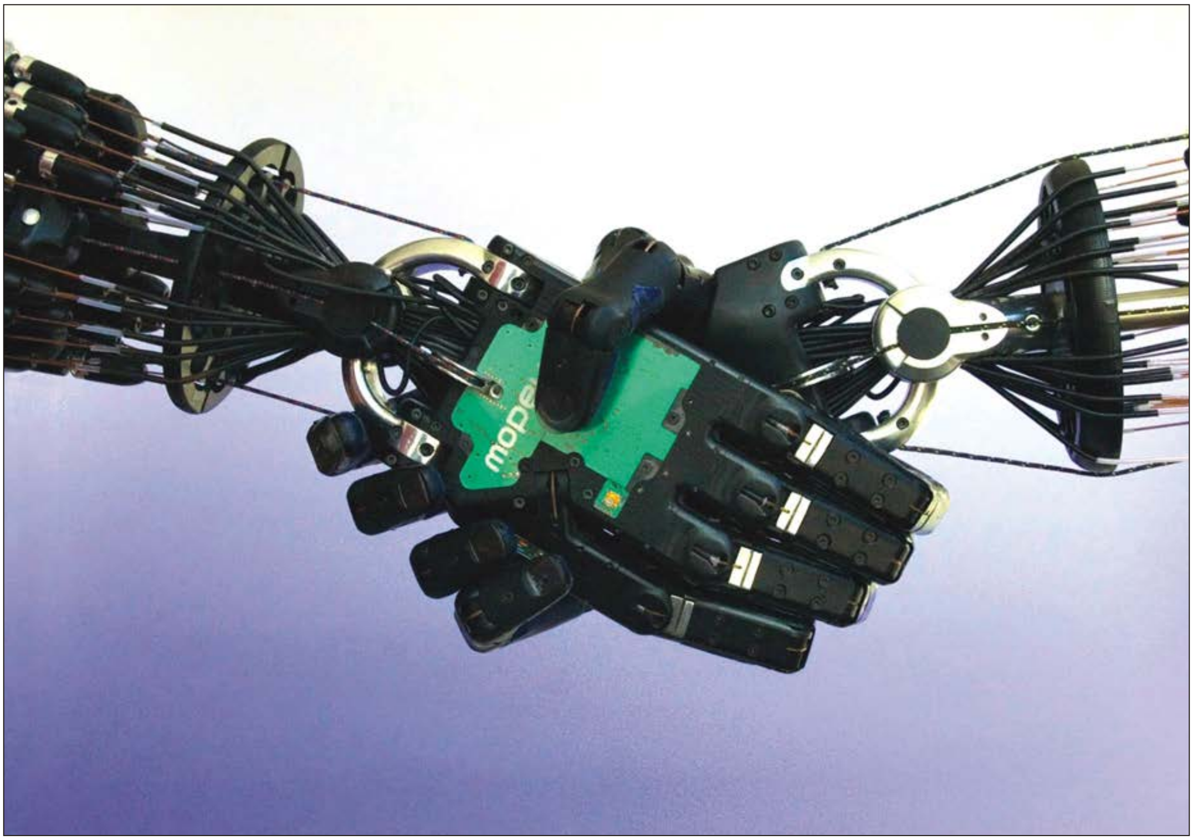

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Wavelet Supersede FFT in MB-OFDM: an Effective Cognitive Spectrum Sensing

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ABSTRACT

The curiosity of human on wireless devices is expanding exorbitantly, emphasizing high data rates and band width requirements. Multiband Orthogonal Frequency Division Multiplexing (MB-OFDM) is the technique that victuals high data rate. Studies manifests that most of the licensed bands are not exercised in an efficient way thereby leading to the progression of cognitive radio which allows the secondary users to access and activate the free band of primary users. Moreover, sensing the free holes is the prior concern in CR cycle. With the existence of diverse spectrum sensing methods each with its own pros and cons, this study is mainly subjected about the enhancement of energy detection method owing to its ease, simplicity and monotony. The Fast Fourier Transform (FFT) block of the above method is replaced with Discrete Wavelet Transform (DWT) as it can operate in both time and frequency domains. Four wavelet families are discussed in this study. The results are perceived from the probability of detection (p_d) versus Signal to Noise Ratio (SNR) graph.

Key words: Cognitive radio, spectrum sensing, energy detection, fast Fourier transform, discrete wavelet transform

INTRODUCTION

Spectrum is a boon to wireless communication. The usage of the allocated spectrum varies depending upon the geographical areas and over different time. Analysis and research shows that this precious spectrum is underutilized (Federal Communication Commission, 2002; Pei-Pei *et al.*, 2010). Since the network operators had invested a huge amount of money in buying this spectrum rescheduling the frequency spectrum becomes necessary. But rescheduling the spectrum is highly impossible task. As a consequence new technique which could solve these issues needs to be developed. This led to the development of cognitive radio which is an advanced version of Software Defined Radio (SDR). It is an artificial intelligence based system that senses the environment and utilizes this information to provide service to the customers (Mitola, 2000). The various jobs of cognitive radio include spectrum sensing, spectrum management and spectrum sharing. The first step in cognition cycle is spectrum sensing (Haykin, 2005). Spectrum sensing is performed to find the spectrum holes which in turn tells that whether the primary is present or not (Garello and Jia, 2011). Spectrum sensing becomes vital because the signal is affected by fading and path loss (Sahai *et al.*, 2004). Primary users have high precedence over the frequency band than the secondary users. If the spectrum is free the secondary users can occupy the spectrum for their application and upon the arrival of the primary user they have to immediately vacate the spectrum in order to avoid interference with the primary users (Avila *et al*., 2012a). Spectrum sensing is followed by spectrum decision, spectrum mobility and spectrum sharing. In spectrum decision phase the CR finds out the data rate, mode, bandwidth etc. Based on the information collected it chooses the available band to satisfy the needs of the user (Akyildiz *et al*., 2006). In spectrum mobility section the cognitive radio changes its operating frequency to the available band. This leads to uninterrupted transmission of data. In the spectrum sharing phase it shares the spectrum with other cognitive users and maintains a cordial relationship with them. Spectrum sensing methods can be classified into three types namely matched filter method, cyclostationary method and energy detection method (Cabric *et al*., 2004). The simplest among them is energy detection method (Malik *et al*., 2010). The main advantage is that it does require any prior knowledge at the receiver (Zhan and Li, 2010). In matched filter method the unknown signal is correlated with the known signal to detect the presence of primary user (ElRamly *et al*., 2011). It requires knowledge about the unknown signal. In cyclostationary method feature detection is performed to detect the user. It is a time consuming method and complex when compared to energy detection method (Prithiviraj *et al*., 2011). The performance of all the three methods is analyzed with the help of three parameters. They are defined as probability of detecting the signal when it is present, Probability of missed detection: missing to detect the signal when it is present, probability of false alarm: making a decision that the signal is available when it is actually off. A high probability of false alarm leads to poor utilization of the spectrum. Spectrum is freely available and not occupied by the primary users. Probability of missed detection lead to interference with the primary users (Ghasemi and Sousa, 2007). This study aims at replacing the fast Fourier transform of the energy detection method by wavelet transform. Various wavelet families and their comparison are discussed in this study.

ENERGY DETECTION

The block diagram of energy detection method is as shown in Fig. 1. Energy detection method is the most common spectrum sensing method. This is often preferred because it has low implementation complexity. In this method, the received signal is filtered by a band pass filter and this output is squared and integrated to produce the result. It is then passed to the Fast Fourier Transform block which is followed by windowing. FFT and windowing gives power spectral density

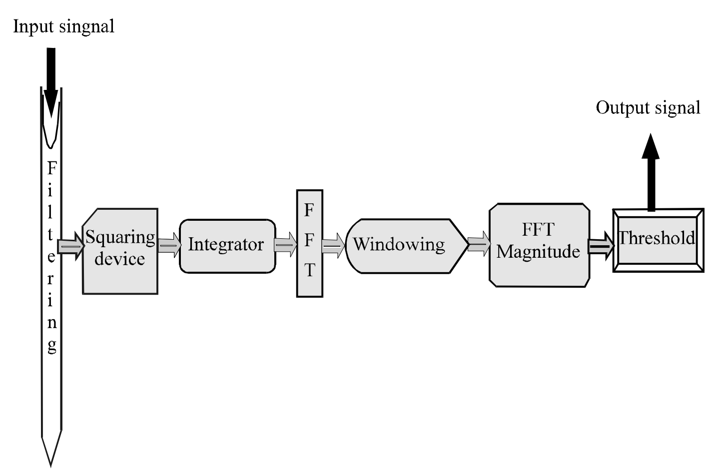

Fig. 1: Block diagram of energy detection method

of the signal. In energy detection method, the energy of the available radio spectrum is measured and then it is compared with a threshold to decide the presence of the primary user (Avila *et al.*, 2012b).If the measured energy lies below the threshold, it declares that the primary user is absent. When the measured energy lies above the threshold, it is considered that the primary user is present. Energy detection does not require any prior information about the primary users i.e., knowledge about the type of modulation used for transmission of signal, phase or any other information about the primary user. So, it is the most widely used spectrum sensing technique (Zhu *et al.*, 2008).

The outcomes of energy detection methods are y0 and y1 as follows:

$$y0: x(t) = m(t) \text{ (idle)} \tag{1}$$

$$y1: x(t) = s(t)+m(t), \text{ (occupied)}, t = 1,2,...M \tag{2}$$

where, x(t) is the received signal at the CR terminal, m(t) is the noise, s(t) is the primary user signal and M is the length of data record.

PROPOSED METHODOLOGY

In this study, the fast Fourier transform (FFT) block of the energy detection method given in Fig. 1 is replaced by Discrete Wavelet Transform (DWT). The purpose of replacing the blocks is, it is basically a multi-resolution technique offering more advantages than FFT. Four wavelet families namely Haar, Daubechies, Symlet and Coiflet have been discussed. There are some similarities between FFT and DWT. Some of them are (1) in both the transforms the properties of the matrices are similar and (2) The inverse matrix is the transpose of the original. But Fourier transform performs on frequency domain whereas wavelet transform performs on both time and frequency domain. No local information is available in Fourier transform. DWT is widely used in places where the noise is severe because the data could be more effectively recovered using DWT than FFT. The main advantage of wavelet transform is that based on the frequency components it adjusts the time and frequency windows (Zheng *et al.*, 2005). These features makes it applicable in applications like watermarking, pattern recognition, image compression, signal processing etc. (Al Wadi *et al.*, 2011). DWT is computed by filtering and scaling (Jiang *et al.*, 2011). Both low pass and high pass filtering is performed. The high pass filtering produces original information and low pass filtering gives approximations. The output of the filters is then passed to decimator. Decimation process improves the scale. The filtering and decimation processes are repeated until the goal is reached. The number of iterations depends upon the signal. The DWT of the signal could be obtained by adding the coefficients of the filter banks (Das *et al.*, 2011). Out of four wavelets discussed in this study Haar wavelet is the simplest one. It divides the signal into two signals which is half in its length. One sub-signal gives the average and the other sub-signal gives the difference. It is widely preferred because of its simplicity and fast nature (Mahmoud *et al.*, 2007). Since, it is only two elements wide any drastic change will not be reproduced in the high frequency coefficients. Hence it is not suitable for denoising process in signal processing. Daubechies wavelet transform are expensive and more complex than Haar transform. They are the extended version of Haar family with longer filters which provides smooth scaling and wavelet functions. The Daubechies family has maximum number of vanishing moments. Vanishing moments are responsible for smoothening of the wavelet system. The number of vanishing moments is half of the number of coefficients. They have even indices and the indices represent coefficients. For example D20 indicates that it has 20 scaling and wavelet coefficients. Also they have linear frequency response and non linear phase response. When compared to Haar transform it can be easily implemented (Idi and Kamarudin, 2012). Symlet wavelet is the modified version of Daubechies wavelet. The properties of both Symlet and Daubechies are same. It is closely symmetric. It has even index similar to dB. It is more suitable for denoising applications (Chavan *et al.*, 2011). Coiflet wavelet being symmetric has scaling functions at vanishing moments. There are N/3 vanishing moments for wavelet functions and N/3-1 vanishing moments for scaling functions. Wavelet functions of Coiflet can be easily obtained by reversing the order of scaling functions and changing the sign of second one. These scaling functions describe the scaling properties of the wavelet which is helpful in reconstructing the wavelet.

RESULTS AND DISCUSSION

Figure 2 and 3 gives a comparative study between FFT and DWT. Figure 2 is plotted between various families of DWT of the same order and FFT. Figure 3 is plotted between DWT and FFT for various windows. It is clear that DWT overrules the performance of FFT. The superiority of DWT is because it gives the local information. FFT has only sine and cosine functions whereas DWT has infinite basis functions which could be used to extract the exact information which is nothing but the probability of detection. Lesser sensing time to detect the primary users in turn enhances the system performance.

Figure 4 shows the output for various orders of Coiflet family. Probability of detection increases as the order increases. Under the same p_d say 90% there is an improvement of around 3 dB when the order increases from 2 to 10. As a result the sensing time reduces and the presence of primary users can be detected.

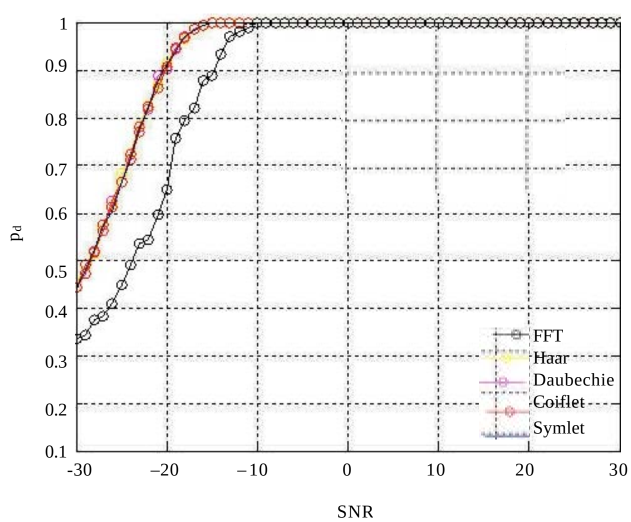

Fig. 2: Signal to noise ratio (SNR) versus probability of detection (p_d) comparison between FFT and DWT

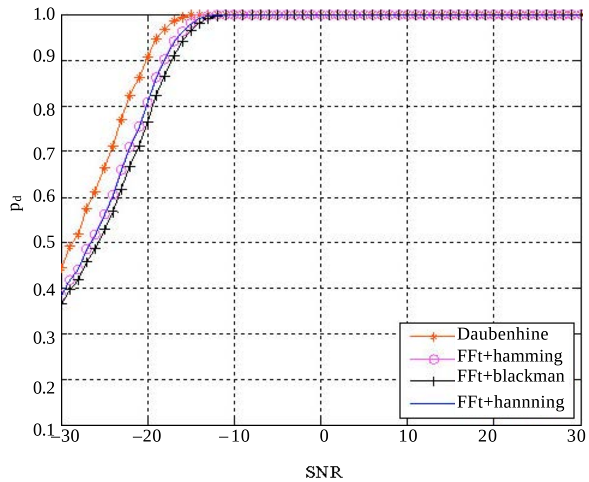

Fig. 3: Signal to noise ratio (SNR) versus probability of detection (p_d) comparison between DWT and FFT for various windows

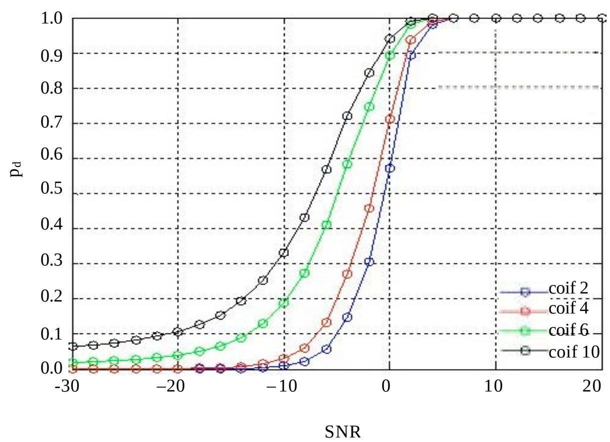

Fig. 4: Signal to noise ratio (SNR) versus probability of detection (p_d) comparison of Coiflet wavelet for various orders

Figure 5 gives the probability of detection versus SNR curve for various orders of Daubechies. Under the same p_d say 90% there is significant improvement as the order increases from 2 to 10. With the increase in order the probability of detection increases. The usage of the spectrum and spectrum holes could be identified in a short span of time and the secondary users can occupy the free spectrum.

Figure 6 gives the output of Symlet. It is plotted for various orders. With the increase in order the length of filter increases. This in turn improves the approximation level. In addition the regularity also increases with increase in order. All these things make the probability of detection task a quicker and better one. In this study enhancement of energy detection method is done by using the DWT whereas in the study proposed by Zhao *et al*. (2010) enhancement of energy detection method is done using K point FFT. As the FFT point increases probability of detection increases. In the study give n by Kapoor *et al*. (2011) the performance of traditional energy detection method is enhanced by replacing periodogram block. Instead of periodogram modified

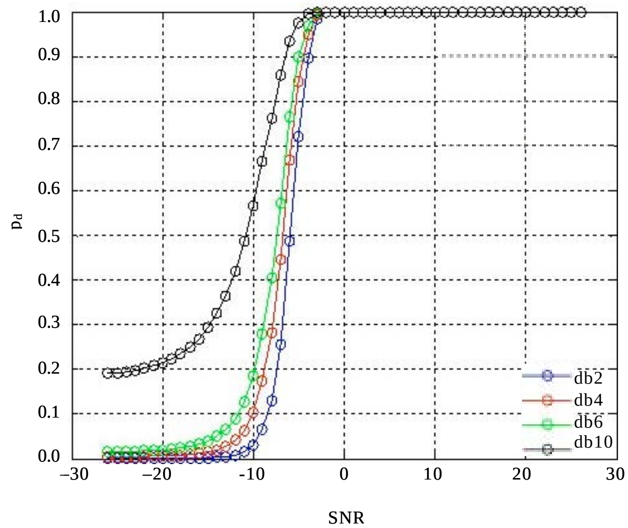

Fig. 5: Signal to noise ratio (SNR) versus probability of detection (p_d) comparison of Daubechies wavelet for various orders

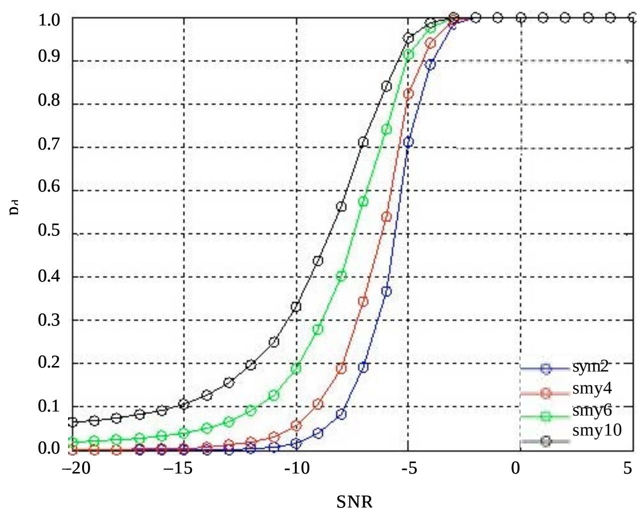

Fig. 6: Signal to noise ratio (SNR) versus probability of detection (p_d) comparison of Symlet Wavelet for different orders

periodogram and welch method are used. Welch method is preferred because it reduces the noise in the estimated spectra when compared to the traditional method. In addition Kaiser Window is used to reduce the spectral leakage. In the study proposed by Prithiviraj *et al*. (2011). Cyclostationary method is used instead of energy detection method. Cyclostationary method gives better results than energy detection method complex and time consuming one. The processing time is more and it is not a flexible method. In the study given by Avila *et al*. (2012a,b) FFT based energy detection method used and it is trained using neural network. Back propagation algorithm is used to train the system (Tang *et al*., 2010). In Back propagation method the input is given to the input layer and the output is taken from the output layer. There may be one or more hidden layers. Using a two-phase propagate-adapt cycle the network learns a predefined set of input-output example pairs. To the first layer of network unit the input pattern is applied as stimulus and it is propagated through each upper layer until an output is generated. From the output pattern the error is determined and by changing the weights, the error can be minimized. This algorithm uses supervised learning where the network is trained with a set of predefined inputs and outputs and the error is calculated. Kapoor *et al*. (2011) discussed the matched filter based spectrum sensing method, in which incoming signal is correlated with the known signal. This method requires prior knowledge about the signal. In the study proposed by Zhu *et al*. (2008) traditional energy detection method is used and instead of single threshold two thresholds are set to detect the primary user. The main drawback of energy detection method is misinterpretation of noise as signal when the noise level is high. This problem is overruled by double detection method. Usage of double threshold improves the spectrum sensing performance. In the traditional energy detector method squaring operation is performed for the output of the FFT block. In the study proposed by Arora *et al*. (2011) probability of detection is enhanced by performing cubing operation. Receiver Operating Characteristics (ROC) curves shows that there is one order of magnitude improvement. In the study given by Malik *et al*. (2010), the performance of FFT based energy detection, cyclostationary method and matched filter detection is compared and it is concluded that cyclostationary method gives better results for very low SNR at the cost of complexity and long processing time. One of the wavelet transform discussed in this study named Daubechies wavelet is utilized by Idi and Kamarudin (2012) to process the radar image.

CONCLUSION

Most of the time wireless spectrum remains underutilized. These necessities the need for cognitive radio which is used to find the spectrum holes and from the information gathered, unused frequency bands could be utilized in an efficient manner. In this study energy detection method is chosen since it does know require any prior knowledge. To enhance the performance of the energy detection method fast Fourier transform is replaced by wavelet transform. Four wavelet families are discussed and their performances are analyzed. It can be concluded that as the order of the family's increases probability of detection increases which helps to find the spectrum holes and based on the needs of the user the free spectrum could be occupied until the arrival of the primary user.

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