectrum sensing, the wideband signal is sampled at the Nyquist rate. This method can be in the following ways

Wavelet Detection: In this method, it uses wavelet transform to detect spectral irregularity in the given structure thereby it identifies the frequency location and power spectral density of a received signal. The wavelet detection is shown in Fig. 5.

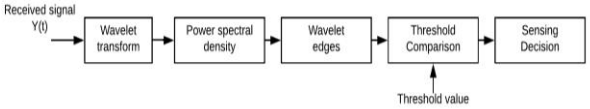

Fig. 5. Wavelet detection

Multi-band joint detection: The main objective of multi-band joint detection is to find an optimum value of the threshold vector, which increases the probability of detection and minimizes the false alarms.

In this technique, multiple frequency bands are sensed at a time to find the best availability of frequency channels. Here the energy of a received signal is compared with the threshold value to decide whether the band is occupied or not. The multi-band joint detection is shown in Fig. 6.

Filter bank based sensing: The filter bank method uses the power spectral density of the received signal to find out the best available frequency channel.

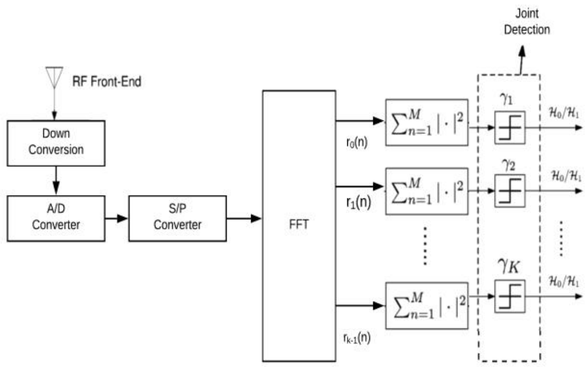

Fig. 6. Multi-band joint detection

Non-blind compressive wideband spectrum sensing: Non-blind compressive wideband spectrum sensing determines the parameters of wideband signals such as sparsity level, number of measurements needed. The sparsity level can find by identifying the number of occupied frequency channels within a band of interest and the number of measurements needed is the functions of sparsity level and measurement matrix.

The authors proposed a two-step method for minimizing the sampling rate [19], [20]. In the first step sparsity level is estimated, in the second step based on the sparsity level number of measurements are adjusted, then a signal is reconstructed from a few numbers of samples later energy detection is applied to sense the spectrum

Blind compressive wideband spectrum sensing: The previous method requires the sparsity level of a wideband signal to find the activity of a primary user, but obtaining sparsity level is a very complex process especially in the case of an exchange of traffic data between sensing nodes. So the alternative approach is blind compressive wideband spectrum sensing, the author proposed a discrete cosine transform method [21] for estimating the sparsity level of a signal without requiring any prior knowledge.

Comparison of Wideband spectrum sensing: The Nyquist based spectrum sensing gives better performance at the cost of high sampling rates and high power consumption.

- Compressive spectrum sensing takes a few samples and less sensing time to give a good performance; it further minimizes the recovery error with dynamic estimation of sparsity level. But the estimation of a sparsity level of a wideband signal is a complex process.
- The authors are suggested to use the location of an active frequency channel in compressive spectrum sensing [22], [23] instead of the sparsity level of the wideband signal.

III. Future Scope / Future Research Directions

- In the case of cyclostationary spectrum sensing technique, there is a scope of further investigation is needed in the reduction of power consumption, in sample covariance matrix method there is the scope of further investigation in the reduction of complexity.
- In the case of wideband spectrum sensing handling of noise uncertainty and estimation of sparsity level are challenges so there is a scope of further in these areas.
- The detection of primary users is always effected by fading, noise and shadowing. Cooperative spectrum sensing [24]-[27] can address these issues to some extent, but it suffers from increasing overhead. So there is further investigation is needed in the case of mobility effect in cooperative spectrum sensing.
- Cognitive radio technology can be used with wireless sensor networks [28], [29] to improve network performance i.e., to maximize network lifetime and optimizing energy consumption.
- Beam-forming combined with cognitive technology can be one of the future promising technique for dynamic spectrum access. So there is a further investigation is needed in the case of MIMO based compressive sensing [30].

IV. Conclusion

The increasing demand for internet access created a shortage of spectrum resource; cognitive radio technology is one of the promising technology which has an ability to address spectrum shortage. In this paper, recent advancement in both narrowband and wideband spectrum sensing techniques are reviewed in-depth to provide merits and demerits of each technique. This review concludes that there is a further scope of research in the areas like mimo based compressive sensing, mobility effect in cooperative sensing and one-bit compressive sensing techniques.

Conflict of Interest

The authors declare no conflicts of interest.

Author Contributions

Under the supervision of Subhashree Mishra and Subhansu Sekar Singh, Srinivas samala has conducted a literature review of spectrum sensing techniques of cognitive radio technology and wrote the paper; all authors had approved the final version.

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