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Ultra-Wideband Spectrum Hole Identification Using Principal Components and Eigen Value Decomposition

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ABSTRACT

Ultra-Wideband Spectrum Hole identification using Principal Components and Eigen Value Decomposition evolve a method of detecting spectrum hole from complex and corrupted wide band spectrum signal, due to the effect of noise spectrum hole detection is usually a challenge in wideband signal, as the presence of noise give rise to error alert, that is, noise can be misconstrued for signal. Dimensionality reduction was first used as the first level of denoising technique, Principal component Analysis (PCA) was used in dimensioning Wide Band Spectrum Data; this was able to reduce the noise level in the signal which made it convenient for Fast Fourier Transform (FFT) to act on it. FFT was used to decompose the signal to 64 sub band channels and on further reduction using principal Component Analysis (PCA), a 32 Level sub-band decomposition was carried out. Eigen Value generated shows that the magnitude of the signal to Noise ratio between Eigen Value 1 to 19 was high enough to show the that there exist a signal, while between 20 to 32 shows no signal by implication it indicates that these areas have high possibility of unoccupied spectrum holes.

Keywords: Noise Reduction, Eigen Value, Principal Component Analysis, Dimensionality Reduction, Cognitive Radio, Wide-Band Spectrum, Covariance Matrix

1. INTRODUCTION

One of the fundamental challenges affecting the performance of communication systems is the undesired impact of noise on a signal [1]. Various factors influence the integrity of data in communication systems. These include; multi-path, shadowing and noise. Generally, noise can be generated from heat sources, front end of linear systems and superposition of wireless hosts in the same location in a network. In communication systems, filters are used to eliminate noise from the signals received. The filters used are designed to be sensitive to only specific frequencies, and such filters make the developed system to be big and expensive. It is expected to have in them as hardware which can be reconfigured with support for the processing of digital signals. It is therefore imperative that advanced systems should have programmable filters and also have the ability to remove noise from signals at any given frequency.

Cognitive Radio (CR) technology is an auspicious aspect of advanced communication technology. It employs a full-duplex communication which comprises a transmitter and receiver (wideband) whose parameters can be varied in accordance to that of the surrounding. These systems are however greatly influenced by noise generated by the system itself. Cognitive Radio can detect a wide range of bands simultaneously which leads to noise-generation as a result of interference. Also, CR is drenched by noise, in a full-duplex communication when transmitters in the same location transmit signals simultaneously from the same network channel. CR systems are also susceptible to noise as a result of non-linearity of systems and from thermal sources. Radio systems today run on a unique frequency band utilizing a selected spectrum access system but virtually all of them fail to sense their radio spectrum-environment. Studies show the underutilization of radio spectrum at any given instance (place or time). Therefore, it is important to note that a radio that is able to detect and decode its immediate radio spectrum environment, pinpoint and utilize idle spectrums is capable of supporting higher bandwidth services, thus maximizing the efficiency of a spectrum which translates to less dependency on centralized management of a spectrum [2].

This is made possible by a radio which intelligently selects which spectrum to access. CRs are able to achieve this. Cognitive radios can hop from one vacant spectrum to another in order to increase the efficiency of the spectrum while supporting wideband services. 70% of the spectrum assigned at any given time or space lies vacant and unused. The rudiments of cognitive radio aid the dynamic access of spectrum at run-time. Cognitive users maximize the efficient use of the spectrum and gives priority to the essential users (primary) whenever they revert to the use of hole. Conventional filters are unable to adjust to varying frequencies and multi-bands. This necessitates the use of noise-diminution method to eliminate noise from a signal at any given frequency. This is done by readjusting, eliminating redundant parameters when carrying out the operation. Various noise-reduction methods have been developed which use search optimization algorithms [3][4].

Concisely, using a noise reduction technique, a noisy signal undergoes filtering and the resulting output is analyzed against a reference signal to ascertain the error. Adaptive de-noising aims at obtaining the best result that significantly reduces error. Past researches used search optimization algorithms based on gradient-descent which begins with an initially defined guiding factor patterned after the gradient's slope used to locate the desired minima on error surface. However, these algorithms can only determine the minima local to a multiple modal error surface which is largely subject to the correct choice of the starting variables [5]. For example, Least Mean Square (LMS) has been used before now; the algorithm starts with a variable of step size which is the parameter that manipulates the speed of the convergence of the algorithm. Furthermore, decline in performance is experienced for stochastic and non-linear use, some other technique-based algorithms [6].

However, few research papers in noise cancellation have been published as regards Cognitive Radio (CR), which might be because the cognitive radio technology itself is an emerging communication technology. Conventional communication systems use filters to cancel noise during communication. Besides noise cancellation during usual communication, a CR system can also employ de-noising techniques during the spectrum sensing phase to increase the accuracy of sensing [7]. Although few survey papers are found that review denoising techniques for the spectrum sensing phase of cognitive communication, collective review of denoising techniques applicable to all the communication phases of cognitive radio have not been published yet. This paper aims to provide a of denoising techniques using PCA that are applicable to all the communication phases of the cognitive radio network and give a performance analysis of these techniques. As shown in Figure 1, denoising techniques can be classified into three categories:

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The frequency analysis based de-noising techniques allows for the examination of signal affected by noise in the frequency and time domain. Examples of tec hniques under this category are empirical.

2. MATERIAL AND METHOD

2.1 COGNITIVE RADIO

In Cognitive Radio, the merit intelligent radio offers enables cognition of vacant bands which is suitable for use by secondary users. It however is vulnerable to hacking and intrusion which can lead to a deviation from the correct path of detection. CR sensors use Artificial Intelligence (AI) in determining if a band is idle or not. The sensor is misinformed of the availability status of a primary user if a hacker is able to replicate a signal that corresponds to that being used by a primary user. This causes the sensor to abandon that band in search for other bands and this can also be considered as noise. A sensor also moves away from an environment inhabited by primary users where noise emanates from. A sensor that can distinguish between noise and interference in an inhabited signal can resolve to the usage or non-usage of a band according to the results. In this research work, we will analyze the impact of noise. In this paper, we came up with an enabling technique for realizing CR and enabling dynamic access to spectrum during operation [8].

2.2 NOISE

Priority is given to the primary user after the efficient utilization of spectrum by cognitive use. From the inception of Cognitive Radio, noise has been proven to be the biggest challenge to the success of CR. Spectrum sensing on the other hand is known to be the propelling function for expedient spectrum access. An overview of techniques used for spectrum sensing indicates an outstanding performance can be achieved using sensors that take into account some unique features of a primary user signal with the limitation of long observation period [9]. For rapid signal sensing, random matrix theory-based techniques are used [10]. The terminal of a Cognitive Radio node makes use many antennas. The easiest technique used to discover a signal in Additive white Gaussian Noise (AWGN) for unary antennas involves a comparison between the energy received and a selected threshold within a given period of time T. Energy detectors (ED) is best when the signal to be sensed is entirely unidentified, which makes it impossible for use when a secondary user has a little foreknowledge of the signal to be detected. This is due to its easy implementation [9][11]. Moreover, for its generality, the ED is commonly used. We will sense the occurrence of primary users in this case, which radiates a signal x (t) over a period of time. This is computed as depicted in equation,

$$\begin{cases} y(t) = n(t) & : \ H_0 \\ y(t) = x(t) + n(t) & : \ H_1 \end{cases} \tag{1}$$

where y(t) is the signal received, x(t) is the transferred signal which is stochastic or deterministic yet unidentified and n(t) is the presumed additive white Gaussian noise. Matching the output of detector with a threshold which results in the noise energy in Figure 1 is used for sensing the primary signal out [12].

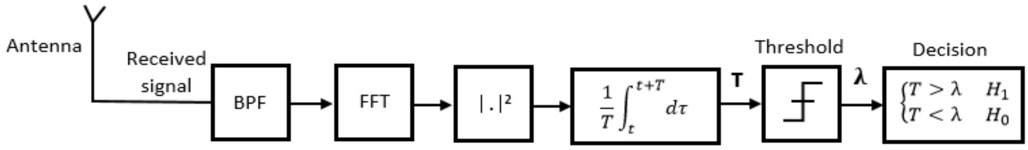

FIGURE 1. Energy Detection Model

2.4 FILTERS

Adapting to changing frequencies could be challenging. To that end, noise reduction technique must be employed to eliminate noise from a signal of any by realigning reducing redundant parameters during an operation. Several de-noising techniques for eliminating noise have been proposed with search optimization algorithms inclusive [5-13]. Concisely, the noisy signal picked up undergoes filtering of which the result is weighed against a reference signal to get the error. The job of adaptive noise reduction is to explore the best result that reduces the level of error. Early researches utilized search optimization algorithms based on gradient-descent which begins with an already known guiding factor patterned after the slope of the gradient to pinpoint the preferred minima of a multiple modal error surface which is heavily reliant on the suitable choice of the starting parameters [5]. An example is how LMS algorithm begins with a parameter of step size which operates as the manipulating parameter for the algorithm to converge. A step size of bigger value delivers a great steady state alteration while a smaller step size reduces the speed of convergence of the algorithm [14]. These types of algorithms encounter deterioration of performance for non-linear and stochastic noise [16].

Conventional communication systems use filters to cancel noise during communication. Besides noise cancellation during usual communication, a CR system can also employ denoising techniques during the spectrum sensing phase to increase the accuracy of sensing [5-7]. Although few survey papers dwell on review in the area of denoising techniques for the spectrum sensing phase of cognitive communication, collective review of denoising techniques applicable to all the communication phases of cognitive radio have not been published yet. This paper aims to provide a denoising techniques using PCA that are applicable to all the communication phases of the cognitive radio network and give a performance analysis of these techniques. As shown in Figure 2, denoising techniques can be classified into three categories: (1) Time-frequency analysis-based noise cancellation methods permit the examination of signal affected by noise in both the time and frequency domain. Examples of techniques under this category are empirical, (2) Power Spectral Density (PSD) is projected for use in continuous spectra. A vital characteristic of stochastic noise is its PSD which is approximated by a function identified as periodogram function, and (3) CR presents the merits of autonomous radios which are able to detect a vacant band making it utilizable by

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secondary users. Similarly, when noise emanates from the surrounding as primary users inhabit the band, the sensor travels to other hops for Detection. If a sensor can distinguish whether a signal has noise or interference, the sensor can make inferences based on the result it receives. The contrast between a noise signal and noise is as shown in Figure 2.

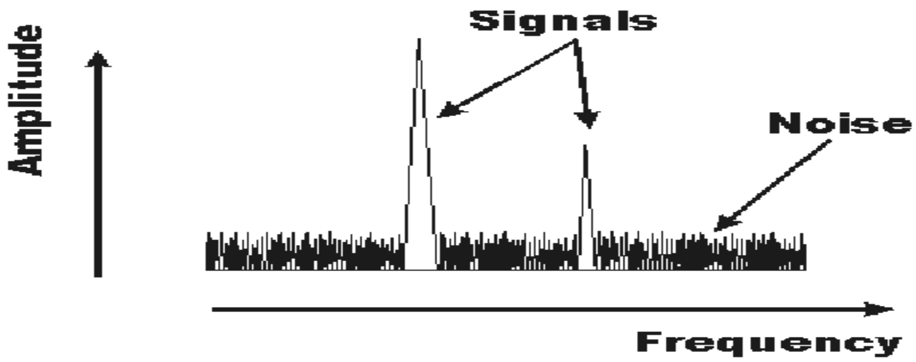

FIGURE 2. Noise and Amplitude Range of an FTT of Signal x (t)

2.5 EXISTING CHALLENGES OF SPECTRUM HOLE DETECTION

The problem of error alert has been an issue in the area of Spectrum hole detection in cognitive radio, and this is largely due to lack of adequate technique for detecting edge. Accuracy still remains an issue in this research area, most often noise could be mistaken for Signal hole. If the signal can be devoid of noise less complex technique will detect hole This will also improve speed of detection with lesser complexities [1][2].

2.6 POWER SPECTRAL DENSITY DETECTION

Measurement is usually done using power spectral density (PSD) and is intended for continuous spectra evaluation. Power spectral density (PSD) is a key characteristic of random noise. Periodogram is a function that approximates the PSD. For instance, a series (x_1, x_2, x_3 …... x_n) has its periodogram computed as:

$$S\left(e^{jw}\right) = \frac{1}{2\pi N} \left| \sum_{n-1}^{N} x_n e^{j\omega n} \right|^2 \quad (2)$$

where, ω (radians/sample), frequency (Hz), and sampling frequency (Fs).

Periodogram gives the approximate value of PSD for a given signal of the signal described by the sequence. Power spectral density was used in getting the approximate location of spectrum hole available. This also will further be improve upon with the help of the thresholding technique to get the exact location. Note Figure 4 is a graphs of wideband signals, the graph shows protruded point which indicates the area where the hole have been occupied, while the protruded points indicates vacant hole positions, these points will be further decomposed and optimized.

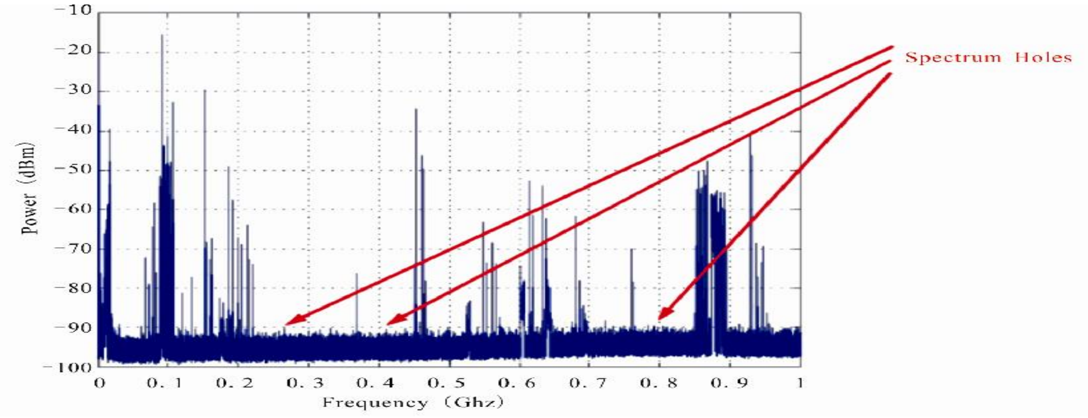

FIGURE 3. Measuring Spectrum Across a 900 kHz-1 GHz Band (Lawrence, USA) [4]

Figure 3 shows a graph of Power spectrum density corrupted with noise, there is probability of error in this situation, the need for denoising is therefore important. In Figure 4 represent number of samples for sub band channels. The system will halt sensing if the mean value of R from K (K<N) is comparable to a centroid with 1H for any selected SUs, else any of these will make known its immediate result causing the other sensors to carry on with sensing. Therefore, the subsequent report becomes the result of the analysis.

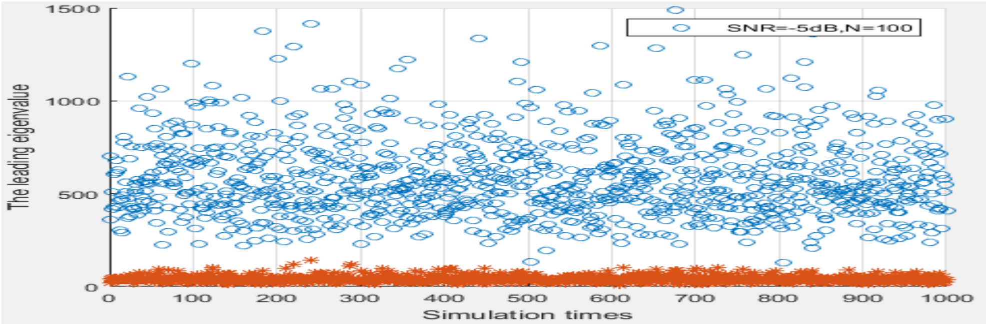

FIGURE 4. Statistics Realization Distance Between Signal and Noise [2]

Samples match the previous SU Just before P (K<P<N). The evaluation for all samples is the result of local evaluation from the previous sensor. As a result, the fusion centre makes preliminary choices can be made rapidly and revised when local detection evaluation is captured [33]. A successive means of collaborative channel state evaluation is adopted, to ensure consistency in spectrum detection and to also sense the incidence of primary signal swiftly while averting collision between Pus and Sus [34]. The characteristics of a sensed signal are computed successively for

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every sensor using the relation where the number of entered samples is K out of N [2].

$$S_R = \frac{1}{K}\sum_{I=1}^{K} S_k \quad (3)$$

2.7 DIMENSIONALITY REDUCTION

One of the vital and ground-breaking techniques of machine learning is dimensionality reduction [12]. The novel dimensionality data gathered for cognitive ratio likely comprises a great number of features although these characteristics are very much correlated and redundant with noise. Therefore, the intrinsic dimensionality of the gathered data is much less than the primary characteristics. Dimensionality reduction tries to remove a lesser dimensionality expression while maintaining nearly all vital information. The most popular dimensionality reduction technique in use is Principal Component Analysis (PCA) [17]. The variance of a set of data captured by PCA is the vital information used to uncover a subspace that is able to optimally contain the variance of the original spectrum dataset [9]. The dimension reduction method utilizes the information embedded in respective strongholds to contract and develop a vector of lesser dimension. The methods used cast a signal vector from one space of this reduction is depicted in Figures 5 and 6.

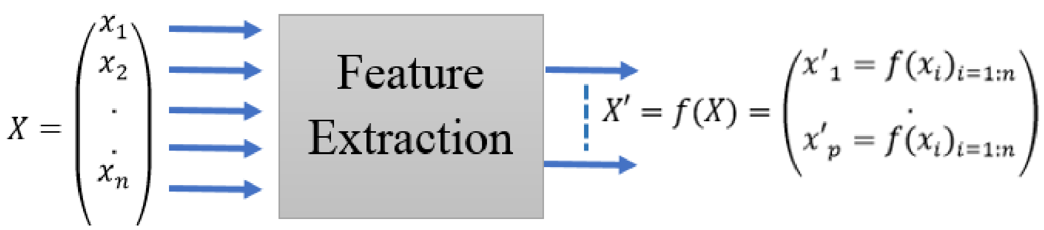

FIGURE 5. The Principal of Features Extraction.

2.8 PRINCIPAL COMPONENT ANALYSIS

PCA is the most popular technique employed in data evaluation techniques. In a quantitative database acquired signals, n, is represented by m variables in which case m is large. It is extremely difficult to interpret the data structure and the closeness between observations by mere computation of single valued variables descriptive statistics or the use of a correlation matrix. PCA can be described as a technique that project observations to a K-dimensional space (K<<N) [15] from an N-dimensional space made up of N variables such that optimal level of information is contained on the first dimensions.

FIGURE 6. PCA in Dimensionality Reduction [27].

PCA breaks a big set of variables into smaller units of variables which retains nearly all the information contained in the larger set. PCA as a mathematical procedure modifies a cluster of closely related variables into a lesser number of unrelated variables known as Principal Components [21,22]. From Figure 9, the PCA dataset describes a whole collection chosen from the spectrum data. The work is centered upon datasets commonly referred to as sample data. A set of data can be mathematically represented in so many ways using variance, standard deviation, mean and covariance. Vectors are represented in lower case bold, matrices are denoted in uppercase bold while other elements are written in subscripts.

$$x= [x_1, x_2, x_3 \ldots\ldots\ldots\ldots\ldots\ldots x_n] \tag{4}$$

Every row ($\mathbf{x}_i$), comprise measurements for just a single variable. Every column represents a spectrum. From the primary depiction of data, it is difficult to predict the relationship between different spectrums. We re-express our data in PCA form, we wish to linearly transform the value of the spectrum data to Matrix Y (m-by-m) for some Matrix P (m-by-m).[23,24]

$$Y = PX \tag{5}$$

The primary data X is denoted by t is projected to the columns of P which is referred to as change of basis. The dilemma is the choice of re-expressing data which is dependent on the characteristics Y is expected to show. The underlying assumption of Principal Component Analysis is linearity and also the variables in the modified matrix should not be correlated. This translates to the covariance matrix representing Y, CY and is expected to have entries that are diagonally off with nigh zero proximity. PCA also assumes big variables which stand for important dynamics while small variance depict noise [25, 26]. This is a change of basis, where the original data X which represent the t is being projected on to the columns of P. We must now decide what the best way of re-expressing the data is, and this depends on what features we wish Y to exhibit.

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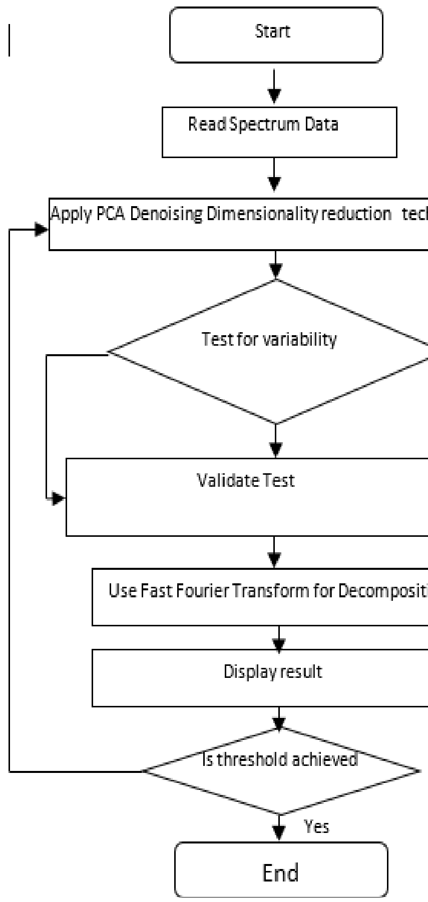

FIGURE 7. Flow Diagram of The Process

A fundamental assumption of PCA is linearity, and secondly, the variables in the transformed matrix should be uncorrelated [14][27,28]. This means that the covariance matrix corresponding to **Y**, **C***Y*, should have off-diagonal entries as close to zero as possible. PCA also makes another assumption: Large variances represent important dynamics, while small variances represent noise [30,31]. A flow process how the result of this work was achieved is shown in Figure 7, while dimensionality reduction is shown using PCA in in Figures 8,9,10, and 11.

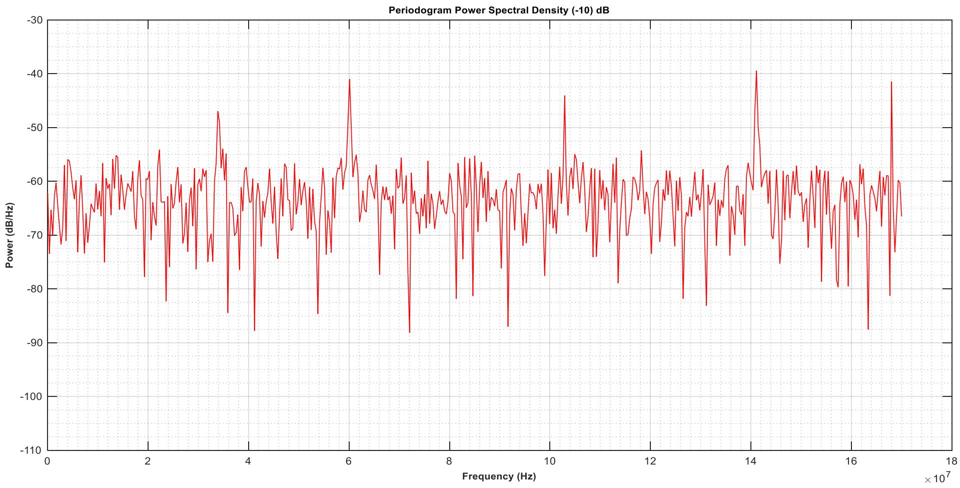

FIGURE 8. Graph of Periodogram Power Spectral Density with Noise

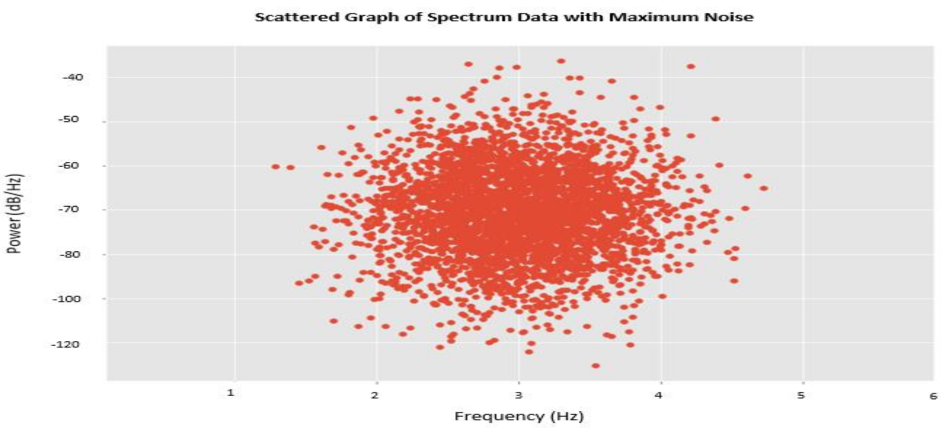

FIGURE 9. PCA Graph of Spectrum Data with Noise

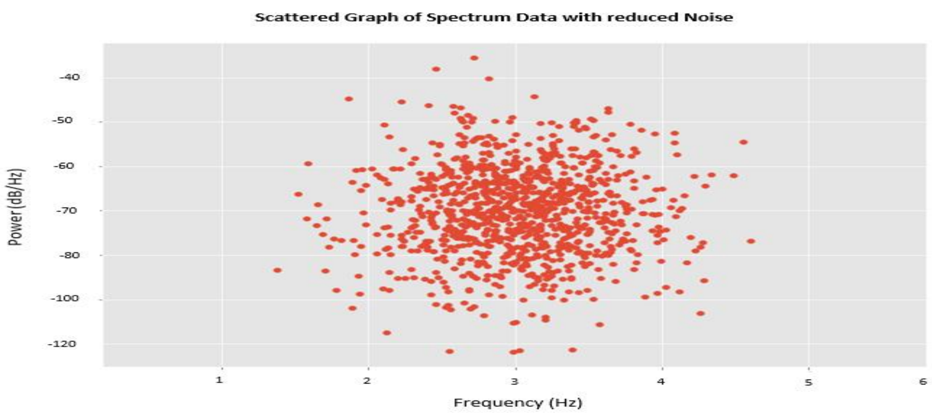

FIGURE 10. PCA Graph of Spectrum Data with Reduced Noise

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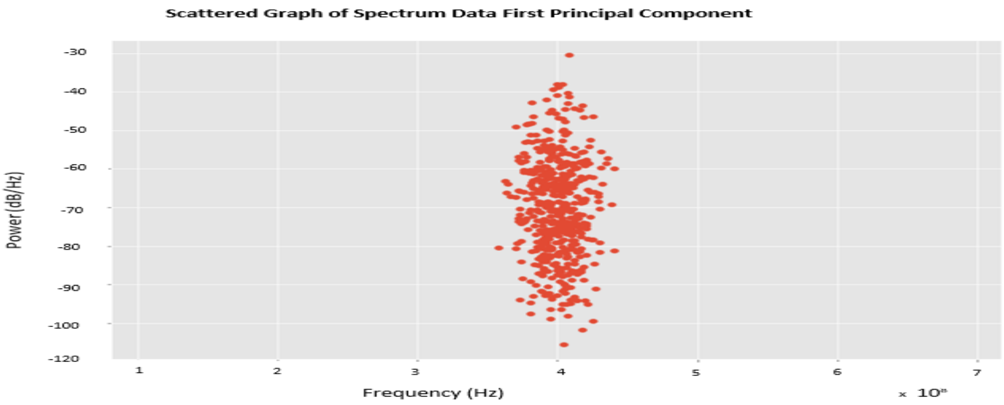

FIGURE 11. Graph of Spectrum Data with First Principal Component

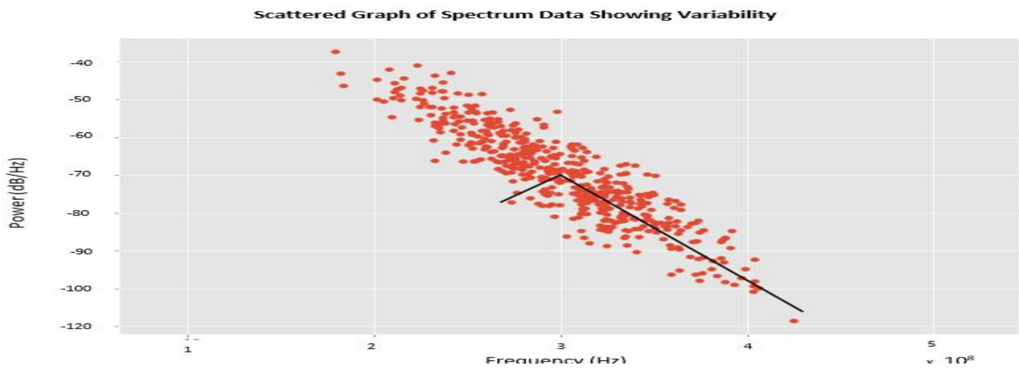

FIGURE 12. Test for Variability

A process for de-noising is shown in Figure 13, the result of the principal component as first level of de-noising process.

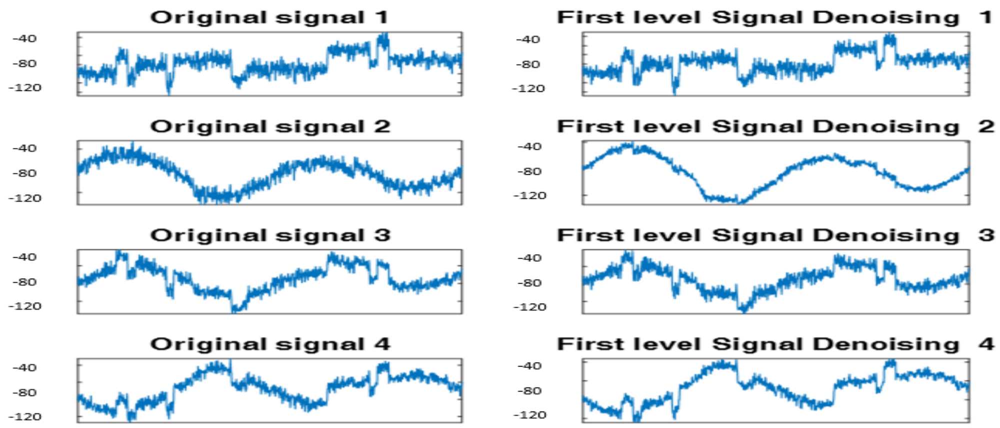

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FIGURE 13. Denoising Concept

The fast Fourier transform (FFT) is denoted by:

$$X(k) \triangleq \sum_{n=0}^{N-1} x(n) e^{-j2\pi nk/N} \quad (6)$$

where k represents the k^{th} frequency sample, N stands for the number of time/frequency samples, n represent the sampling instant.
To decompose a signal into N=64 sub-band channels using FFT, the following relationship holds and also shown in Figure 14,

$$y_k(n) = \sum_{m=n-(N-1)}^{n} x(m) e^{-jw_k m}, k = 0, \ldots, 63 \quad (7)$$

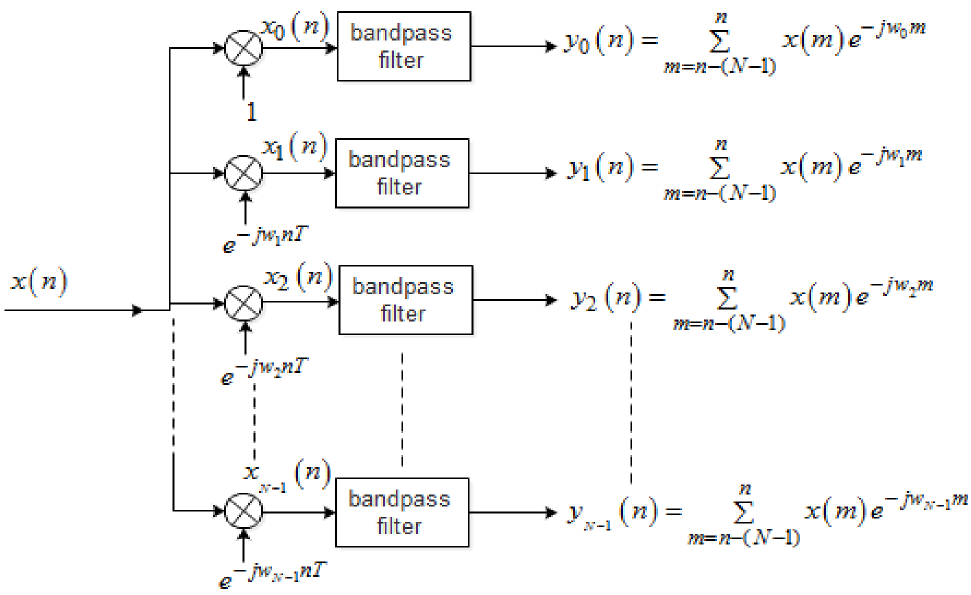

FIGURE 14. Decompose a Signal Into N=64 Sub-band Channels Using FFT

The input signal for the work will be an ultra-wideband signal comprising of single tone and chirp signals spread across the entire frequency spectrum in Figure 15. For this work, the ultra-wideband signal is in the GHz range, and in order to achieve good resolution of the signal, the signal will be decomposed into 64 sub-band channels using fast Fourier transform. The input signal is shown below before it is corrupted with AWGN noise, and after it is corrupted with AWGN at signal-to-noise ratio of -10dB. Equation 5 represents the signal input with corresponding frequency at time t,

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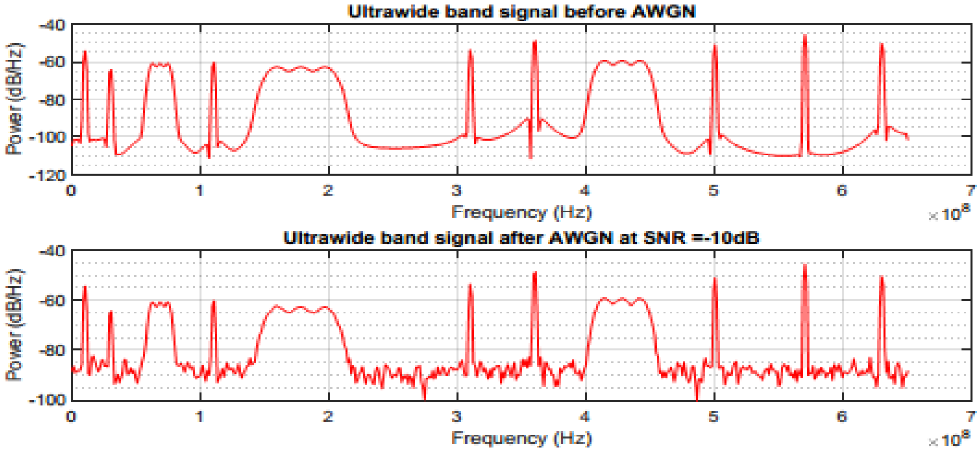

FIGURE 15. Chirp Signals Spread Across The Entire Frequency Spectrum.

$$x(t) = x_1(t) + x_2(t) + x_3(t) + x_4(t) + x_5(t) + x_6(t) + x_7(t) + x_8(t) + x_9(t) + x_{10}(t) + x_{11}(t) \tag{9}$$

where A_i is the amplitude of the i^{th} signal $x_i(t)$ with corresponding frequency f_i, f_{i_0} is the starting frequency of the i^{th} chirp signal $x_i(t)$ with corresponding final frequency f_{i_1}. T_i is the time taken to sweep from f_{i_0} to f_{i_1}. ϕ_{i_0} is the initial phase of the signal $x_i(t)$.

$$\left.\begin{array}{c}
x_1(t) = A_1 \, sin(2\pi f_1 t) \\
x_2(t) = A_2 \, sin(2\pi f_2 t) \\
x_3(t) = A_3 \, sin\left[\phi_{3_0} + 2\pi\left(f_{3_0} t + \frac{k_3}{2} t^2\right)\right], \phi_{3_0} = 0, k_3 = \frac{f_{3_1} - f_{3_0}}{T_3} \\
x_4(t) = A_4 \, sin(2\pi f_4 t) \\
x_5(t) = A_5 \, sin\left[\phi_{5_0} + 2\pi\left(f_{5_0} t + \frac{k_5}{2} t^2\right)\right], \phi_{5_0} = 0, k_5 = \frac{f_{5_1} - f_{5_0}}{T_5} \\
x_6(t) = A_6 \, sin(2\pi f_6 t) \\
x_7(t) = A_7 \, sin(2\pi f_7 t) \\
x_8(t) = A_8 \, sin\left[\phi_{8_0} + 2\pi\left(f_{8_0} t + \frac{k_8}{2} t^2\right)\right], \phi_{8_0} = 0, k_8 = \frac{f_{8_1} - f_{8_0}}{T_8} \\
x_9(t) = A_9 \, sin(2\pi f_9 t) \\
x_{10}(t) = A_{10} \, sin(2\pi f_{10} t) \\
x_{11}(t) = A_{11} \, sin(2\pi f_{11} t)
\end{array}\right\} \tag{10}$$

The Eigenvalues are computed from the covariance matrix of each sub-band channel using [21]:

$$(\mathbf{A}_i - \boldsymbol{\lambda}_i \mathbf{I})\mathbf{x} = \mathbf{0} \tag{11}$$

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here $\mathbf{A}_i$ is the $n \times n$ square matrix of sub-band channel i, $\boldsymbol{\lambda}_i$ is the Eigenvalues of sub-band channel i, x is a nonzero $n \times 1$ column vector, and $\mathbf{I}$ is the $n \times n$ identity matrix. The use of the logarithm operator is needed because the cognitive radio is one in which the parameters to be sensed are dynamic and always changing. Secondly, it possible to use logarithms because the units involved are cancelled out by the ratio computation. The decomposition of the input signal into 64 sub-band channels using FFT yields the following coefficients in each sub-band channel.

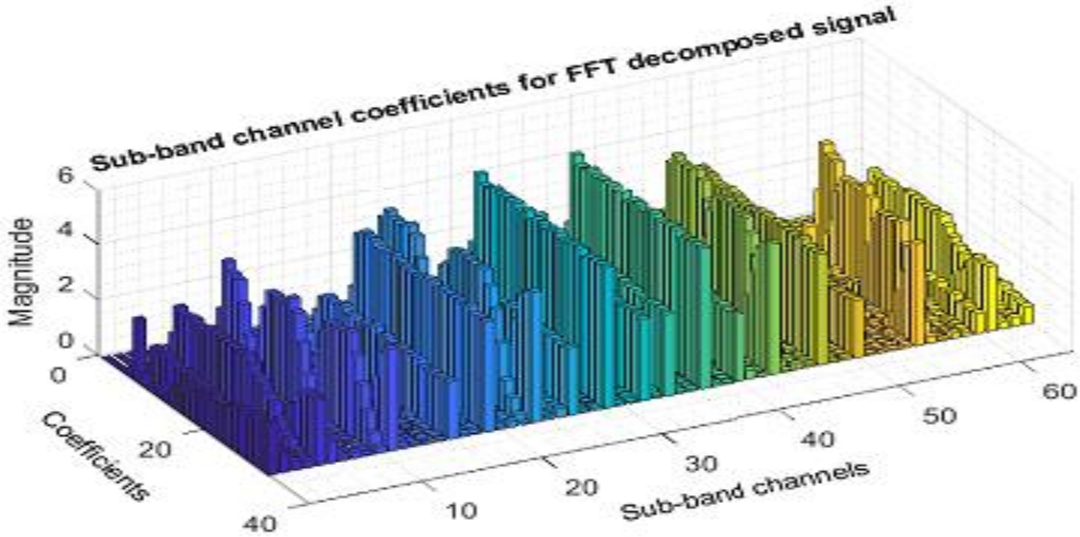

FIGURE 16. There are 32 Principal Components in Each of The 64 sub-band Channels

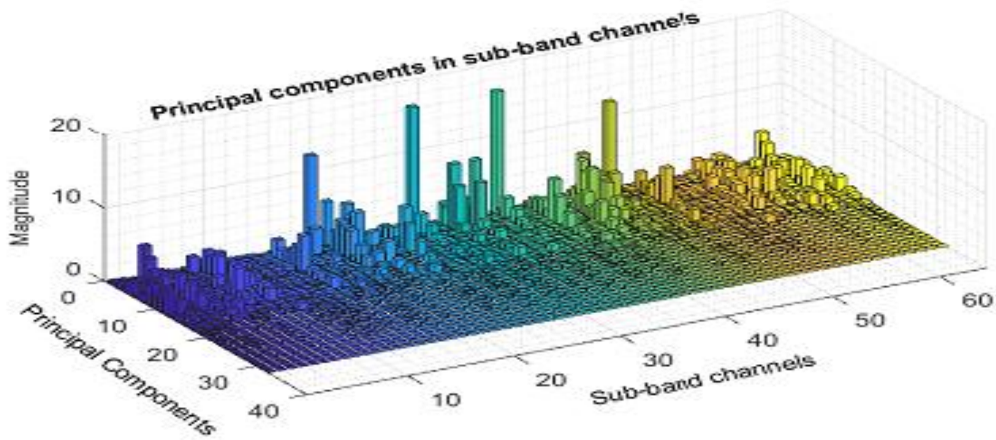

FIGURE 17. Sub-band Channel Coefficient of FFT Decompose Signal

There are 32 principal components in each of the 64 sub-band channels. However, the Eigenvalues shown in figure 18 reveals that for each sub-band channel, the principal components contributing most are those corresponding to Eigenvalues 1 to 16. Hence, in each sub-band channel we will extract only the principal components with these Eigenvalues.

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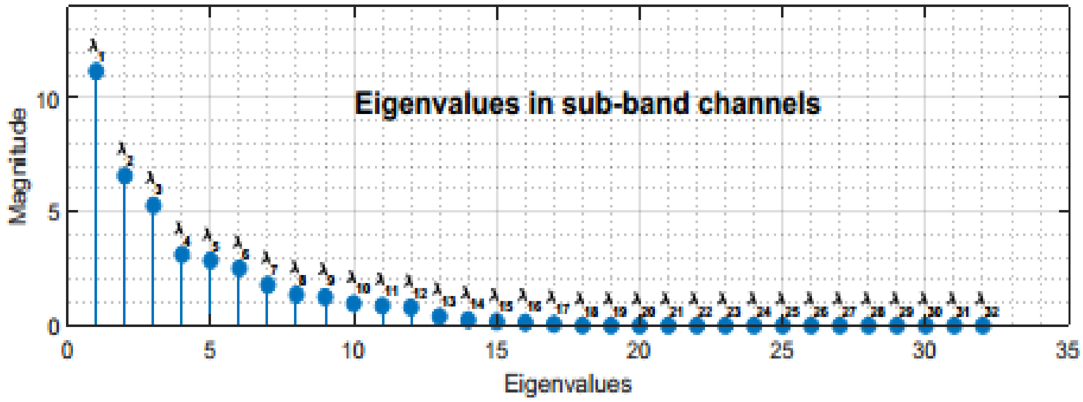

FIGURE 18. Principal Components with These Eigenvalues.

The reduced principal components are shown below where only the principal components corresponding to Eigenvalues 1 to 16 have been extracted.

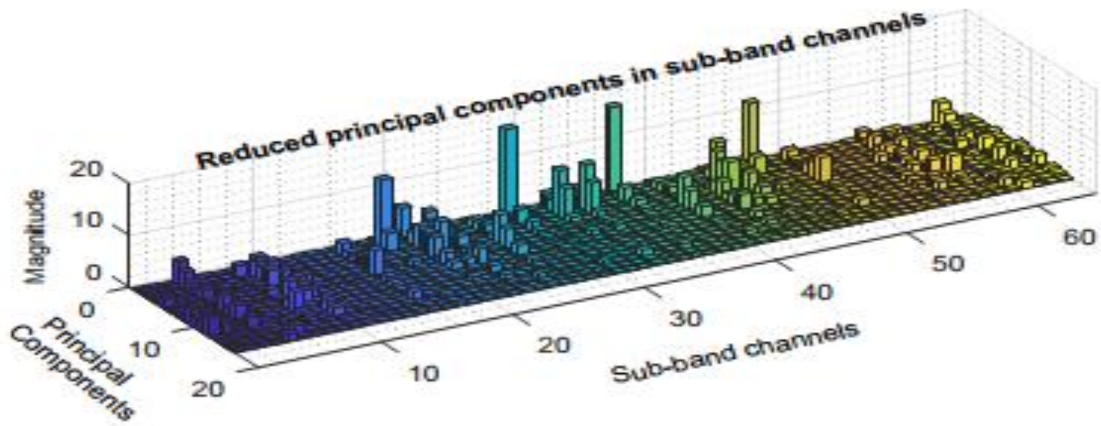

FIGURE 19. The Reduced Principal Component.

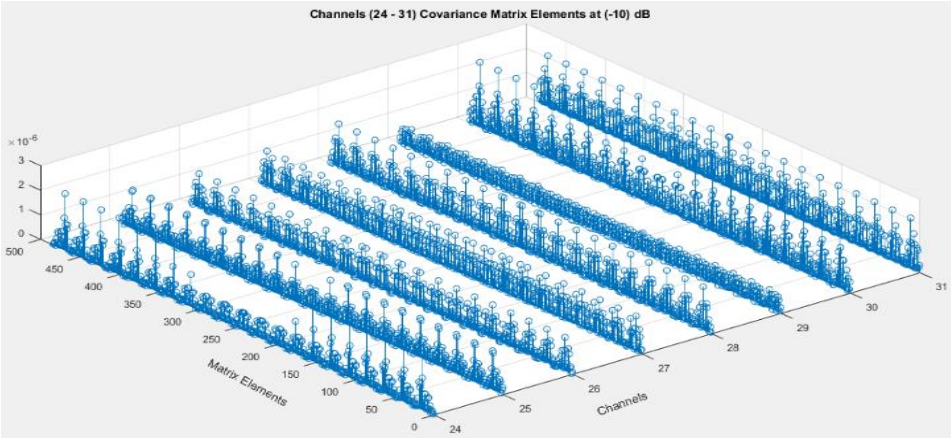

FIGURE 20. Covariance Matrix Elements for Sub-band Channels 24 to 31.

Channels which have high energy content within the channels shown in figure 20, they have their covariance matrix representation with high values as well. This can be explained by the fact in those sub-band channels, the strength of the signal content have a pervasive effect; the noise noise elements are almost non-existent. From the foregoing therefore, channels with high energy levels and by implication high covariance matrix values are likely to be more accurately detected in spectrum sensing than other sub-band channels. Let us define a second matrix $\mathbf{Q}$ with dimension $m \times n$, and let it be associated with $\mathbf{X}$ the original input signal through a linear transformation matrix $\mathbf{Z}$ i.e.

$$\mathbf{QX} = \mathbf{Z} \tag{12}$$

In (7), $\mathbf{X}$ is the original data set, and $\mathbf{Z}$ is the representation or projection of $\mathbf{X}$. Let $\mathbf{q_i}$ be the rows of $\mathbf{Q}$, $\mathbf{x_i}$ be the columns of $\mathbf{X}$, and $\mathbf{z_i}$ be the columns of $\mathbf{Z}$. By dot product notation, $\mathbf{QX}$ can be expressed as:

$$\mathbf{QX} = \begin{bmatrix} \mathbf{q_1} \\ \vdots \\ \mathbf{q_m} \end{bmatrix} \begin{bmatrix} \mathbf{x_1} & \cdots & \mathbf{x_n} \end{bmatrix} \tag{13}$$

Thus:

$$\mathbf{Z} = \begin{pmatrix} \mathbf{q_1 x_1} & \cdots & \mathbf{q_1 x_n} \\ \vdots & \ddots & \vdots \\ \mathbf{q_m x_1} & \cdots & \mathbf{q_m x_n} \end{pmatrix} \tag{14}$$

where each column of $\mathbf{Z}$ is expressed as:

$$\mathbf{z_i} = \begin{bmatrix} \mathbf{q_1 x_i} \\ \vdots \\ \mathbf{q_m x_i} \end{bmatrix} \tag{15}$$

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The columns of $\mathbf{z}_i$ are depicted as the principal components above.

3. DISCUSSION OF RESULT

Using PCA to transform data, the principal components that perform most were extracted, from the graph in figure 16.17 and 18, it was discovered that at convergence the final extracted principal component is given in Figure 19. By this we have achieve dimensionality reduction and have been able to confine the search area to the minimal area, while in the case of noise the noise, its spread is found across the entire data set meanwhile still have a bit of noise to contend with Thresholding Signal to Noise Ratio value to 10dB, the simulation was repeated, and the results obtained are shown in Figure 18. Some sub-band channels were classified as UNOCCUPIED at SNR value of 10dB by the proposed thresholding scheme as shown; they include the interval between 20 to 32. The implication of Figure 17 in spectrum sensing is that the Eigenvectors which correspond to Eigenvalues 20 to 32 contain negligible signal energy and mostly noise which can be discarded, whereas Eigenvalues 1 to 19 have the concentration of the signal energy. From the foregoing therefore, discarding these rows produces the principal components shown in Figure 14.

4. CONCLUSION

This work was able to use dimensionality reduction to increase the possibility of detecting spectrum hole location by confining the signal to a very small space, noise reduction was enhanced by first exploiting the properties of principal component Analysis which helped in reducing the complexity that is usually associated with noise. This gave rise to a better performing Fast Fourier Transform (FFT) technique which was used to decompose the signal into 64 sub-band channel and later reduced to 32. The range of channel within the likelihood of been unoccupied were determined from the Eigen values of the principal components which shows that there is high possibility of spectrum hole between 1 to 16 of the Eigen Value.

REFERENCES

[1] Sahai & D. Cabric, “Spectrum sensing: fundamental limits and practical challenges,” IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks, 2005.

[2] J. R. Krier & I. F. Akyildiz, “Active self-interference cancellation of passband signals using gradient descent," Personal Indoor and Mobile Radio Communications, IEEE 24th International Symposium on, London, pp. 1212-1216, 2013.

[3] J. Agajo, Onyebuchi Nosiri, Okeke Benjamin Chukwuejekwu, Okoro Patience N, Matlab and Simulink Based Simulation of Wideband Code Division Multiple Access [WCDMA], International Journal of Engineering and Technical Research (IJETR), (2015)

[4] J. Okhaifoh, J. Agajo, V.E Idigo Optimizing Digital Filter for Effective Signal Processing International Journal of Engineering and Innovative Technology (IJEIT) Volume 2, Issue 3, (2013)

[5] Identification," IEEE Transactions on Instrumentation and Measurement, vol. 61, no. 2, pp. 554-563, 2012.

[6] N. Kaabouch & W. Chen Hu, Handbook of Research on Software-Defined and Cognitive Radio Technologies for Dynamic Spectrum Management, 2014.

[7] S. H. Mankad & S. N. Pradhan, "Application of Software Defined Radio for Noise Reduction Using Empirical Mode Decomposition," Advances in Computer Science, Engineering & Applications, vol. 166, pp. 113-121, 2012.

[8] H. Reyes, S. Subramaniam, & N. Kaabouch, "A spectrum sensing technique based on autocorrelation and Euclidean distance and its comparison with energy detection for cognitive radio networks," Elsevier Comput. Elect. Eng. J., vol. 52, pp. 319-327, 2015.

[9] S. Hou, Robert C. Qiu Z. Chen, Z. HuSVM and Dimensionality Reduction in Cognitive Radio with Experimental Validation SVM and Dimensionality Reduction in Cognitive Radio with Experimental Validation SVM and Dimensionality Reduction in Cognitive Radio. Journal of Computer Science Networking and Internet Architecture (2015).

[10] M. Riahi Manesh, A. Quadri, S. Subramaniam, N. Kaabouch, "An Optimize SNR Estimation Technique Using Particle Swarm Optimization Algorithm," IEEE Annual Computing and Communication Workshop and Conference, in press.

[11] X. Chen, F. Hou, H. Huang†, X. Jing Principle Component Analysis Based Cooperative, Spectrum Sensing in Cognitive Radio, 16th International Symposium on Communications and Information Technologies (ISCIT), (2017).

[12] G. Saxena, S. Ganesan, & M. Das, "Real time implementation of adaptive noise cancellation," Electro/Information Technology, IEEE International Conference on, Ames, pp. 431-436, 2008.

[13] D. K. Yadaw, P & Singh, "Performance Comparison of Various Techniques in Denoising the Speech Signal," International Journal of Software & Hardware Research in Engineering, vol. 1, no. 1, 2013.

[14] N. K. Rout, D. P. Das, & G. Panda, "Particle Swarm Optimization Based Active Noise Control Algorithm Without Secondary Path

[15] N. Karaboga & B. Cetinkaya, "A novel and efficient algorithm for adaptive filtering: Artificial bee colony algorithm," Turk J Elec. Eng. & Comp Sci., vol.19, no.1, 2011.

[16] A. QUADRI, A Review of Noise Cancellation Techniques for Cognitive Radio Journal of Electrical Engineering and Systems Science Signal Processing. (2018),

[17] U. Mlakar, & I. Fister, "Hybrid self-adaptive cuckoo search for global optimization," Swarm and Evolutionary Computation, vol. 29, pp. 47-72, 2016.

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

[18] C. Y. Chang & D. R. Chen, “Active noise cancellation without secondary path identification by using an adaptive genetic algorithm”, Instrumentation and Measurement, IEEE Transactions on, vol. 59, no. 9, pp. 2315-2327, 2010.

[19] N. Kaabouch, Y. Chen, W. C. Hu, J. W. Anderson, F. Ames, & R. Paulson, “Enhancement of the asymmetry-based overlapping analysis through features extraction,” Journal of Electronic Imaging, vol. 20, no. 1, pp. 013012-013012, 2011.

[20] N. Karaboga & B. Cetinkaya, “Design of digital FIR filters using differential evolution algorithm,” Circuits Systems and Signal Processing Journal, vol. 25, pp. 649-660, 2006.

[21] W. Gao, & S. Liu, “Improved artificial bee colony algorithm for global optimization,” Information Processing Letters, vol. 111, no. 17, pp. 871-882, 2011.

[22] A. Quadri, M. Riahi Manesh, & N. Kaabouch, (2019) “Denoising Signals in Cognitive Radio Systems Using An Evolutionary Algorithm Based Adaptive Filter”, IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference, pp. 1–7, 2016.

[23]. A. Quadri ; M. Riahi Manesh ; N. Kaabouch (2016) , Denoising Signals in Cognitive Radio Systems Using An Evolutionary Algorithm Based Adaptive Filter, IEEE 7th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON), DOI: 10.1109/UEMCON.2016.7777854

[24] R. Pradeep., T. GopinathInterference and Noise detection in a Cognitive Radio Environment, *IOSR Journal of Electronics and Communication Engineering (IOSRJECE) ISSN : 2278-2834 Volume 2, Issue 4 PP 16-19*, .(2012),

[25] A. Mariani, A. Giorgetti, M. Chiani, , Effects of Noise Power Estimation on Energy Detection for Cognitive Radio Applications, IEEE Transactions on Communications, *(2011)* VOL. 59, NO. 12,

[26] R. Elrharras, R. aadane, M.Wahbi, A.Hamdoun, Applied Mathematical Sciences, Vol. 8, 2014, no. 160, 7959-7977 http://dx.doi.org/10.12988/

[27] Y. Zeng, Y. Liang, A. Hoang, & R. Zhang, “A Review on Spectrum Sensing for Cognitive Radio: Challenges and Solutions,” EURASIP Journal on Advances in Signal Processing, vol. 2010, pp. 1-16,

[28] R. Tandra & A. Sahai, “Fundamental limits on detection in low SNR under noise uncertainty,” Proceedings of the International Conference on Wireless Networks, Communications and Mobile Computing, vol. 1, pp. 464–469, 2005.

[29] M. Riahi Manesh, N. Kaabouch, & H. Reyes, “Aggregate Interference Power Modeling for Cognitive Radio Networks Using Bayesian Model,” IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference, pp. 1-6, 2016.

[30] J. Agajo, I. C. Obiora-Dimson, O.B. Chukwuejekwu &N.Nathaniel, CC3000 Wifi Base Configuration of Gateway For Internet Accessibility in Monitoring Variables Via Wireless Sensor Systems , IEEE Based African Journal of Computing & ICT, (2015)Vol 8. No. 3.

[31] B. C. Okeke Lazarus, J. Agajo ,Okpe G. Kabis S.D, Analysis and Estimation of Time of Arrival and Received Signal Strength in Wireless Communication for Indoor Geolocation, journal of Wireless Sensor Networks, jwsn, Vol 3, number 1, DOI-0015, (2016),,pp55-65

[32] M. & J. Žídek, "Use of adaptive filtering for noise reduction in communications systems," Applied Electronics (AE), International Conference on, pp. 1-6, 2010.

[33] M. Riahi Manesh, N. Kaabouch, H. Reyes, & W.C. Hu, “A Bayesian approach to estimate and model SINR in wireless networks,” International Journal of Co

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)