ENERGY DETECTION TECHNIQUE FOR SPECTRUM SENSING IN COGNITIVE RADIO

Submitted in partial fulfillment of the Degree of

Bachelor of Technology

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by

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Certificate

This is to certify that project report entitled " ENERGY DETECTION TECHNIQUE FOR SPECTRUM SENSING IN COGNITIVE RADIO" submitted by Prema Ram(101020),Vinay Kushwaha(101122) and Raj Anand(101129) in partial fulfillment for the award of degree of Bachelor of Technology in Electronics and Communication Engineering to Jaypee University of Information Technology, Waknaghat, Solan has been carried out under my supervision.

This work has not been submitted partially or fully to any other University or Institute for the award of this or any other degree or diploma.

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Summary

By using Shannon's sampling formula, the problem of the detection of a deterministic signal in white Gaussian noise, by means of an energy-measuring device, reduces to the consideration of the sum of the squares of statistically independent Gaussian variates. When the signal is absent, the decision statistics has a central chi-square distribution with the number of degrees of freedom equal to twice the time-bandwidth product of the input. When the signal is present, the decision statistics has a non-central non-centrality parameter λ equal to the ratio of signal energy to two-sided noise spectral density. Since the non-central chi-square distribution has not been tabulated extensively enough for our purpose, an approximate form was used. This form replaces the non-central chi-square whose degrees of freedom and threshold are determined by the non-centrality parameter and the previous degrees of freedom.

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CHAPTER-1

COGNITIVE RADIO: INTRODUCTION

Cognitive radio is a new paradigm of designing wireless communication systems which aims to enhance the utilization of the radio frequency (RF) spectrum. The motivation or should we say the necessity is the scarcity of the available frequency spectrum, increasing demand, caused by the emerging wireless applications for mobile users. Most of the available radio spectrum has already been allocated to existing wireless systems, however, and only small parts of it can be licensed to new wireless applications. Nonetheless, a study by the Spectrum Policy Task Force (SPTF) of the Federal Communications Commission (FCC) has showed that some frequency bands are heavily used by licensed systems in particular locations and at particular times, but that there are also many frequency bands which are only partly occupied or largely unoccupied. For example we have a case that of spectrum band allocated to cellular networks in the USA which reach the highest utilization during working hours, but remain largely unoccupied from midnight until early morning.

The major factor that leads to inefficient use of the radio spectrum is the spectrum licensing scheme itself. In traditional spectrum allocation based on the command-and-control model, where the radio spectrum allocated to licensed user is not used, it cannot be utilized by unlicensed users and applications. Due to this static and inflexible allocation, legacy wireless systems have to operate only on a dedicated spectrum band, and cannot adapt the transmission band according to the changing environment. For example, if one spectrum band is heavily used, the wireless system cannot change to operate on another more lightly used band.

The right to access the spectrum is generally defined by frequency, space, transmit power, spectrum owner (i.e. licensee), type of use, and the duration of license. Normally, a license is assigned to one licensee, and the use of spectrum by this licensee must conform to the specification in the license (e.g. maximum transmit power, location of base station). In the current spectrum licensing scheme, the license cannot change the type of use or transfer the right to other licensee. This limits the use of the frequency spectrum and results in low utilization of the frequency spectrum. Essentially, due to the current static spectrum licensing scheme, spectrum holes or spectrum opportunities arise. Spectrum holes are defined as frequency bands which are allocated to, but in some locations and at sometimes not utilized by, licensed users, and, therefore, could be accessed by unlicensed users.

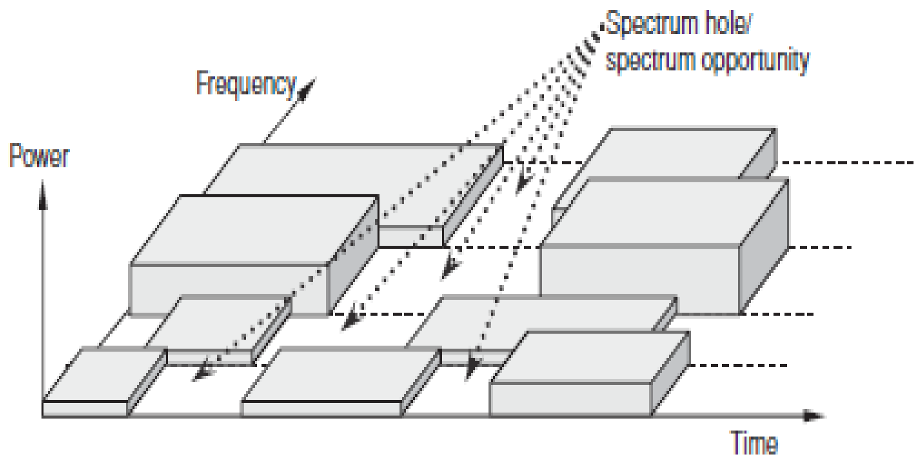


Fig1: Spectrum hole [2]

The limitations in spectrum access due to the static spectrum licensing scheme can be summarized as follows:

- Fixed type of spectrum usage: In the current spectrum licensing scheme, the type of spectrum use cannot be changed. For example, a TV band which is allocated to National Television System Committee (NTSC)-based analog TV cannot be used by digital TV broadcast or broadband wireless access technologies. However, this TV band could remain largely unused in many locations due to cable TV systems.
- Licensed for a large region: When a spectrum is licensed, it is usually allocated to a particular user or wireless service provider in a large region (e.g. an entire city or state). However, the wireless service provider may use the spectrum only in areas with a good number of subscribers, to gain the highest return on investment. Consequently, the allocated frequency spectrum remains unused in other areas, and other users or service providers are prohibited from accessing this spectrum.
- Large chunk of licensed spectrum : A wireless service provider is generally licensed with a large chunk of radio spectrum (e.g. 50 MHz). For a service provider, it may not be possible to obtain license for a small spectrum band to use in a certain area for a short period of time to meet a temporary peak traffic load. For example, a cdma2000 cellular service provider may require a spectrum with bandwidth of 1.25MHz or 3.75MHz to provide temporary wireless access service in a hotspot area.

- Prohibit spectrum access by unlicensed users: In the current spectrum licensing scheme, only a licensed user can access the corresponding radio spectrum and unlicensed users are prohibited from accessing the spectrum even though it is unoccupied by the licensed users. For example, in a cellular system, there could be areas in a cell without any users. In such a case, unlicensed users with short-range wireless communications would not be able to access the spectrum, even though their transmission would not interfere with cellular users.

1.1FUNCTIONS OF COGNITIVE RADIO

The main functions of cognitive radio to support intelligent and efficient dynamic spectrum access are as follows:

• Spectrum sensing: The goal of spectrum sensing is to determine the status of the spectrum and the activity of the licensed users by periodically sensing the target frequency band. In particular, a cognitive radio transceiver detects an unused spectrum or spectrum hole (i.e. band, location, and time) and also determines the method of accessing it (i.e. transmit power and access duration) without interfering with the transmission of a licensed user. Spectrum sensing can be either centralized or distributed. In centralized spectrum sensing, a sensing controller (e.g. access point or base station) senses the target frequency band, and the information thus obtained is shared with other nodes in the system. Centralized spectrum sensing can reduce the complexity of user terminals, since all the sensing functions are performed at the sensing controller. However, centralized spectrum sensing suffers from location diversity. For example, the sensing controller may not be able to detect an unlicensed user at the edge of the cell. In distributed spectrum sharing, unlicensed users perform spectrum sensing independently, and the spectrum sensing results can be either used by individual cognitive radios (i.e. non-cooperative sensing) or shared with other users (i.e. cooperative sensing). Although cooperative sensing incurs a communication and processing overhead, the accuracy of spectrum sensing is higher than that of non-cooperative sensing.

• Spectrum analysis: The information obtained from spectrum sensing is used to schedule and plan spectrum access by the unlicensed users. In this case, the communication requirements of unlicensed users are also used to optimize the transmission parameters. Major components of spectrum management are spectrum analysis and spectrum access optimization. In spectrum analysis, information from spectrum sensing is analyzed to gain knowledge about the spectrum holes (e.g. interference estimation, duration of availability, and probability of collision with a licensed user due to sensing error). Then, a decision to access the spectrum (e.g. frequency, bandwidth, modulation mode, transmit power, location, and time duration) is made by optimizing the system performance given the desired objective (e.g. maximize the throughput of the unlicensed users) and constraints (e.g. maintain the interference caused to licensed users below the target threshold).

• Spectrum access: After a decision is made on spectrum access based on spectrum analysis, the spectrum holes are accessed by the unlicensed users. Spectrum access is performed based on a cognitive medium access control (MAC) protocol, which intends to avoid collision with licensed users and also with other unlicensed users. The cognitive radio transmitter is also required to perform negotiation with the cognitive radio receiver to synchronize the transmission so that the transmitted data can be received successfully. A cognitive MAC protocol could be based on a fixed allocation MAC (e.g. FDMA, TDMA, CDMA) or a random access MAC (e.g. ALOHA, CSMA/CA) .

• Spectrum mobility: Spectrum mobility is a function related to the change of operating frequency band of cognitive radio users. When a licensed user starts accessing a radio channel which is currently being used by an unlicensed user, the unlicensed user can change to a spectrum band which is idle. This change in operating frequency band is referred to as spectrum handoff. During spectrum handoff, the protocol parameters at the different layers in the protocol stacks have to be adjusted to match the new operating frequency band. Spectrum handoff must try to ensure that the data transmission by the unlicensed user can continue in the new spectrum band.

1.2 COMPONENTS OF COGNITIVE RADIO

The major functions of cognitive radio, which are required to adapt the transmission parameters according to the changing environment, can be represented through a “cognitive cycle”. The different components in a cognitive radio transceiver which implement these functionalities are shown in figure below.

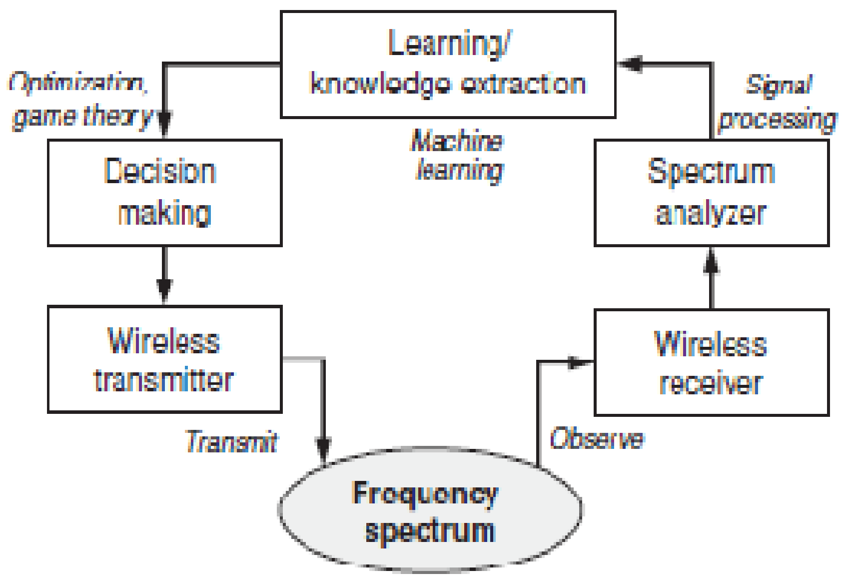


Fig 2: Components in a cognitive node [2]

• Transmitter/receiver: A software-defined radio-based wireless transceiver is the major component with the functions of data signal transmission and reception. In addition, a wireless receiver is also used to observe the activity on the frequency spectrum (i.e. spectrum sensing). The transceiver parameters in the cognitive radio node can be dynamically changed as dictated by higher layer protocols.

• Spectrum analyzer: The spectrum analyzer uses measured signals to analyze the spectrum usage (e.g. to detect the signature of a signal from a licensed user and to find spectrum holes for unlicensed users to access). The spectrum analyzer must ensure that the transmission of a licensed user is not interfered with if an unlicensed user decides to access the spectrum. In this case, various signal-processing techniques can be used to obtain spectrum usage information.

• Knowledge extraction/learning: Learning and knowledge extraction use the information on spectrum usage to understand the ambient RF environment (e.g. the behavior of licensed users). A knowledge base of the spectrum access environment is built and maintained, which is subsequently used to optimize and adapt the transmission parameters to achieve the desired objective under various constraints. Machine learning algorithms from the field of artificial intelligence can be applied for learning and knowledge extraction.

• Decision making: After the knowledge of the spectrum usage is available, the decision on accessing the spectrum has to be made. The optimal decision depends on the ambient environment – that is, it depends on the cooperative or competitive behavior of the unlicensed users. Different techniques can be used to obtain an optimal solution. For example, optimization theory can be applied when the system can be modeled as a single entity with a single objective. In contrast, game theory models can be used when the system is composed of multiple entities each with its own objective. Stochastic optimization may be applied when the states of the system are random.

1.3 SPECTRUM SENSING

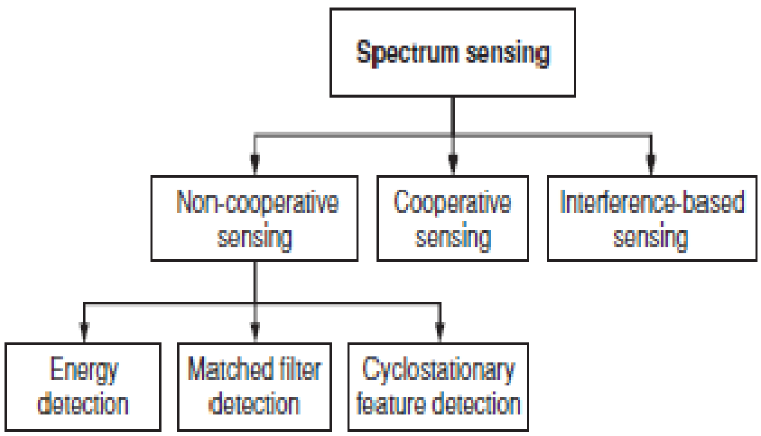


Fig 3:Different types of spectrum sensing in the physical layer [2]

The objective of spectrum sensing is to detect the presence of transmissions from licensed users. There are three major types of spectrum sensing, namely, non-cooperative sensing, cooperative sensing, and interference-based sensing. These will be described below.

1.3.1 Non-cooperative transmitter sensing

Non-cooperative spectrum sensing is used by an unlicensed user to detect the transmitted signal from a licensed user by using local measurements and local observations. The model for signal detection at time t can be described as:

$$x(t) = \begin{cases} n(t), & H_0 \\ h\, s(t) + n(t), & H_1 \end{cases}$$

where x(t) is the received signal of an unlicensed user, s(t) is the transmitted signal of the licensed user, n(t) is the additive white Gaussian noise (AWGN), and h is the channel gain. Here, H0 and H1 are defined as the hypotheses of not having and having a signal from a licensed user in the target frequency band, respectively. The performance of a spectrum sensing technique is generally measured in terms of the probability of correct detection (Pd), the probability of false alarm (Pf), and the probability of miss (Pm). Mathematically, Pd = Probability {decision = H1|H1}, Pf = Prob {decision = H1|H0}, and Pm = Probability {decision = H0|H1}.

The three different methods in non-cooperative sensing are as follows:

1.3.2 Matched filter detection or coherent detection: Matched filter detection is generally used to detect a signal by comparing a known signal (i.e. a template) with the input signal. A matched filter will maximize the received SNR for the measured signal. Therefore, if the information of the signal from a licensed user is known (e.g. modulation and packet format), a matched filter is an optimal detector in stationary Gaussian noise. Since a template is used for signal detection, a matched filter requires only a small amount of time to operate. However, if this template is not available or is incorrect, the performance of spectrum sensing degrades significantly. Matched filter detection is suitable when the transmission of a licensed user has pilot, preambles, synchronization word or spreading codes, which can be used to construct the template for spectrum sensing.

1.3.3 Cyclostationary feature detection: The transmitted signal from a licensed user generally has a periodic pattern. This periodic pattern is referred to as cyclostationarity, and can be used to detect the presence of a licensed user. A signal is cyclostationary (in the wide sense) if the autocorrelation is a periodic function. With this periodic pattern, the transmitted signal from a licensed user can be distinguished from noise, which is a wide-sense stationary signal without correlation. In general, cyclostationary detection can provide a more accurate sensing result and it is robust to variations in noise power. However, the detection is complex and requires long observation periods to obtain the sensing result. A pattern recognition scheme based on a neural network can be used to implement cyclostationary feature detection for spectrum sensing.

1.3.4 Transmitter energy detection: Energy detection is the optimal method for spectrum sensing when the information from a licensed user is unavailable. In the case of energy detection, the output signal from a bandpass filter is squared and integrated over the observation interval. A decision algorithm compares the integrator output with a threshold to decide whether a licensed user exists or not. In general, the energy detection performance deteriorates (e.g. Pm increases) when the SNR decreases.

An energy detection algorithm was proposed in for a non-fading environment and the expressions for probability of detection Pd and probability of false alarm Pf were obtained as follows:

P_d=Q($\sqrt{2\gamma}$,$\sqrt{\lambda}$) and P_f=$\Gamma(m,\frac{\lambda}{2})/\Gamma$(m), where γ is the SNR of the received signal, λ is the energy detection threshold, Γ (·) and _(·, ·) are the complete and incomplete gamma functions, espectively, and $Q(\cdot)$ is the generalized Marcum Q-function. In the presence of shadowing and multipath fading, the probability of detection can be obtained from: Pd = $\int_x Q(\sqrt{2y},\sqrt{\lambda}) f_y(x)dx,$ where fγ (x) is the probability distribution function of SNR under fading.

The two shortcomings of energy detection are:

(1) It is susceptible to the uncertainty of noise power.

(2) It can only detect the presence of the signal but cannot differentiate the type of signal (e.g. signals from secondary users sharing the same channel with the primary user). Therefore, the detection error would be high in presence of signal sources other than the licensed user.

1.3.5 Cooperative sensing

An unlicensed transmitter may not always be able to detect the signal from a licensed transmitter due to its geographic separation and channel fading. For example, the transmitter and receiver of the unlicensed user cannot detect the signal from the transmitter of the licensed user since they are out-of-range. This is referred to as the hidden node problem. In this case, when the transmitter of the unlicensed user transmits, it will interfere with the receiver of the licensed user. To solve the hidden node problem in non-cooperative transmitter sensing, cooperative spectrum sensing can be used. In cooperative sensing, spectrum sensing information from multiple unlicensed users are exchanged among each other to detect the presence of licensed users. The cooperative spectrum sensing architecture can be either centralized or distributed. Using cooperative exchange of spectrum sensing information, the hidden node problem can be solved and the detection probability can be significantly improved in a heavily shadowed environment. However, this incurs a greater communication and computation overhead compared with non-cooperative sensing. For cooperative sensing, two different networks (i.e. a sensor network and an operational network) can be deployed to perform spectrum sensing and access, respectively. In this case, the sensor network collects spectrum usage information of licensed users which can be processed by a central controller. Then a spectrum usage map is created and distributed to the operational network of unlicensed users for optimizing the spectrum access.

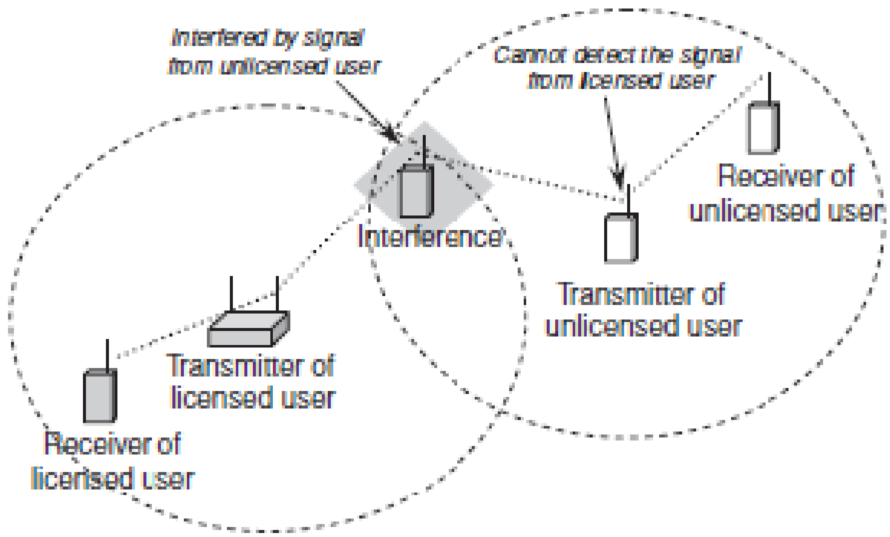


Fig 4: Hidden Node problem [2]

1.3.6 Interference-based sensing

Interference-based sensing was proposed by the FCC. In this case, the sensing algorithm will measure the noise/interference level (from all sources of signals) at the receiver of the licensed user. This information is used by an unlicensed user to control the spectrum access (e.g. by computing expected interference level) without violating the interference temperature limit. Alternatively, an unlicensed transmitter may observe the feedback signal from a licensed receiver to gain knowledge on the interference level.

1.4 POTENTIAL APPLICATIONS OF COGNITIVE RADIO

Cognitive radio concepts can be applied to a variety of wireless communications scenarios, a few of which are described below:

• Next generation wireless networks: Cognitive radio is expected to be a key technology for next generation heterogeneous wireless networks. Cognitive radio will provide intelligence to both the user-side and provider-side equipments to manage the air interface and network efficiently. At the user-side, a mobile device with multiple air interfaces (e.g. WiFi, WiMAX, cellular) can observe the status of the wireless access networks (e.g. transmission quality, throughput, delay, and congestion) and make a decision on selecting the access network to connect with. At the provider-side, radio resource from multiple networks can be optimized for the given set of mobile users and their QoS requirements. Based on the mobility and traffic pattern of the users, efficient load balancing mechanisms can be implemented at the service provider's infrastructure to distribute the traffic load among multiple available networks to reduce network congestion.

• Coexistence of different wireless technologies: New wireless technologies (e.g. IEEE 802.22-based WRANs) are being developed to reuse the radio spectrum allocated to other wireless services (e.g. TV service). Cognitive radio is a solution to provide coexistence between these different technologies and wireless services. For example, IEEE 802.22-based WRAN users can opportunistically use the TV band when there is no TV user nearby or when a TV station is not broadcasting. Spectrum sensing and spectrum management will be crucial components for IEEE 802.22 standard-based WRAN technology to avoid interference to TV users and to maximize throughput for the WRAN users.

• e-Health services: Various types of wireless technologies are adopted in healthcare services to improve efficiency of the patient care and healthcare management. However, using wireless communication devices in healthcare application is constrained by EMI (electromagnetic interference) and EMC (electromagnetic compatibility) requirements. Since the medical equipments and biosignal sensors are sensitive to EMI, the transmit power of the wireless devices has to be carefully controlled. Also, different biomedical devices (e.g. surgical equipment, diagnostic and monitoring devices) use RF transmission. The spectrum usage of these devices has to be carefully chosen to avoid interference with each other. In this case, cognitive radio concepts can be applied. For example, many wireless medical sensors are designed to operate in the ISM (industrial, scientific, and medical) band, which can use cognitive radio concepts to choose suitable transmission bands to avoid interference.

CHAPTER-2

TECHNICAL OVERVIEW

Software used: MATLAB R2010a

2.1 DETECTION OF SPECTRUM HOLES

The starting point for signal detection theory is that nearly all reasoning and decision making takes place in the presence of some uncertainty. Signal detection theory provides a precise language and graphic notation for analyzing decision making in the presence of uncertainty. The general approach of signal detection theory has direct applications in terms of spectrum sensing for cognitive radios. For instance, the secondary users need to detect whether or not a primary user is present in the network.

As an illustration, the probability distribution functions (pdfs) of the received signals at a secondary user are shown in figure below. If the primary user is absent, the pdf is a noise-only distribution. If the primary user's signal is being transmitted, the pdf is signal plus noise distribution. According to a certain criterion (or threshold), the secondary user determines if the primary user is present or not. Depending on whether or not the primary user is present and on the secondary user's decision, there are four possibilities as shown in table below. With the transmission of a primary user, if the secondary user detects the transmission, it is called a "hit"; otherwise, it is called a "miss." In the absence of a primary user, if the secondary user says the primary is "on," the case is called a "false alarm"; otherwise it is the "correct rejection." The false alarm is also called a type-I error and the miss is also called a type-II error. It is evident that the probabilities of all four cases highly depend on the threshold.

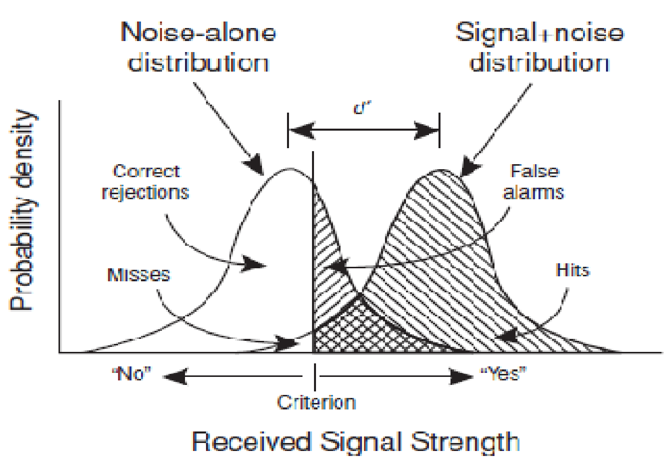


Fig 5: Illustration of a typical detection problem [2]

	Secondary user response "yes"	Secondary user response "no"
Primary user "on"	Hit	Miss
Primary user "off"	False alarm	Correct rejection

Table 1: Signal detection paradigm [2]

2.2 PRACTICAL SPECTRUM SENSING APPROACHES

Energy detection: An energy detector is a non-coherent detector that avoids the complicated coherent receivers required by a matched filter, and can be implemented using spectrum analyzing tools such as fast Fourier transform (FFT).

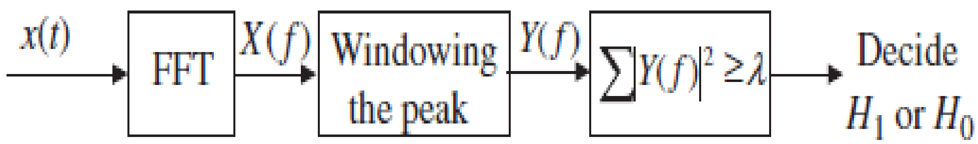


Fig 6: Approach in energy detection [3]

Although an energy detector is very simple to implement, there are several drawbacks:

First, the spectrum sensing speed is relatively slow.

Second, the threshold for detection is very susceptible to the noise level and in-band interference. This is even worse in the frequency-selective and time-varying channels.

Third, an energy detector cannot differentiate modulated signals, noise, and interference. As a result, the benefits of detection and interference cancellation techniques cannot be employed.

Fourth, the primary user and the secondary user cannot be distinguished, while only the primary user's transmission should be protected.

2.3 MODULATION TECHNIQUE INVOLVED

In our project, the modulation technique used is that of Frequency Shift Keying. The particular purpose for using this technique is the fact that at higher frequency the probability of bit error is least when we are employing this method.

2.3.1 Transmitter for BFSK Signal

In Binary frequency shift keying (BFSK) the binary data waveform d(t) generates a binary signal

$$V_{BFSK}(t) = \sqrt{2P_s}\cos[w_o t + d(t)\Omega t] \quad (1)$$

Here d(t)= +1 or -1 corresponding to the logic levels 1 and 0 of the data waveform. The transmitted signal is of amplitude √2Ps and is either

$$V_{BFSK}(t) = S_H(t) = \sqrt{2P_s}\cos[w_o + \Omega t] \quad (2)$$

or

$$V_{BFSK}(t) = S_L(t) = \sqrt{2P_s}\cos[w_o - \Omega t] \quad (3)$$

And thus has an angular frequency $\omega_\circ+\Omega$ or $\omega_\circ-\Omega$ with Ω a constant offset from the nominal carrier frequency $\omega_\circ$. We shall call the higher frequency ω^H (= $\omega_\circ+\Omega$) and the lower frequency ω^L (= $\omega_\circ-\Omega$).We may conceive that the BFSK signal is generated in the manner as shown below. Two balanced modulators are used, one with carrier ω^H and one with carrier ω^L. The voltage values of $p^H(t)$ and of $p^L(t)$ are related to the voltages values of d(t) in the following manner.

d(t)	$p^H(t)$	$p^L(t)$
+1V	+1V	0V
-1V	0V	+1V

Thus when d(t) changes from +1 to -1 p^H changes from 1 to 0 and p^L from 0 to 1. At any time either p^H or p^L is 1 but not both so that the generated signal is either at angular frequency ω^H or at ω^L.

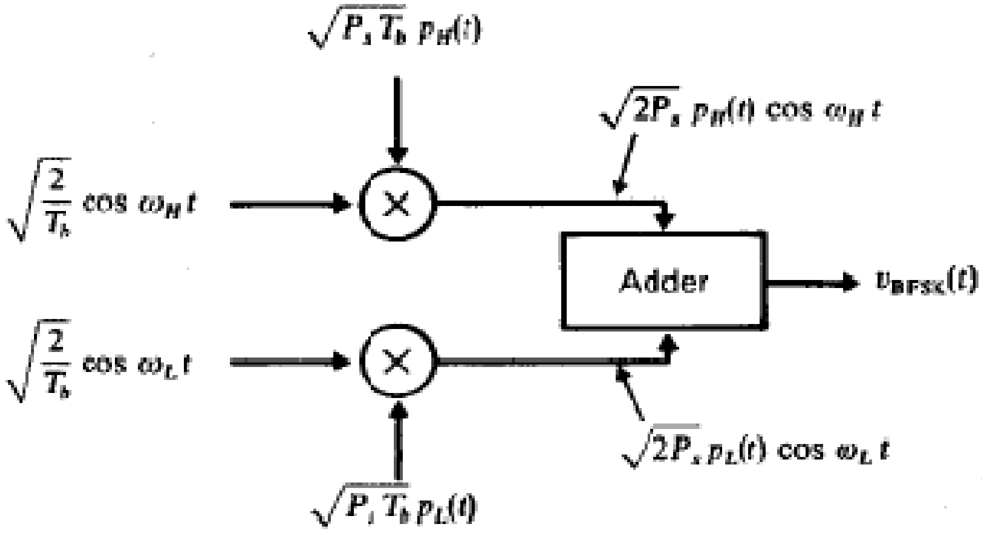


Fig 7: A representation of a manner in which a BFSK signal can be generated. [10]

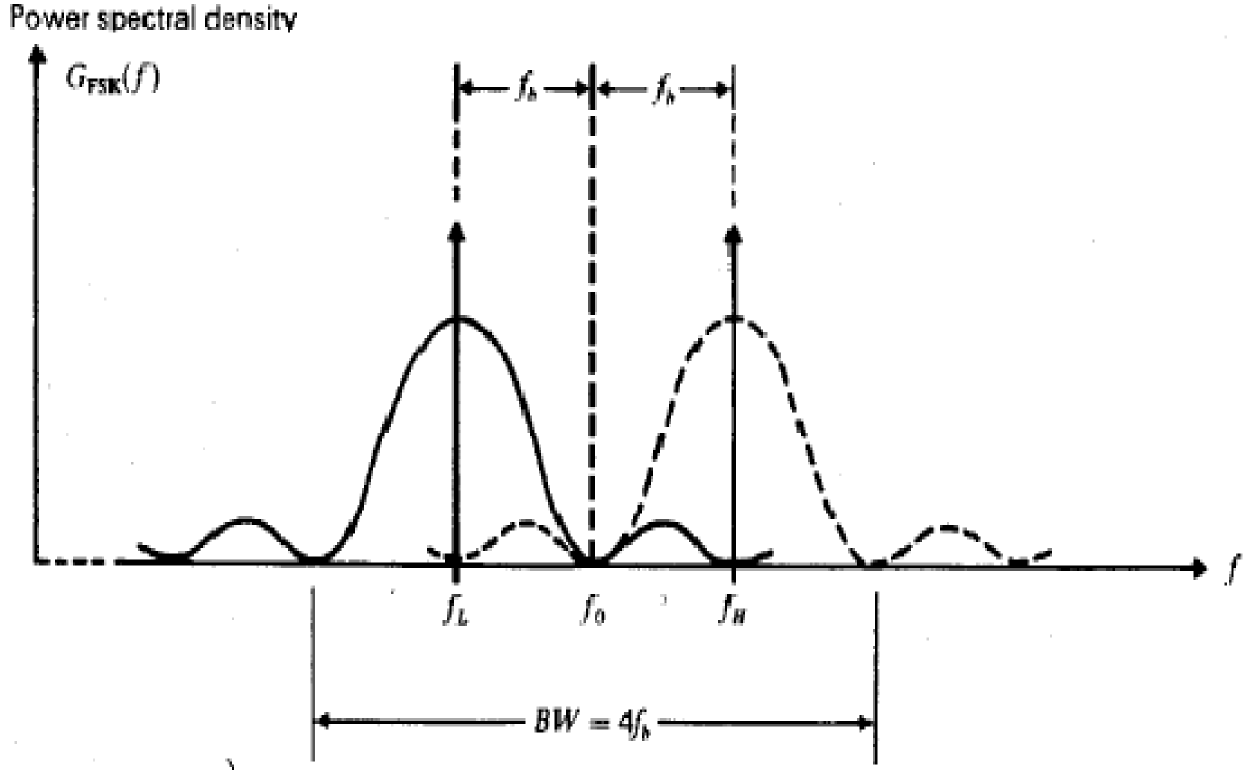


Fig 8: Power spectral densities [10]

2.3.2 Receiver for BFSK Signal

A BFSK signal is typically demodulated by a receiver system as shown in figure. The signal is applied to two bandpass filters one with center frequency at f^H the other at f^L. Here we have assumed, as above, that $f^H - f^L = 2(\Omega/2\prod) = 2f^b$. The filter frequency ranges selected do not overlap and each filter has a passband wide enough to encompass a main lobe in the spectrum. Hence one filter will pass nearly all the energy in the transmission at f^H the other will perform similarly at f^L. The filter outputs are applied to envelope detectors and finally the envelope detector outputs are compared by a comparator. A comparator is a circuit that accepts two input signals. It generates a binary output which is at one level or the other depending on which input is larger. Thus at the comparator output the data d(t) will be reproduced.

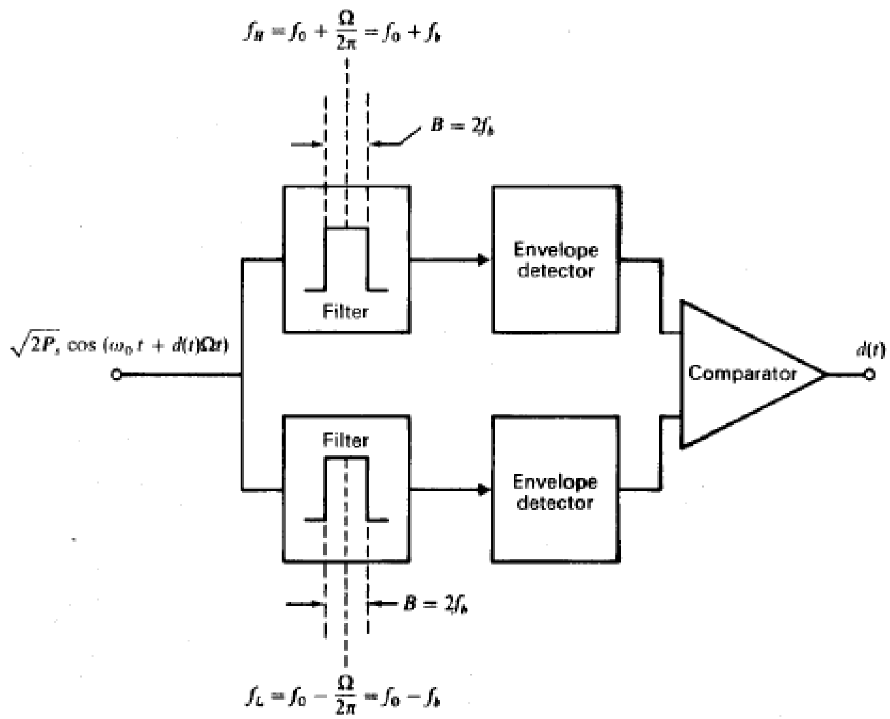


Fig 9: A receiver for a BFSK signal [10]

2.4 THEOREMS AND MATHEMATICAL CONCEPTS

2.4.1 Shannons's Sampling Theorem

The Whittaker-Shannon interpolation formula or sinc interpolation is a method construct a continuous-time bandlimited function from a sequence of real numbers. Given a sequence of real numbers, x[n], the continuous function:

$$X(t) = \sum_{-\infty}^{\infty} x[n].sinc(\frac{t-nT}{T})$$

has a Fourier transform, X(f), whose non-zero values are confined to the region: $|f|<=1/2$ T. When parameter T has units of seconds, the bandlimit, ½ T, has units of cycles/sec (hertz). When the x[n] sequence represents time samples, at interval T, of a continuous function, the quantity fs=1/T is known as the sample rate, and fs/2 is the corresponding Nyquist frequency. When the sampled function has a bandlimit, B, less than the Nyquist f requency, x(t) is a perfect reconstruction of the original function. Otherwise, the frequency components above the Nyquist frequency fold into the sub-Nyquist region of X(f), resulting in distortion.

2.4.2 Additive White Gaussian Noise

Additive white Gaussian noise (AWGN) is one of the channel model in which the only detoriation to communication is a linear addition of wideband noise with a constant spectral density (expressed as watts per hertz of bandwidth) and a Gaussian distribution of amplitude. The model does not account for fading, frequency selectivity, interference, nonlinearity or dispersion. The probability density function p of a Gaussian random variable z is given by:

$$PDF = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}}$$

where z represents the grey level, μ -the mean value and σ -the standard deviation. In our case which is white Gaussian noise μ=0.

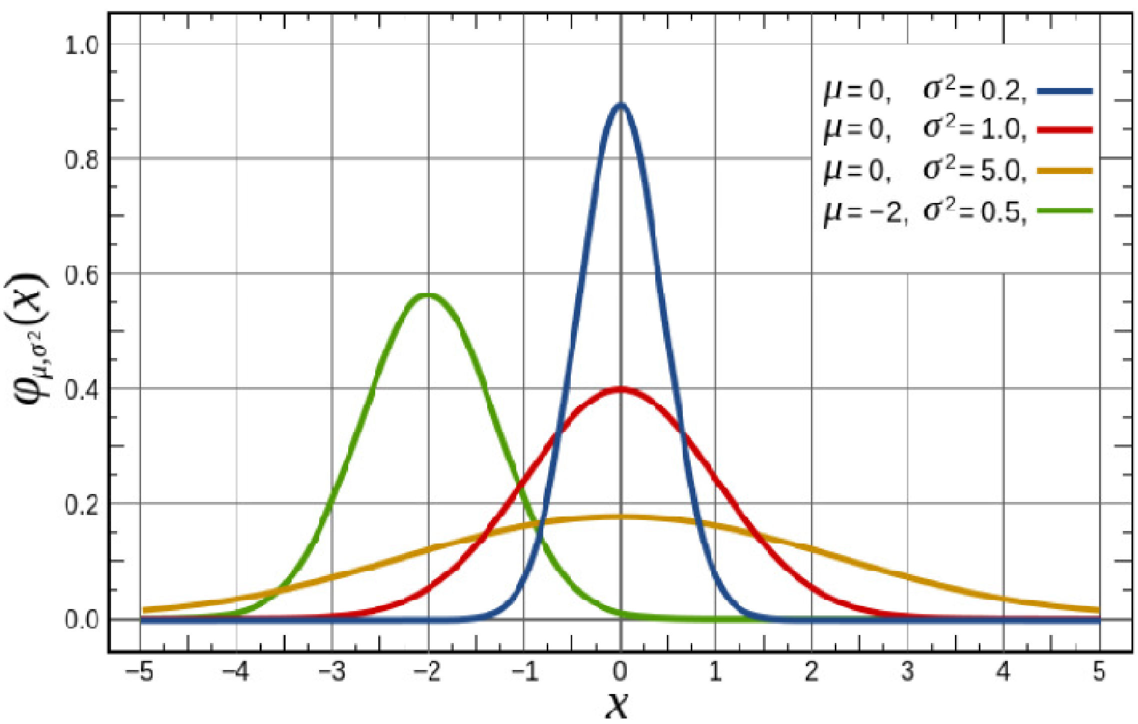


Fig 10: Additive white Gaussian noise [11]

2.4.3 Chi-squared distribution

In probability theory and statistics, the chi-squared distribution with k degrees of freedom is the distribution of a sum of the squares of k independent standard normal random variables. It is one of the most widely used probability distributions in inferential statistics, e.g., in hypothesis testing or in construction of confidence intervals. When there is a need to contrast it with the non-central chi-squared distribution, this distribution is sometimes called the central chi-squared distribution.

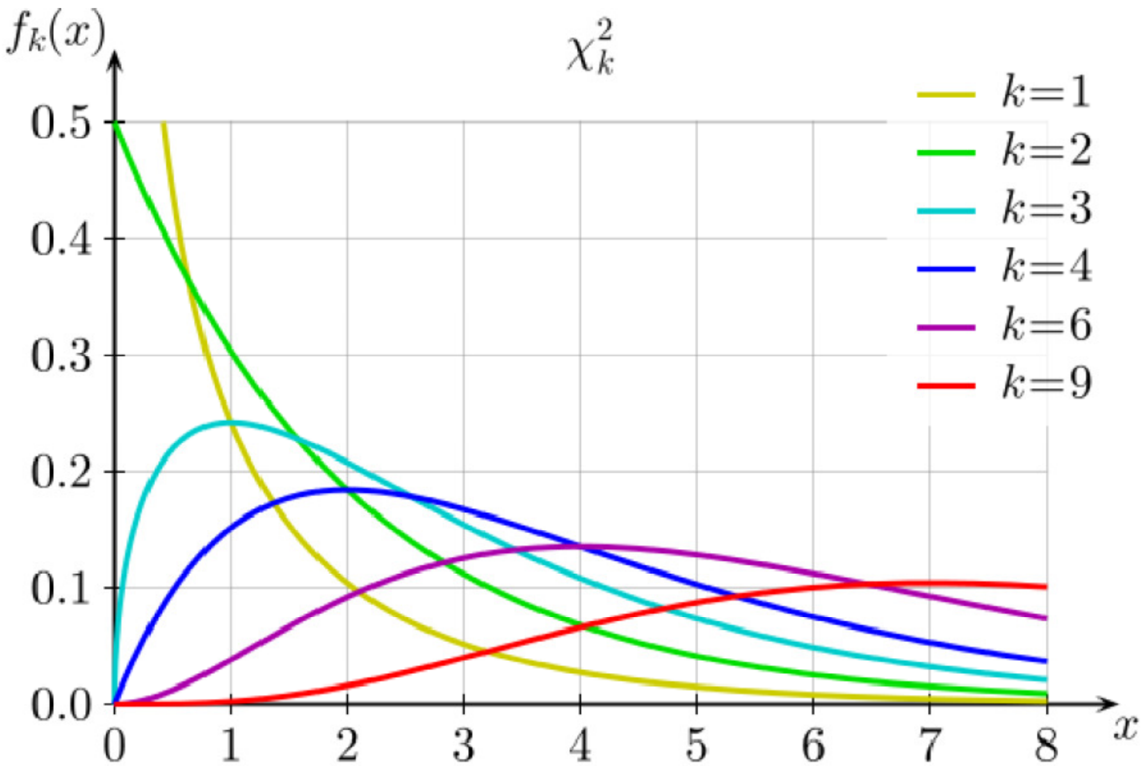


Fig 11: Chi-square distribution [12]

2.4.4 Pearson's theorem

Let us consider r boxes B1, . . . , Br and throw n balls X_1, . . . , Xn into these boxes independently of each other with probabilities

$$P(Xi \epsilon B1) = p1, \ldots, P(Xi = Br) = pr ,$$

so that

$$p1 + \ldots + pr = 1.$$

Let v_j be a number of balls in the jth box:

v_j = #{balls X1, . . . , Xn in the box Bj } = $\sum_{i=1}^{n} I(X_1 \epsilon B_j)$

On average, the number of balls in the jth box will be np_j since

$$Ev_j = \sum_{i=1}^{n} EI(X_1 \epsilon B_j) = P(Xl = Bj) = np_j$$

We can expect that a random variable v_j should be close to np_j. For example, we can use a Central Limit Theorem to describe precisely how close v_j is to np_j. The next result tells us how we can describe the closeness of v_j to np_j simultaneously for all boxes $j \leq r$. The main difficulty in this Theorem comes from the fact that random variables v_j for $j \leq r$ are not independent because the total number of balls is fixed

$$v_1 + \cdots \ldots \ldots \ldots \ldots + v_r = n .$$

If we know the counts in n - 1 boxes we automatically know the count in the last box.

Theorem (Pearson): We have that the random variable

$$\sum_{j=1}^{r} \frac{(v_j - np_j)^2}{np_j} \to^{d} \chi_{r-1}^{2}$$

converges in distribution with (r-1) degrees of freedom.

2.4.5 Goodness-of-fit for continuous distribution.

Let X1, . . . , Xn be samples from unknown distribution P and consider the following hypotheses:

$$H_o : P = P_o$$

$$H_1 : P \neq P_o$$

for some particular, possibly continuous distribution P_o . To apply the chi-squared test above we will group the values of Xs into a finite number of subsets. To do this, we will split a set of all possible outcomes χ into a finite number of intervals I_1, . . . , Ir as shown in figure below:

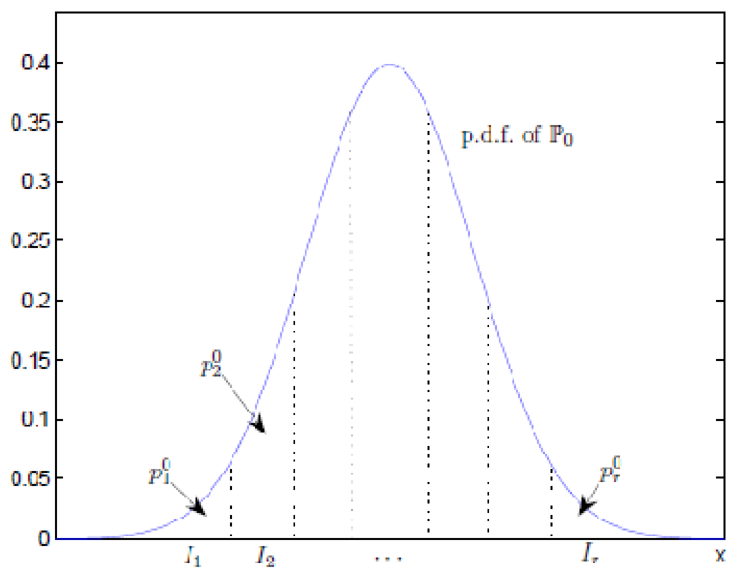


Fig 12: Discretizing continuous distribution

The null hypothesis H_o, of course, implies that for all intervals

$$P(X \in Ij) = P_o (X \in Ij) = p_j^o$$

Therefore, we can do chi-squared test for

$$H_o': P(X \in Ij) = p_j^o \text{ for all } j \leq r$$

$$H_1' = \text{otherwise}$$

Asking whether H_0' holds is, of course, a weaker question that asking if H_0 holds, because H_0 implies H_0' not the other way around. There are many distributions different from P that have the same probabilities of the intervals $I_1, \ldots,$ Ir as P. On the other hand, if we group into more and more intervals, our discrete approximation of P will get closer and closer to P, so in some sense H_0' will get closer to H_0. However, we cannot split into too many intervals either, because the χ^2_{r-1}-distribution approximation for statistic T in Pearson's theorem is asymptotic.

CHAPTER-3

Methodology

We proceed from the only known fact that our signal is deterministic and the noise considered here is additive white Gaussian noise. In the absence of much knowledge concerning the signal, it seems appropriate to use an energy detector to determine the presence of a signal. The energy detector measures the energy in the input wave over a specific time interval. It is assumed here that the noise has a flat band-limited power density spectrum. By means of a sampling plan, the energy in a finite time sample of the noise can be approximated by the sum of squares of statistically independent random variables having zero means and equal variances. The energy detector consists of a square law device followed bay finite time integrator. The output of the integrator at any time is the energy of the input to the squaring device over the interval Tin the past. The noise prefilter serves to limit the noise bandwidth; the noise at the input to the squaring device has a band-limited, flat spectral density.

3.1 Fourier Transform

Using Fourier transform theory, the frequency spectrum of the continuous time waveform x(t) can be written

$$\mathrm{X(f)}=\int_{-\infty}^{\infty} x(t)^{-j2\pi f t}\mathrm{dt}$$

And the time waveform can be expressed in terms of its spectrum as

$$\mathrm{x(t)}=\int_{-\infty}^{\infty} X(f)e^{j2\pi f t}\mathrm{df}$$

Since this is true for any continuous function of time, x(t), it is also true for x_s(t)

$$X_s\mathrm{(f)}=\int_{-\infty}^{\infty} x_s(t)e^{-j2\pi f t}\mathrm{dt}$$

Replacing x_s(t) by the sampling representation

$$X_s(\mathrm{f})=\int_{-\infty}^{\infty}[\sum_{n=-\infty}^{\infty} x(t)\delta(t-nT)]e^{-j2\pi ft}\mathrm{dt}$$

The order of the summation and integration can be interchanged and it can be written as

$$X_s(\mathrm{f})=\sum_{n=-\infty}^{\infty} x(nT)\, e^{-j2\pi fnT}$$

This equation is the exact form of a Fourier series representation of X_s(f), a periodic function of frequency having period 1/T. The coefficients of the Fourier series are x(nT) and they can be calculated from the following integral:

$$\mathrm{x(nT)=T}\int_{-\frac{1}{2T}}^{\frac{1}{2T}} X_2(f)\, e^{j2\pi fnT}\mathrm{df}$$

The last two equations are a Fourier series pair which allow calculation of either the time signal or frequency spectrum in terms of the opposite member of the pair.

3.2 Energy detection

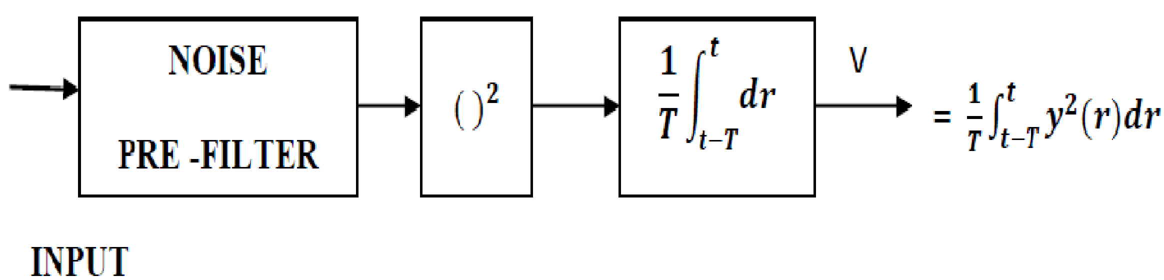


Fig 13: Squaring Integrator device [1]

The detection is a test of the following two hypotheses

1) Ho : The input y(t) is noise alone:

a) y(t)=n(t)

b) E[n(t)]=0

c) Noise spectral density = No, (two-sided)

d) Noise bandwidth = W cycles per second.

2) H1 : The input y(t) is signal plus noise :

a) y(t)=n(t)+s(t)

b) E[n(t) + s(t)] = s(t).

The output of the integrator is denoted by V and we concentrate on a particular interval, say, (0, T), and take the test statistic as V or any quantity monotonic with V. We shall find it convenient to compute the false alarm and detection probabilities using the related quantity.

$$V' = \frac{1}{No2}\int_0^T y^2(t)dt \tag{1}$$

It is known that a sample function, of duration T, of a process which has a bandwidth W (negligible energy outside this band) is described approximately by a set of sample values 2TW in number. Starting with a low pass process, we can express the noise in the form of

$$n(t) = \sum_{i=-\infty}^{\infty} a_i sinc(2wt - i) \tag{2}$$

where,

$$sinc(x) = \frac{\sin(\prod x)}{\prod x} \quad \text{and}$$

$$a_i = n(\frac{i}{2W}) \tag{3}$$

each a, is a Gaussian random variable with zero mean and with the same variance which is the variance of n(t), therefore

$$\sigma_i^2 = 2N_{o2}\text{W}, \text{ all i,} \tag{4}$$

Using the fact that:

$$\int_{-\infty}^{\infty} sinc(2Wt - i) sinc(2Wt - k)dt = \frac{1}{2}\text{W}, \quad \text{i=k}$$

$$= \quad 0, \qquad \text{i} \neq k \tag{5}$$

We may write

$$\int_{-\infty}^{\infty} n^2(t)dt = \frac{1}{2W} \sum_{i=-\infty}^{\infty} a_i^2 \tag{6}$$

Over the interval (0, T), n(t) may be approximated by a finite sum of 2TW terms, as follows:

$$n(t) = \sum_{i=1}^{2TW} a_i \, sinc(2Wt - 1), \qquad 0 < t < T \tag{7}$$

Similarly, the energy in a sample of duration T is approximated by 2T W terms of the right-hand side of eqn 6:

$$\int_0^T n^2(t)dt = \frac{1}{2W} \sum_{i=1}^{2TW} a_i^2 \tag{8}$$

We can see that (8) is No2 V' , with V' here being the test statistic under hypothesis Ho.

$$\frac{a_i}{\sqrt{2WN_{02}}} = b_i \tag{9}$$

which makes

$$\text{V'} = \sum_{i=1}^{2TW} b_i^2 \tag{10}$$

Thus, V' is the sum of the squares of 2TW Gaussian random variables, each with zero mean and unity variance. V' is said to have a chi-square distribution with 2TW degrees of freedom. We will now consider the input y(t) when the signal s(t) is present. The segment of signal duration T may be represented by a finite sum of 2TW terms.

$$\text{s(t)}=\sum_{i=1}^{2TW} \alpha_i \text{sinc(2Wt-i)}, \tag{11}$$

where

$$\alpha_i = s(\frac{i}{2W}) \tag{12}$$

By following the same reasoning as above, we can approximate the signal energy in the interval (0,T) by

$$\int_0^T s^2\text{(t)dt}=(\frac{1}{2}\text{W})\sum_{i=1}^{2TW} \alpha_i^2 \tag{13}$$

We define the coefficient ßi by

$$\beta_i = \frac{a_i}{\sqrt{2WN_{02}}} \tag{14}$$

$$\frac{1}{N_{o2}} \int_0^T s^2\text{(t)dt}=\sum_{i=1}^{2TW} \beta_i^2 \tag{15}$$

Using eqn (11) and (2), the total input y(t) with the signal present can be written as:

$$\text{y(t)}=\sum_{i=1}^{2TW} (a_i + \alpha_i)\text{sinc(2Wt-i)} \tag{16}$$

The energy of y(t) in the interval (0,T) is approximated by

$$\int_0^T y^2\text{(t)dt}=(\frac{1}{2W})\sum_{i=1}^{2TW} (a_i + \alpha_i)^2 \tag{17}$$

Under the hypothesis HI, the test statistic V’ is

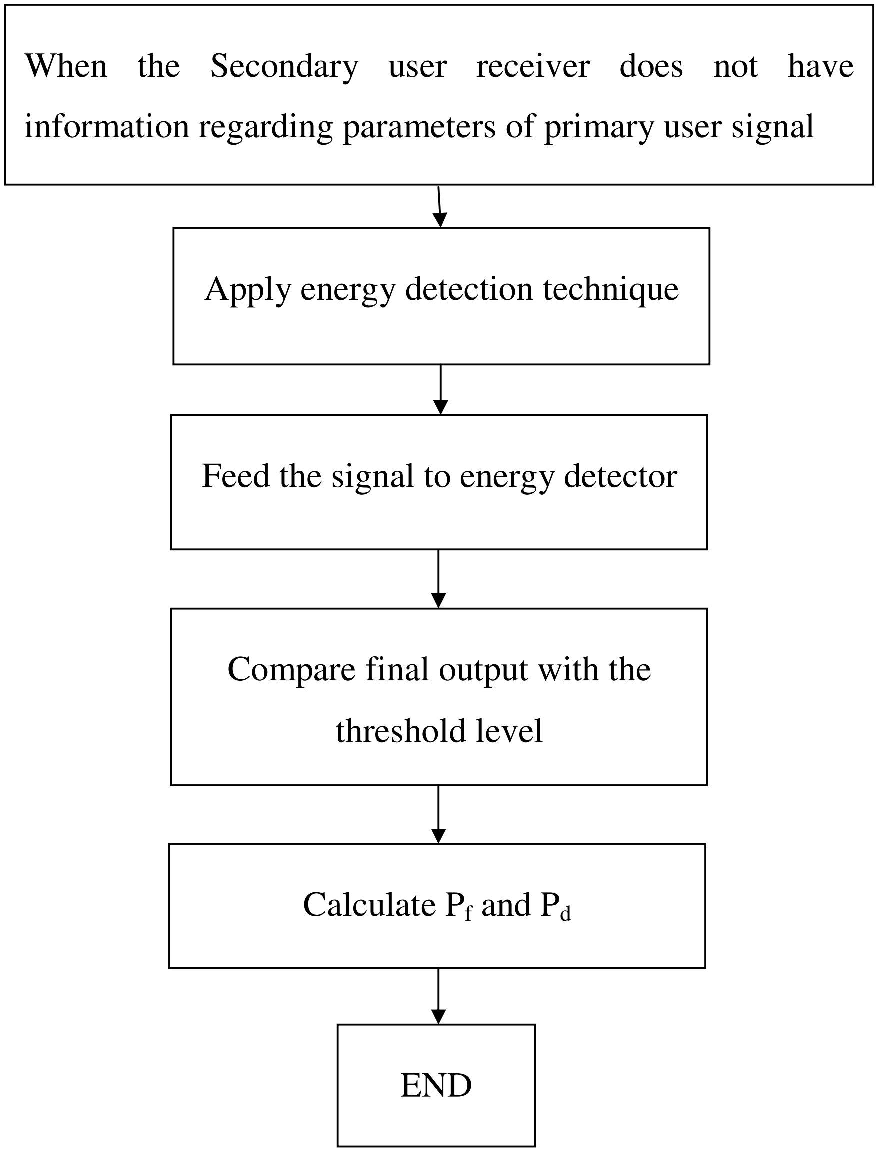
$$V' = (\frac{1}{N_{o2}})\int_0^T y^2(t)dt = \sum_{i=1}^{2TW}(b_i + \beta_i)^2 \tag{18}$$

The sum in eqn (18) is said to have a non-central chi-square distribution with 2TW degrees of freedom and a non-centrality parameter , given by

$$\Lambda = \sum_{i=1}^{2TW}\beta_i^2 = \frac{1}{N_{o2}}\int_0^T s^2(t)dt = \frac{E_s}{N_{o2}} \tag{19}$$

Λ is the ratio of signal energy to noise spectral density, provides a convenient definition of signal-to-noise ratio.

3.3 Flow Chart



3.4 Computation of Detection and False Alarm Probabilities

The probability of false alarm Q0 for a given threshold $V_T{}'$ is given by

Qo = Prob {V' > $V_T{}'$ | Ho} = Prob { $\chi^2 2TW > V_T{}'$ }.

The far right hand side of previous equation indicates a chi-square variable with 2TW degrees of freedom. For the same threshold level $V_T{}'$ the probability of detection Q_d is given by

Q_d= Prob{V' > $V_T{}'$ | H1 } = Prob { $\chi^2 2TW(\lambda) > V_T{}'$ }.

The symbol $\chi'^2 2TW(\lambda)$ indicates a noncentral chi-square variable with 2TW degrees of freedom and noncentrality parameter ; in our case = Es / N02 , and is defined as the signal-to-noise ratio. As mentioned above, extensive tables exist for the chi-square distribution, but the non-central chisquare has not been as extensively tabulated. Approximations were taken for this.

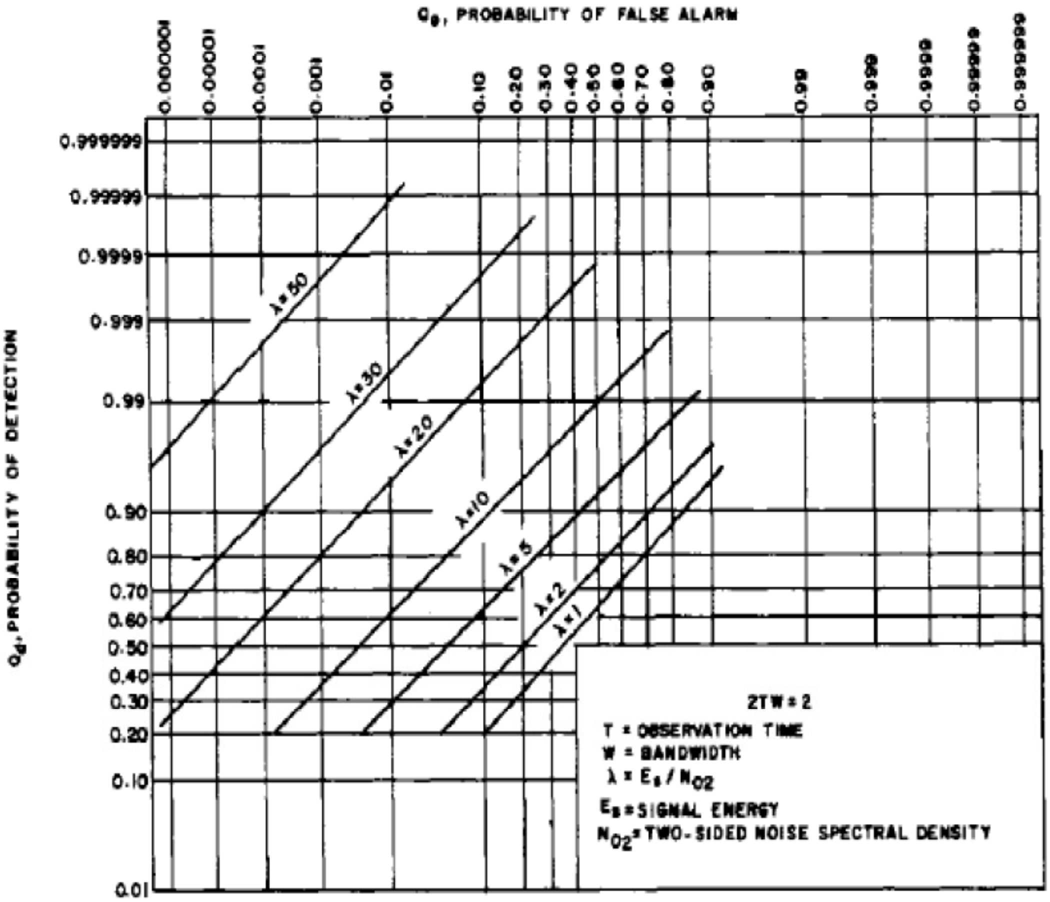


Fig 14: Receiver Operating Characteristics (ROC) curve (1) [1]

X axis: Q_o, Probability of False Alarm

Y axis: Q_d,Probability of Detection

T=Observation Time

W=Bandwidth

2TW=2

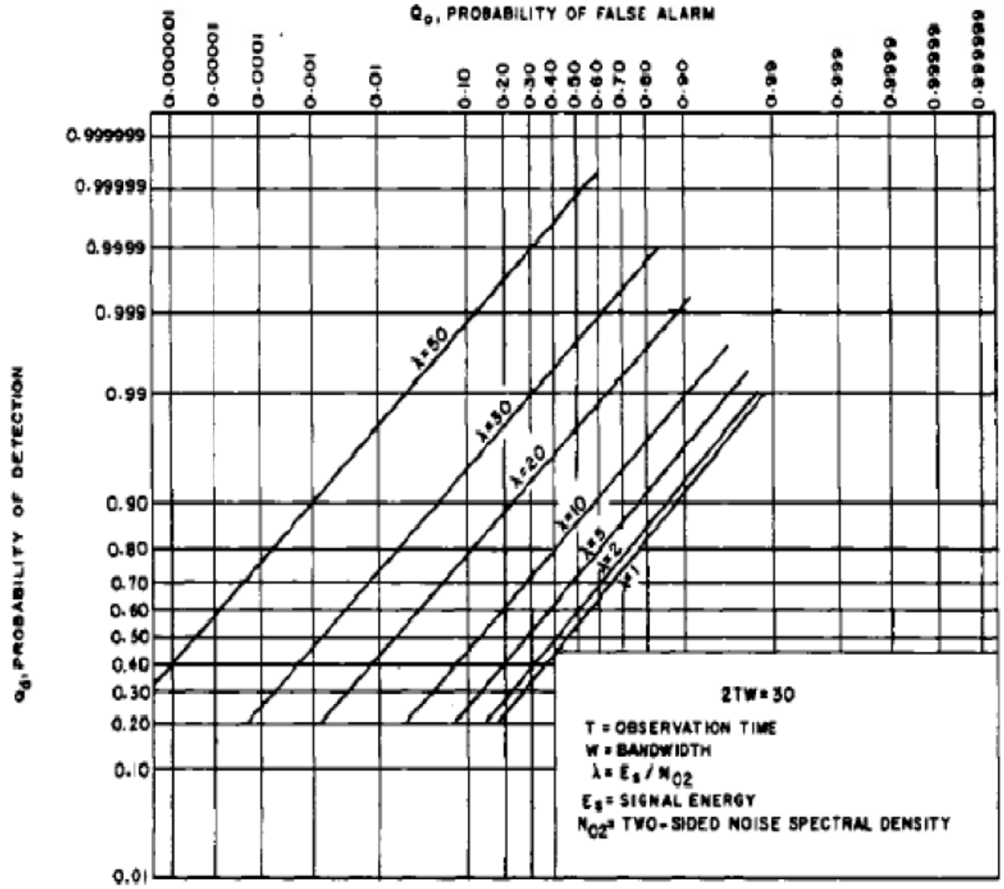


Fig 15: Receiver Operating Characteristic(ROC) curve (2) [1]

It is interesting to see how 2TW and the signal-to-noise ratio λ vary for given false alarm and detection probabilities. Figure shown above gives such a relationship for various Q_o and Q_d. It is clearly seen that increasing 2TW, the number of degrees of freedom, causes an increase in the required signal-to-noise ratio. A natural question is: why does increasing the time-bandwidth product increase the required signal-to-noise ratio. It has been suggested that the answer lies in the increased incoherence of the noise which tends to “dilute” the signal energy, somewhat analogously to the suppression encountered in incoherent detection.

CHAPTER-4

Results

According to the model of signal detection at time t, when only noise is present i.e. n(t), it is null hypothesis. When signal plus noise with some channel gain is received at the receiver, it is alternate hypothesis.

In this graph binary signal is sent through channel with some additive white Gaussian noise using Frequency shift keying.

Binary Information = `1 0 1 0 1`

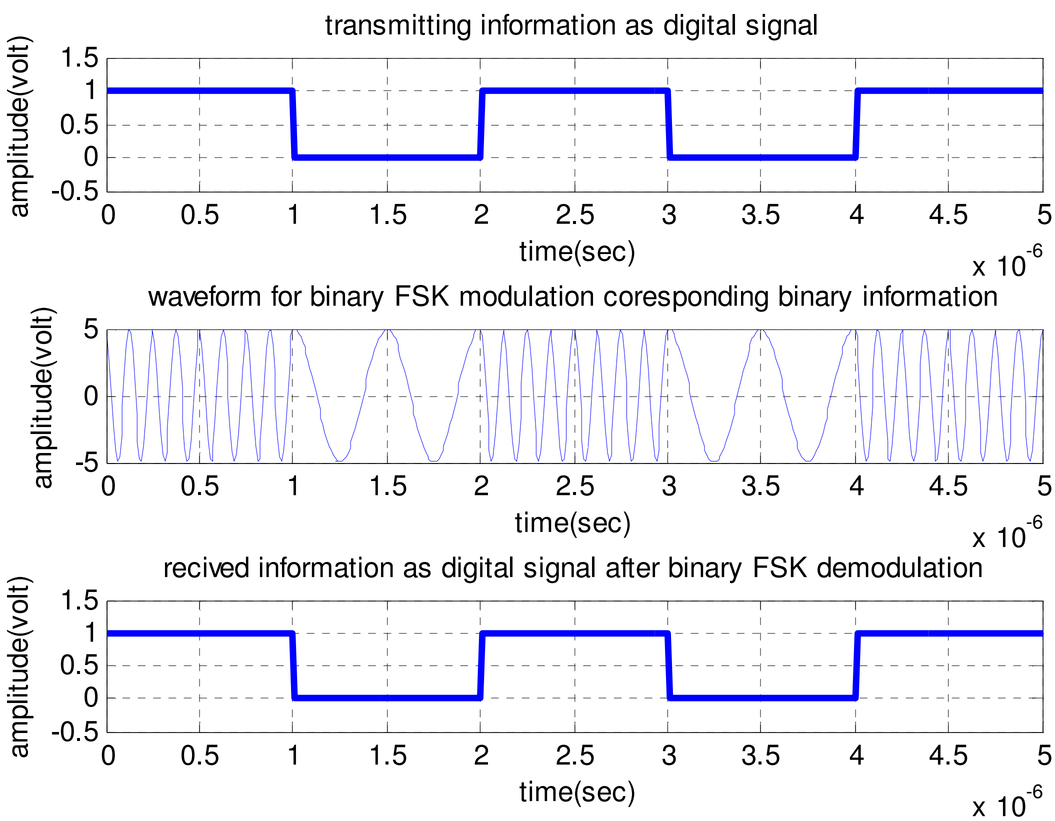


Fig 16 (a) : FSK modulation of binary information

OUTPUT:

Non-central chi-sqaure distribution and following Alternate Hypothesis

Then its power spectral density graph is shown below for the received signal at the receiver.

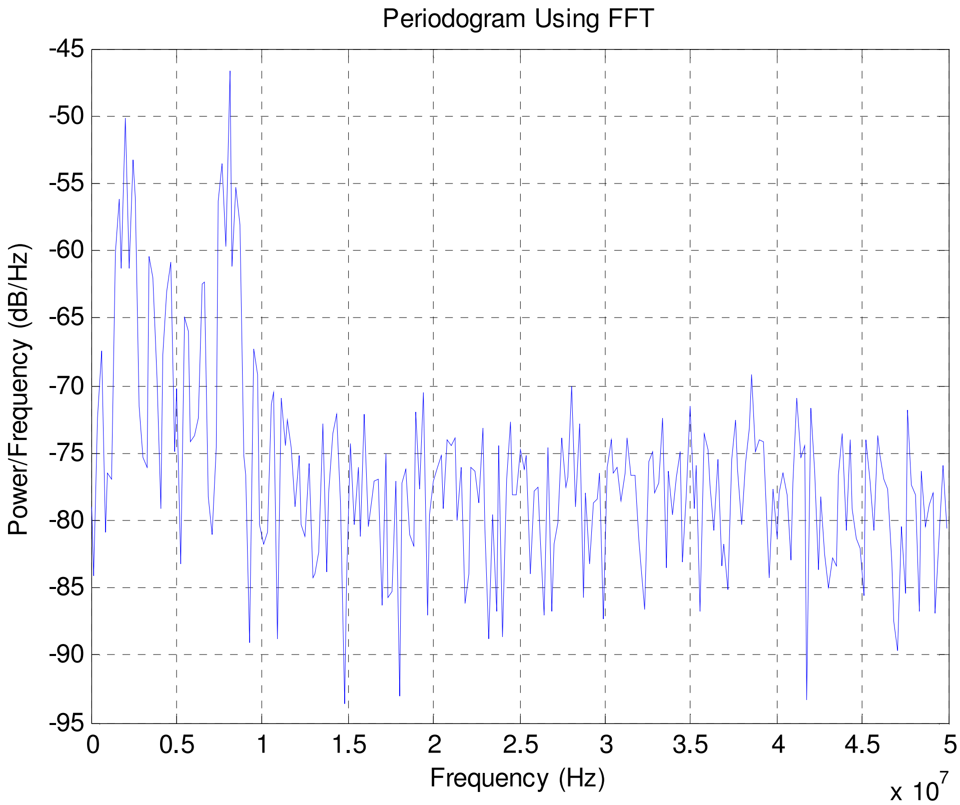


Fig 16 (b) : Power Spectral Density of received signal

When only noise is received at the receiver, it is Null Hypothesis. Here power spectral density of noise is shown below.

OUTPUT:

Central chi-square distribution i.e. means it is following Null hypothesis.

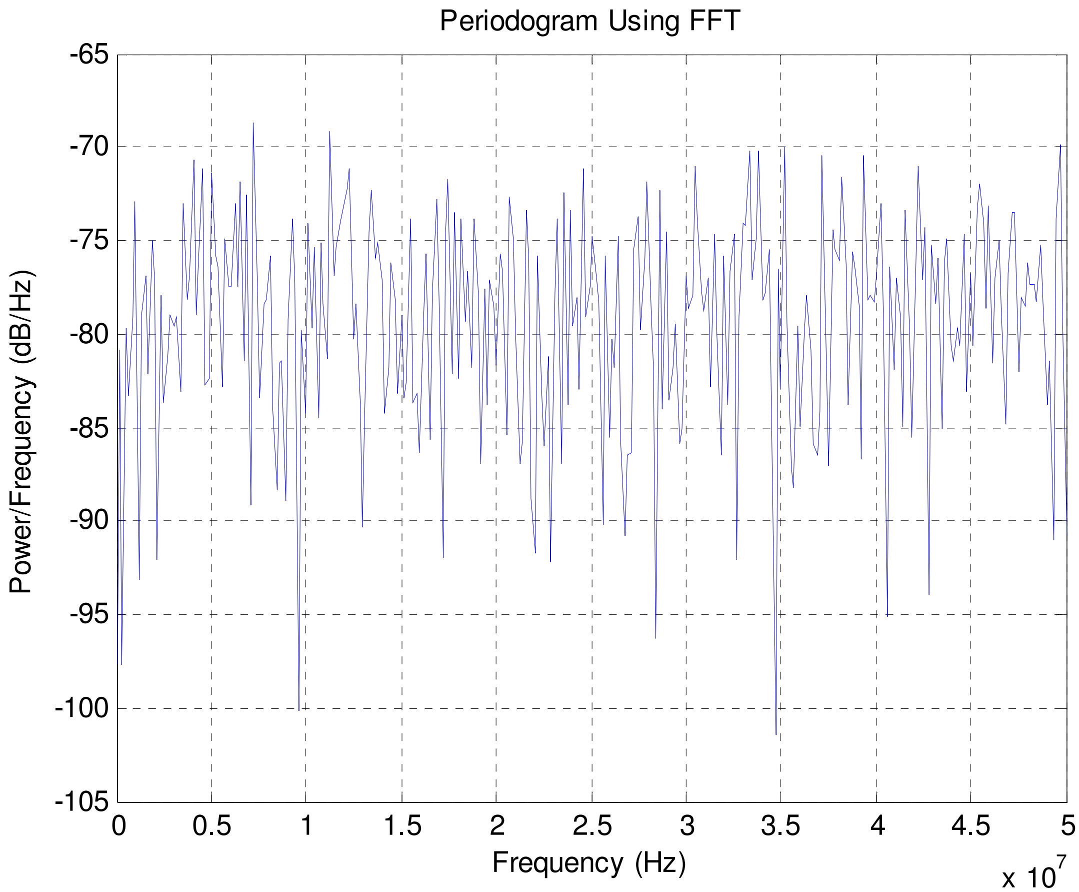


Fig 16 (c): Power spectral density of noise

In this graph red line represents the presence of users and green dotted line represents the false detection of spectrum. If availability is 1, means spectrum is used by some user, it may be primary or secondary user. If availability is 0, means spectrum is not used by any of the user. When the value of green dotted line is 1, means user is not present but it is showing that user is there.

Graph has been plotted for different values SNR, Probability of false alarm and percentage of occupancy with their respective values of threshold where number of users are 25 and having bandwidth = 250 Hz.

Threshold = 1.0174

percentage of occupancy = 0.5

SNR = - 20

Probability of false alarm = 0.001

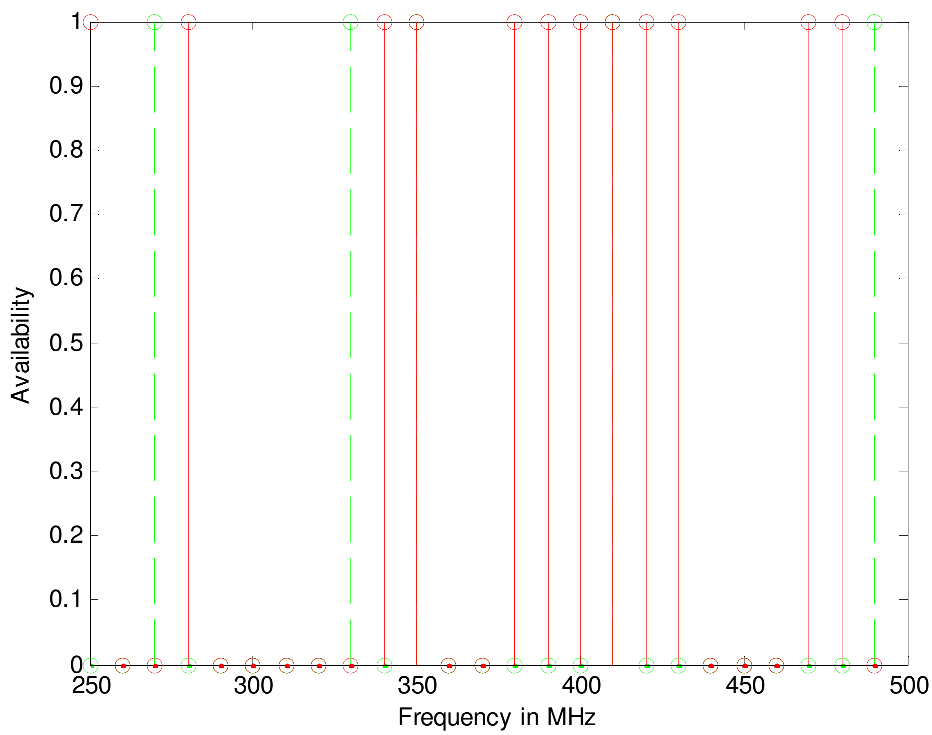


Fig 17 (a)

Threshold = 1.0174

percentage of occupancy = 0

SNR = - 20

Probability of false alarm = 0.001

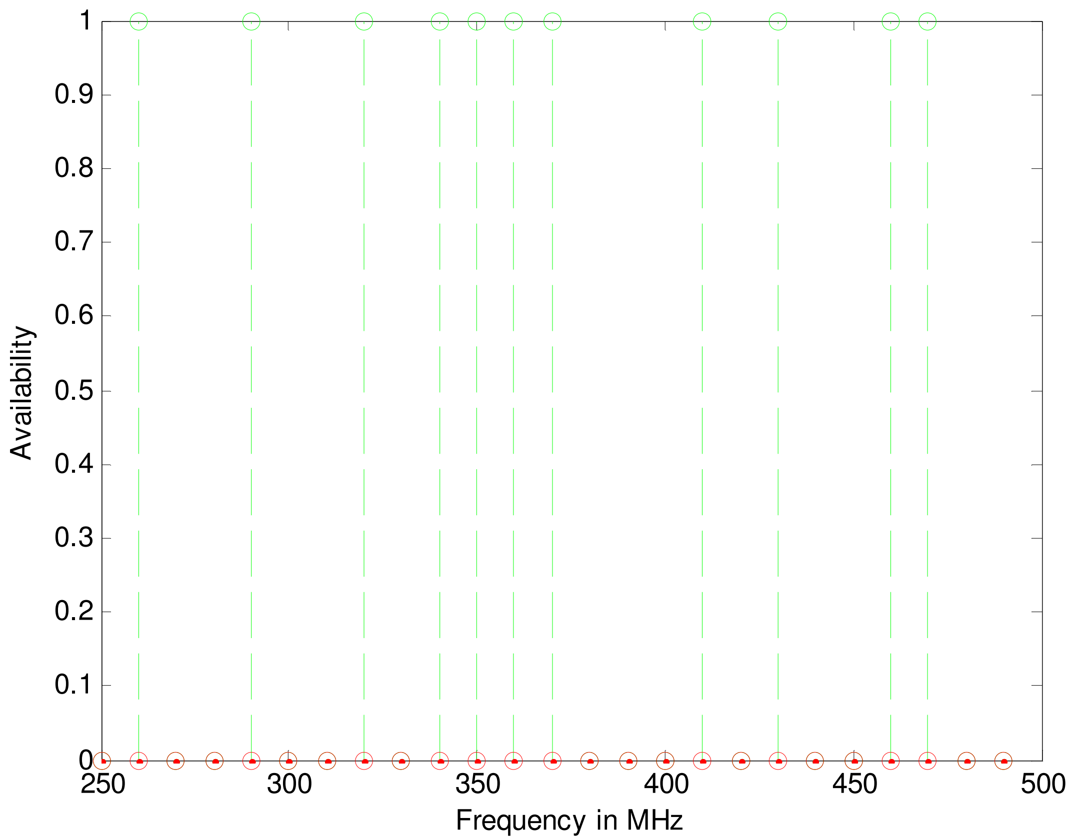


Fig 17 (b)

Threshold = 1.0174

percentage of occupancy = 1

SNR = - 20

Probability of false alarm = 0.001

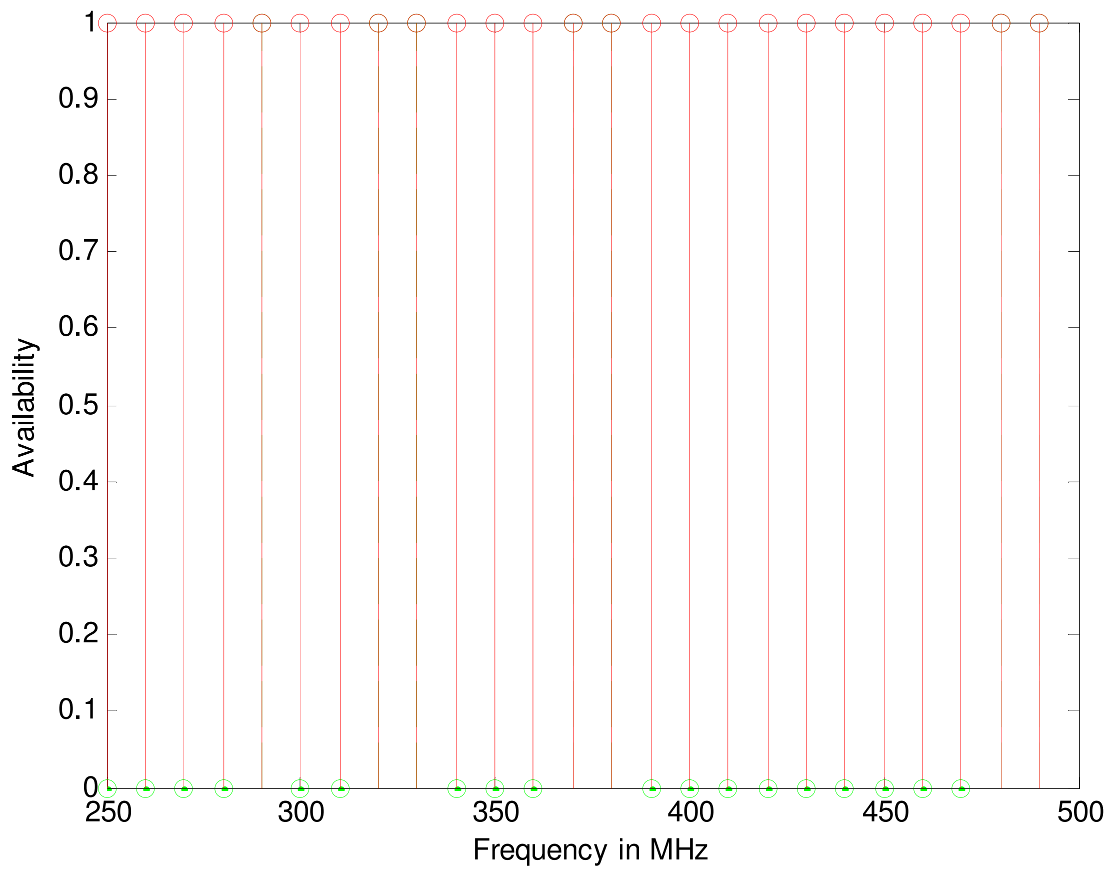


Fig 17 (c)

Threshold = 1.0174

percentage of occupancy = 0.5

SNR = - 100

Probability of false alarm = 0.001

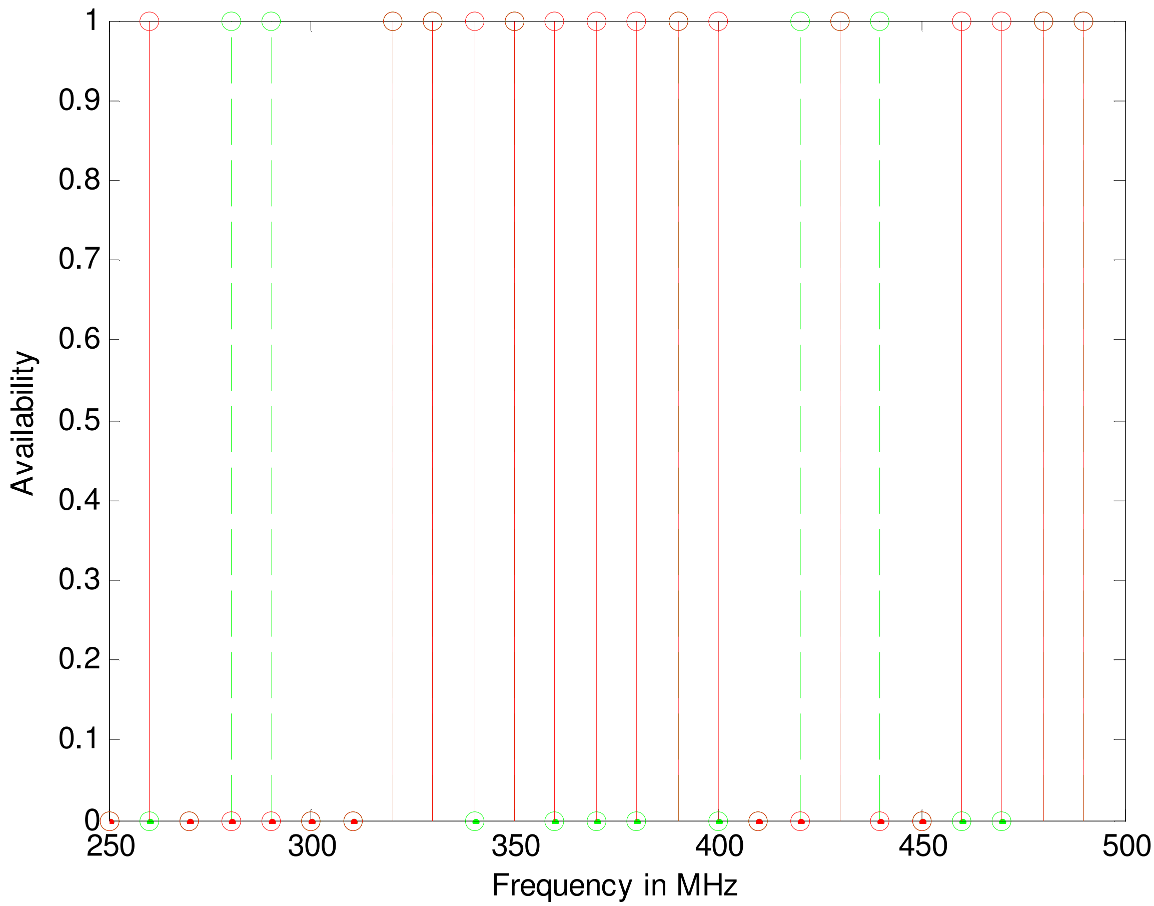


Fig 17 (d)

Threshold = ∞

percentage of occupancy = 0.5

SNR = - 100

Probability of false alarm = 0.000

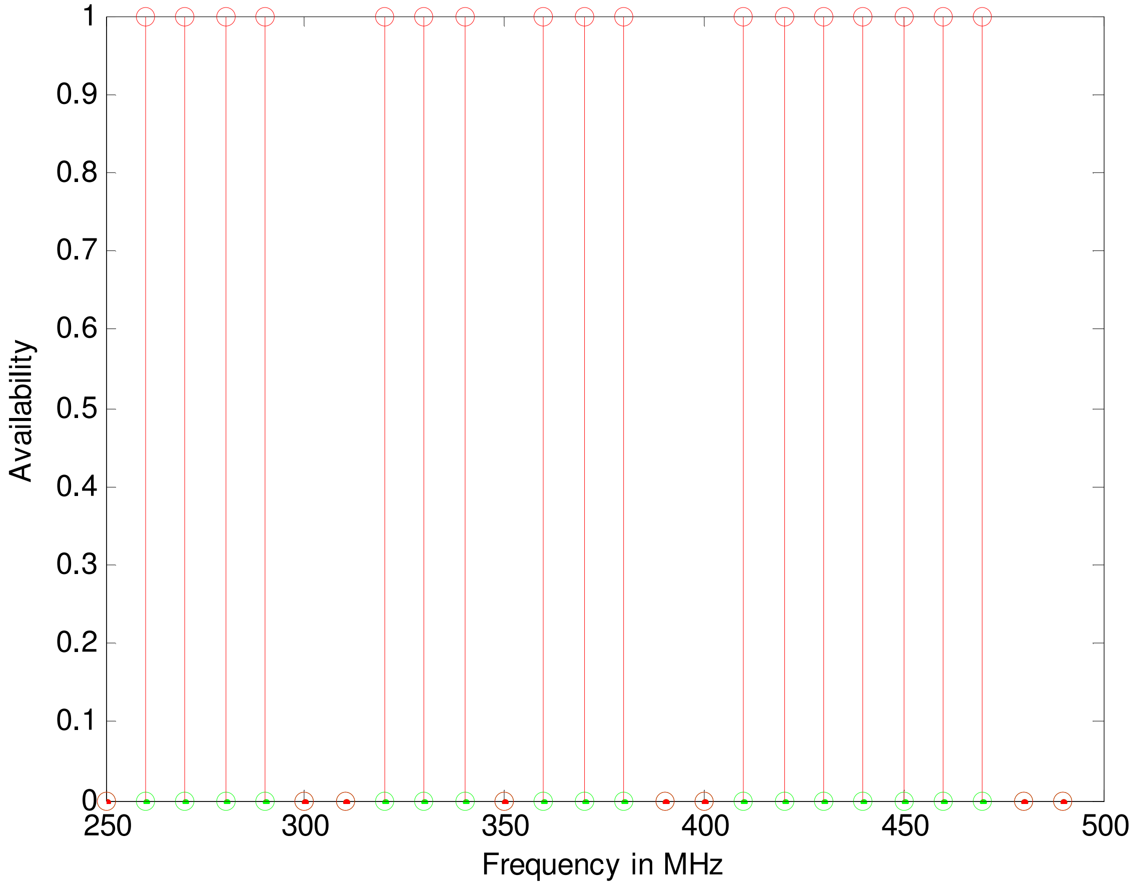


Fig 17 (e)

Conclusion

If the form of a signal to be detected is unknown, it appears appropriate to consider an energy detector as a device for deciding whether or not the signal is present. Since an energy detector does not care about anything but the amount of energy in the given observation time, the form of the signal does not affect the conditional probability that a threshold will be exceeded when the signal is present. Of course, it is assumed that the noise is zero mean Gaussian. By using Shannon's sampling theorem, one can show that the energy in a finite time interval can be described as a sum of the square of a number of statistically independent Gaussian variates if the noise input is Gaussian and has flat spectral density over a limited bandwidth.

Although in this project we have taken the point of view that the unknown signal is of deterministic form, there is nothing in it which changes results for any signal, known or unknown, deterministic or random, provided the probability of detection is considered a conditional probability of detection where the condition is a given amount of signal energy; i.e., if the signal present has a certain amount of energy, then its detection probability is given as shown in this project, regardless of where the signal comes from. It may come from a random process, or may be a one-shot affair, or may come from a process which repeats signals of the same form at regular or irregular intervals.

Challenges

The main challenge was to provide the similar input signal to our detector as a physical receiver would have received. Since the cost of Universal Software Radio Peripheral is quite high we are bound to use Matlab coding and functions. And so quite a few assumptions were made which sometimes contradicted result.

The second most important challenge in this project is to manage the tradeoff between probability of false alarm and correct detection.

References

[1]. Harry Urkowitz, “Energy Detection of Unknown Deterministic Signals”; Proceedings of the IEEE, Vol. 55, NO. 4, APRIL 1967 .

[2]. Ekram Hussain, Dusit Niyato, and Zhu Han; “Dynamic Spectrum Access and Management in Cognitive Radio Networks”; Cambride University Press 2009 .

[3]. Yang Xiao , Fei Hu;” Cognitive Radio Networks”; CRC Press; 2009

[4]. Shipra Kapoor and Ghanshyam Singh; “Non-Cooperative Spectrum Sensing:A Hybrid Model Approach”; IEEE; 2011

[5]. Joseph Mitola III;”Cognitive Radio Architecture The Engineering Foundations of Radio XML”; A Sons, John Wiley & INC., Publication; 2006

[6]. R. Tandra and A. Sahai, “SNR walls for signal detection”, Selected Topics in Signal Processing, IEEE Journal of vol. 2, no. 1, pp. 4-17, Feb 2008

[7]. Alexander M. Wyglinski, Maziar Nekovee, and Y. Thomas Hou; “Cognitive Radio Communications and Networks Principles and Practice”; Elsevier; 2010

[8]. Waleed Ejaz, Najam ul Hasan, Seok Lee and Hyung Seok Kim; “I3S: Intelligent spectrum sensing scheme for cognitive radio networks”; Eurasip Journal on Wireless Communications and Networking ; 2013

[9]. Amir Ghasemi and Elvino S. Sousa; “Spectr um Sensing in Cognitive Radio Networks: Requirements, Challenges and Design Trade-offs”; IEEE; 2008

[10]. Herbert Taub and Donald L. Schilling, “Principles of communication system”, McGraw Hill Publication

[11]. http://en.wikipedia.org/wiki/Additive_white_Gaussian_noise.

[12]. http://en.wikipedia.org/wiki/Chi-squared_distribution.