FPGA IMPLEMENTATION OF SPECTRUM SENSING TECHNIQUES FOR CR STANDARDS

A THESIS SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF TECHNOLOGY

in

VLSI DESIGN AND EMBEDDED SYSTEM

by

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Odisha. India. 769008.

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Under the Guidance of

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2012 – 14

Dedicated to
Neel, Yamini, Kalpesh and Khushboo

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ODISHA, INDIA-769008

CERTIFICATE

This is to certify that the thesis report entitled **"FPGA Implementation of Spectrum Sensing Techniques For CR Standard"** is submitted by **Suravaram Seshagiri Rao** bearing Roll No.**212EC2146** in partial fulfillment of the requirements for the award of **Master of Technology** in **Electronics and Communication Engineering** with specialization in **"VLSI Design and Embedded System"** during session 2012-14 at National Institute of Technology, Rourkela.

This thesis is an authentic work carried out by him under my supervision and guidance. To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other university/institute for the award of any Degree or Diploma.

Date: 2nd June, 2014

Prof. S. M. Hiremath
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Abstract

Radio spectrum is a limited and valuable natural resource in wireless communications. The conventional spectrum allocation policies are causing a serious problem of spectrum scarcity to the emerging wireless technologies. On the other hand, the studies reveal that most of the licensed spectrum is underutilized. For efficient spectrum utilization, FCC is allowing the sharing of the licensed spectrum with unlicensed users. Cognitive radio is a technology which addresses the issue of spectrum sharing with the help of dynamic spectrum access. Spectrum sensing is a fundamental and essential module in cognitive radio which detects the presence of licensed users in the spectrum. To avoid the harmful interference from an unlicensed user to the licensed user, cognitive radio (CR) has to sense the spectrum efficiently so the spectrum sensing has to be carried out effectively.

In this thesis, different spectrum sensing methods are analyzed and amongst the energy detection method has been considered for FPGA implementation. The parameters such as probability of false alarm and probability of detection are analyzed from Receiver Operating Curves of energy detection method. The energy detection technique in both time domain and in frequency domain has been implemented. The time domain implementation consists of three modules such as energy detector, threshold estimation and a decision module. The complete energy detection module is downloaded onto Spartan-3E FPGA and the validity of functionality is verified through Chipscope Pro core analyzer .In frequency domain implementation the input samples are transformed into frequency domain using FFT IP core generator. A simple model of covariance based spectrum sensing is also been implemented using HDL design.

ACKNOWLEDGEMENT

I take this opportunity to thank and express my deep sense of gratitude to **Prof. S M Hiremath** for his guidance, valuable suggestion and encouragement at every step of my project. Really, I am indebted to him for his excellent and enlightened guidance and especially for providing the freedom in choosing the approach towards my project.

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S Seshagiri Rao

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1. Overview

1.1 Introduction

As the radio spectrum is limited, the spectrum scarcity problem is increasing with the extensive development of new wireless technologies. Government agencies regulate the spectrum allocation and their policy of static spectrum allocation is also adding to the spectrum scarcity.

According to the FCC's spectrum policy task report (2002) [**1**], the utilization of radio spectrum is from 15% to 85% in the frequency band below 3 GHz, which shows that the most of the spectrum is underutilized. The FCC report also includes allowing secondary users to share the spectrum with primary users for the efficient utilization of spectrum. The primary users are having license and assigned with fixed spectrum bands whereas secondary users are unlicensed users can access spectrum of primary users without causing harmful interference.

The spectrum band which is allocated to primary user but not used by primary user is called spectrum hole or spectrum white space. By allocating the white spaces to the secondary users improves the spectrum utilization. To share the licensed spectrum with secondary users there is need for dynamic spectrum access instead of static spectrum allocation policy which is a bottle neck for the spectrum effective utilization.

The dynamic spectrum allocation or opportunistic spectrum sharing is having many challenges like detection of white spaces effectively for which the spectrum has to be sensed continuously. The white spaces are detected in order to share the spectrum with secondary user. As the primary users have pre-emptive access to the spectrum, the spectrum has to be relinquished to primary users when it tries to access the spectrum in order to avoid harmful interference. These challenges are well addressed by cognitive radio technology. Cognitive radio technology is based on software defined radio which has an ability to sense its surroundings and change its operating parameters according to the requirements. Cognitive radio based unlicensed use is the core technology in the IEEE 802.22 standard [**2**], designed to operate in white spaces of TV spectrum ranges from 54-862 MHz on non-interfering basis with incumbent users or primary users. The focus area of IEEE 802.22 standard is rural broadband wireless access.

To avoid the harmful interference with the incumbent users, spectrum has to be sensed carefully. Spectrum sensing is the main module in Cognitive Radio which detects the white spaces by processing the received signal and takes the decision whether incumbent signal is present or not.

1.2 Fundamentals of Cognitive Radio

1.2.1 Introduction to Cognitive Radio

Cognition means a mental deed or process of attaining knowledge through practice and senses. The ITU GSC describes cognitive radio as a system that has the ability to sense and has information about its working environment and can be taught to adjust its operating criterion dynamically and independently. Cognitive radio allows accessing the spectrum dynamically for the efficient utilization of the spectrum. Software defined radio is the core on which the concept of Cognitive Radio has been established [1]. Addition to the functioning of software defined radio, the CR has ability to sense its environment and change its operating parameters dynamically.

- **Software Defined Radio**

Software define radio (SDR) is a transceiver for communication which performs all characteristic functions of a communication system such as modulation/demodulation, amplification, mixing, detection etc. with the help of software. This software functionality can be structured on reconfigurable hardware and this can be applied in numerous communication systems. Depending upon the type of system, the software can be changed on the hardware and the required functionality can be achieved [**3**].

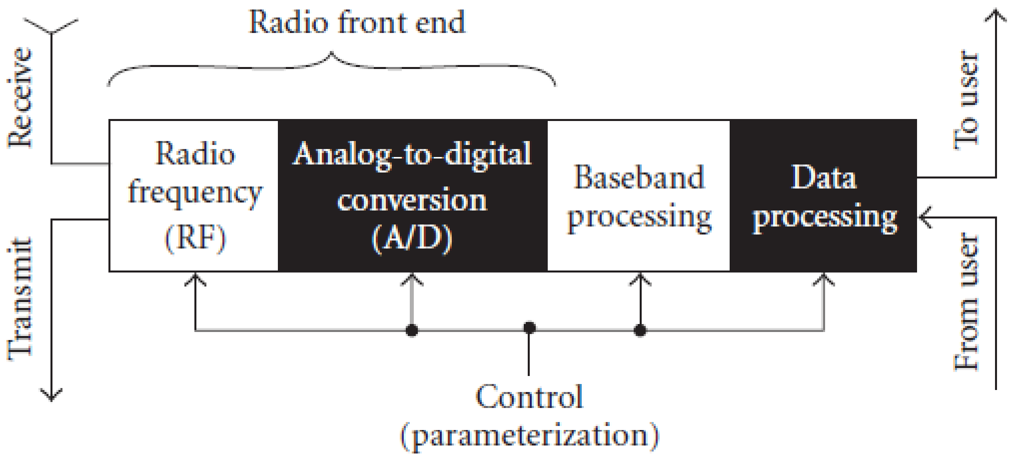

Fig. 1.1 Transceiver of software defined radio [**4**]

In the figure it is seen that a control bus supplies the parameters to the processing units. The parameters supplied by control bus describe the requirement of the desire standard and this makes the SDR transceiver to be different from conventional transceiver.

1.2.2 Cognitive Capability

The cognitive capability of a CR is a process of observing the outside environment in order to find unused radio spectrum and govern suitable communication parameters to acclimatize to the ever-changing radio environment. Mitola is the first to explain the cognitive capability in terms of cognitive cycle in the case of which "*a cognitive radio continually observes the environment, orients itself, creates plans, decides, and then acts*" [**4**].

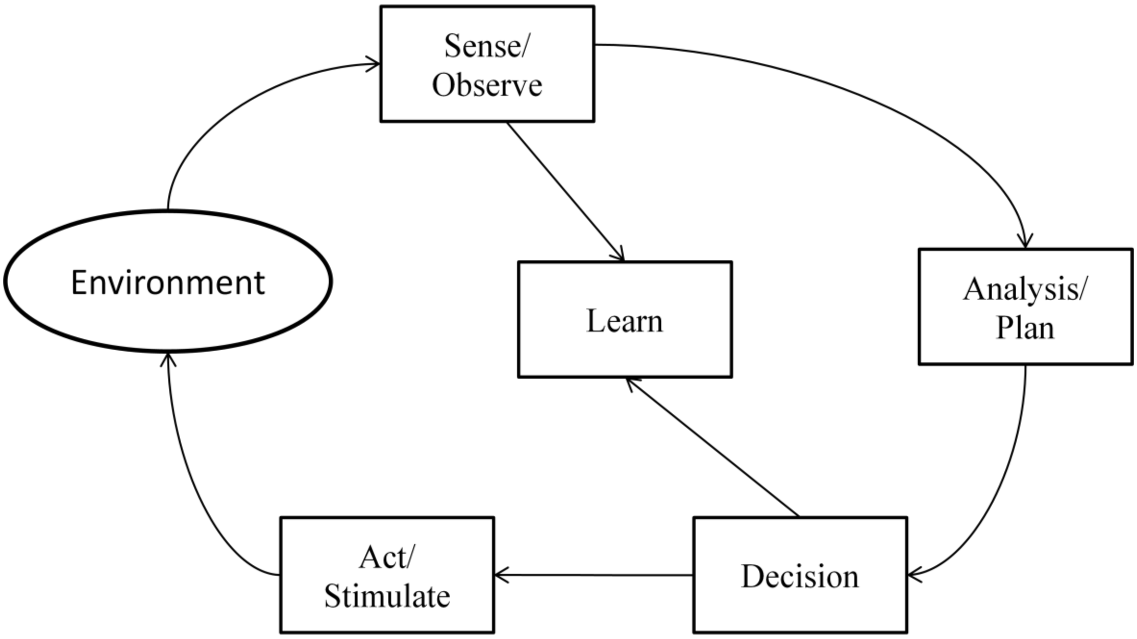

Fig: 1.2 Cognitive cycle

The process of *sensing* the outside world determines the presence of spectrum hole. The observations taken by the sensing will be supply into *plan* cycle processes in which further used, but they also supply to *learn* module to learn and remember. The *learning* allows the system to learn from the experiences. The *analysis* process is responsible for generating and analyzing work streams which may be taken, i.e. determines data rate, bandwidth, frequency, power, modulation, etc. At the *decision* stage of the cycle, the CR is chosen appropriate spectrum band for transmission of the signal. The *analysis, decision* and *learning* components constitute the interior portion of the system, which houses the control box of the entire CR, the *Cognitive Engine*. A cognitive engine can be assumed to be like the human brain which can empower the radio device with intelligent solutions. Finally the decision is put into *action* and the operation of the cognitive radio is actually influenced. The *sensing* (or *observation*) and *action* modules represent the interfaces of the CR with the real world [**5**].

1.2.3 Reconfigurability

The CR has the capability to be programmed to work on a wide range of frequencies. A CR can be programmed to transmit and receive on a variety of frequencies and using diverse access technologies that can be implemented on the hardware design portion. Many parameters like transmission and modulation power, communication technology and operating frequency can be combined into the radio and these can be reconfigured numerous times. Depending on the features of the spectrum, these parameters can be altered to change the functionality of the CR to another spectrum band. Moreover, the parameters at transmitter and receiver end as well as the modulation schemes and their appropriate protocol parameters used for the design of radio can also be altered depending on the spectrum requirements [**6**].

1.3 Motivation and Objective

Energy detection technique is the most popular in spectrum sensing techniques because of its simplicity and also it does not need any information about the signal to be sensed. The process of calculating threshold is a challenging task in energy detection schemes. Fading and shadowing may reduce the intensity of primary signal and fixing a high threshold value causes the secondary user to never detect the primary user. On the other hand fixing a low threshold makes the detector so sensitive. So the fixed threshold schemes results in poor utilization of spectrum. The other issue in energy detector is its poor performance under low SNR values.

The main objective of this work is to study the problems in spectrum sensing techniques and to evaluate and analyze the performance of energy detection technique. Energy detection scheme is implemented using HDL design. Architecture for threshold estimator is implemented which calculates the threshold dynamically.

1.4 Organization of the Thesis

Following the chapter 1 the rest of the thesis is organized as follows:

Chapter 2: In this chapter different spectrum sensing methods are discussed and energy detection is considered for the detailed discussion.

Chapter 3: In this chapter performance evaluation of Energy detection technique is carried out using ROC curve.

Chapter 4: In this chapter a complete HDL design of Energy detection technique is discussed and also a preliminary model of covariance based spectrum sensing is implemented. The energy detector is implemented both time domain and frequency domain.

Chapter 5: In these chapter simulation results of all the modules of energy detection and also for covariance based detection is discussed.

Chapter 6: in this chapter conclusion and future work are framed in short.

2. Spectrum Sensing

The objective of the spectrum sensing is to detect the presence of licensed users in the spectrum. This module continuously monitors the spectrum, to avoid harmful interference from secondary users to the primary or licensed users. There are many spectrum sensing methods in the literature.

2.1 Classification of Spectrum Sensing Methods

Based on the requirements for the implementation the sensing methods, the methods generally classified into three types [**7**] :

- Methods depending only on noise power (semi-blind detection)
- Methods independent of both source signal and noise (blind detection)
- Methods depending on both source signal and information of the noise power.

2.1.1 Semi Blind Detection Techniques

These are the detection techniques which require partial information about the primary signal. The popular semi blind detection techniques includes [**8**] :

- Energy detection technique
- Matched filter detection technique
- Cyclo stationary detection technique

❖ **Energy Detection Technique**

This spectrum sensing technique does not require any antecedent information about type of signal. Thus it is most preferably used in cognitive radio networks. It is also called radiometry as it detects the presence or absence of spectral band by computing the energy of the received signal.

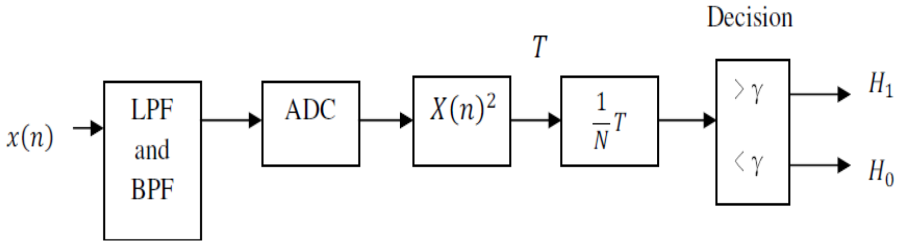

Fig: 2.1Block diagram of energy detection technique [**9**]

Variance of noise is statically determined and the threshold λ is decided. Comparison of energy of received signal with this threshold value decides the presence or absence of signal.

Advantages:

- Implementation simplicity
- Low computational complexities

Disadvantages:

- Highly susceptible to noise level
- Cannot differentiate between modulated signals, noise and interference

❖ **Matched Filter Detection Technique**

Matched filter detection is another signal detection technique that takes structure of signal into consideration for calculating its energy. Performance and cost wise this technique is better than earlier discussed energy detection technique.

Basically matched filter is a linear filter that maximizes signal to noise ratio (SNR) of input signal in presence of additive noise. Knowing the phase of the carrier, it provides coherent detection to demodulate the signal. Fig.2.2 shows the block diagram for primary user detection using matched filter. In this a signal from primary user passes through channel. The channel output is applied to matched filter. It correlates the original signal with time shifted version of signal. The correlated value at the output of matched filter is compared with a predetermined threshold which determines the presence of primary user.

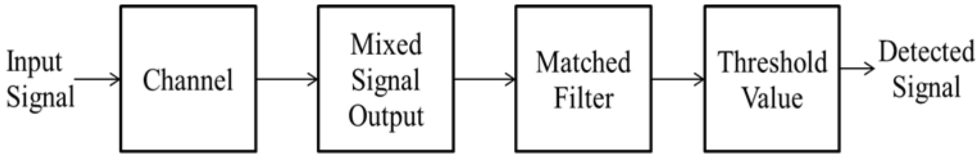

Fig: 2.2Block diagram of matched filter detection

In wireless communication technologies transmission of pilot carrier is necessary for channel estimation. Secondary systems can exploit pilot signals to detect the presence of transmissions of primary systems in their vicinity. Matched Filter (MF) detection achieves optimal signal detection if pilot signal is known. It maximizes the SNR. The threshold value for MF is not same as threshold value taken in ED. In ED threshold value depends on noise variance. MF is performs well in low SNR condition, since MF maximizes power.

Advantages

- It requires short time to achieve a particular probability of false alarm.
- The required number of samples grows as *O* (1/*SNR*) for a target probability of false alarm at low SNR.
- Matched-filtering requires cognitive radio to demodulate received signal.

Disadvantages

- Complexity of sensing device increases due to requirement of receiving unit for all types of signal.
- Various algorithms are used to detect primary user. Thus it consumes more power.
- Pilot carrier transmission is required for channel estimation. But CR might not recognize which network is in operation in that radio environment at that time. Hence CR sensor is unable to know which pilot sequence it is looking for. If it detects incorrect pilot then it detects as that spectrum band is free which is treated as false detection.
- MF requires pilot in every medium for signal transmission. Pilot carriers are

transmitted in downlink direction and pilot carriers are obverted in uplink direction.

- MF is coherent reception method. But in practice it is very difficult to get coherent reception.

❖ **Cyclo-stationary Detection**

MF detection performance is better in low SNR condition. Yet MF requires prior information about signal structure for licensed user detection. If prior knowledge about the signal structure is weak then MF performance is bad. Thus primary user detection can be possible by using cyclo-stationary feature detection with limited information about signal structure.

To detect primary user in spectrum band, it requires periodicity of received signal. The periodicity generally relies on sinusoidal carriers, pulse trains, spreading codes, pilot sequences, cyclic prefixes and other repetitive carriers. These periodicity characteristics signals have spectral correlation and periodic statistics properties. But these properties are not found in random noise signal. Cyclo-stationary feature detection performs better for its noise immunity in low SNR condition than ED method. Still it requires prior knowledge of signal and is able to differentiate primary user signal with CR transmission signal.

CR detects random signals having stochastic noise. The periodic statistics features are extracted using spectral correlation. Fig. 2.3 represents block diagram of cyclo-stationary feature detection. Spectral correlation function is two dimensional functions with cyclic frequency α. It represents power spectral density when α=0.

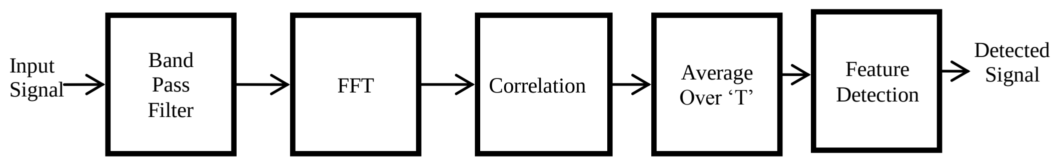

Fig. 2.3 Block diagram of cyclo-stationary detection

Thus the cyclo-stationary signal detection technique is a good detection technique as it performs well with less information about signal structure.

Advantages:

- Accuracy of cyclo-stationary is more than ED and MF.

Disadvantages:

- It is a complex technique in comparison to ED technique.
- It requires larger computational time

2.1.2 Blind Detection Schemes

The spectrum sensing methods which do not depend on the information of the primary signal or noise are called blind detection schemes. The most popular blind detection schemes in the literature are

- Covariance based spectrum sensing
- Eigen value based spectrum sensing

❖ **Covariance Based Spectrum Sensing**

Covariance based spectrum sensing does not need any prior information of signal or noise so it is blind detection technique. This method is based on statistical covariance of the received signals. Since the covariance exploits the correlation between two samples, this method is suitable for highly correlated signals. As the statistical covariance of the noise and the signal are different the methods on statistical covariance are efficient [**10**].

Let us define the following vectors

$$x(n) = [x(n) \quad x(n-1)\ldots \quad x(n-L+1)\ ]^T$$

$$s(n) = [s(n) \quad s(n-1)\ldots \quad s(n-L+1)\ ]^T$$

$$\eta(n) = [\eta(n) \quad \eta(n-1)\ldots \quad \eta(n-L+1)\ ]^T \qquad (2.1)$$

Here L is smoothing factor and the covariance matrix is defined as follows

$$R_x = E[\ x(n)x^T(n)] \qquad (2.2)$$

$$R_s = E[\, s(n)s^T(n)] \tag{2.3}$$

It is verified that

$$R_x = R_s + \sigma_\eta^2 I_L \tag{2.4}$$

If the signal is absent then$R_s = 0$, and the elements of R_x other than diagonal elements are zeros and if the signal is present then R_x is no more a diagonal matrix. So the test static for the covariance based spectrum sensing is the ratio of sum of non diagonal elements to the sum of diagonal elements.

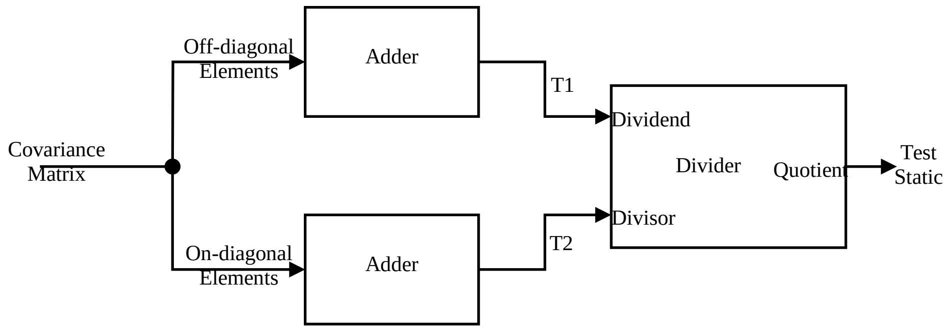

Fig. 2.4 Block diagram of covariance based detection

Here the sum of off diagonal and diagonal elements

$$T_1 = \frac{1}{L}\sum_{n=1}^{L}\sum_{m=1}^{L}|r_{nm}| \tag{2.5}$$

$$T_2 = \frac{1}{L}\sum_{n=1}^{L}|r_{nn}| \tag{2.6}$$

The test static is given as T1/ T2.

- **Eigen Value Based Detection**

Eigen value based detection scheme is considered as blind detection scheme as it requires no information about the signal or noise properties. This method is also based on statistical covariance matrix of the received signal [**11**] .

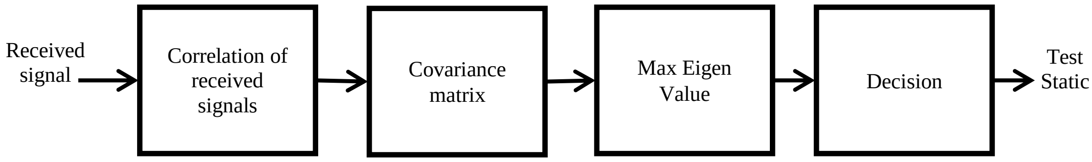

Fig. 2.5 Block diagram of Eigen value based detection

Now define the sample auto correlations of the received signal as

$$\lambda(l) = \frac{1}{N_s}\sum_{m=0}^{N_s-1} x(m)x(m-l), \; l = 0, 1, 2, \dots, L-1 \quad (2.7)$$

From the sample auto correlations form the sample covariance matrix given as

$$R_x(\mathrm{N}_s) = \begin{bmatrix} \lambda(0) & \lambda(1) & \dots & \lambda(\mathrm{L}-1) \\ \lambda(1) & \lambda(0) & \dots & \lambda(\mathrm{L}-2) \\ \vdots & \vdots & \vdots & \vdots \\ \lambda(\mathrm{L}-1) & \lambda(\mathrm{L}-2) & \cdots & \lambda(0) \end{bmatrix} \quad (2.8?)$$

The steps in maximum Eigen value detection algorithm:

Step1: Covariance matrix can be obtained using auto correlation function, so in order to calculated the covariance matrix first derive the auto-correlation of samples of received signal by using eq.(2.7)and represented by λ. Using this correlation covariance matrix is formulated using eq.(2.8)

Step 2: Obtain the maximum Eigen value of the above covariance matrix of samples of received signal and say it be λ_{max} (N_s).

Step 3: Decision of availability of signal is done on the basis of λ_{max} (N_s) such that if λmax(Ns) $= \gamma 6_n^2$ satisfies then signal is present otherwise signal does not exists. Here threshold is set as γ >1.

2.2 Energy Detection Technique:

It is a simple detection because it does not require prior information about structure of signal. Energy detection detects the spectrum by measuring the energy of the received signal in a certain frequency band, also called radiometry. It is the most common detection method for spectrum sensing in cognitive radio networks.

ED is a simple detection technique. The ED is said to be a blind signal detector because it ignores the structure of the signal. ED is based on the principle that, at the reception, the energy of the signal to be detected is calculated. It estimates the presence of a signal by comparing the energy received with a known threshold λ derived from the statistics of the noise.

2.2.1 System Model

The system considered has a licensed user which is considered to be present throughout the sensing time i.e. primary user is changing slowly and a secondary user which is trying to detect primary user by applying energy detection. The problem statement can be formulated on the basis of binary hypothesis testing problem [**12**], where the primary user detection is formulated as follows:

$$H_0\textbf{:}\ Y[n] = W[n] \quad \text{(Primary user absent)} \tag{2.9}$$

$$H_1\textbf{:}\ \ Y[n] = S[n] + W[n] \quad \text{(Primary user present)} \tag{2.10}$$

Where n = 1, 2, 3…N and $Y[n]$ represents the received signal samples, $W[n]$ represents the noise signal samples and $S[n]$ represents the primary signal samples. N represents the no of samples considered for the detection process.

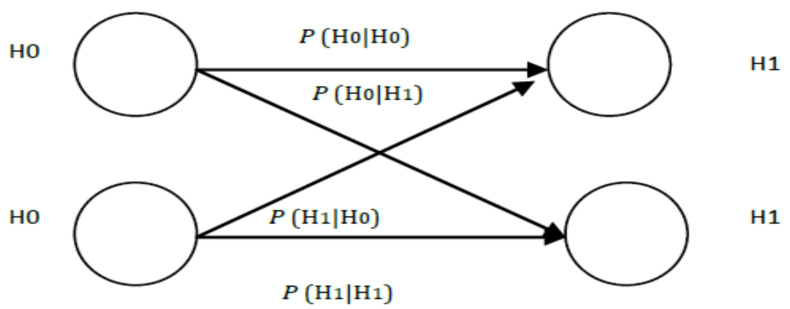

Fig. 2.6 Possible cases in binary hypothesis

The binary hypothesis problem has four different cases:

- (H0|H0): it shows H0 given H0 is true
- (H1|H1): It shows H1 given H1 is true
- (H0|H1): It shows H0 given H1 is true
- (H1|H0):it shows H1 given H0 is true

The hypothesis H0 shows that primary signal is absent and H1 shows that the primary signal is present. Case 1 is true negative, i.e. the primary user is absent and the detection scheme says that the primary user is absent. Case 2 is true positive, i.e. the primary user is present and the detection scheme says the same. Case 3 is missed detection i.e. even though primary signal is present and the detection scheme says that the signal is absent. Case 4 is false alarm i.e. even though the signal is absent; the detection scheme says that the signal is present.

Missed detection leads to harmful interference to the primary users whereas false alarm results in the underutilization of spectrum. So the performance of any detection scheme can be evaluated using these two parameters probability of false alarm and probability of detection. The curve drawn between probability of false alarm and probability detection is called receiver operating characteristic which are used to evaluate the performance of detection scheme.

The fig. 2.7 shows the block diagram of energy detector sensing method [3]. The detection process consists of calculating the energy over given band of interest and comparing it with a threshold to arrive at a decision about the presence of primary user by choosing the one of the hypothesis stated eq. (2.9) and eq. (2.10) is true.

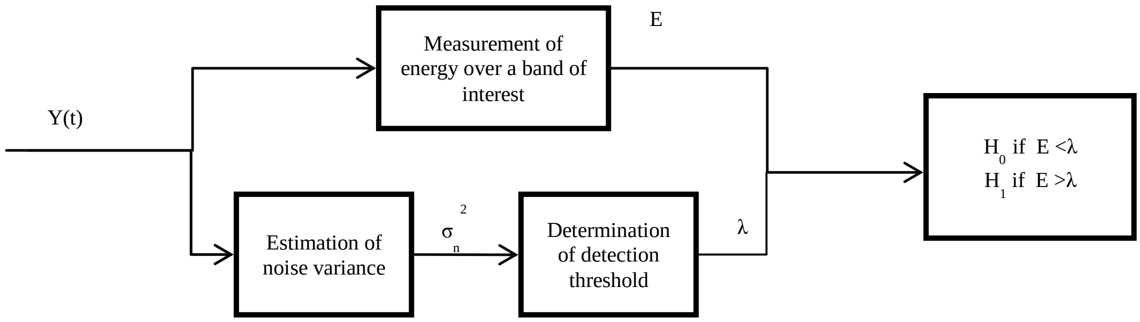

Fig. 2.7 Block diagram of energy detection technique

2.2.2 Measurement of Energy of Received Signal:

Energy of a signal can be calculated in both time domain and also in frequency domain.

❖ **Time Domain Energy Detection**

The initial work related to energy detection in time domain is presented in [**13**] . Fig. 2.8 shows the block diagram of energy detector [**12**].The pre-filter is matched to band of interest of the required signal and then the received signal is passed through ADC to get the sample values of the received signal. The each sample value is squared using squaring device. Finally the energy is available after taking the average of the square sample values. Fig. 2.8 shows time domain energy detector.

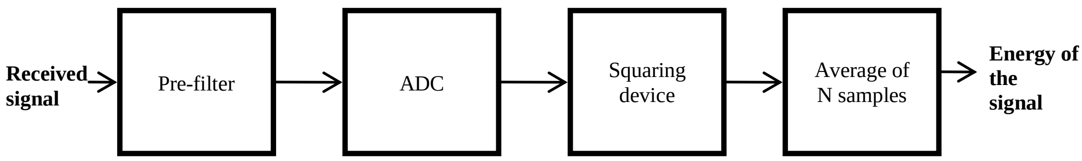

Fig. 2.8Block diagram of time domain energy detector

- **Architecture of Energy Detector:**

This is the first VLSI architecture of energy detector in the literature proposed in [**14**].

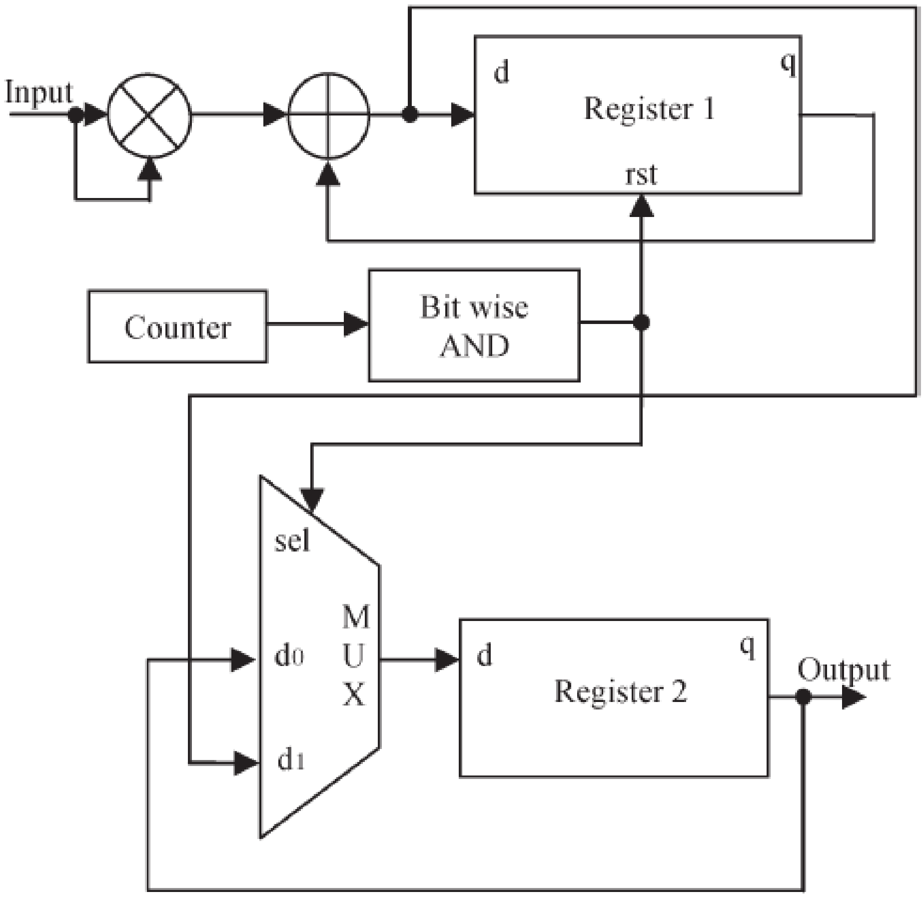

Fig. 2.9 VLSI architecture of energy detector [**14**]

As shown in Fig. 2.9 the input samples are given to a multiplier to get the squared value samples. The adder and register setup functions as an accumulator. The accumulator keeps on adding its inputs until the register receives a control signal from the counter. The counter and bit wise AND gate outputs logic high when the count of the samples reaches the desired value. This control signal is given to the reset of the accumulator i.e. the accumulator starts from zero when the desired counts of samples are accumulated. Thus the energy detector can output the energy periodically where the period is the time taken to accumulate desire number of samples.

❖ **Frequency Domain Energy Detection**

The energy detection scheme in frequency domain is same as in time domain accept that the time domain samples are converted into frequency domain using FFT and then squared. The average of squared samples is taken to find the test static [**15**].

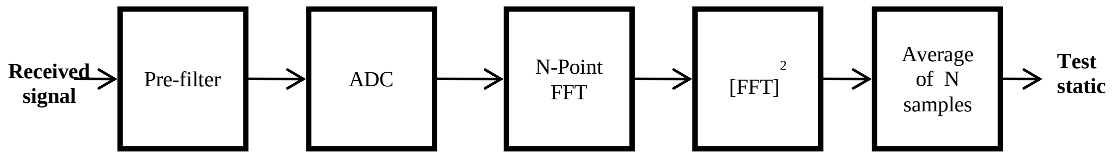

Fig. 2.10 Block diagram of Energy detector in frequency domain

3. Performance evaluation of energy detection technique

The performance of detector is measured with probability of detection (PD) and probability of false alarm (PFA). Performance of energy detector for different values of SNR of the received signal can be characterized through Receiver operating characteristics (ROC) curves.

3.1 ROC Curve for Energy Detection Technique

ROC curve is nothing but reciever operating characterstic curve which gives the information about the performance of the detection scheme. The ROC curve is drawn between probablility of false alarm and probability of detection. Fig. 3.1 shows the ROC curve for AM signal with message frequency 128 Hz and a carrier frequency of 1024 Hz. The signal is sampled at a frequency of 8192Hz and considered 512 numbers of samples are considered for simulation. SNR is taken as -10dB and number of iterations are 3000. Fig .3.2 shows the ROC curve for varying SNR. We can observe that for better SNR there is better probability of detection and also the detection performance is very poor for low SNR values.

The expressions for probability of detection, probability of detection and threshold are considered from [**12**] and given by

$$P_{FA} = Q\left(\frac{\lambda_D - N\sigma_w^2}{\sqrt{2N\sigma_w^4}}\right) \tag{3.1}$$

$$P_D = Q\left(\frac{\lambda_D - N(\sigma_s^2+\sigma_w^2)}{\sqrt{2N(\sigma_s^2+\sigma_w^2)}}\right) \tag{3.2}$$

$$\lambda_D = \sigma_w^2\ (Q^{-1}\ (P_{FA})\ \sqrt{}\ (2N) + N) \tag{3.3}$$

Where

λ_D : Detection threshold

σ_w^2: variance of noise

$P_{FA:}$ Probability of false alarm

N: Number of samples

3.2 SNR versus Probability of Detection Curves

As per FCC, the performance metric is defined as the SNR value at which the probability of detection is 0.9 and probability of false alarm is 0.1. Fig. 3.1 shows the graph between probalbilty of detection and SNR at a fixed value of probability of false alarm of 0.1. We can observe from the graph that the detection performance is very poor at low SNR values. Form this graph we can find performance metric of the detection scheme. Fig.3.4 shows the PD versus SNR curve with varying PFA from which we can observe that as PFA decreses the performance of the detection scheme decreases. For incresing the spectral occupancy PFA should be as low as possible. The graph show that decrease in PFA decreses the probability of detection.

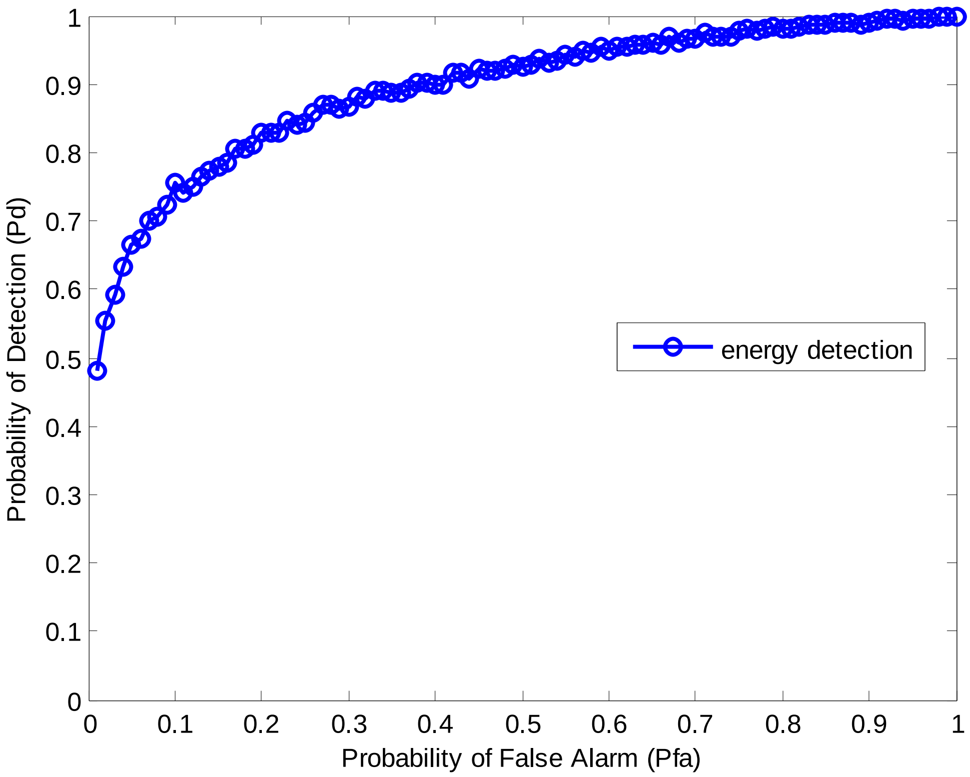

Fig. 3.1 ROC curve for energy detection technique

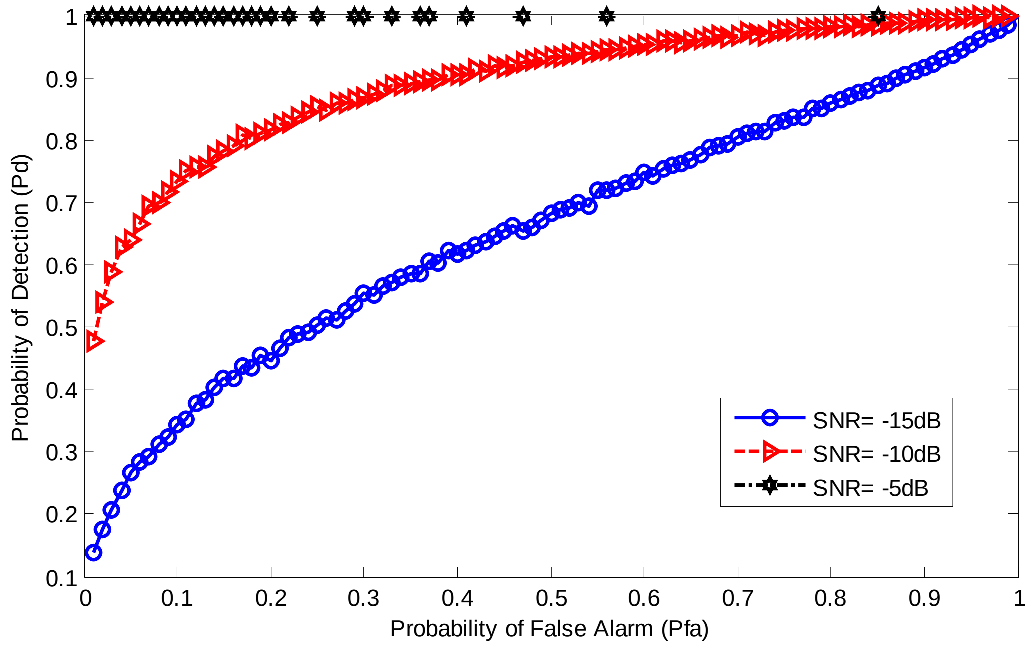

Fig. 3.2 ROC curve for varying SNR

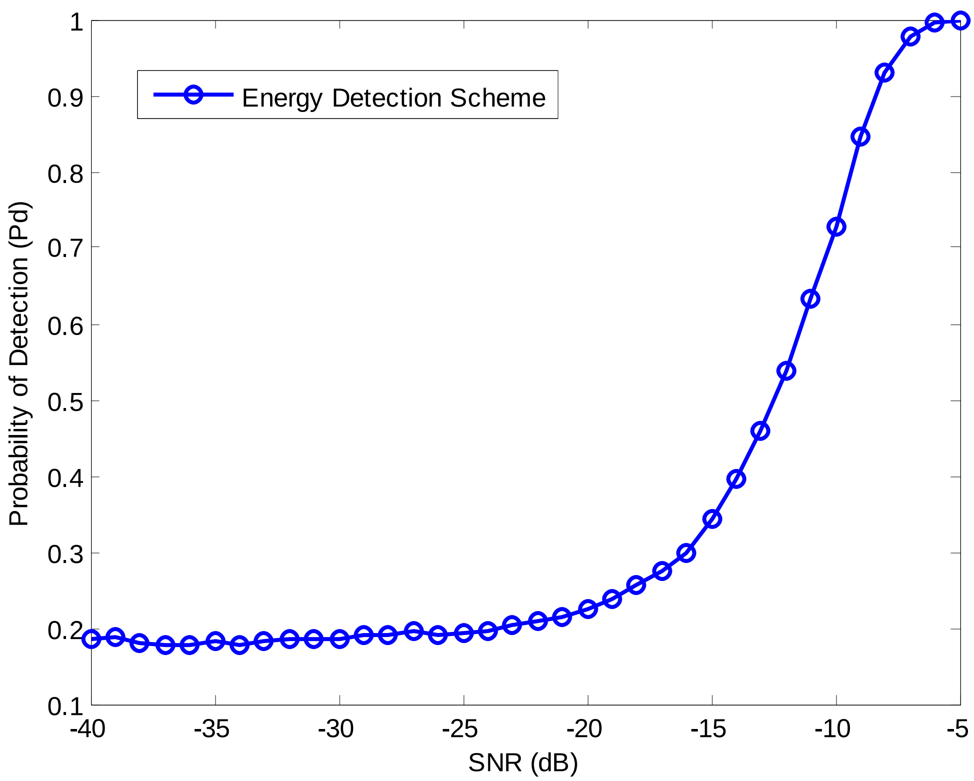

Fig. 3.3 PD versus SNR curve

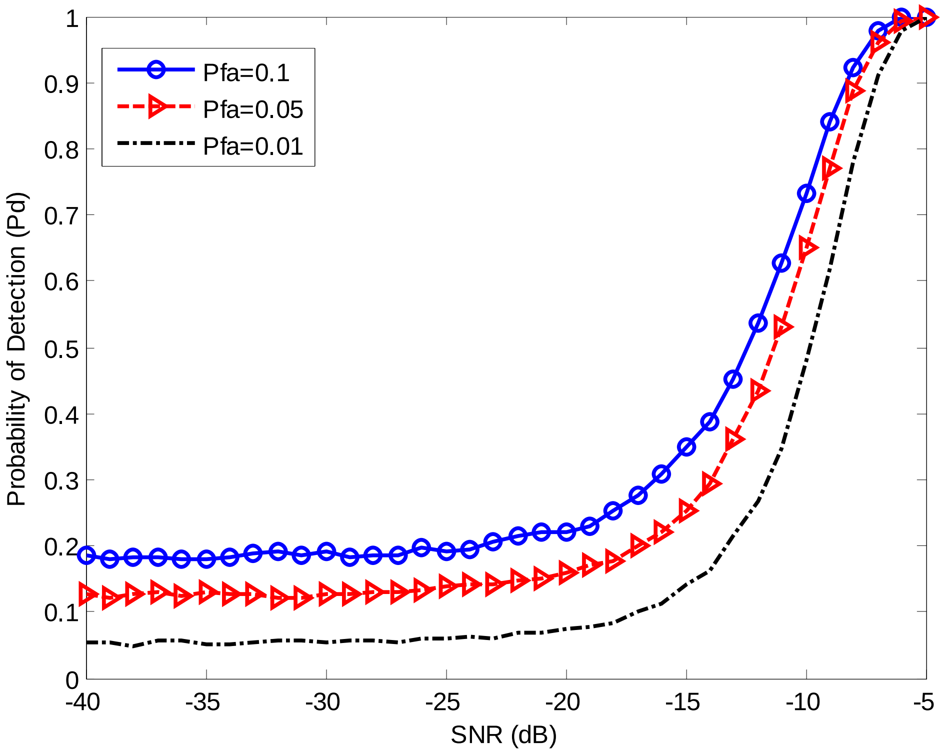

Fig. 3.4 PD versus SNR for variable PFA

3.3 Number Samples versus Probability of Detection

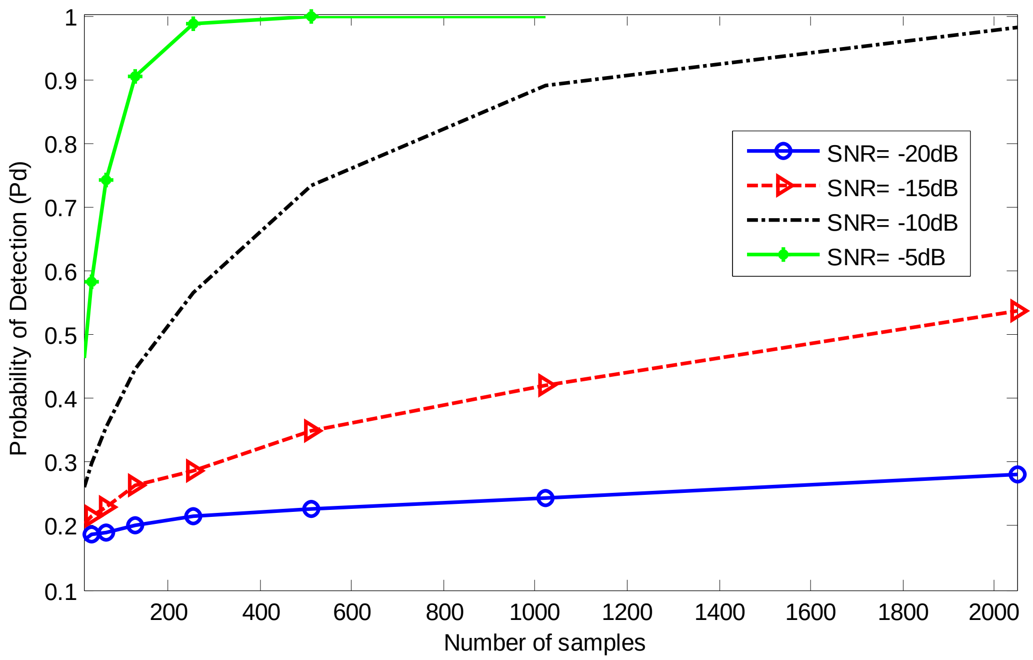

Fig. 3.5 Number of samples versus PD with varying SNR values

Fig 3.5 shows the curve between the number of samples and probability detection with varying SNR values. The sample values are varied as 16, 32, 64, 128, 256, 512, 1024 and 2048. We can observe from the graph that as SNR decreases the number of samples required to obtain a particular Pd, increases. We can also observe that for high SNR values requires less number of samples for achieving good detection capability.

4. Hardware Implementation

4.1 Time Domain Implementation of Energy Detection Technique

There are mainly three main modules in the hardware of energy detection spectrum sensing

- Energy detector
- Threshold estimator
- Decision module

The energy detector module takes the source signal samples as the input and calculates the energy over a desire number of samples. Threshold estimator takes the noise variance, number of samples and probability of false alarm as the input and estimates the threshold dynamically. The decision module takes the inputs source signal energy from energy detector and threshold value from threshold estimator, compares its inputs and arrives at a decision.

4.1.1 Implementation of Energy Detector in Time Domain

The expression for energy of signal consisting of N samples is given by [**14**]

$$\mathbf{E} = \frac{1}{N}\sum_{1}^{N} |Y(k)|^2 \tag{4.1}$$

The equation 2 can be implemented by using a multiplier, adder and followed by a scaling unit as shown in fig. 4.1. The received signal samples are given as input to the multiplier to get the squared value of each sample. These squared samples are accumulated resulting in summation of squared values. A control signal count is maintained in the accumulator which produces the number of squared samples getting accumulated i.e. a counter is used inside the accumulator to generate the count of number of the samples. Finally the sum of the squared values is passed through scaling unit for the process of averaging. Thus the output of scaling unit is the energy of the input digital signal. The block diagram of the energy detector is shown in Fig. 4.1.

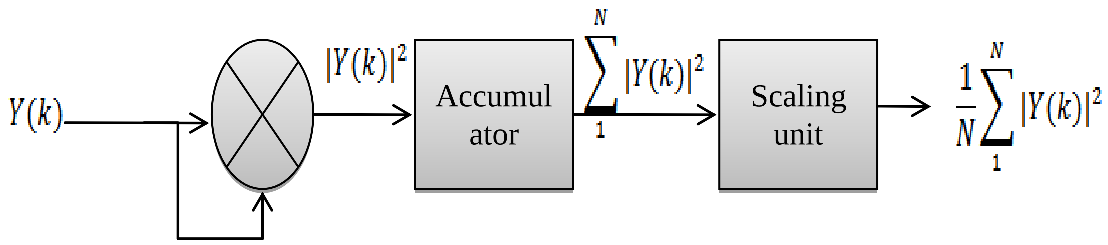

Fig. 4.1 Block diagram of energy detector

4.1.2 Implementation of Threshold Estimator

The expression for threshold is [**12**]

$$\lambda = \sigma_w^2 \left(Q^{-1} (P_{FA}) \sqrt{(2N)} + N \right) \tag{4.2}$$

Threshold estimator consists mainly three blocks as shown in Fig. 4.2.

- Variance calculation using Variance detector
- Inverse q function calculation using ROM
- Square root calculation using logic IP core

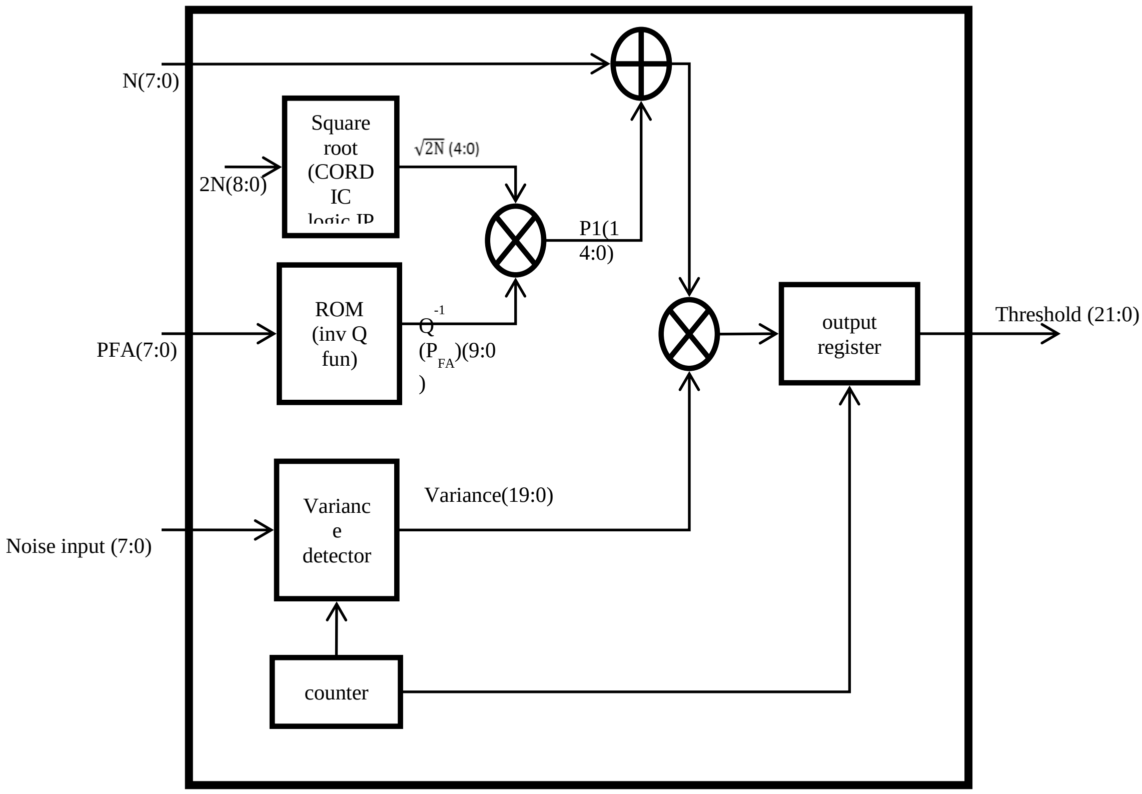

Fig. 4.2 Block diagram of threshold estimator

The threshold equation is mapped into hardware and it the threshold calculated dynamically using above three modules and basic adder and multiplier. After calculating the threshold it is stored in register, which outputs the data on the control logic. The control logic to both variance detector and the output register is provided by a counter which counts the desired number of samples for the implementation.

- **Variance calculation using Variance detector**

The variance detector takes the noise samples as input and outputs its variance. The architecture of variance detector is same as the architecture of energy detector. The noise sample are given as input to the squaring device and then given to accumulator. The accumulator adds up all the inputs until it receives a control signal from the counter. The output of the accumulator is shifted right by required no of bits to get the averaged value. The averaged value is nothing but variance of the noise sequence.

As shown in Fig. 4.2 the input is of eight bit width and output is nineteen bit width, the input width eight bits entirely represents the fractional part and in the output first four most significant bits represents the integer part and remaining bits represents the fractional part.

- **Inverse q Function Calculation using ROM**

As the computation of inverse q function is complex in hardware implementation and also the input PFA is limited within the range of 0.01 to 0.1, this functionality is implemented using ROM. The table 4-I shows the desired PFA values and their corresponding values of inverse q function. As shown in Fig 4.2. the input is eight bits width which represents the fractional part entirely and the output is ten bit width of which the two most significant bits represents the integer part and remaining part represents fractional part [**16**].

Table 4-I Inverse Q function tabular form

PFA	Q^{-1} (P_{FA})
0.01	2.0537
0.02	2.3260
0.03	1.8808
0.04	1.7507
0.05	1.6449
0.06	1.5548
0.07	1.4758
0.08	1.4051
0.09	1.3408
0.1	1.2816

To store the inverse q function values in ROM, fixed point representation of data is considered of data width of ten bits where the two MSB's represent the integer part and remaining eight LSB's represents fractional part. The input PFA is given as reference to the address of the ROM.

❖ **Square Root Calculation using Logic IP Core**

CORDIC IP core provides an algorithm for square root calculation. This square root algorithm works for all positive input values only. Thus input to square root function using CORDIC can be either unsigned integer or unsigned fractions only, not for floating type numbers [**17**].

X_IN represents the input of square root function with input width equal to 'n' then

- for unsigned integer type input, input range lie in between 0 <= X_IN < +2**n
- for unsigned fraction type input, input range lie in between 0 <= X_IN < +2

Output width is automatically decided by the CORDIC function block depending on input width. Also coarse rotation function is not required for square root calculation so it is disabled for this application in CORDIC IP. Also for integer type input, output is of pure integer form with rounded to ceil (if required).

Example: Let say input X_In is set to be of 10bits of integer type and X_OUT is output:

- X_IN : “0001000000” => 64

  X_OUT: “001000” => 8

- X_IN: “0000001000” => 8

  X_OUT: “000011” => 3

4.1.3 Decision Module

The decision module takes the inputs energy and threshold and outputs signal present as shown in Fig. 4.3. If the energy is greater than the threshold than the signal present is high otherwise it is made low.

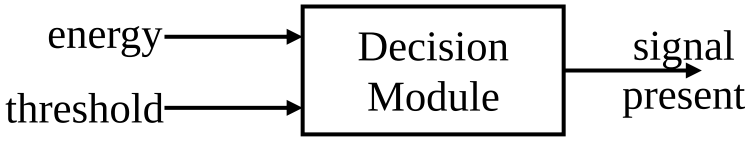

Fig. 4.3 Block diagram of decision module

4.2 Energy Detection in Frequency Domain

Energy detection in frequency domain consists of mainly three modules as shown in Fig. 4.4, such as FFT core, Squaring module, Averaging module.

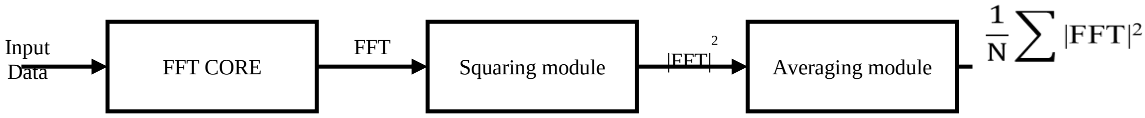

Fig. 4.4 Block diagram energy detector in frequency domain

4.2.1 FFT Core

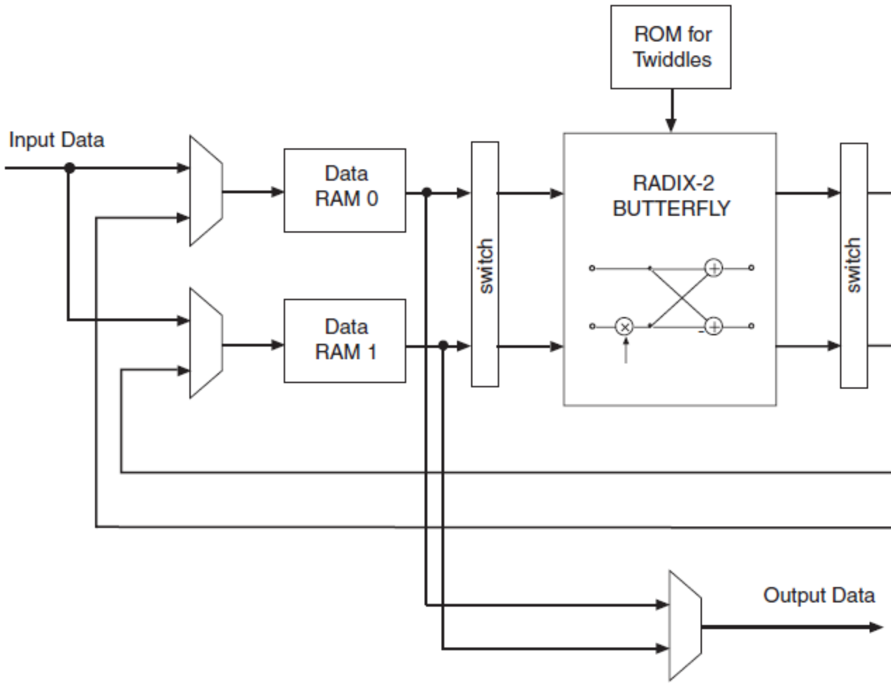

Fig. 4.5 Architecture of FFT core

The implementation of FFT is done with the help of XILINX FFT IP CORE [**18**] which uses Cooley-Turkey algorithm. The data loading begins with the start signal, which leads directly to the calculation phase. Data is applied in a contiguous burst. The input data is stored in RAM, real data and imaginary data stored in their respective RAM. In the Fig. 4.5 we can observe a RADIX-2 BUTTERFLY for which twiddle factors are given through a ROM. Here optimization of resources is achieved as the processed butterfly output is fed back to the input of butterfly. The next data set is taken by the core after the calculation phase is completed for the previous input data. The signal XN_index is generated as output which indicates the index of the data which is given serially and XK_index is the index of the output samples [**18**].

After done is high, the data is given to squaring device which separately squares the obtained outputs from the FFT core (XK_re, XK_im) and adds them to get the squared value of the FFT of the input sample. The squared FFT samples are given to the averaging module which accumulates the desired number of FFT's and then shifts the result to output the average value

4.3 Hardware Implementation of Covariance Based Spectrum Sensing

The calculation of covariance matrix involves involve following steps

- Calculation of mean of input data
- Calculation of deviation of input data from mean
- Multiplication of deviation matrix with its transpose

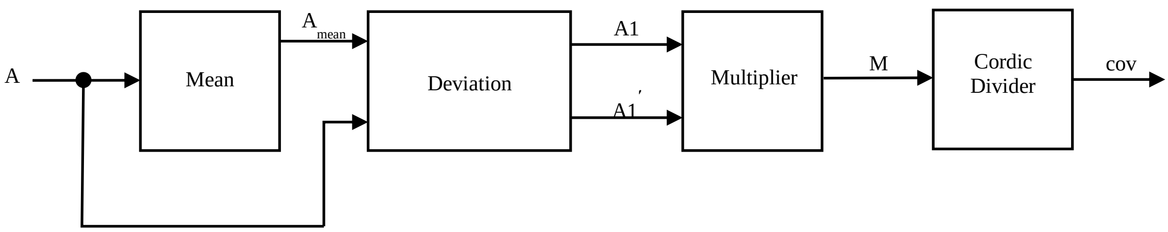

Fig. 4.6 Block diagram for covariance matrix calculation

The input data matrix is fed as an array to the mean calculation module where the mean of observations of each variable in the data is carried out as each column in input data matrix represents a variable. The mean value is subtracted from each of its observation using deviation module to get the deviation input data from mean. The multiplier module gives the product of deviation matrix and its transpose. Finally divider modules perform the averaging and output the covariance matrix.

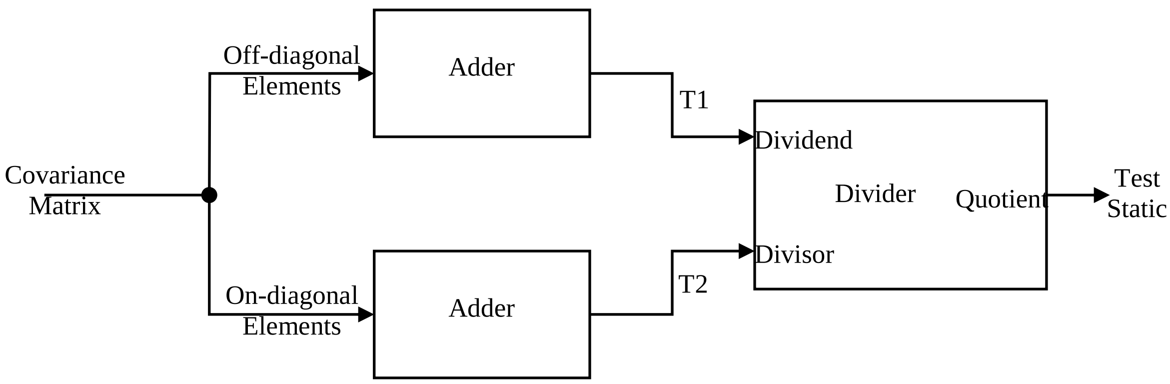

Fig. 4.7 Block diagram of Covariance based spectrum sensing

After obtaining the covariance matrix the off diagonal elements and diagonal elements are added separately to get T1 and T2 respectively. The T1 and T2 are given to divider where the quotient is nothing but the test static. If the test static is greater than one than signal is present else there is no signal.

5. Simulation Results of Energy Detection in Time Domain

5.1 Simulation Setup for Energy Detection Technique:

To verify the functionality of the energy detection technique, a numerically controlled oscillator is considered as the signal source and pseudo random sequence generator is considered as a noise source. The output of the numerically controlled oscillator is added with the random sequence to produce a source signal for the energy detector. The energy detector outputs the energy of the input source signal. NCO gives the output in reference to a value, which is generated by counter in this implementation. In this simulation, sine wave is generated using NCO.

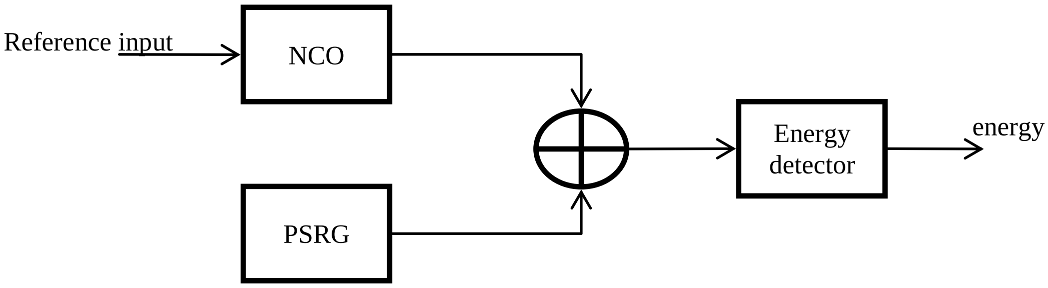

Fig. 5.1 Simulation set up for energy detector

5.1.1 Pseudo Random Sequence Generator

The pseudo random sequence generator is a linear feedback shift register where the feedback is XOR operation of the two most significant bits [**19**]. The pseudo random sequence of generator outputs a random number at every rising edge of the clock. The table 5-I shows the process of generation of random sequence, we can observe that the sequence repeats itself after 15 clock cycles. For n bit random sequence generator the sequence is periodic with a period of (2^n-1).

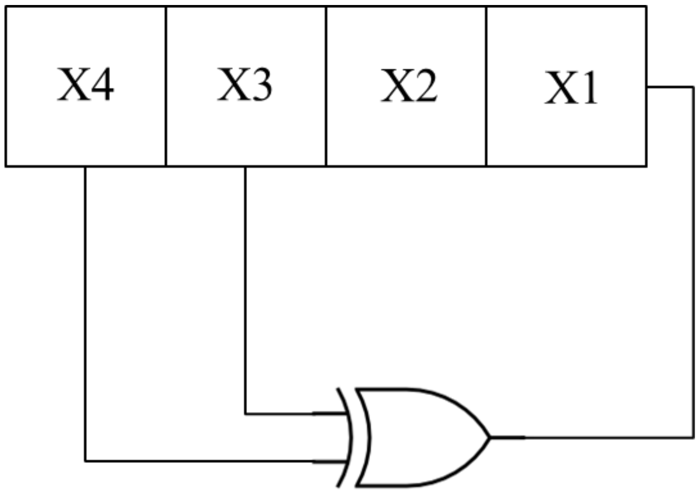

Fig. 5.2 Pseudo random sequence generator

Table 5-I Sequence Generated by PRSG

X_1	X_2	X_3	X_4	X_3 XOR x_4	PN sequence
0	0	0	1	1	1000
1	0	0	0	0	0001
0	1	0	0	0	0010
0	0	1	0	1	0100
1	0	0	1	1	1001
1	1	0	0	0	0011
0	1	1	0	1	0110
1	0	1	1	0	1101
0	1	0	1	1	1010
1	0	1	0	1	0101
1	1	0	1	1	1011
1	1	1	0	1	0111
1	1	1	1	0	1111
0	1	1	1	0	1110
0	0	1	1	0	1100
0	0	0	1	1	1000

5.1.2 Numerically Controlled Oscillator:

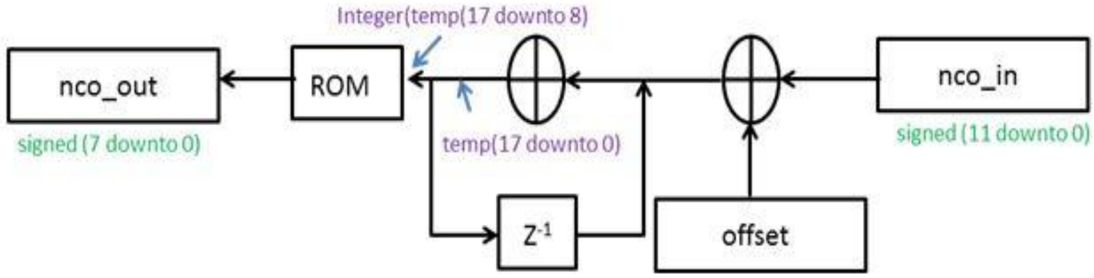

Fig. 5.3 Block diagram of NCO

Numerically controlled oscillator [**20**] is nothing but an integrator which accumulates the input value and maps it into predefined values for sine and cosine stored in RAM. The resolution of these values depends on the number of bits used to store the values. Because of the symmetry of the sinusoidal, only the values for any of quarter wave period of the wave are enough to produce the same over whole period. This illustration is shown in Fig. 5.3.

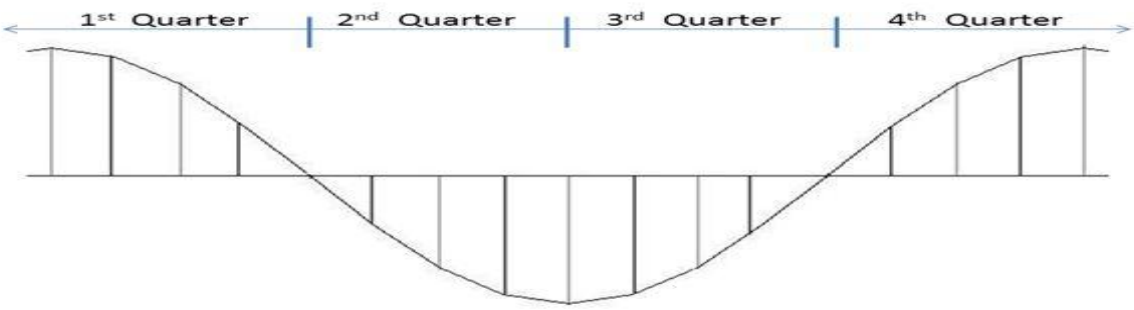

Fig. 5.4 Cosine wave

The cosine waveform is shown in Fig. 5.4. It can be observed from Figure. That with the knowledge of values in the any one quarter, the values in remaining three quarters can be evaluated with appropriate change in its angle. The relation between the values of four quarters can be given as follows:

For $0 \leq \Theta \leq \Pi/4 \rightarrow COS\Theta$

For $\Pi/4 \leq \Theta \leq \Pi/2 \rightarrow - COS(\Pi/2 - \Theta)$

For $\Pi/2 \leq \Theta \leq 3\Pi/4 \rightarrow - COS(\Theta - \Pi/2)$

For $3\Pi/4 \leq \Theta \leq \Pi \rightarrow COS(\Pi - \Theta)$

❖ **Operation of NCO**

The input to the NCO, ‘coin’, is in ‘signed’ 12-bit format. It is converted to 18-bit by doing sign extension. It is added to the ‘offset’ input, which is of ‘signed’ 18-bit format and equal to 1/16. The sum is delayed by a unit delay and is also added to the inputs. The 10 most bits of the addition result are converted to an integer as COSROM address. This address is mapped to the data values in COSROM. This data values are of ‘signed’ 8-bit format. This data value is given as output of NCO i.e. ‘nco_out’.

5.1.3 Simulation Results of Energy Detector

The waveform shows the simulation result of energy detector where one input data_in1 is from NCO and the other input data_in2 is from random sequence generator, both the inputs are added to give data_sum which is input to the energy detector. The signal output_valid is used as flag to show that the energy detector completed its processing and the available energy output is valid. It is shown in the waveform that it takes 16 clock cycles to get the valid output.

Table 5-II device utilization summary for energy detector

Device utilization summary		
Logic utilization	**Used**	**Available**
No. of slices	7	4652
No. of flip flops	12	9312
No. of 4 input LUT’s	2	9312
No. of bonded IOBs	14	232

No. of GCLKs	1	24

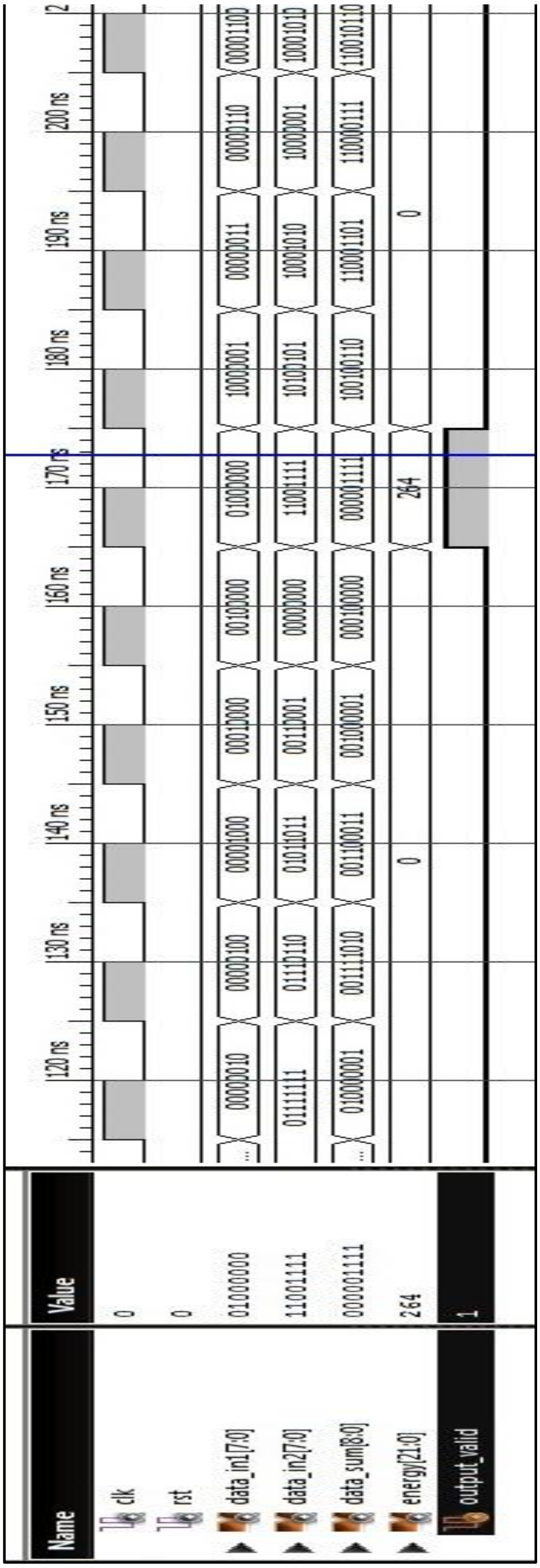

Fig. 5.5 Simulation results for energy detector

5.2 Simulation Results of Threshold Estimator

The waveform shows the simulation result of threshold estimator where the inputs are variance of random sequence, number of samples and probability of false alarm .the output is threshold which is made available after 16 clock cycles to the input applied.

Table 5-III device utilization summary for threshold estimator

Device utilization summary		
Logic utilization	**Used**	**Available**
No. of slices	72	4656
No. of MULT18X18SIO's	4	20
No. of flip flops	79	9312
No. of 4 input LUT's	112	9312
No. of bonded IOBs	38	232
No. of GCLKs	1	24

5.3 Simulation Results of Decision Module

The inputs of the decision module are energy and threshold as shown in Fig. 5.6. These two input signals are compared and output is shown as the signal signal_present after every 16 clock cycles.

Table 5-IV device utilization summary for threshold estimator

Device utilization summary		
Logic utilization	**Used**	**Available**
No. of slices	402	4656
No. of MULT18X18SIO's	188	20
No. of flip flops	752	9312
No. of 4 input LUT's	17	9312
No. of bonded IOBs	5	232
No. of GCLKs	1	24

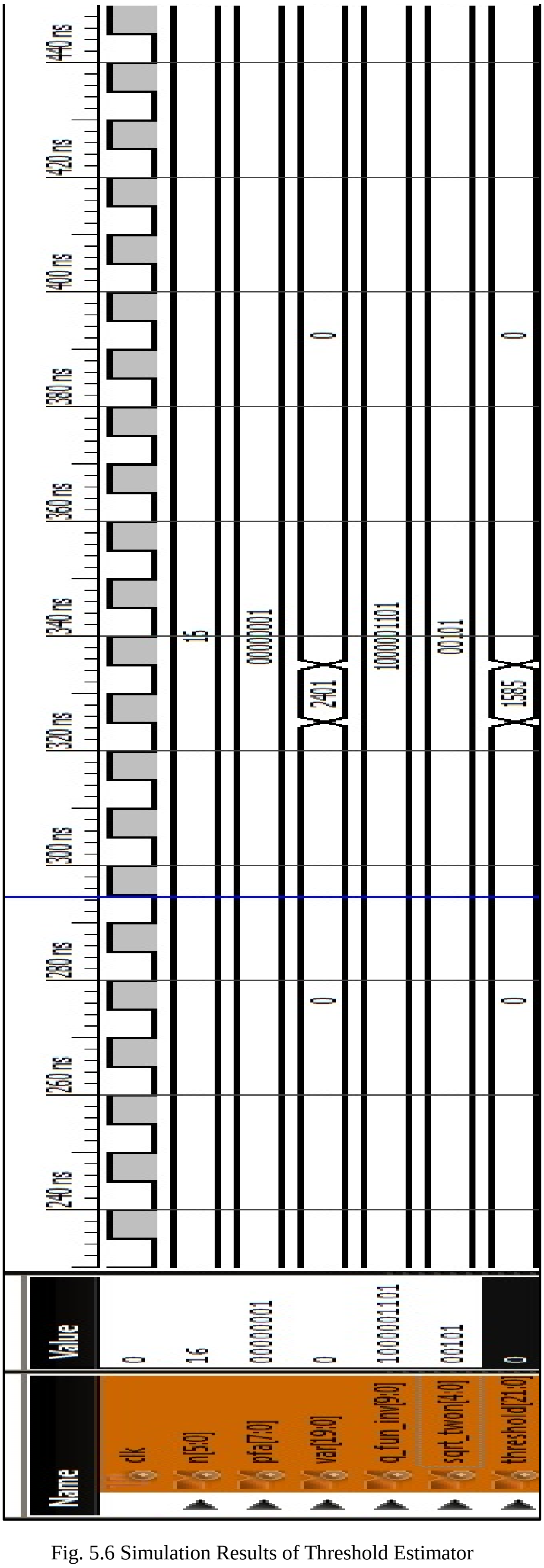

Fig. 5.6 Simulation Results of Threshold Estimator

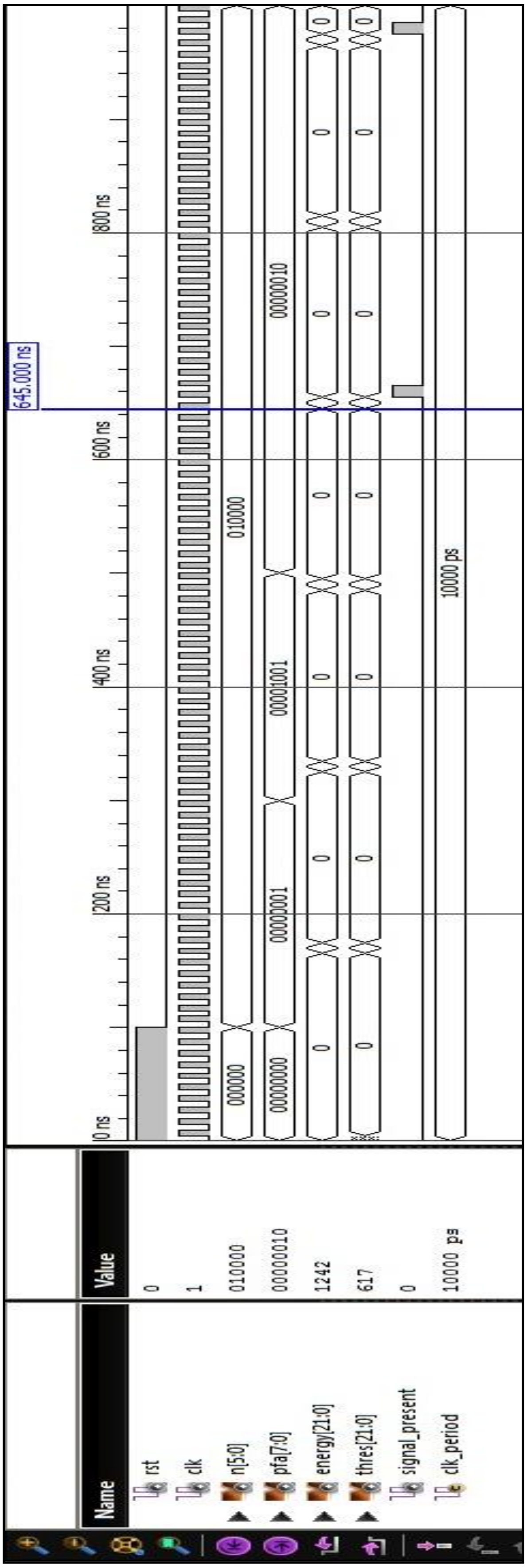

Fig. 5.7 Simulation results of Decision module

5.4 Validation of Energy detection technique on Spartan-3E FPGA board using Chip scope Pro:

Table 5-V core utilization summary of energy detection technique

Core utilization	
LUT count	379
FF count	290
BRAM count	2

5.4.1 Output Waveforms

The Fig. 5.8 shows the ChipScope pro output waveforms, where the DataPort_1 and DataPort represent the energy and threshold signals respectively and the DataPort(0) represents the output of energy detection technique which shows the signal is present or not. We can observe that output is changing for every 16 clock cycles from the Figure.

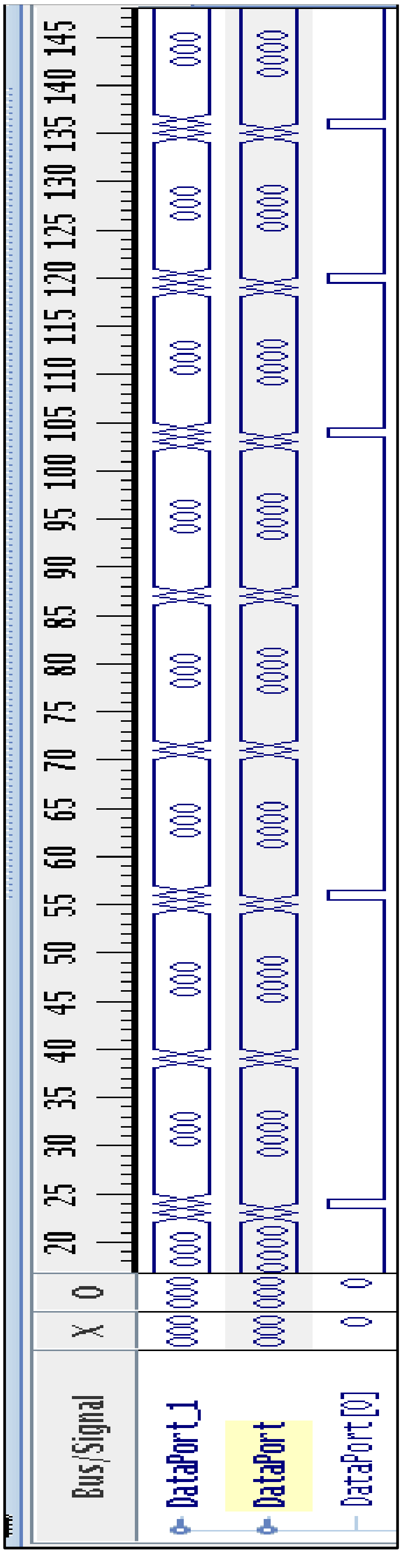

Fig. 5.8 Output waveforms of energy detection in time domain using chipscope pro

5.5 Simulation Results for Energy Detector using FFT

The simulation waveforms for energy detection using FFT is shown in Fig. 5.9. The signal ED_in is input to the FFT core, XK_re and XK_img are the real and imaginary parts of the FFT of the input. XN_index and XK_index are the indices of the input and output of the FFT core. We can observe in the waveforms that the core takes the next set of input only after the done signal is high. Even though the input data is give as contiguous, the data is loaded into core only after the processing of its previous input. Signal data_valid shows the validity of averaged value which is the output of the module shown in waveforms as average.

Table 5-VI device utilization summary for energy detector using FFT

Device utilization summary		
Logic utilization	**Used**	**Available**
No. of slices	1127	4656
No. of MULT18X18SIO's	20	20
No. of flip flops	447	9312
No. of 4 input LUT's	2080	9312
No. of bonded IOBs	37	232
No. of GCLKs	1	24

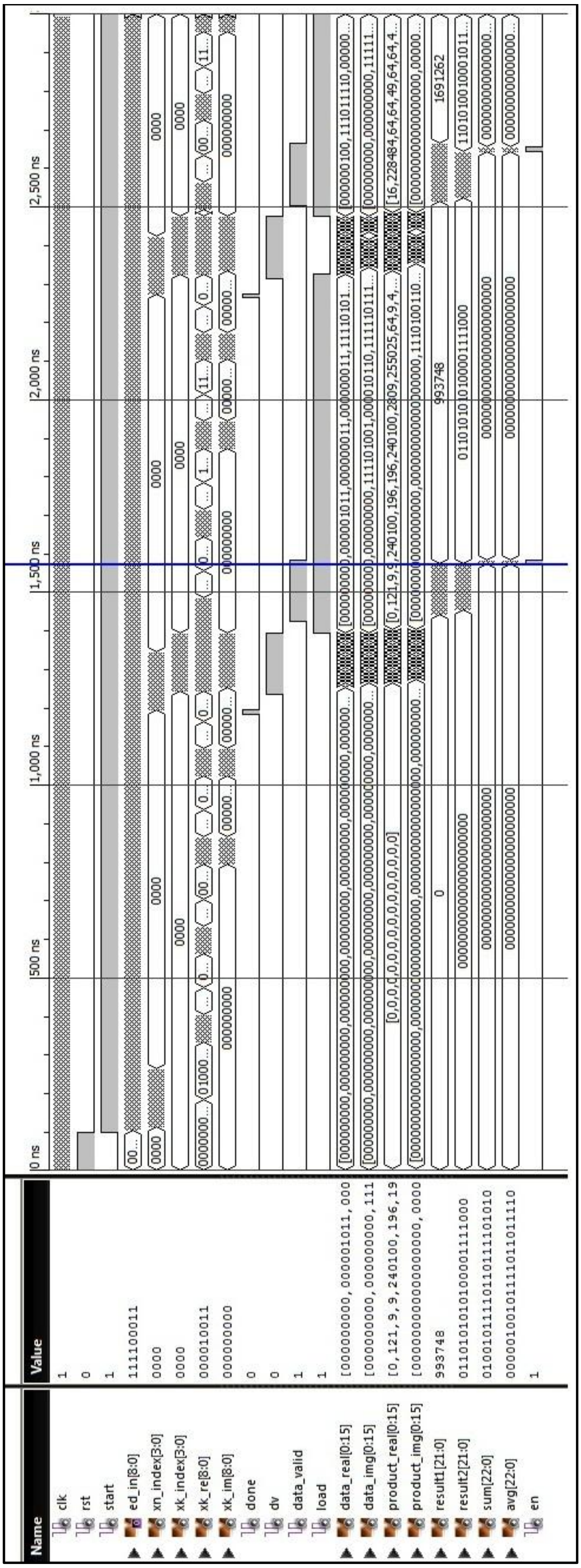

Fig. 5.9 Simulation results for energy detector using FFT

5.6 Simulation Results for Covariance Based Spectrum Sensing

The simulation waveforms are shown in Fig 5.10. The In_data signal is the input data stream applied to the detector and the cov_slv is the covariance output of the corresponding data input. The sum of the diagonal elements is represented by ut_sum signal and sum of the diagonal elements are represented by d_sum signal. The test signal represents the ratio of ut_sum to d_sum, if it is greater than one primary signal is present otherwise it is absent.

Table 5-VII device utilization summary for covariance based spectrum sensing

Device utilization summary		
Logic utilization	**Used**	**Available**
No. of slices	1398	4656
No. of MULT18X18SIO's	20	20
No. of flip flops	351	9312
No. of 4 input LUT's	2411	9312
No. of bonded IOBs	20	232
No. of GCLKs	1	24

It has been observed that time domain implementation of energy detection technique is very less complex compared to energy detection technique in frequency domain. But in frequency domain implementation the FFT point can be changed dynamically so this is an efficient design when considered number of samples for the design varies.

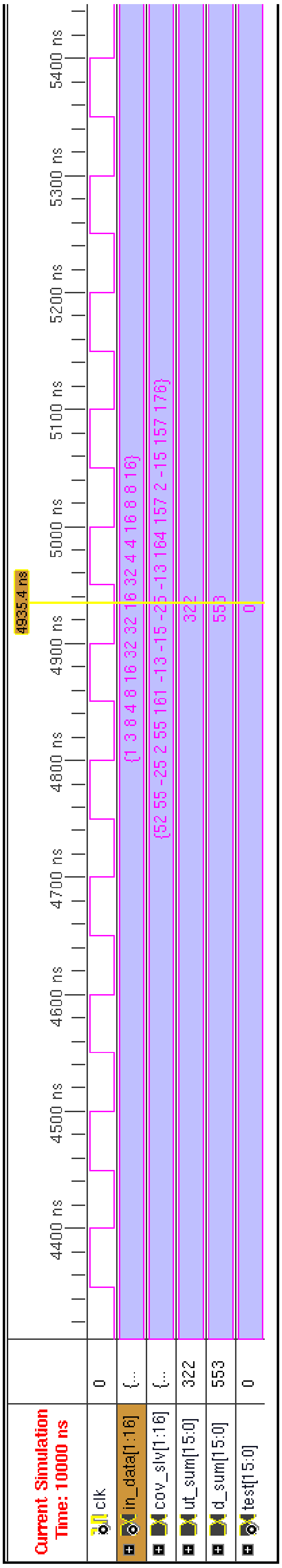

Fig. 5.10Simulation results for covariance based spectrum

6. Conclusion

6.1 Conclusion

The rapid growth of new wireless technologies has resulted in a serious problem of spectrum scarcity. Thus Spectrum sensing techniques have become an integral part of the solution for this problem. The problems of different spectrum sensing schemes have been analyzed and energy detection technique has also been considered for the implementation.

The performance of the implemented technique is evaluated using ROC curve and it has been observed that the performance is very poor at low SNR. By observing the plot between number of samples and probability of detection, it is conferred that the performance at low SNR can be improved with increasing number of samples.

In this implementation, threshold is calculated as a function of number of samples, probability of false alarm and noise variance. A preliminary work has been done to calculate threshold dynamically and architecture has been proposed for hardware implementation of the same. The complete design of Energy detection technique is downloaded on to Spaertan-3E FPGA board and the functionality is validated using Chipscope Pro analyzer. It is seen that the design is implemented with very less hardware but the latency increases with increased number of samples.

6.2 Future Work

The energy detection technique can be implemented in real time using on board ADC of FPGA. Pipelining concept can be used to decrease the latency of the design. The performance of energy detection scheme can be improved by developing models for the calculation of threshold by optimizing the parameters such as probability of false alarm, number of samples and variance of noise. Novel spectrum sensing methods like Eigen value based detection can be implemented in for better performance at low SNR.

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