



# FPGA IMPLEMENTATION FOR THE HARDWARE ARCHITECTURE USED IN CYCLOSTATIONARY DETECTOR

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## ABSTRACT

Cognitive radio is one of the modern techniques which is evolved for utilising the unused spread spectrum effectively in wireless communication. Sensing of spectrum holes in a particular spectrum is one of the important concepts in implementing a CR system. In cognitive radio system the foremost concept is sensing the holes (spaces) in the frequency spectrum allotted and it facilitates a way that how effectively and efficiently the bandwidth is used by finding the spectrum holes in a designated spectrum. Among the various methods available for spectrum sensing, cyclostationary detection is found to be more effective and efficient. This cyclostationary feature mainly focuses on detecting whether the primary user is present or absent. By using cyclic cross-periodogram matrix, the calculation of threshold of a signal is carried out to find the existence of noise or signal. The difficulty in evaluating the targeted threshold can be overcome by means of training an artificial neural network and extract cyclostationary feature by FFT accumulation method. This paper is proposing hardware architecture for cyclostationary feature detection using FFT accumulation method and artificial neural network. The proposed method is implemented using FPGA. From the synthesis report it is found that the maximum frequency of operation is 78MHz.

**Keywords:** cognitive radio, cyclostationary, FFT, energy detector, FPGA, neural network etc.

## INTRODUCTION

We have been witnessing the heavy demand and increase number of users in wireless communication systems and its applications. The usage of frequency bands or spectrum is strongly regulated and allocated to specific communication technologies. The enormous majority of frequency bands are allocated to licensed users who are steered by standards. There are several organizations working on standards [1] for frequency allocation, such as the European Telecommunications Standards Institute (ETSI), the International Telecommunication Union (ITU) and the European Conference of Postal and Telecommunications Administrations (CEPT).

According to OFCOM consultation report [2], a substantial amount of spectrum termed as white space is obtainable subjected to time and site basis. The report outlines that over 50% of locations are likely to have more than 150 MHz of spectrum interleaved and that even at 90% of locations around 100 MHz of interleaved spectrum might be available. In addition, the shifting to the Digital Terrestrial Television (DTT) eases for OFCOM to clear many bands such as the 800 MHz (channels 61-69) for future cognitive radios.

One of the major issues in the cognitive radio technology is spectrum sensing. In cognitive radios, the system recognizes the electromagnetic environment by sensing the spectrum. At the Royal Institute of Technology in Stockholm, in the year 1998, Sir Joseph Mitola-III [3] has conceived the concept of cognitive radio. Since then Cognitive Radio has become solution to the crowded spectrum problem by introducing the opportunistic usage of the frequency bands [4]. Provided the licensed users should not have occupied these frequency bands. The components in the cognitive radio have the ability to measure, sense; learn the parameters related to the radio

channel [5], [6] and also have the information regarding the availability of radio spectrum, power, the user requirements, applications and also its operating restrictions. In the dialect of cognitive radio, the primary user (PU) is the user who has higher priority on the usage of allotted frequency spectrum. Secondary user is the user who has lower priority.

The secondary user should access the spectrum in such a way that it does not create any sort of interference to the existing primary user. The secondary user too will have the cognitive radio capabilities, like sensing whether the spectrum band is being used by any primary user and also to change its own radio parameters in order to utilise the unused band spectrum hole. If the spectrum sensing is not done properly, the cognitive radio system gives inaccurate information about the radio environment, and the system will try to use the spectrum which a primary user uses and does not use the spectrum which the primary user is not utilising. There by causing interference to the primary user. This results in several performance degradation of the cognitive radio system and the primary user [7].

Many researchers believe that cyclostationary feature detection is more suitable choice than matched filter and energy detector techniques [8]. The matched filter detector which is a coherent type detector requires prior knowledge about primary user's waveform. A non-coherent energy detector does not require any such sort of prior knowledge about waveforms. It measures energy in each narrowband channel and determines the presence of a primary user if the energy detected in a narrow band channel is higher than a certain threshold. However, to achieve high receiver sensitivity, a low threshold has to be used. In some cases, the threshold has to be lower than the noise floor, in which case the detection fails. Because of



the presence of CR user's interference, the noise is most likely non Gaussian and this makes the problem more complicated. Even if it is easy to implement energy detector, it is highly prone to in-band interference and changing the noise levels [9] and it cannot differentiate between signal power and noise power.

Most of the signals encountered in wireless communications are cyclostationary, whereas the noise is stationary. Sinusoidal carriers, repeating codes, cyclic prefixes, hopping sequences, pulse trains are some of the important features of a wireless communication signal which is cyclostationary and because of the signal's mean value, autocorrelation function it exhibits periodicity. We are very interested in periodicity of a signal because of its usefulness in performing the functions like detection, identification and estimation of the received signal [10]. The block diagram of cyclostationary detection is shown in Figure-1.



**Figure-1.** Block diagram of cyclostationary detection.

In a particular signal due to modulation and coding, the statistical features like mean and auto correlation changes with respect to time and so the signal exhibits regenerative periodicity which is the distinctive property of cyclostationary process [5].

Cyclostationary feature detection can be achieved by following methods [1]

FFT Accumulation Method (FAM).

Striped Spectrum Correlation Method (SSCM).

We arrive at cyclic cross periodogram which is time smoothed represented in matrix form using these methods. In the cross periodogram the signal's correlation values are imparted. The matrix will bring out the signal or noise which is dealt as an input to the detector. The size of the matrix is got decided by the sampling rate and the cyclic frequency. Threshold value is predicted by an artificial neural network (ANN). Interconnection of neurons forms an ANN. By properly training the ANN the value of cyclic cross periodogram threshold is determined in the cyclostationary feature detection process.

## SPECTRUM SENSING

For many years now, to detect the signal CR spectrum sensing system model is adapted. As per the theory of signal detection [11] the spectrum sensing by CR is modelled as follows. Considering the channel with path loss, multipath fading and time dispersions the primary

user's received signal is represented as  $x(n)=s(n)+w(n)$ , where  $s(n)$  is the primary user's signal and  $w(n)$  is the white noise.

The intention of spectrum sensing is to make a decision between the two binary hypothesis testing with:

$$H_0: x(n) = w(n) \quad (1)$$

$$H_1: x(n) = s(n) + w(n) \quad (2)$$

Where  $H_0$  represents the null hypothesis i.e, the signal of primary user is absent.  $H_1$  represents the hypothesis that the signal of primary user is present. Probability of miss detection ( $P_{md}$ ) and Probability of false alarm ( $P_f$ ) are the key parameters to measure the performance of Spectrum detection. When a busy channel is found unoccupied (idle), Miss Detection occurs. This means that the detector has not detected the signal  $H_1$  hypothesis. When an unoccupied (idle) channel is found to be busy, false alarm occurs. This means that the probability of the detector having detected the signal ( $H_0$ ) [12]. The following definitions holds good:

$$P_{md} = P_r(H_0/H_1) \quad (3)$$

$$P_f = P_r(H_1/H_0) \quad (4)$$

The Probability of detection,  $P_d$ , is defined as

$$P_d = P_r(H_1/H_1) = (1 - P_{md}) \quad (5)$$

Along with the above mentioned parameters, Spectrum sensing time is yet another essential parameter to be considered for the analysis. When the PU wants to come back to use their licensed spectrum there should not be any interference. So, the sensing time should be maintained as short as possible. IEEE 802.22 standard on cognitive radio has formulated on the sensing time, that it should be not more than two seconds [13]. Frequency resolution, bandwidth, power and area consumption are the other essential implementation parameters which to be considered.

### A. 802.11 Subcarrier format

The frame structure of an 802.11a contains a preamble field followed by a signal field and multiple data fields. Preamble is transmitted at the burst start with known magnitude and phase. Synchronization and channel equalization is accomplished with preamble. The signal field contains the length, modulation type, and data rate information. Then the input data bits are appended to complete the burst [14]. The Figure-2 shows the Frame structure of 802.11a.

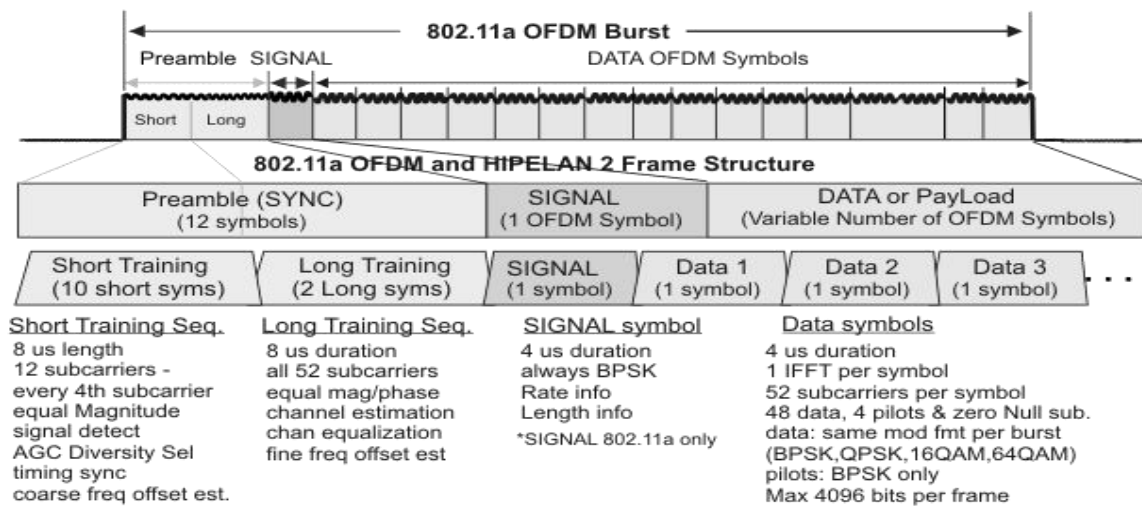


Figure-2. 802.11a Frame structure.

In 802.11a/g, the subcarriers are each 312.5 KHz wide. The composition of 802.11a/g comprises of 64 subcarriers which is achieved by dividing the Channel bandwidth (20 MHz) with subcarrier bandwidth (312.5 KHz). This may be considered as 64-point FFT/IFFT. These 64 subcarriers can independently modulate to carry part of the input data stream. In 802.11a/g the guard subcarriers are the first six subcarriers placed at the lower end of the channel and next five subcarriers placed at upper end of the channel. These sub carriers are considered as guard bands that restricts Inter-channel Interference (ICI) with the adjacent channels on both the lower and upper side. These guard bands are always inactive or null. The

Direct Conversion subcarrier (DC), at the center is also inactive.

In the 802.11a/g frame remaining 52 subcarriers, 4 are reserved to be used as pilot subcarriers. The pilot subcarriers hold only timing and frequency information which helps the receiver in sync with the transmitted signal. Out of 64 subcarriers the pilot subcarriers are positioned at -21, -7, 7 and 21 nodes. The pilots that carry information, is not information derived from the input data. Final only 48 subcarriers are available to be modulated with input data [15]. The Figure-3 shows the Subcarrier format of 802.11a.

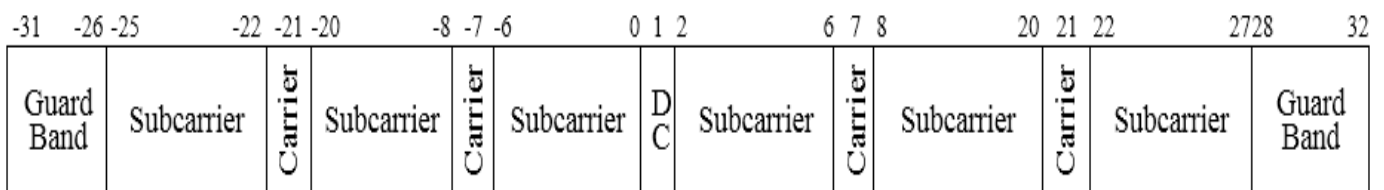


Figure-3. 802.11a Subcarrier format.

## B. Floating point representation

Floating point number as shown in the Figure-4 is represented in 3 fields i.e., as sign, exponent, mantissa. A 16-bit word is divided as 1 bit for the sign, for exponent it is 4 bits and for the significance 11 bits. Since the exponent field is 4 bits, it can be used to represent exponents between -8 and 7. The first 11 bits of mantissa are represented in binary form is stored in significant field namely  $m_0m_1\dots m_{10}$ . It is usually fractional value of the given number. 1's complement/2's complement or sign-and-modulus is not used to represent an exponent. Instead we use a biased representation for exponent field like E+4. In this case, the number 4 is added to the desired exponent E called the exponent bias.

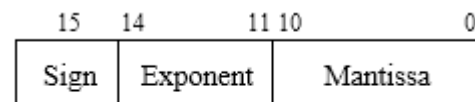


Figure-4. Floating point representation.

The input signal is represented as in Figure-5 that has 16 bits real and 16 bits imaginary value.

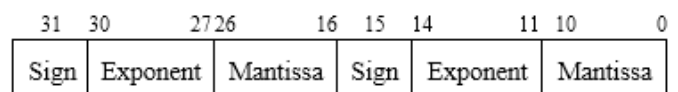


Figure-5. Signal representation.



For 64 point FFT operation the following floating point operations are vital.

- Floating point addition
- Floating point multiplication

Follow the following steps for Floating point addition

- a) Equalize the exponents.

The operand with the smaller exponent should be rewritten by increasing its exponent and shifting the point leftwards.

- b) Mantissa terms are added.
- c) If necessary the result is normalized.

By executing step 3 the point will shift either left or right, and the exponent may increase or decrease.

- d) If needed the number may be rounded.
- e) If the result doesn't normalize then repeat Step 3.

Follow the following steps for Floating point multiplication

- a) Multiply two floating-point values, first multiply their magnitudes and then add their exponents.
- b) Then value is rounded and result is normalized
- c) The sign of the product is the exclusive-or of the signs of the operands.

- If two numbers have the same sign, their product is positive.

- If two numbers have different signs, the product is negative. [16]

### CYCLOSTATIONARY FEATURE DETECTION ALGORITHM

Data signal is a modulated stationary random signal where it's mean and auto correlation shows periodicity. Due to the Cyclostationarity feature this modulated random signal is detected even in the presence of background noise. Signal  $x(t)$  is considered to be second order cyclostationary, if its mean and autocorrelation are periodic with a period  $T_0$ , i.e.:

$$M_x(t+T_0) = M_x(t) \quad (6)$$

$$R_x(t+T_0, \tau) = R_x(t, \tau) \quad (7)$$

Then, the periodic function  $R_x(t, \tau)$  may be expressed as

$$R_x(t, \tau) = \sum_{n=-\infty}^{+\infty} R_x^{\frac{n}{T_0}}(\tau) e^{j2\pi \frac{n}{T_0} t} \quad (8)$$

Equation (8) is known as cyclic autocorrelation functions. Let  $\alpha$  represent the frequencies  $\{n/T_0\}_{n \in \mathbb{Z}}$ , referred to as cycle frequency. From the Fourier transform of the cyclic autocorrelation function (7) the spectral

correlation density (SCD), or cyclic spectral density, can be obtained as

$$S_x^\alpha(f) = \int_{-\infty}^{\infty} R_x^\alpha(\tau) e^{i2\pi f \tau} d\tau \quad (9)$$

Since the signals being analysed are defined over a finite time interval  $\Delta t$ , the cyclic spectral density is only an estimation. Time smoothing and frequency smoothing methods are used to estimate the cyclic spectral density or SCD. For general cyclic spectral analysis time smoothing algorithms are considered to be more computationally efficient [17]. An estimate of the SCD can be obtained by the time-smoothed cyclic periodogram given by

$$S_x^\alpha(f) = S_{x_{Tw}}^\alpha(t, f) \Delta t \quad (10)$$

Where  $\Delta t$  is the total observation time of the signal. The cycle frequency resolution of the estimation,  $\Delta\alpha$ , is determined by  $\Delta\alpha = 1/\Delta t$ . Where  $T_w$  is the short-time FFT window length. The spectral components generated by each short-time Fourier transform have a resolution of  $\Delta f = 1/T_w$ . In addition, there is an overlap factor, denoted by  $L$ , between each short-time FFT.

The FFT accumulation method which is a time-smoothing algorithm is proved to be computationally effectual than frequency-smoothing algorithms. For the time discrete expressions of SCD, we define the sampled signal

$$x(n) = x(n \cdot \frac{1}{f_s}) \quad (11)$$

Where  $f_s$  indicates the sampling frequency. Furthermore, we assume parameter  $N$  ( $n=1, 2, \dots, N$ ) represents the total number of discrete samples within the observation time. The Figure-6 gives the block diagram for Principle of cyclostationary Detector.

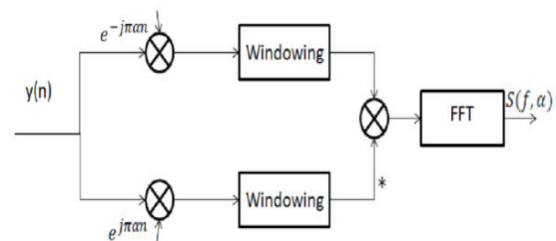
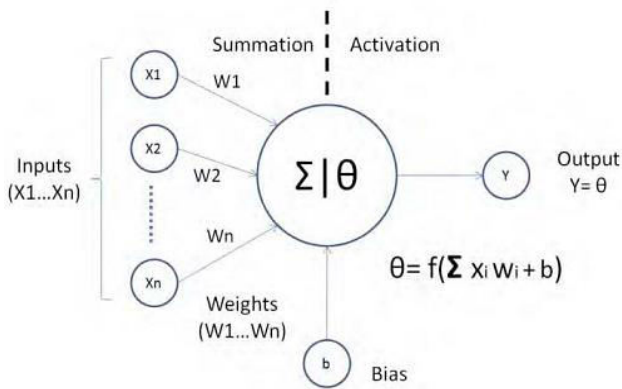


Figure-6. Principle of cyclostationary detector.

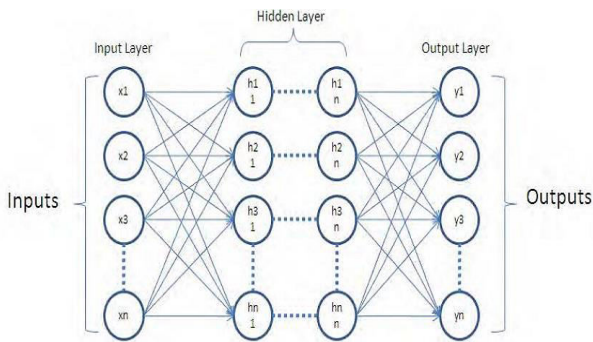
A neural network is trained to optimize the threshold value to detect whether the signal is present or not. The ANNs are built with neuron which consists of  $n$  number of inputs along with weights of each input. The actual functionality of a neuron is represented by the summation part [13]. Depending on the application, the summation node's output is fed to an activation function. The Figure-7 shows the general representation of neural network.





**Figure-7.** General representation of a neuron with inputs, weights and activation function.

For the back propagation neural network application, the most frequently used activation function is the hyperbolic tangent (tanh) sigmoid function (referred to as tansig in Matlab) [10], [18]. The Figure-8 gives the back propagation neural network



**Figure-8.** Representation of an ANN with n number of input, hidden and output layers.

The sigmoid function is given below

$$f(n) = \frac{e^n - e^{-n}}{e^n + e^{-n}} \quad (12)$$

The error is calculated as per the following equation

$$E = \sum_i E_i \quad (13)$$

$$E_i = \frac{1}{2} \sum_i (t_i - y_i)^2 \quad (14)$$

E represents the summation of all the errors,  $E_i$  is Error due to single output ( $y_i$ ), corresponding target  $t_i$  and the weights are updated after the error calculation by using the following method.

$$\Delta W_i = \epsilon((t_i - y_i)x_i) \quad (15)$$

$$W_i = W_i - \Delta W_i \quad (16)$$

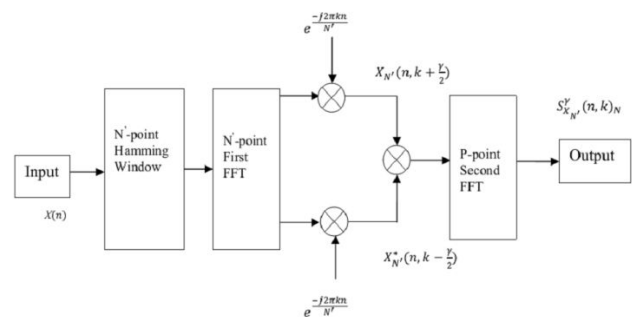
Where  $\Delta W_i$  is change in weight of the  $i^{\text{th}}$  connection corresponding to the input  $x_i$  and  $W_i$  is the value of the old weight,  $\epsilon > 0$  is the learning rate used in calculating weight change.

## HARDWARE IMPLEMENTATION OF CYCLOSTATIONARY DETECTION ALGORITHM

Due to modulated signal's periodicity, the Spectral redundancies occurs and by these spectral components are widely separated and correlation is maintained by the Cyclostationary signals [18]. With the operating frequency of 5 GHz, the cyclic cross periodogram is realized with executing IEEE 802.11a signal as input to FFT accumulation method. Cyclostationary feature detection is described in following steps:

Determine the points of cyclic frequency, the complex envelopes are estimated efficiently by means of a sliding  $N'$  point FFT, followed by a downshift in frequency to baseband. Sliding windows are very useful in the analysis of dominant cyclic features. In our simulations we decided to use Rectangular window. A Fourier Transform of these windowed signals is conducted to continue the computation in the frequency domain. The Spectral Correlation Function is computed for each frame, and then normalize by taking its mean. Using the spectral correlation function we can detect the primary user.

OFDM signals scheme helps us better in this process because of its flexibilities in digital communications techniques. The input to FAM which is OFDM Signal contains 64 sub-carrier out of which 52 are pilot and data subcarriers, 11 are guard sub-carriers and 1 is DC null. The OFDM signal is formed by totally 64 points IFFT. There are 4 pilot subcarriers out of 64 subcarriers and the data subcarriers are present at the positions other than pilot subcarriers. The index point 0 is the DC null. Figure-9 gives the FFT Accumulation method architecture.



**Figure-9.** Architecture of FFT Accumulation method.

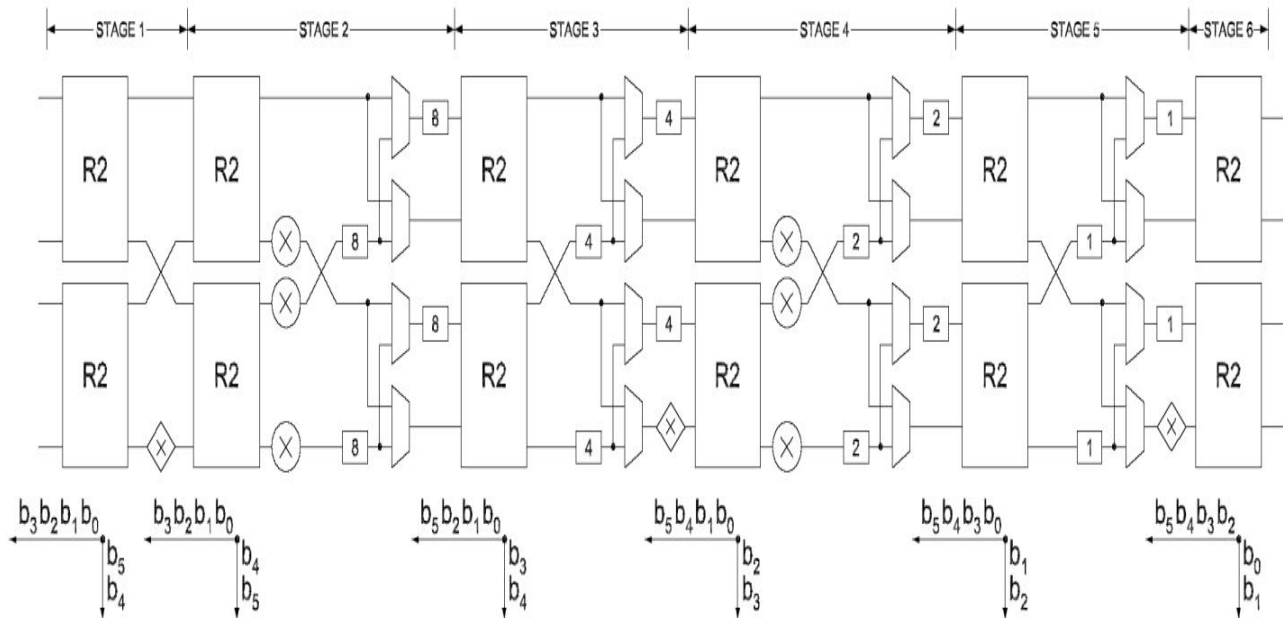
The FAM is implemented by forming a two dimensional arrays from  $X(kT)$ , where  $k$  varies from 0 to  $N-1$ . In this, the columns representing constant frequencies which are obtained by applying Hamming window to the input, Fast Fourier Transformed and then down converted to baseband.

The major hardware part of the cyclostationary detection algorithm is FFT. The design pipelined FFT



hardware architectures of radix- $2^2$  was a milestone. Then, radix- $2^2$  was extended to radix- $2^k$ . Moreover, there are many designs proposed for radix- $2^k$  single-path delay feedback (SDF) architectures, but many designs are not proposed for feedforward ones which is called multi-path delay commutator (MDC). We are proposing radix- $2^k$  feedforward (MDC) FFT architectures for this application. In feedforward architectures radix- $2^k$  can be used for any number of parallel samples which is a power of two. The

proposed designs very high throughputs can be achieved, which enables them to suit for high speed applications. When several samples in parallel are to be processed, it requires a few hardware resources than parallel feedback ones. The proposed 64 point FFT architecture is shown in the Figure-10. These architectures are meant to be more hardware-efficient and make them very attractive for the computation of the FFT.



**Figure-10.** Proposed 64 point feedforward architecture.

### FPGA IMPLEMENTATION

The real and imaginary part of the digital formatted signal  $x(n)$  are multiplied with hamming window. Initially both the real and imaginary parts of the 64 input signals are passed through the FFT module. For implementation we have considered 64 point feed forward FFT architecture. The output signal down sampled and then passed to second stage of FFT architecture. For fast computation the congregated signals are then passed through an artificial neural network. The two neurons named pilot signals average value and data subcarrier forms the part of the input layer. In the hidden layer 5

neurons were used for simulation. Then the signal is compared with threshold value for the presence of primary user. Primary user is present if the value is greater than threshold value.

The above proposed architecture is coded in VHDL. The simulation result is shown in Figure-11. The code is synthesized using Virtex 6 FPGA and the RTL diagram is shown in Figures 12 and 13. The Table-1 shows the device utilization summary. Maximum Frequency of Operation is 77.735MHz and Selected Device is 6vlx75tff784-3.

**Table-1.** Device utilization: Selected device: 6vlx75tff784-3.

S. No.	Name of logic	Used	Available	Utilisation in %
1	Number of slice Registers	5515	93120	5%
2	Number of slice LUTs	18339	46560	39%
3	Number of fully used LUT-FF pairs	4562	19292	23%
4	Number of bonded IOBs	44	360	12%
5	Number of BUFG/BUFGCTRLs	2	32	6%
6	Number of 78E1s	26	288	9%

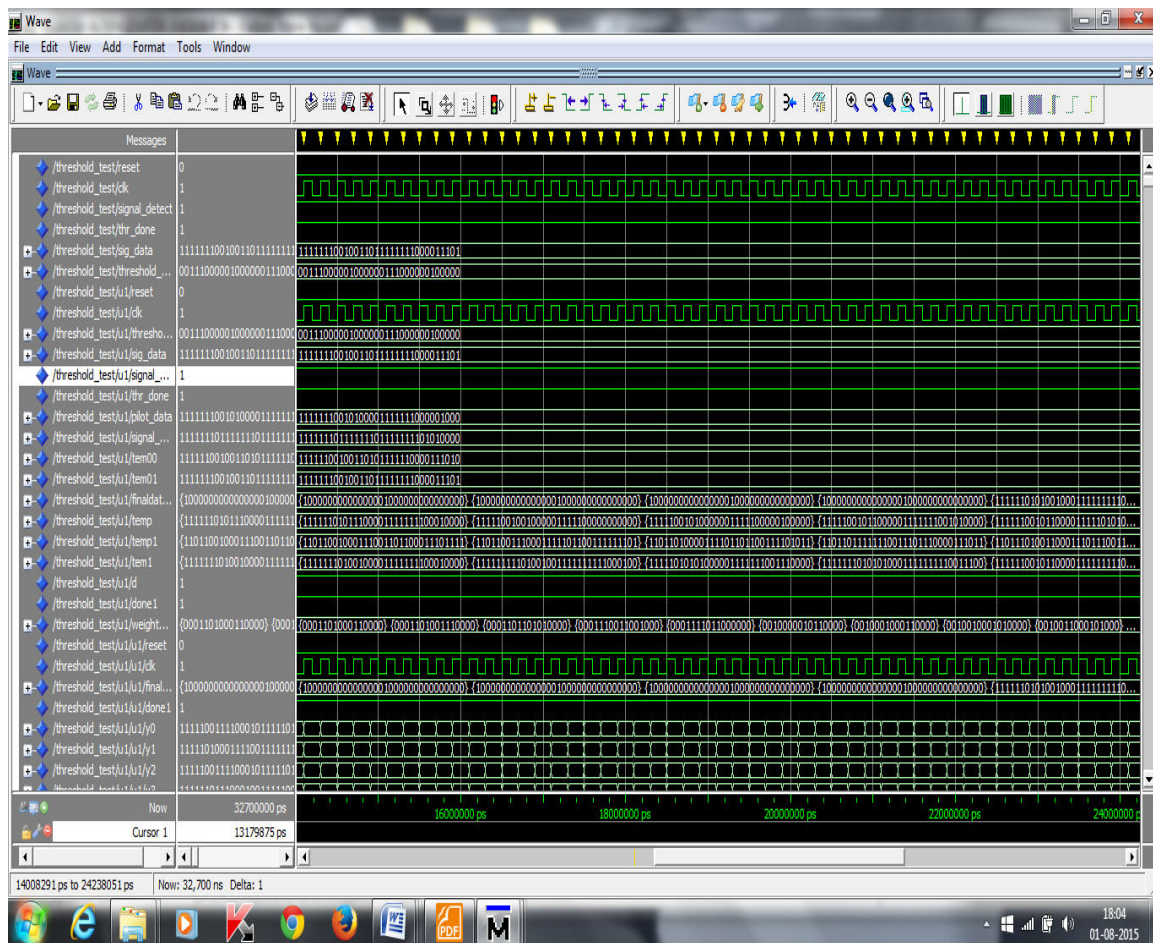


Figure-11. Simulation result of cyclostationary detector.

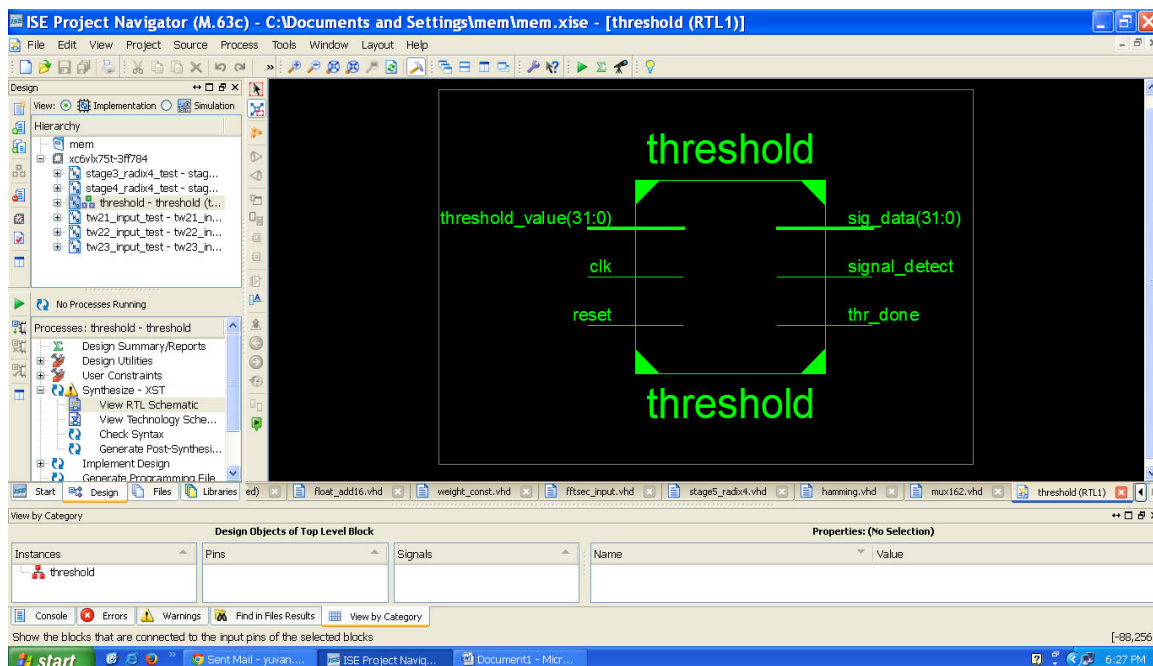


Figure-12. RTL view of top module.



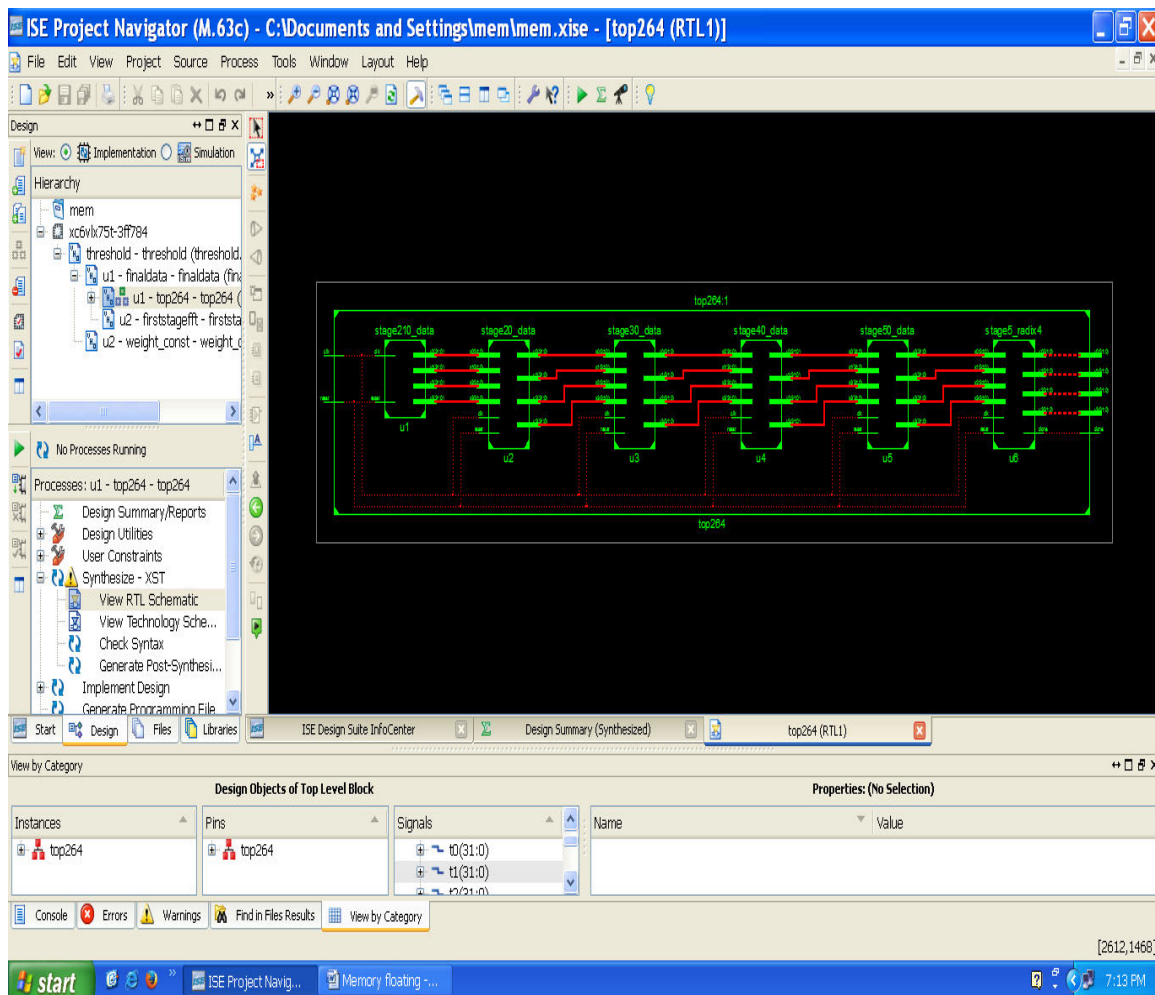


Figure-13. Part of RTL diagram.

## CONCLUSIONS

In this paper to predict the thresholds, an artificial neural network has been trained from the features of cross-periodogram matrix of signal statistics to explore the presence of primary user. FFT accumulation method has been implored for sample vectors. The proposed ANN Scheme clearly indicates the strength of the artificial neural network to detect the presence of spectrum holes. The proposed hardware architecture will improve the performance of the detector. The proposed architecture is simulated using CAD simulation tool and the code is synthesized using Xilinx CAD tool. From the synthesize report we found that the maximum frequency of operation is 78 MHz. The proposed hardware will work for 802.11a signal as its input signal frequency is around 5 GHz. The future work of this project is to implement in ASIC environment to further increase the speed of operation and reduce power and area.

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