Research Article

Advanced Multiresolution Wavelet Based Wideband Spectrum Sensing Technique for Cognitive Radio

Jai Sukh Paul Singh,¹ Mritunjay Kumar Rai ,¹ Gulshan Kumar ,²
Rajwinder Singh,³ Hye-Jin Kim ,⁴ and Tai-hoon Kim⁵

¹Department of Electronics and Communication Engineering, Lovely Professional University, India

²Department of Computer Science and Engineering, Lovely Professional University, India

³Department of Electronics and Communication Engineering, Beant College of Engineering and Technology, Gurdaspur, India

⁴Business Administration Research Institute, Sungshin W. University, 2 Bomun-ro 34da-gil, Seongbuk-gu, Seoul, Republic of Korea

⁵Department of Convergence Security Engineering, Sungshin W. University, Republic of Korea

Correspondence should be addressed to Gulshan Kumar; gulshan3971@gmail.com

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An advance multiresolution wavelet based approach for wideband spectrum sensing for cognitive radio system is proposed in this paper. Prime focus is made on the coarse detection part for interweaved system, in which unoccupied spectrum can be used efficiently by the cognitive users. Quick and immediate shifting over the sensed vacant channel is extremely vital and is a challenging task. To overcome this issue, fast and efficient spectrum sensing technique is proposed for cognitive radios by improvising the Discrete Wavelet Packet Transform (DWPT) for multiresolution interweaved systems. This proposed scheme not only increases the system speed but also reduces complexity. Simulation results are used to analyse the system performance and numerical analysis for computing system complexity.

1. Introduction

To solve the problem like spectrum scarcity and spectrum underutilization, an emerging technology came into existence. The technology that can adapt changing environment and learn from the past experience is referred to as cognitive radio (CR) [1, 2]. Moreover, this paradigm automatically changes its parameters of operation like modulation techniques, transmission power, and other physical layer parameters with any variation in real-time environment conditions. Spectrum Allocation techniques [3–5] and its utilization are important factors in cognitive radio networks. Therefore, to control this spectrum underutilization which leads to spectrum scarcity, several bodies, and commission, headed by the Federal Communications Commission (FCC), are taking actions to make this new paradigm of cognitive radio work.

Working of cognitive radio is based on spectrum sensing, spectrum sharing, spectrum management, and spectrum mobility [6]. Due to these features, it is anticipated that

cognitive radios can solve the problem of spectrum underutilization and scarcity. Basic characteristics of cognitive radios are cognitive-abilities, awareness, and adaptation. Spectrum sensing plays an important role, which makes user aware of the surrounding conditions. For sensing, signal processing techniques are used and these techniques should be precise with low complexity. Various spectrum sensing techniques are developed for signal identification such as cyclostationary, filter bank multicarrier (FBMC) that are being used in radars sensing. All these techniques no doubt have accuracy but are complex, making the system slow and not feasible for real-time working scenario. The other techniques based on the Fast Fourier Transform (FFT) are less complex and easy to implement but lag sensing accuracy. To form balance between accuracy and complexity, IEEE 802.22 work group in [7] suggested two-stage sensing architecture. This two-stage sensing provides trade-off between fast signal processing and accuracy.

In this paper, cognitive radio for cellular network is proposed, which has fast spectrum sensing based on the two-layer sensing architecture suggested by IEEE 802.22 standards [7]. In this paper the proposed system model has two-stage architecture; signal processing using Discrete Wavelet Packet Transform (DWPT) and energy detection using Infinite Impulse Response (IIR) poly-phase filters are proposed. DWPT is used to analyse interested spectrum band based on the multiresolution technique, while energy detection using IIR Poly-Phase filters identify the signal type and signal strength. Numerical analysis is done for analysing the complexity while simulation result shows the performance of the proposed scheme making the system feasible to be used for spectrum sensing for cognitive radio in real-time environment.

The remainder of this paper is organized as follows. Section 2 covers the present state of research focusing spectrum sensing techniques and detailing out the research gaps. Comparative numerical analysis of the proposed system model with the existing models for computing complexity is done in Section 3. In Section 4, the performance evaluation is done discussing the simulation environment in Section 4.1 and simulation results in Section 4.2. Section 5 concludes the research work.

2. Present State of Research

Spectrum scarcity has significantly increased due to increasing population and demand of high speed Internet on move. This spectrum scarcity is not primary due to lack of spectrum. The main cause is due to the spectrum underutilization by the traditional defined spectrum allocations, *i.e.*, assigning fixed proportion of the spectrum to the licensed user. No doubt this static spectrum allocation technique provides interference-free communication but at the same time raises the severe problem of spectrum scarcity. Dynamic spectrum access is required to override this problem, which started with the paradigm of Software Defined Radio (SDR), adaptive radios, and latest one being cognitive radios. Reviewing all the sensing techniques such as energy detection, cyclostationary, wavelets, or filter bank, they have been employed to restrict down or enhance one or more parameters of interest. Energy detection technique is one of simple and widely used real-time techniques for sensing as it does not require any prior knowledge about the signal. Accuracy is the major problem associated with energy detection, whereas filter bank multi-carrier based sensing techniques have accuracy but increase complexity which increases delay thereby degrading the system performance.

Keeping in mind the cognitive radio for real-time cellular communication, a system is required which has fast sensing and at the same time has high accuracy (*i.e.*, negligible false alarms and missed detection). Enormous work has been carried out over *pros and cons* of various sensing techniques used for cognitive radio. Satheesh et al. in [9] analysed the performance of energy detection and cyclostationary detection using Binary Frequency Shift Keying (BFSK), Binary Phase Shift Keying (BPSK), and Gaussian Minimum Shift Keying (GMSK) signals considering noise uncertainty as the prime

factor. This paper concluded that cyclostationary detector outperforms energy detector under high noise uncertainty conditions at price of increased complexity. Haleh Hossein et al. in [10] proposed Wavelet Packet based Multicarrier Modulation (WPMCM) technique for Ultra-Wideband (UWB) system to mitigate the effects of interference from primary signal. Wavelet transform is used for spectrum sensing and lagrange multiplier for power allocation to minimize Bit Error Rate (BER) at the receiver end. Mohamed El-Hady M. Keshk et al. in [11] proposed Automatic Digital Modulation Recognition (ADMR) for both Orthogonal Frequency Division Multiplexing (OFDM) and Multicarrier Code Division Multiple (MCCDMA) access systems using discrete transforms and Mel-Frequency Cepstral Coefficients (MFCCs). As per observation the proposed technique performs better in terms of increased sensing speed and reduced complexity than Discrete Cosine Transform (DCT) and Discrete Sine Transform (DST).

H. Errachid Adardour et al. in [12] proposed a novel technique to study the effect of mobility of secondary user on spectrum sensing of cognitive radio system in real-time environment. The study concluded that mobility causes an adverse negative effect on sensing performance of the network. In [13] Ying Liu et al. present improved wavelet decomposition for different wireless signals based on interference. In this work, control mechanism is proposed to achieve good resolution. Moreover, this technique reduces computational complexity and makes the implementation easier in real-time communication network. In [14] L. C. Jiao et al. proposed a novel sensing technique to detect the spectrum holes, which reduces greatly the quantity of sensing information required for detection. The proposal is based on simple Matrix Matching Pursuit (MMP) algorithm for spectrum sensing based on Vector Matching Pursuit (VMP) and Revised Matching Pursuit (RMMP) to obtain higher performance.

Youngwoo Youn et al. in [8] proposed fast spectrum sensing algorithm using the Discrete Wavelet Packet Transform (DWPT) and filtering schemes. The proposed algorithm has simple structure and less computational complexity as compared to other conventional schemes. Singh et al. in [4] proposed a collaborative sensing mechanism for solving two major issues of energy detection method, *i.e.*, noise uncertainty and hidden node problem. To overcome noise uncertainty, M-ary Quadrature Amplitude Modulation (QAM) technique is proposed that increases the overall performance reducing probability of false alarm and probability of missed detection by 3% at the same latency time, whereas cooperative fusion sensing with a combination of AND and OR logic is used to solve hidden node problem. Ali Eksim et al. in [15] proposed the use of WRAN (IEEE 802.22) to rural areas in which TV white spaces can be used opportunistically without causing any harmful interference to the existing TV receivers. Ali Eksim et al. later in 2011 [16] proposed an effective pilot tone detection method based on Goertzel Algorithm and tested the proposed method to detect actual Digital Television (DTV) signal. The proposed method proves out to be fast and more efficient spectrum sensing capabilities. Djaka Kesumanegara in his thesis [17] proposed a fast spectrum sensing in WRAN (IEEE 802.22) based on Discrete

Wavelet Packet Transform focusing on the coarse detection. Complexity of the system is reduced and sensing becomes faster. In the next section, the system model for the proposed scheme proposed in this paper is discussed and compared with the existing model closely related to the proposed model.

3. System Model and Mathematical Analysis

Discrete Wavelet Transform (DWT) is designed from the multiresolution analysis that decomposes the given signal space into approximate space “X” and detail spaces “Y” is expressed as

$$X_{i+1} = X_i \oplus Y_i = Y_i \oplus Y_{i-1} \oplus X_{i-1} \quad (1)$$

where Y_i is the orthogonal complement of X_i in X_{i+1} and $\oplus$ represents the orthogonal sum of two subspaces. Two spaces Y_i and X_i are constructed by orthonormal scaling functions “ $\phi_{i,j}$ ” and orthonormal wavelet functions “ $\psi_{i,j}$ ”, respectively. Scaling function “ $\phi_{i,j}$ ” and wavelet function “ $\psi_{i,j}$ ” are obtained as

$$\phi_{i,j}(t) = 2^{i/2} \phi(2^i t - j) = \sum_z l_{z-2j} \phi_{i+1,j}(t) \quad (2a)$$

$$\psi_{i,j}(t) = 2^{i/2} \psi(2^i t - j) = \sum_z h_{z-2j} \phi_{i+1,j}(t) \quad (2b)$$

with high-pass filter “ $h_{z-2j} = \langle \psi_{i,j}, \phi_{i+1,z} \rangle$ ” and low-pass filter, “ $l_{z-2j} = \langle \phi_{i,j}, \phi_{i+1,z} \rangle$ ”, where $\langle \rangle$ means inner product. Using these functions, DWT of a given signal, “ s ” provides scaling coefficients and wavelet coefficients. The scaling coefficient “ a ” at the i^{th} level j^{th} time is computed by

$$a_{i,j} \langle s, \phi_{i,j} \rangle = \sum_z l_{z-2j}^* \langle s, \phi_{i+1,z} \rangle = \sum_z l_{z-2j}^* a_{i+1,z} \quad (3)$$

The wavelet coefficient “ b ” at the i^{th} level and j^{th} time is

$$b_{i,j} \langle s, \psi_{i,j} \rangle = \sum_z h_{z-2j}^* \langle s, \phi_{i+1,z} \rangle = \sum_z h_{z-2j}^* a_{i+1,z} \quad (4)$$

Figure 1(a) describes the 2-level decomposition of DWT and Figure 1(b) shows its frequency separation. Discrete Wavelet Packet Transform (DWPT) differs from Discrete Wavelet Transform (DWT) in the decomposition of detail space. DWT decomposes only the approximation space, while DWPT decomposes approximate as well as detail space. Therefore, frequency separation is more uniform in DWPT as compared to DWT. Figure 2(a) shows the 2-level decomposition of DWPT and Figure 2(b) represents its frequency separation property. To implement this terminology for cognitive radio sensing technique, energy and power of the channels need to be computed which is done using energy detection based on wavelet filter banks [18]. IIR Poly-Phase filter banks are used which have great frequency selectivity and reduced complexity. The detailed description of power detection using IIR Poly-Phase filtering is done in the following subsection.

3.1. Proposed Model. In this subsection, the proposed model is described. As suggested by IEEE WRAN report in [7],

Djaka Kesumanegara in [17] and Youn in [8] mentioned two-way sensing architecture as shown in Figure 3 for cognitive radio. RFE stands for Radio Frequency Equipment and MAC stands for Media Access Control. This architecture consists of two phases. In the first phase, coarse detection based on energy detection schemes is performed to select the unoccupied channel. And in the second phase, one of the channels is examined by the feature sensing to identify the incoming signal type and detect weak signals.

In this proposed technique power detection is done using wavelets, which is widely used in image processing or other applications which involve edge detection. In this approach wavelets are used for detecting edges in power spectral density of wideband channel for spectrum sensing. The edges in power spectral density are the boundary between spectrum holes; hence, it helps to find vacant bands [19]. Based on this information, this wavelet based detection technique can be used for spectrum sensing in cognitive radio systems.

Power of each band/channel and its subbands/channels can be calculated from scaling and wavelet coefficients expressed in (3) and (4). The wavelet filter banks with Infinite Impulse Response (IIR) filters are explained in [18]. The main advantages of IIR Poly-Phase filter banks are good frequency selectivity and low complexity. The conventional two-channel wavelet filters can be represented by two-channel IIR Poly-Phase filters like the following equations:

$$L(z) = E_{00}(z^2) + z^{-1}E_{01}(z^2) \quad (5a)$$

$$H(z) = E_{00}(z^2) - z^{-1}E_{01}(z^2) \quad (5b)$$

where “ $L(z)$ ” and “ $H(z)$ ” are conventional IIR low-pass filter and high-pass filter, respectively, and “ E_{00} ” and “ E_{01} ” are all-pass filters. Figure 4 shows the two-channel IIR Poly-Phase filter bank. It decimates a signal before the filtering and uses all-pass filters with small number of filter coefficients comparing to the original low-pass and high-pass filter. This makes the complexity low.

In Figure 4, “ $x_0(n)$ ” and “ $x_1(n)$ ” represent even and odd indices of “ $r(n)$ ”. “ $y_0(n)$ ” is the equivalent to the output of the low-pass filter “ $L(z)$ ” and “ $y_1(n)$ ” is the equivalent to the output of the high-pass filter, “ $H(z)$ ”.

The detailed power measurements using wavelets are explained in [20]. If a received signal, “ $r(t)$ ”, is periodic signal with period, “ T ”, then the power of this signal is computed by

$$P = \frac{1}{T} \int_0^T r^2(t) dt \quad (6)$$

where “ $r(t)$ ” can be expressed as

$$r(t) = \sum_j a_{i_0,j} \phi_{i_0,j}(t) + \sum_{i \geq i_0} \sum_j b_{i,j} \psi_{i,j}(t) \quad (7)$$

where “ $a_{i_0,j}$ ” are the scaling coefficients and “ $b_{i,j}$ ” are the wavelet coefficients computed earlier in (3) and (4),

FIGURE 1: Decomposition of DWT and its frequency separation.

FIGURE 2: Decomposition of DWPT and its frequency separation.

FIGURE 3: Two-stage sensing architecture.

respectively. Using this, the power of the signal can be computed easily.

$$P = \frac{1}{T} \left[\int_0^T \left\{ \sum_j a_{i_0,j} \phi_{i_0,j}(t) + \sum_{i \geq i_0} \sum_j b_{i,j} \psi_{i,j}(t) \right\}^2 dt \right] \quad (8a)$$

$$P = \frac{1}{T} \int_0^T \left\{ \sum_j a_{i_0,j} \phi_{i_0,j}(t) \right\}^2 dt + \frac{1}{T} \int_0^T \left\{ \sum_{i \geq i_0} \sum_j b_{i,j} \psi_{i,j}(t) \right\}^2 dt \quad (8b)$$

$$P = \frac{1}{T} \left[\sum_j c_{i_0,j}^2 + \sum_{i \geq i_0} \sum_j d_{i,j}^2 \right] \quad (8c)$$

where “ T ” is the time period and “ a, b, c, d ” are the scaling coefficients. “ ϕ ” and “ ψ ” are the orthogonal scaling

FIGURE 4: Poly-phase structure of 2-channel IIR filter.

and orthogonal wavelet function. The list of symbols and notations are described in Table 1.

3.2. System Complexity. Complexity of the scheme is computed on the basis of involved mathematical operation (only real multiplications). In DWT, there is $\log_2 N$ level decomposition and only the output of low-pass filter goes to the next level, whereas in DWPT the output of both low-pass and high-pass filters goes to next level as shown in Figure 13. Therefore, the complexity of the system is compared with other schemes having total number of real multiplications for “ N ” sequences in Table 2. From the above results, the total real multiplications of the IIR Poly-Phase filtering schemes for DWT are smaller than conventional wavelet Finite Impulse Response (FIR) filtering scheme and the Fast Fourier Transform (FFT) for large input sequences, “ N ”. Infinite Impulse Response (IIR) poly-phase filtering schemes for DWPT have almost the same complexity order, “ $N \log_2 N$ ”. The proposed algorithm reduces the complexity and makes spectrum sensing faster using the multiresolution property. The complexity of the proposed scheme considering both stages is expressed as

TABLE 1: List of symbols and notations.

Description	Notation/Symbol	Equation no.
Approximate Space	X_i	(1)
Detailed Space	Y_i	(1)
Orthogonal Sum	$\oplus$	(1)
Orthogonal Scaling Function	$\phi_{i,j}$	(2a), (2b), (3), (7), (8a), (8b), (8c)
Orthogonal Wavelet Function	$\psi_{i,j}$	(2a), (2b), (4), (7), (8a), (8b), (8c)
Low Pass Filter	$l_z/L(z)$	(2a), (2b), (5a), (5b)
High Pass Filter	$h_z/H(z)$	(2a), (2b), (5a), (5b)
All Pass Filter	E_{00}, E_{01}	(5a), (5b)
Scaling Coefficient	s, a, b	(3), (4)
Power	P	(6), (8a), (8b), (8c)
Time Period	T	(6), (8a), (8b), (8c)
Generated Signal	$x(t)$	(10)
Amplitude Modulated Signal	$y(t)$	(10), (11)
Received CPE Signal	$r(t)$	(6), (7), (11)
Number of Real Multiplication/Sequence	N	(9a), (9b), (9c), (9d), Table 2.
Length of High,Low Pass Filter	L	(9a), (9b), (9c), (9d)
Total Bandwidth	B_t	Algorithm 1
Channel Bandwidth	B_c	Algorithm 1
Amplitude	A	Algorithm 1
Frequency	$Freq(f_i)$	Tables 3 and 4.
Attenuation Factor	a_i	(11), Tables 3 and 4.
Carrier Frequency	F_c	(10)
Sampling Frequency	F_s	(10)
Noise	$n(t)$	(11)
Probability of Detection	Pd	(12), (16)
Probability of Missed Detection	Pmd	(16)
Mean	m	(12), (13)
Standard Deviation	sd	(12), (13)
Probability of False Alarm	Pfa	(13)

TABLE 2: Number of mathematical operations showing the complexity of the technique [8].

Technique	Number of Mathematical Operation
FFT	$= (N/2) \log_2 N \rightarrow$ Complex Multiplication $= 2 N \log_2 N \rightarrow$ Real Multiplications
5 dB FIR Discrete Wavelet Transform*	$= 20 \text{ Coeff.} (N + N/2 + \dots + N/2^{\log_2 N - 1})$ $= 40 (N - 1)$
Butterworth Poly-Phase IIR Filter for DWT*	$= 4 \text{ Coeff.} (N/2 + \dots + N/2^{\log_2 N})$ $= 4 (N - 1) \rightarrow$ 2-Level $= 6 (N - 1) \rightarrow$ 4-Level
5 dB FIR Discrete Wavelet Packet Transform*	$= 10 \text{ Coeff.} (2N + \dots + 2^{\log_2 N} (N/2^{\log_2 N}))$ $= 10 (2 N \log_2 N) \rightarrow$ 2-level
Butterworth Poly-Phase IIR for DWPT*	$= 3 \text{ Coeff.} (2N/2 + \dots + 2^{\log_2 N} N/2^{\log_2 N})$ $= 3 (N \log_2 N)$

*Only Real Multiplication.

$$\text{Complexity} = 2LN + 2\frac{LN}{2} + \dots + \frac{2LN}{2^{\log_2(N-1)}} \quad (9a)$$

$$= 2LN + (2^0 + 2^1 + \dots + 2^{\log_2 N - 1}) \quad (9b)$$

$$= 2LN + 2\frac{LN}{2} + \dots + \frac{2LN}{2^{\log_2(N-1)}} \quad (9c)$$

$$= 4LN - 4N \quad (9d)$$

where “ L ” is the length of high-pass and low-pass filters and “ N ” is total number of real multiplications. If $L \ll N$, the complexity becomes almost negligible. In the Discrete Wavelet Packet Transform, the outputs of high-pass filter go through the next operation. This is the main difference between discrete wavelet transform and Discrete Wavelet Packet Transform.

4. Performance Evaluation

In this section, simulation environmental setup is discussed and the working of the system model based on the artificial scenario is described in detail. The graphical representation of the obtained simulation results is analysed and shown in the following subsection.

4.1. Simulation Environment. A simulation environment is created using MATLAB R2015b (v8.6.0.267246). Five primary (Licensed) users sharing one common Customer Premise Equipment (CPE) are connected as shown in Figure 5. CPE act as the moderating device for sensing the required frequency band of interest by cognitive radio users. Each primary user signal is considered to be a band-pass signal having maximum bandwidth of 100 KHz. The total bandwidth or the scanning range of the system is configured to 1.6 MHz with 16 channels. Total bandwidth “ $B_t = 1.6 \text{ MHz}$ ” and channel bandwidth “ $B_c = 100 \text{ KHz}$ ”; therefore, the maximum number of channels will be “ $B_t/B_c = 1.6 \text{ MHz}/100 \text{ KHz} = 16$ ”. The fading channel is considered to be Additive White Gaussian Noise (AWGN) channel having zero mean and unit variance.

Since the total number of channels is 16, 4-level decomposition is performed which is calculated using “ $\log_2(B_t/B_c)$ ”, i.e., “ $\log_2 16 = 4$ ”. Figure 6 represents 4-level separation of the frequency band based on the above simulation environment. If primary user lies between the frequency bands from 0 to 100 KHz, the power of that channel will be greater than all other channels. The 4-level decomposition of the signal is done using Discrete Wavelet Packet Transform (DWPT). To detect the presence of primary signal, two-channel butterfly IIR Poly-Phase filter is used in the simulation. The total number of data to be computed is 8000 sequences. The algorithm for this proposed system model is in Algorithm 1.

4.2. Simulation Results. Simulation is done using “*wptdec*” toolbox present in MATLAB R2015b (v8.6.0.267246). There are 5 primary users and 1 CPE acting as a base station. CPE performs sensing and informs the secondary users about the vacant channels and further process of decision making is

FIGURE 5: Simulation model setup.

done by the Medium Access Control (MAC) of the corresponding secondary user. This research is focused only on fast sensing mechanism using wavelet packet decomposition; therefore, MAC decision making is out of scope of the paper. MAC decision making protocol is discussed in [21]. Primary user signal is taken as amplitude modulated signal and is generated using MATLAB *ammod* function and is expressed as

$$y(t) = \text{ammod}(x(t), F_c, F_s) \quad (10)$$

where $x(t)$ is the input signal with F_c as the carrier frequency and F_s as the sampling frequency.

The received signal, “ $r(t)$ ”, after passing through the AWGN is the combination of all primary user signals and noise, which can be numerically expressed as

$$r(t) = \sum_{i=1}^5 a_i [y_i(t)] + n(t) \quad (11)$$

where “ a_i ” is the attenuation factor and “ y_i ” is primary user for the i^{th} user. “ $n(t)$ ” is the AWGN having zero mean and unit variance. The frequency of primary user’s is taken to be within 0 to 1.6 MHz, i.e., the scanning range of the CPE.

The simulation parameters are tabled in Table 3. The centre frequencies of the five primary users are fixed at 100 KHz, 400 KHz, 700 KHz, 1100 KHz, and 1500 KHz, respectively. This can be seen in Figure 7(a) as peaks over the frequency 100, 400, 700, 1100, and 1500 KHz. The signal “ $y(t)$ ” is passed over the AWGN channel which adds white Gaussian noise to the signal having Signal to Noise Ratio (SNR) per sample as 3-15 dB for all channels. The transmitted signal $y(t)$ and received signal at the CPE over 3 dB, 5 dB, 7 dB, 10 dB, and 15 dB is shown in Figure 7. In this proposed technique advance multiresolution based Discrete Wavelet Packet Transform of the signal is done and shown in Figure 8(a). The output of the signal is measured as “ $r(t)$ ” as the received signal and is numerically express in (11) and plotted

FIGURE 6: Number of channels and its decomposition levels.

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(1) procedure Sensing using Wavelet Based Energy Detection
(2)   Initialize:  $1 B_t, B_c, A, Freq. \triangleright B_t \rightarrow$  Total Bandwidth,  $B_c \rightarrow$  Channel
      Bandwidth,  $A \rightarrow$  Amplitude,  $Freq. \rightarrow$  Frequency
(3)   Transmission Over AWGN channel
(4)   Set Iteration = 0
(5)   Perform Discrete Wavelet Packet Transform(DWPT)
(6)   if Iteration= Rl then                                 $\triangleright Rl = \log_2(B_t/B_c) = 4$ 
(7)     Compute the Power of the channel
(8)   else
(9)     Go to Step (5)
(10)  end if
(11)  Arrange channels in ascending order of Power
(12)  Inform the channel order to MAC Layer     $\triangleright$  MAC  $\rightarrow$  Medium Access Control
(13) end procedure

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ALGORITHM 1: Algorithm for the proposed system model.

in Figure 8(b). Due to this noise, shifting in the peaks is noticed in the received signal, " $r(t)$ " as seen in Figure 8(b).

In this proposed scheme, the signal processing is improved for multiresolution wideband signal for cognitive radio as shown in Algorithm 1. After the wavelet decomposition, the energy for the each wavelet packet is calculated using the *wenergy* function. This function returns the percentages of energy within the each terminal nodes of the tree. The pseudo-code of this proposed algorithm is shown in Algorithm 1. This computed percentage energy of each channel is plotted as power as seen in Figure 8(c). It is observed that channel "9" has the lowest power of " -1.8 dBW", while channel "1" has the highest power of approx. " 12 dBW", thereby conveying a direct message that channel "1" has highest probability of being used, while channel "9" has the highest probability of not being used. So assigning channel "9" to secondary user reduces the risk of interference with primary user. Therefore channel "9" is assigned as the highest priority and channel "1" as the least.

For the quick sensing, the channels are sorted in the ascending order of power in dBW as shown in Figure 8(d). The channel with the lowest power is assigned 1st index and channel with the highest power in the end. This sorted channel list is forwarded to the MAC for spectrum decision making to make cognitive radio network function. This sorting of the channels speeds up the decision making process. The

least probable used channel, i.e., channel "9" is given priority and assigned first to the secondary user. After the allocation of channel to first secondary user, the next least probable used channel i.e., channel "5" (~ -0.5 dBW), is assigned to the next secondary user and this way the process continues. Using this proposed technique, half of the tasks of decision making of MAC is done by physical layer sensing mechanism which reduces the overall latency period of the cognitive radio system and makes the system fast. Moreover, in all other exiting techniques discussed in Section 2, during immediate emergence of primary user, fresh detection of vacant channels is done, which is not required in this proposed mechanism. As in this proposed scheme sorted channel list is made, which keeps on being updated during sensing. In case of immediate emergence of primary user, the next channel from the sorted channel list is allocated to the secondary user. This solves the problem of delayed sensing in cognitive radio networks or call drops in cellular communication systems. Appendix discussed the working of *wpdcc* and *wenergy* functions of MATLAB. The 4-level tree decomposition of DWPT is shown in Figure 12 and simulated energy at each node is plotted in Figure 13.

To test the proposed model in dynamical changing environment, the centre frequencies of the primary user are varied and the effect of this dynamic changing real-time environment on the performance of the system is measured.

FIGURE 7: Simulation results using wavelet based energy detection method.

TABLE 3: Simulation parameters of attenuation factor.

Attenuation Factor	Value	Frequency	Value
a_1	0.05	f_1	100 KHz
a_2	0.025	f_2	400 KHz
a_3	0.0125	f_3	700 KHz
a_4	0.006	f_4	1100 KHz
a_5	0.003	f_5	1500 KHz

FIGURE 8: Simulation results using wavelet based energy detection method.

All the other simulation parameters are kept constant except the centre frequency of the 5th primary user (PU5) which is randomly varied from 600 KHz to 1300 KHz. The simulation parameters in this case are shown in Table 4, where f_1, f_2, f_3, f_4 are the centre frequency for PU1, PU2, PU3, PU4, respectively, whereas the centre frequency for PU5 is varied and simulated power using the wavelet packet transform is plotted for the same in Figure 9. Figure 9(a) shows the effect of change

in frequency of primary user on computed power of each channel and Figure 9(b) shows the sorted channel list.

Comparative performance analysis of the proposed advanced multiresolution wavelet technique is also done, in which the receiver operating characteristics (ROC) curve for proposed wavelet technique is compared with simple wavelet transform, DWT, and DWPT. The simulation result for ROC is analysed calculating the probability of false alarm (P_{fa})

FIGURE 9: Different changing frequency of primary user.

TABLE 4: Simulation parameters of attenuation factor with different frequencies.

Attenuation Factor	Value	Frequency	Value	Frequency	Value	Frequency	Value
a_1	0.05	f_1	100 KHz	f_1	100 KHz	f_1	100 KHz
a_2	0.025	f_2	400 KHz	f_2	400 KHz	f_2	400 KHz
a_3	0.0125	f_3	700 KHz	f_1	700 KHz	f_1	700 KHz
a_4	0.006	f_4	1100 KHz	f_4	1100 KHz	f_4	1100 KHz
a_5	0.003	f_5 (Blue)	600 KHz	f_5 (Green)	900 KHz	f_5 (Red)	1200 KHz

FIGURE 10: Comparative ROC analysis of proposed technique.

versus probability of detection (P_d). The comparative ROC curve for the Proposed Advance Multiresolution Wavelet with the other wavelet techniques is graphed in Figure 10.

Probability of false alarm (P_{fa}) is varied from 0 to 1 and probability of detection (P_d) is calculated using the following expression:

$$P_d = \text{normcdf}(\lambda, m, sd) \quad (12)$$

where normcdf is a MATLAB function to compute normal CDF at each value of " λ " using the corresponding mean " m " and standard deviation " sd ". " λ " is the threshold which is calculated using

$$\lambda(i) = \text{norminv}(P_{fa}, m, sd) \quad (13)$$

where norminv is a MATLAB function to compute normal inverse of each value of P_{fa} using corresponding mean " m " and standard deviation " sd ".

The normal CDF is given as follows:

$$\text{normcdf} = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^x e^{-(t-\mu)^2/2\sigma^2} \quad (14)$$

The normal inverse is given as follows:

$$\text{norminv} = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-(t-\mu)^2/2\sigma^2} \quad (15)$$

FIGURE 11: Signal over different environmental conditions.

The complementary receiver operating characteristics for the same are also performed in which Probability of Missed Detection (P_{md}) is analysed with respect to probability of false alarm (P_{fa}). Probability of missed detection is calculated using

$$P_{md} = 1 - P_d \quad (16)$$

In the end proposed model is also tested for critically faded channels. In this case the signal is passed over AWGN channel with different SNRs. Various simulation processes were repeated to test the extreme conditions, and only four of them are presented in this paper, i.e., “3 dB”, “5 dB”, “7 dB”, and “10 dB”. “3 dB” is considered as the worst channel and “10 dB” as the best channel condition. Same signal is passed over all the four channels and output of the same is graphed in Figure 11. 1st row shows the transmitted signal, 2nd row shows the received distorted signal, 3rd row shows the computed power, and 4th row shows the sorted channel list. From the graph of the received signal, the worst channel, i.e., 3 dB, is highly distorted and the best channel, i.e., 10 dB, is least distorted. Below 3 dB, where simulation failed, no energy within the channels is detected. Therefore, 3 dB SNR is considered as the minimum SNR required for the cognitive radio network to work for wavelet sensing technique for cognitive radios.

5. Conclusion

Fast and efficient spectrum sensing technique using Advance Multiresolution Wavelet Transform is proposed by improving the Discrete Wavelet Packet Transform Technique.

This proposed technique is a hybrid approach which is a combination of feature detection using wavelets and sensing using energy detection method. Wavelet Packet Transform provides accuracy, while energy detection method reduces complexity, making the systems fast and efficient. Simulative testing of the proposed scheme is done and results show the performance of the overall system. Fast sensing is achieved which reduces the latency period to nanoseconds. This scheme is also tested over different channel conditions and it performs efficiently till SNR 3 dB. However, below 3 dB, the performance deteriorates extremely and system fails. Therefore, 3 dB SNR is considered as the minimum SNR required for the cognitive radio network. Moreover, during immediate emergence of primary user, fresh detection of vacant channels is not required in this proposed mechanism. This proposed scheme can be implemented in real-time environment, where immediate emergence of primary user is too often and unpredictable. Therefore, quick and immediate shifting over the sensed vacant channel is of great importance and is a challenging task. So to mitigate this issue, fast and efficient spectrum sensing technique is required. This proposed scheme can be implemented for cellular networks where the problem like call drop can be solved as an application of cognitive radios.

Appendix

wpdec Toolbox

wpdec is a one-dimensional wavelet packet analysis function. In this wavelet packet method generalization of wavelet

FIGURE 12: DWPT tree decomposition.

FIGURE 13: Wavelet decomposition plot at every node.

decomposition is done that offers a richer signal analysis. Wavelet packet atoms are waveforms indexed by three naturally interpreted parameters: position and scale as in wavelet decomposition, and frequency. For a given orthogonal wavelet function, a library of wavelet packets bases is generated. Each of these bases offers a particular way of coding signals, preserving global energy and reconstructing exact features. The wavelet packets can then be used for numerous expansions of a given signal. Simple and efficient algorithms exist for both wavelet packets decomposition and optimal decomposition selection. Adaptive filtering algorithms with direct applications in optimal signal coding and data compression can then be produced.

In the orthogonal wavelet decomposition procedure, the generic step splits the approximation coefficients into two parts. After splitting, we obtain a vector of approximation coefficients and a vector of detail coefficients, both at a coarser scale. The information lost between two successive approximations is captured in the detail coefficients. The next step consists in splitting the new approximation coefficient vector; successive details are never reanalysed. In the corresponding wavelet packets situation, each detail coefficient vector is also decomposed into two parts using the same approach as in approximation vector splitting. Figure 12 shows the simulation Discrete Wavelet Packet Decomposition Tree of the proposed system model where the simulation results at every node are plotted in Figure 13.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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