Joint Sub-Nyquist Wideband Spectrum Sensing For Cognitive Radio Networks

PROJECT REPORT

Submitted in partial fulfillment of the requirements for the award of the Degree of Master of Technology in Department of Electronics and Communication Engineering with specialization in Communication Systems by the A P J Abdul Kalam Kerala Technological University

by

KEERTHANA M S
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CERTIFICATE

Certified that this project titled ***"Joint Sub-Nyquist Wideband Spectrum Sensing For Cognitive Radio Networks"*** *is a bonafide record of the work done by* ***KEERTHANA M S*** *(Reg. No. TKM20ECCS08) under my supervision, in partial fulfillment of the requirements for the award of the Degree of Master of Technology in Electronics and Communication Engineering with specialization in Communication Systems by the A P J Abdul Kalam Technological University.*

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Acknowledgement

At the outset, I find it my obligation to thank the Almighty God for giving me necessary wisdom to complete this project successfully.

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ABSTRACT

Due to the unique and significant role that radio frequency (RF) spectrum plays in wireless communications, it is an essential but closely regulated resource. Wireless services have increased RF spectrum demand, which has resulted in a dearth of spectrum resources. Cognitive radio has been developed as a result of a lack of available spectrum and the primary users' inefficient use of spectral resources. Cognitive radio is one of the trendiest and most promising techniques for maximising spectrum utilization in next-generation cellular networks. The essential prerequisite for next cognitive radio networks is wideband spectrum sensing. Future cognitive technologies will need advanced sensing techniques for speedy, active spectrum hole identification across a range of frequencies. Cooperative spectrum sensing is the approach for evaluation of white space when several secondary users work in the collaboration is proposed here. Enhancing sensing efficiency, lowering computing complexity, and increasing spectrum usage by white space devices are all achieved by incorporating prior data from the geolocation database. The geolocation database's prior information combined with the sensing scheme improves spectrum sensing performance while minimising complexity, making it more suitable for low-power cognitive devices.

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Chapter 1

Introduction

As wireless communications have grown in popularity, huge data rates and service coverage have become extremely important. But spectrum scarcity appears to be a serious impediment for wireless communication systems [1]. According to the Federal Communication Commission's (FCC) most recent study, the licenced spectrum is only very seldom used both geographically and over time [2]. Spectrum sensing is a crucial and proactive method for gathering information about the ambient spectrum's availability. This method allows secondary users to dynamically access the spectrum as they need it while maintaining the prime users right to get services of a high standard [3]. Cognitive radio (CR) technology was first introduced as a result of the shortage of spectrum and the licenced users insufficient utilisation of the allocated spectral resources. An advanced software-defined radio known as a "cognitive radio" is depicted in Fig 1.1 automatically detects RF stimuli from its environment and intelligently adjusts its operational settings to network infrastructure while satisfying user needs. A key requirement for cognitive radio networks is that they effectively take advantage of underutilised spectrum (also known as spectral opportunities) without negatively affecting the PUs because cognitive radios are regarded as secondary users for accessing the licenced spectrum. The operating settings that PUs use to share spectrum with cognitive radio networks are not required to be disclosed or altered. The capacity to recognise spectral possibilities independently without the aid of PUs is known as spectrum sensing, and it is regarded as one of the most important elements of cognitive radio networks. In a typical cognitive radio situation, unlicensed secondary users take advantage of opportunities to access the licenced spectrum that the primary users are now not using. Cognitive capability and reconfigurability are the two characteristics of the cognitive radio. The ability of radio technology to acquire or sense information from its radio environment is known as cognitive capability and reconfigurability enables the cognitive radio to dynamically program itself in accordance to the radio environment.

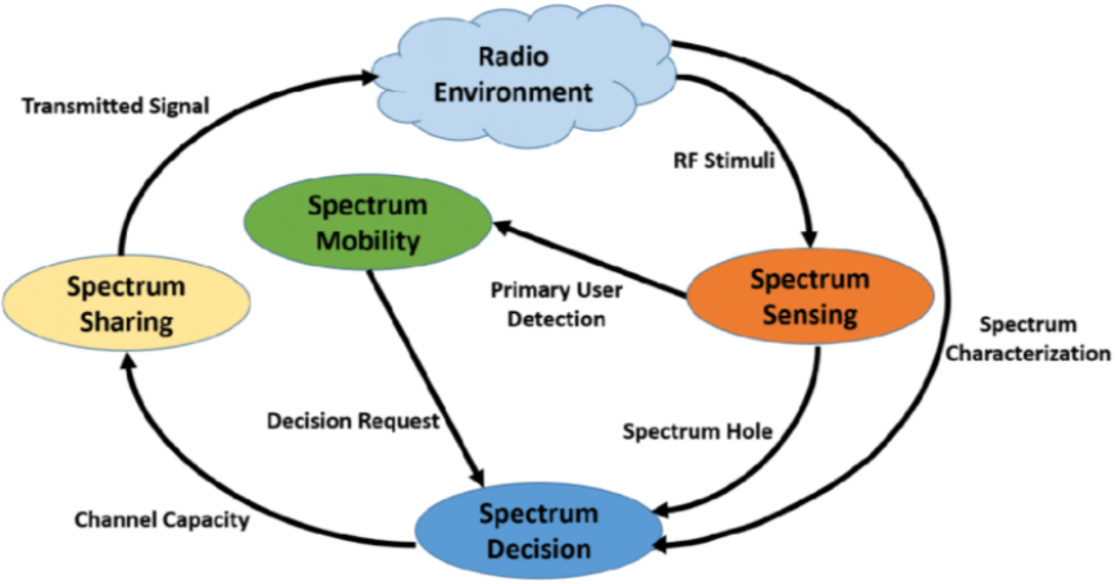


Figure 1.1: Cognitive Radio

Narrowband and wideband spectrum sensing are the main components of spectrum sensing technology. Spectrum sensing classification is depicted in Fig 1.2. While wideband spectrum sensing seeks to evaluate a broad frequency band whose bandwidth typically exceed the coherence bandwidth of the channel, narrowband spectrum sensing primarily seeks to determine the state of a single spectrum at a time [4]. Wideband spectrum sensing is widely acknowledged as a successful strategy for addressing the growing demand for broadband access and the limited supply of available spectrum. However, the rising bandwidth makes it difficult to deploy traditional WSS approaches, and that is why sub-Nyquist spectrum sensing has received a lot of interest. In this paper, we mainly concentrate on wideband spectrum sensing. Wideband spectrum sensing has proposed compressive sensing strategies to achieve sub-Nyquist rate sampling, which alleviates the hardware and power limitations of the traditional

Nyquist sampling technique [13]. There are different sub-Nyquist sampling techniques are used, including an analog to information converter (AIC), a multi-rate sampling (MRS), a multicoset sampling (MCS), and a modulated wideband converter (MWC). In this work we use modulated wideband converter based sub-Nyquist sampling.

Compressive sensing techniques are extremely susceptible to multipath fading, shadowing, noise uncertainties, and channel issues. The cooperative spectrum sensing technique is used in this work to address these issues. This is the best method for evaluation of white space when multiple secondary user work in the collaboration. All local nodes scan the licensed band and give their decision to central fusion center. The fusion center then combine the results of various secondary user using soft fusion or hard fusion rules and give the aggregate decision whether the alloted spectrum is occupied or not. Transfering spectral support that recovered from various secondary users to a fusion center that decides the spectrum occupancy state improves detection performance [14].

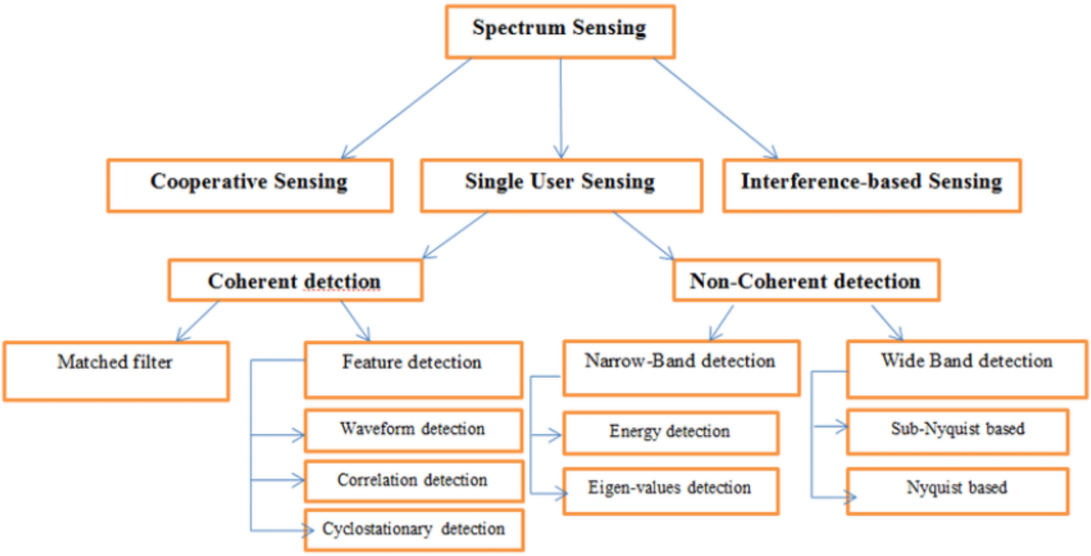


Figure 1.2: Spectrum Sensing Classification

The white space devices in TV White Space (TVWS) use the geolocation database to identify the unused TV channels. Spectrum sensing is more expensive in terms of hardware complexity and energy consumption for cognitive devices with limited resources. The geolocation database, however, requires relatively minimal technology and is much easier to set up. The white space devices first determine their position and look up available spectrum in the geolocation database. The database system then provides a list of the currently active channels along with their maximum allowable transmit strengths. Integrating pertinent data from a geolocation database speeds up detection and simplifies computation. This work also includes prior knowledge from the geolocation database and proposes a low-complexity hybrid approach of sub-nyquist wideband cooperative spectrum sensing based on modulated wideband converters.

Chapter 2

Literature Review

This section, presents an overview of some works related to the proposed approach. H. Sun et.al., proposed a method in Computationally Tractable Model of Energy Detection Performance Over Slow Fading Channel [5]. In many wireless communication applications, energy detection (ED) has been extensively employed to find unknown deterministic signals. In this paper, the Wald distribution is used in place of the log-normal distribution to construct an equation for the average probability of detection over a slow fading channel that is computationally tractable. A square-law combining (SLC) scheme was used to examine the detection performance of the energy detection over a number of independent and identically distributed (i.i.d.) slow fading channels. It has been demonstrated that the theoretical expression and the experimental findings closely match each other.

Z. Tian et.al., proposed a method in Wavelet Approach to Wideband Spectrum Sensing For Cognitive Radios [6]. In this paper, a wavelet-based method for effective wideband channel spectrum sensing is developed. This method uses the wavelet methodology to sense the spectrum of wideband channels and formulates the cognitive spectrum identification task as a spectral edge detection problem. With no prior knowledge of the number of piecewise smooth subbands present within the desired frequency range, the proposed algorithms are capable of simultaneously identifying all of them by scanning across a large bandwidth. This proposed plan offers a powerful radio sensing architecture to find and identify signal spectrum holes.

Z. Quan et.al., proposed a method in Optimal Multiband Joint Detection For Spectrum Sensing in Cognitive Radio Networks [7]. This paper introduces multiband joint detection, an unique wideband spectrum sensing approach. The fundamental approach is to address the simultaneous detection of primary users over a bank of narrowband subbands as opposed to focusing on a single band at a time. In order to increase spectral efficiency and decrease interference, this technique transformed the joint detection issue into a class of optimization problems. This paper provides some helpful guidelines for creating distributed wideband spectrum sensing algorithms for cognitive radio networks.

S. Kirolos et.al., proposed a method in Analog-to-Information Conversion via Random Demodulation [8]. Radio frequency transmissions with extremely high bandwidth are involved in a lot of signal processing issues in radar and communications. This poses a significant obstacle for systems that might try to sample these signals at high rates using an analog-to-digital converter (ADC), in accordance with the Shannon/Nyquist sampling theorem. But in these cases, the signal's information level is frequently far lower than the actual bandwidth, raising the question of whether more effective methods for assessing such signals may be created. In this study, a technique for creating a low-rate collection of digital measurements using modulation, filtering, and sampling is proposed.

H. Sun et.al., proposed a method in Wideband Spectrum Sensing With Sub-Nyquist Sampling in Cognitive Radios [9]. For wideband spectrum sensing, a Multi-rate Asynchronous Sub-Nyquist Sampling (MASS) approach is suggested. The likelihood of a successful recovery is presented together with the corresponding spectral recovery requirements. MASS has a lower sample rate than earlier methods, making it a desirable method for cognitive radio networks. In this method, the wideband signal is sampled at various sub-Nyquist rates using parallel low-rate samplers. Compressive sensing analysis is used to derive conditions for recovering the entire spectrum. According to the results of simulations, MASS is more capable of compressing data than Nyquist sampling methods. MASS has been observed to be robust against a lack of temporal synchronisation and to have outstanding performance in fading/shadowing circumstances, in contrast to other sub-Nyquist sampling systems. In conclusion, the suggested MASS not only offers advantages such as low sampling rate, high energy-efficiency, and compression capabilities, but is also more easily implemented in CR networks when there is fading or shadowing.

C.P. Yen et.al., proposed a method in Wideband Spectrum Sensing Based on Sub-Nyquist Sampling [10]. This work addresses the problem of multiple active spectrum subband detection over a wide range of frequency bands. Since performing Nyquist sampling on the wideband signal is either impossible or prohibitively expensive, wideband spectrum sensing presents a number of significant challenges. This work suggests multicoset sampling, a sensing strategy based on a sub-Nyquist sampling method. It is similar to the polyphase implementation of the Nyquist sampling but uses fewer A/D converters. A technique has been developed that uses the sub-Nyquist samples to instantly estimate the power spectrum of the target wideband signal. Contrary to traditional sub-Nquist methods, which first rebuild the wideband signal from the sub-Nyquist samples, this method does not use sub-Nyquist samples. A constant-false-alarm energy detector for the frequency bins from the statistical distribution of the suggested power spectrum estimator, which is also reported in this paper. Through simulation results, the effectiveness of the proposed sub-Nyquist sampling-based multiband spectrum sensing approach is demonstrated.

X. Wang et.al., proposed a method in Sub-Nyquist Spectrum Sensing Based on Modulated Wideband Converter in Cognitive Radio Sensor Networks [11] .The success of the Internet of Things depends on the widespread deployment of wireless sensor networks. Sub-Nyquist spectrum sensing based on the modulated wideband converter is described, taking into account dynamic spectrum access and the constrained spectrum resources in cognitive radio sensor networks. Since several carrier frequencies are typically used to modify transmission signals, the desired spectrum can be represented as a multiband signal. The frequency support reconstruction technique is the most crucial component of the modulated wideband converter (MWC). The majority of reconstruction techniques, however, demand for sparse information, which is challenging to gather in real-world situations. A blind multiband signal reconstruction technique, known as the statistical multiple measurement vectors (MMV) iterative approach, is used in this paper to get over the aforementioned issue. Using different numbers of sampling channels, simulation results demonstrate that the statistics MMV iterative method can accurately assess the support of the multiband signal in a wide range of signal-to-noise ratios.

R. Dionisio et.al., proposed a method in Combination of a Geolocation Database Access with Infrastructure Sensing in TV bands [12]. This paper outlines the technical specifications and execution of a geolocation database supported by an outdoor spectrum monitoring network. The geolocation database and the sensor network's application programming interface (API) implement a successful and secure connection to successfully collect sensing data and send it there for post-processing. Overall, this hybrid strategy is a viable option for the efficient utilisation of TV white spaces as well as for coexisting with dynamic incumbent systems such unregistered wire-free microphones or digital TV broadcast signals.

N. Wang et.al., proposed a method in Database-augmented Spectrum Sensing Algorithm For cognitive Radio [13]. This paper proposes a unique database-augmented spectrum sensing technique for a secondary access to the TV White Space (TVWS) spectrum. The proposed database-augmented sensing algorithm is based on a geolocation database approach that already exists for identifying incumbents, such as Digital Terrestrial Television (DTT) and Program Making and Special Events (PMSE) users, but is combined with spectrum sensing to further improve the protection to these primary users (PUs). For their opportunistic access to TVWS, the secondary users' (SUs') spectral efficiency is also stated in closed form. By merging a previously created power control based geolocation database and an adaptive spectrum sensing algorithm, the suggested database-augmented sensing method surpasses the existing stand-alone geolocation database model in terms of spectrum efficiency for SUs and PU protection.

Z. Qin et.al., proposed a method in Data-Assisted Low Complexity Compressive Spectrum Sensing on Real-Time Signals Under Sub-Nyquist Rate [14]. In order to identify spectrum gaps in a decentralised cognitive radio, this paper presents a novel hybrid system that combines compressive spectrum sensing with a geolocation database. In the hybrid architecture, it is recommended that a geolocation database algorithm be maintained locally at secondary users in order to remove the extra transmission link to a centralised remote geolocation database. To enhance detection performance for wideband spectrum sensing under sub-Nyquist sampling rates and to reduce the computational complexity of signal recovery, a data-assisted non-iteratively reweighted least squares (DNRLS)-based compressive spectrum sensing technique is suggested. This is achieved by utilising the locally saved outcomes of the geolocation database method. The proposed framework is also implemented on real-time “from atmosphere” signals and data after being validated by TVWS’s simulated signals and data.

Y. Ma et.al., proposed a method in Joint Sub-Nyquist Spectrum Sensing Scheme with Geolocation Database Over TV White Space [15]. Combining real-time spectrum sensing with a geolocation database is a viable strategy to improve detection resolution with less computational effort in order to optimise alternatives for white space device spectrum access. Using a hybrid approach of sub-Nyquist wideband spectrum sensing and a geolocation database, which is proposed in this study, it is possible to detect the surrounding spectrum accurately with fewer measurements and less computationally intensive methods. By modifying two iterative methods to include a priori data from a geolocation database, it is now possible to execute spectrum sensing across TV white space only on a small subset of possibly empty channels. With better detection capabilities and a lower necessary sampling rate, the proposed joint approach speeds up the sensing process, while the updated channel knowledge from wideband spectrum sensing reduces the danger of interferences to the dynamic incumbent users.

G.P.Aswathy et.al., proposed a method in Joint Sub-nyquist Wideband Spectrum Sensing and Reliable Data Transmission for Cognitive Radio Networks over White Space [16]. A simpler joint sub-Nyquist wideband spectrum sensing technique is suggested for white space devices. Less complex wideband spectrum sensing is made possible by the Orthogonal Matching Pursuit (OMP) algorithm and modulated wideband converter. Information from the geolocation database may be useful for TV spectral band spectrum sensing. Other wideband spectrums, on the other hand, do not currently have access to the geolocation database, making geolocation database independent spectrum sensing necessary. However, if it is made available for any bandwidth, the prior channel occupancy status from the geolocation database reduces the total number of measurements, computational cost, sub-Nyquist sampling ratio, and total sensing latency. Surprisingly, it decreases the amount of computation time and iterations needed to recover the spectral support. The geolocation database's prior information combined with the sensing technique improves spectrum sensing performance with a minimum of complexity, making it more appropriate for low-power cognitive devices.

G.P.Aswathy et.al., proposed a method in Joint Sub-Nyquist Cooperative Wideband Spectrum Sensing for Cognitive Radio Networks [17]. The cognitive radio technology is one of the best promising methods for maximising the use of spectrum resources for next-generation wireless communication networks. The spectral diversity of unlicensed users is used by the cooperative spectrum sensing method. By sending recovered spectral support from various secondary users to a master device, which jointly determines the spectrum occupancy state, this improves detection performance. This is a hybrid strategy that incorporates prior knowledge from a geolocation database to lessen computing complexity and increase detection effectiveness. This method reduces the computational and implementation complexity in contrast to conventional cooperative spectrum sensing systems.

V Gupta et.al., proposed a method in Cooperative Fusion Rules in Spectrum Sensing [18]. Cooperative spectrum sensing(CSS) is the best method for evaluation of white space when multiple secondary user work in the collaboration. All local nodes scan the licensed band and give their decision to central fusion center. Central fusion center then aggregate the local nodes decision by soft fusion or hard fusion rules and give the final conclusion whether white space is available or not. Cooperative spectrum sensing enhances the spectrum detection efficiency by reducing the effect of fading and shadowing using spatial diversity and also reduced noise uncertainty problem. The simulation result in this article shows a relative comparison between various soft fusion and hard fusion rule. Soft fusion rule has high value of the detection efficiency in comparison of the hard fusion scheme at the cost of bandwidth.

Chapter 3

Proposed Methodology

The proposed spectrum sensing scheme's system architecture is depicted in Fig 3.1 [16]. It is primarily made up of a sensor network with numerous sensor nodes actively engaged in continuous wideband spectrum sensing. As a resource for TV spectral bands, the geolocation database is available. The sensor nodes initially verify the geolocation database's state for spectrum occupancy. The sensor nodes determine the initial spectrum occupancy status along with the prior information from geolocation database and provide the information to the master device. Local decisions made by the slave device are transferred to the fusion center. To get a precise spectrum support for the signal, several fusion rules are applied in the master device. In the interim, the geolocation database is also updated. The master device assigns the slave white space devices the available frequency slots after determining the spectral occupancy status.

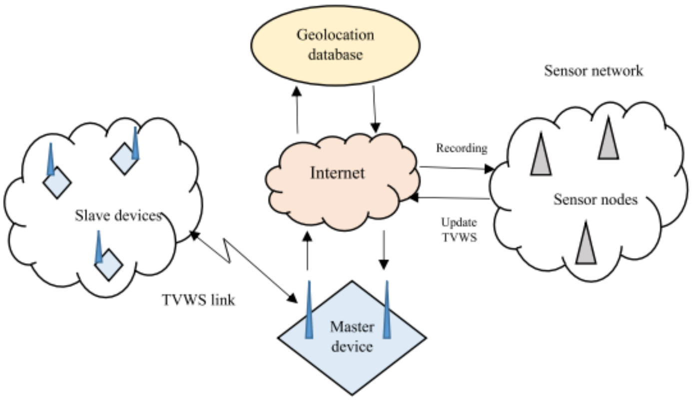


Figure 3.1: System Architecture

3.1 Block Diagram of the Proposed Scheme

The proposed framework's block schematic is presented in Fig 3.2 [16]. The spectral opportunities are identified using the partial measurements in this sub-nyquist wideband spectrum sensing technique. Wideband signals are captured at a sub-nyquist rate. Using a combination of a priori geolocation database knowledge and spectrum sensing techniques, this can be accomplished. The geolocation database made available for TV spectrum is used to manage the white space device used by TVWS. In this scenarios, the white space devices locate themselves geographically and search a geolocation database to find any vacant spectral bands nearby. By effectively utilising the available spectral holes, spectrum utilisation can be increased. The vacant frequency bands are assigned to the secondary users by using this innovative hybrid approach of sub-Nyquist wideband cooperative spectrum sensing, which relies on modulated wideband converters and prior data from the geolocation database.

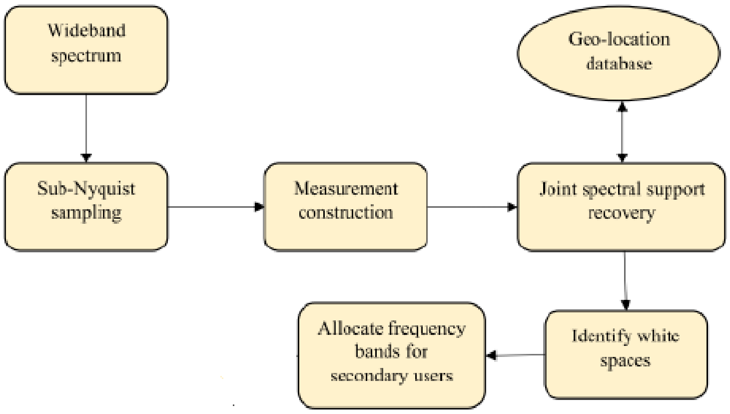


Figure 3.2: Block diagram of the Proposed Scheme

3.2 Signal Model

Assume that the received signal $x(t)$ can be represented as,

$$x(t) = s(t) + \eta(t) \tag{3.1}$$

where $s(t)$ denotes the primary user signal and $\eta(t)$ is the Additive White Gaussian noise (AWGN).

The primary user signal, $s(t)$ is modelled as analog multiband signal given by

$$s(t) = \sum_{j=1}^{K} \sqrt{E_j B_j} \sin c\left(B_j t\right) \exp\left(2\pi f_j t\right) \tag{3.2}$$

where E_j denotes the energy of each primary user j, B_j the bandwidth assigned and f_j is the frequency assigned to primary user j. In equation $\eta(t)$ has zero mean and variance $\sigma_n^2 \quad i.e. \quad \eta(t) \sim \mathcal{N}\left(0, \sigma_n^2\right)$. Consider the case where the wideband continuous-time signal $x(t)$ is being observed. The frequency-domain representation of $x(t)$ yields a sparse spectrum with the majority of its energy contained within a small number of frequency subbands that are mutually exclusive. The W subbands of the wideband spectrum are evenly distributed. Assume that B represents the uniform bandwidth for each segment. The index range for the narrowband segments is 0 to W − 1. Assume that the wideband contains K active bands. Let S stand for the collection of spectral support indices denoted by S = $[S_1 \quad S_2.....S_K]$. Wideband spectrum sensing's primary goal is to locate the available spectrum, or, more accurately, the active channel set S. The secondary users are given access to the wideband empty spectrum (white space) after S has been recovered [13].

3.3 Sub-Nyquist Wideband Spectrum Sensing

Sub-Nyquist techniques are attracting increasing interest in both academia and industry due to the limitations of high sampling rates or the high implementation complexity of Nyquist systems. Sub-Nyquist broadband acquisition refers to the acquisition of broadband signals at sampling rates below the Nyquist rate and the identification of spectrum opportunities based on these partial measurements. Because of their success in recovering samples at sub-Nyquist sampling rates, compressed sensing techniques (CS) have attracted considerable attention in the signal processing field. For this approach to be successful, it is assumed that the broadband under consideration is sparse in its frequency range. The CS attempts to recover the sparse signal

U from the partial measurement vector V by resolving the following underdetermined system of linear equations,

$$V = \phi^T \psi U = AU \tag{3.3}$$

where A represents the m x W sensing matrix. In order to provide an almost exact solution to the aforementioned set of underdetermined equations defined by equation (3.3), the sensing matrix A is optimally selected based on a number of unique requirements. The restricted isometric property (RIP), which alone determines whether the system of equations is solvable, is the primary property of the sensing matrix.

3.4 Joint Spectral Support Recovery Using Prior Geolocation Database Information

A compressive modulated wideband converter [13] is used in this work to sample and capture signals. Each sensor node implements the modulated wideband converter in a branch that samples the signal at a sub-Nyquist rate. One can create a low-dimensional sensing matrix from these low-rate data. The next step is to recover the spectral support using the orthogonal matching pursuit (OMP) method. Our suggested procedure before support recovery also takes into account the history data of the geolocation database. In Fig 3.3 modulated wideband converter (MWC) is depicted. The sensor nodes pick up the signal $x(t)$, which is sampled using MWC at a sub-Nyquist rate, from the neighbouring spectrum. It is made up of a bank of low pass filters, analog-to-digital converters, and mixers that operate at a low sampling

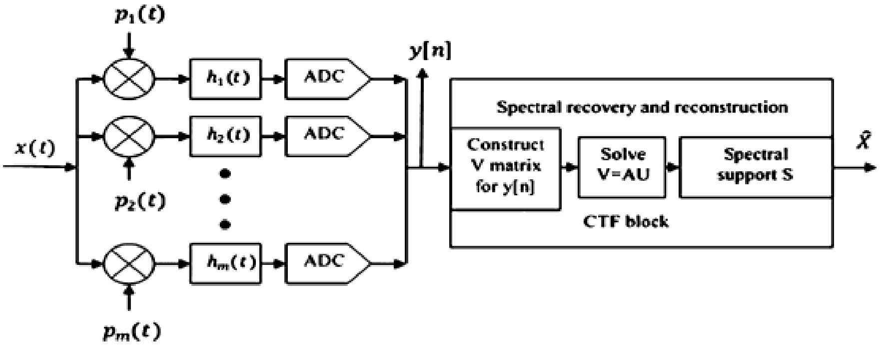


Figure 3.3: Modulated Wideband Converter based Wideband Spectrum Sensing.

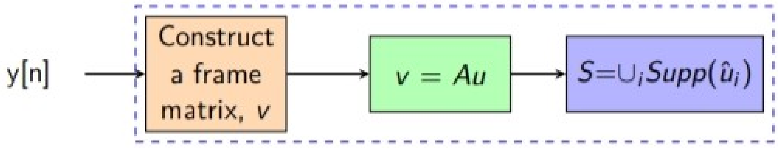


Figure 3.4: Continuous-to-Finite block.

rate. The same signal $x(t)$ is supplied to the MWC with sampling branches. In each mixer 'i', $x(t)$ is multiplied using a mixing waveform $p_i(t)$. This function must be periodic (period $= T_p$) and it is a piece-wise constant function which alternates its value between +1 or 1 at equal time intervals, M_s

$$p_i(t) = \alpha_{il}; \quad l\frac{T_p}{M_s} \leq t \leq (l+1)\frac{T_p}{M_s}; 0 \leq l \leq M_s - 1 \tag{3.4}$$

$$\alpha_{il} \in \{+1, -1\}; 1 \leq i \leq m \tag{3.5}$$

The aliasing of the spectrum from each band to the baseband is ensured by the mixing procedure. The signal spectrum in each branch 'i' of the LPF is truncated by $h_i(t)$. A low-rate ADC is subsequently used to sample the filtered signal. The OMP algorithm is used by the continuous-to-finite block (CTF) shown in Fig 3.4 to recover the spectral support, S. The OMP approach is chosen over alternative l1 minimisation algorithms because of its higher execution speed and reduced complexity. This decreases the computational cost and sensing delay. The recovery technique incorporates a priori knowledge about the channel occupancy to further simplify it and minimise the number of measurements. Local spectrum sensing only needs to be carried out on a small subset of frequency channels because the database contains the information on the pre-occupied channels. The output measurement matrix from the MWC is represented by $y[n]$. The matrix Q is first calculated by the CTF block as,

$$Q = \sum_{n=-\infty}^{\infty} y[n]y[n]^T \tag{3.6}$$

Using the eigen value decomposition (EVD), the Q matrix is transformed into the matrix V,

$$[V, d] = \mathrm{EVD}[Q, \hat{K}] \tag{3.7}$$

where $d = \mathrm{diag}\left\{\lambda_1, \lambda_2, \ldots \lambda_K\right\}$ represent the K principal eigenvalues, while V represents their corresponding eigenvectors. The lower dimensional measurement matrix, v, is created by combining the eigen vectors V with the eigenvalue matrix d.

$$v = V\sqrt{d} \tag{3.8}$$

Consider the system of linear equations represented by,

$$v = Au \tag{3.9}$$

where A is the sensing matrix. It is well known that v in equation (3.9) is row-sparse, meaning that there aren't many rows in the matrix with non-zero entries. These rows' indices match S, an unknown spectral support. The sparsest solution to problem (3.9) has a spectral support that exactly matches support S. The matrix v can be estimated as joint K-sparse because there are K significant row vectors. As a result, OMP is applied to the lower-dimensional matrix v to recover the sparsest vector, $\hat{u}$. The unknown spectral support (S) is known as,

$$S = \bigcup_i \mathrm{Supp}\left(\hat{u}_i\right) \tag{3.10}$$

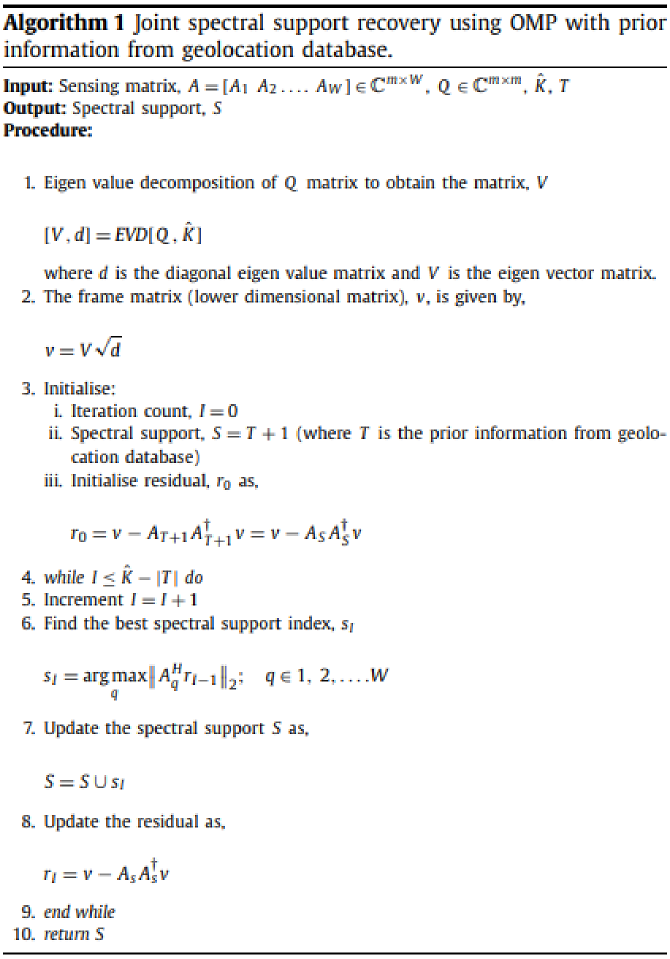
To reduce computation complexity, the proposed wideband-based spectrum sensing incorporates channel status information from a geolocation database. The locations of the occupied channels will be included in the sensing framework. The wideband spectrum sensing based on modulated wideband converters in this work can therefore take advantage of the past information. The spectral occupancy status from the geolocation database displays which spectral bands are expected to be occupied. Using this prior knowledge about the indices of the associated rows with large norm, we may optimise the recovery performance with fewer observations using sub-Nyquist sampling. Let T to represent the available information from the geolocation database so that $T \subset [0, W-1]$. T is associated to the original spectral support S as,

$$S = T \cup \Delta / \Delta_e \tag{3.11}$$

where the equation $\Delta := S/T$ is equivalent to the spectral indices of the recently active channels and $\Delta_e := T/S$ is equivalent to the spectral indices of the recently free channels. Each iteration of the OMP recovery algorithm selects the column of A that has the strongest correlation with the remaining portion of the signal. The measurement matrix v is then adjusted for its contribution, and the residual is iterated. The locations of non-zero rows of u are indicated by the indices of the selected columns of A. The active channel set S is equivalent to the recovered spectral support. The OMP algorithm is changed in the proposed work to incorporate data from a geolocation database into the recovery procedure. This approach builds an estimation of the signal at each iteration, making it easier to understand how to include T as an initial condition in the recursion. Because these relevant columns in the measurement matrix may be used or reserved by the licenced users, the initialization of the support recovery is updated based on the prior data from the geolocation database. Therefore,before starting the iteration, the residual is initialized as

$$r_0 = v - A_{T+1} A_{T+1}^{\dagger} v \tag{3.12}$$

where $T \subset [0, W-1]$ is added with 1 as the corresponding column indices of A start from 1. Algorithm 1 provides a description of the suggested algorithm. The processing flow of Algorithm 1 is similar to that of conventional OMP. The initial residue is modified to include the prior information from the geolocation database, and fewer iterations will be required. OMP reduces the cost of computing in low-power resource-constrained sensor node. K iterations are used by conventional OMP to recover the K-sparse signal. Only $K - T$ iterations are necessary for OMP because T indices are known (found in the geolocation database). The channel occupancy status of the geolocation database gives a priori information of some of the occupied channels that might be blocked or used by licenced users. It is important to note that only a few potentially vacant bands must be used for local spectrum sensing.



Algorithm 1 Joint spectral support recovery using OMP with prior information from geolocation database.

```
Input: Sensing matrix, $A = [A_1\ A_2 \ldots .\ A_W] \in \mathbb{C}^{m \times W}$, $Q \in \mathbb{C}^{m \times m}$, $\hat{K}$, $T$
Output: Spectral support, $S$
Procedure:

 1. Eigen value decomposition of $Q$ matrix to obtain the matrix, $V$
      $[V, d] = EVD[Q, \hat{K}]$
    where $d$ is the diagonal eigen value matrix and $V$ is the eigen vector matrix.
 2. The frame matrix (lower dimensional matrix), $v$, is given by,
      $v = V\sqrt{d}$
 3. Initialise:
     i. Iteration count, $I = 0$
    ii. Spectral support, $S = T + 1$ (where $T$ is the prior information from geolocation database)
   iii. Initialise residual, $r_0$ as,
          $r_0 = v - A_{T+1}A^{\dagger}_{T+1}v = v - A_S A^{\dagger}_S v$
 4. while $I \le \hat{K} - |T|$ do
 5. Increment $I = I + 1$
 6. Find the best spectral support index, $s_I$
      $s_I = \arg\max_q \| A^H_q r_{I-1} \|_2;\quad q \in 1,\ 2, \ldots .W$
 7. Update the spectral support $S$ as,
      $S = S \cup s_I$
 8. Update the residual as,
      $r_I = v - A_s A^{\dagger}_s v$
 9. end while
10. return $S$
```

Figure 3.5: Algorithm 1

Chapter 4

Fusion Rules in Cooperative Spectrum Sensing

Cooperative spectrum sensing is the best method for assessing of white space when several users work in colloboration [18]. This method improves the detection of spectrum efficiently by decreasing the effect of fading, shadowing using spatial diversity and also noise uncertainity problems are reduced.

4.1 Hard Fusion Rules

In hard fusion rule, the secondary users send their local decisions to the fusion center, which then makes a final decision based on the local decisions it has received from the secondary users. There are mainly three types of fusion rules : OR rule, AND rule and K out of N rule.

AND Rule

In this rule, the fusion center determines the channel is occupied only when it gets all the local decisions from secondary users as channel is occupied.

OR Rule

In OR rule, the fusion center decides that the channel is occupied only when it gets at least one local decision from secondary users as channel is occupied.

K out of N Rule

This rule is also called as majority rule. If the fusion center gets information from N number of nodes and if the least K number of nodes send that the channel is occupied then only it decides the channel is occupied.

4.2 Proposed Soft Fusion Rule

Sub-Nyquist wideband sensing requires collaboration among several SUs since this measurements are very susceptible to channel degradations. Consider there are J concurrent secondary users in the local area, and they all jointly sense the wideband to find the active channel set S. The same primary broadcasts are used in the received signals at the SUs, however each SU is affected differently by fading and shadowing from the common primary user transmitter. As a result, all SUs have a similar sparse support that has a range of amplitudes.

The suggested cooperative spectrum sensing method could be broken down into the following 3 steps:
1) Each Secondary user implements a modulated wideband converter that independently samples the signal.
2) Based on subspace decomposition, measurement matrix $v^{(j)}$ is built at each secondary user from its sub-Nyquist samples. Following that, the local matrix $v^{(j)}$ is transferred to the fusion center.
3) By combining measurements from various SUs, the fusion centre determines the active channels and makes a more precise global sensing judgement.
The fusion centre computes the associated reconstruction matrix $A^{(j)}$ based on the measurement matrix $v^{(j)}$ and sent from each SU and then uses the shared signal support across $u^{(j)}, j = 1, \ldots, J$, across all SUs to find the active channels. At each SU, the following relationship can given as:

$$v^{(j)} = \mathbf{A}^{(j)} u^{(j)}, \quad 1 \leq j \leq J \tag{4.1}$$

The fusion centre combines measurements from all SUs to identify the original active channels by taking advantage of the shared common sparse support that the J SUs have. Grouping the rows of the $u^{(j)}, j = 1, \ldots, J$, with the same indices, forms ζ_s matrix.

$$\zeta_s = [\underbrace{u^{(1)}[1]^T \cdots u^{(J)}[1]^T}_{u[1]^T} \cdots \underbrace{u^{(1)}[W]^T \cdots u^{(J)}[W]^T}_{u[W]^T}]^T \tag{4.2}$$

where the i-th row of $u^{(j)}$ and j-th SU is indicated by $u^{(j)}[i]$.

Additionally, ζ_s can be divided into blocks by concatenating blocks $u^{(j)}[q]^T, q = 1, \ldots, W$ and the block size is determined by the number of SUs J. A block K-sparse matrix can be used to model ζ_s because there are at most K-sparse channels that are occupied. Consequently, the block index that accounts for the highest residual norm among all SUs is chosen in each iteration, i.e.

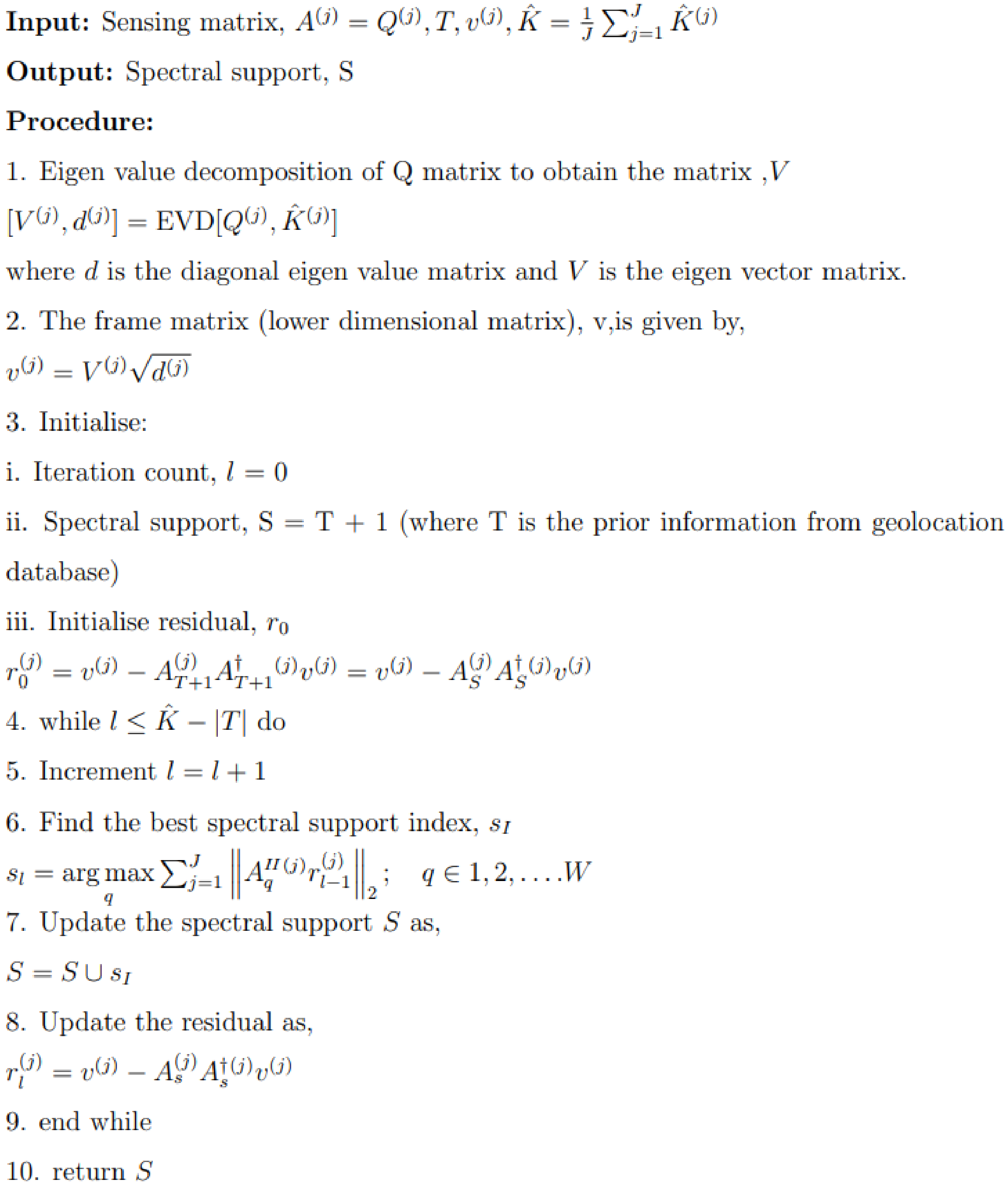
$$s_l = \arg\max_q \sum_{j=1}^{J} \left\| A_q^{H(j)} r_{l-1}^{(j)} \right\|_2; \quad q \in 1, 2, \ldots .W, \tag{4.3}$$

where $r_{l-1}^{(j)}$ represents the residue at $(l-1)$-th iteration at j-th secondary user, $A_q^{(j)}$is the l-th column in $A^{(j)}$and selected index is s_l. Algorithm 2 describes the comprehensive algorithm for the proposed joint support recovery using soft fusion rule at the fusion centre. The fusion center takes the average $\hat{K}$ as,

$$\hat{K} = \frac{1}{J} \sum_{j=1}^{J} \hat{K}^{(j)} \tag{4.4}$$

The cooperative spectrum sensing using this proposed soft fusion rule shows better performance than the cooperative spectrum sensing using hard fusion rules.

Algorithm 2: Measurement fusion in the proposed cooperative sensing scheme



```
**Input:** Sensing matrix, $A^{(j)} = Q^{(j)}, T, v^{(j)}, \hat{K} = \frac{1}{J}\sum_{j=1}^{J} \hat{K}^{(j)}$
**Output:** Spectral support, S
**Procedure:**
1. Eigen value decomposition of Q matrix to obtain the matrix ,$V$
   $[V^{(j)}, d^{(j)}] = \mathrm{EVD}[Q^{(j)}, \hat{K}^{(j)}]$
   where $d$ is the diagonal eigen value matrix and $V$ is the eigen vector matrix.
2. The frame matrix (lower dimensional matrix), v,is given by,
   $v^{(j)} = V^{(j)}\sqrt{d^{(j)}}$
3. Initialise:
   i. Iteration count, $l = 0$
   ii. Spectral support, S = T + 1 (where T is the prior information from geolocation database)
   iii. Initialise residual, $r_0$
   $r_0^{(j)} = v^{(j)} - A^{(j)}_{T+1} A^{\dagger}_{T+1}{}^{(j)} v^{(j)} = v^{(j)} - A^{(j)}_{S} A^{\dagger}_{S}{}^{(j)} v^{(j)}$
4. while $l \leq \hat{K} - |T|$ do
5.     Increment $l = l + 1$
6.     Find the best spectral support index, $s_I$
       $s_l = \arg\max_{q} \sum_{j=1}^{J} \left\| A_q^{H(j)} r_{l-1}^{(j)} \right\|_2 ; \quad q \in 1, 2, \ldots . W$
7.     Update the spectral support $S$ as,
       $S = S \cup s_I$
8.     Update the residual as,
       $r_l^{(j)} = v^{(j)} - A_s^{(j)} A_s^{\dagger(j)} v^{(j)}$
9. end while
10. return $S$
```

Figure 4.1: Algorithm 2.

Chapter 5

Performance Evaluation

The simulation results for the proposed sub-Nyquist cooperative wideband spectrum sensing technology employing various fusion rules are shown in this section.

5.1 Simulation Setup

Consider a wideband signal that the cognitive user has received, $x(t) \in F = [0, 10]$ GHz. The wideband is divided into W = 195 bands, each with a B = 50 MHz bandwidth. Let K represent the number of bands that are active, such that $K \leq W$. For the simulation, $K = 10$ is selected. To model the analog wideband signal, we apply equation (3.1). We use the MWC and OMP algorithm to assess the effectiveness of the suggested spectrum sensing strategy. The number of active channels is chosen at random as K=$|S|$=10. Thus α= 5% represents the channel occupancy ratio. The spectral support S and the prior information from the geolocation database T are selected at random from $[0, W-1]$. The size of the previously identified component, τ , from the geolocation database ranges from 0 to K. If $\tau = 0$, there is no prior geolocation database information; if τ=K, the geolocation database information is 100 percent reliable. To find the spectral holes, we combine the suggested sub-Nyquist wideband spectrum sensing technique with prior data from a geolocation database. The recovered spectral support $\hat{S}$ is compared against the original active channel set S to assess the success rate under 1000 Monte Carlo trials.

5.2 Results and Discussion

Hard Fusion Rules

In Fig 5.1, the success rate of detection for AND rule is evaluated. It can be seen that success rate is maximum at maximum SNR. The success rate is minimum at minimum SNR. When the SNR is equal to 0 dB the success rate is 0.3. When SNR is equal to 5 dB the success rate is 0.5. When SNR is equal to 20dB the success rate attain the maximum value.

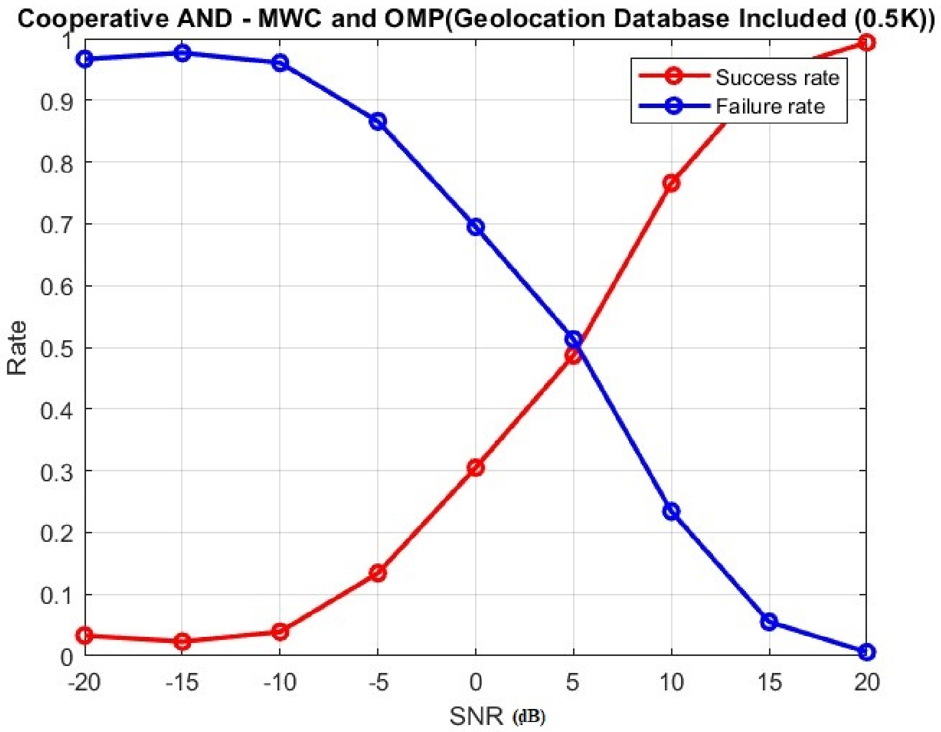


Figure 5.1: The Success Rate of Detection for AND Rule

In Fig 5.2, The success rate of detection for OR rule is evaluated. When SNR equals to 0 dB the success rate is just above 0.5. When SNR equals to 5 dB the success rate is 0.8. The success rate attains the maximum value when SNR equals to 20 dB. In Fig 5.3, the success rate of detection for K out of N rule is evaluated. When SNR is equal to 0 dB the success rate is 0.4. When SNR is equal to 5 dB the success rate is 0.6. Clearly, the performance of every technique gets improved with higher SNR levels. It is observed that OR-rule offers the highest values of success rate detection and AND rule offers minimum values of success rate. Majority-rule offers an intermediate solution.

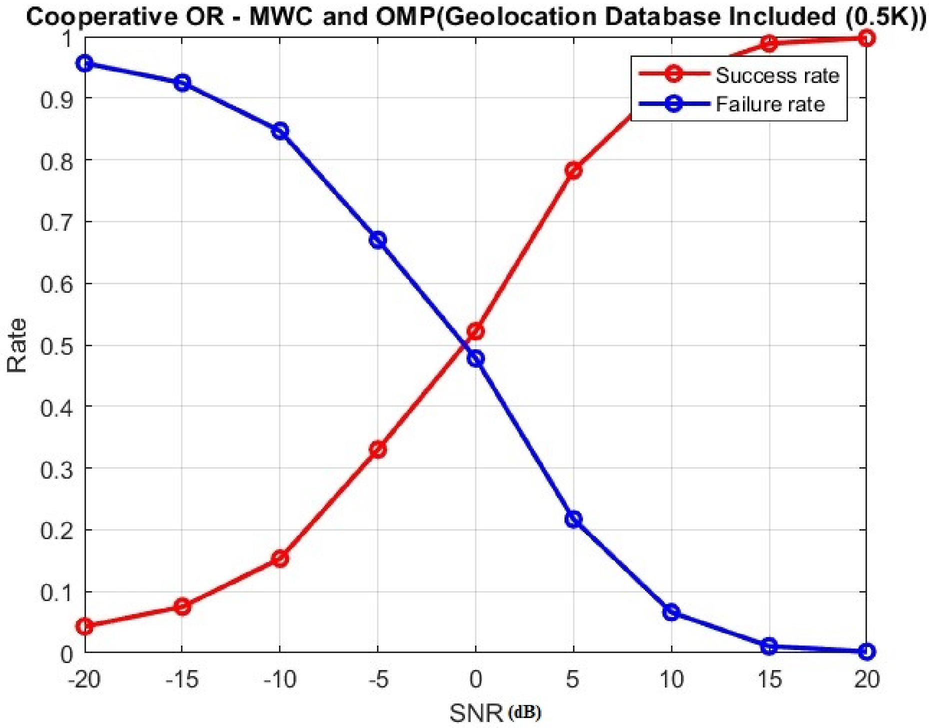


Figure 5.2: The Success Rate of Detection for OR Rule

Soft Fusion Rule

In Fig 5.4, the success rate for proposed soft fusion rule is evaluated. When SNR equals to 0 d B the success rate is above 0.5 and which is approximately equal to 0.6. When SNR equals to 5 dB the success rate is above 0.8. The success rate is maximum at maximum SNR. This shows that the success rate obtained using this soft rule is higher than the success rate obtained using the hard fusion rules. It is observed that the proposed soft fusion rule offers better performance than the hard fusion rules.

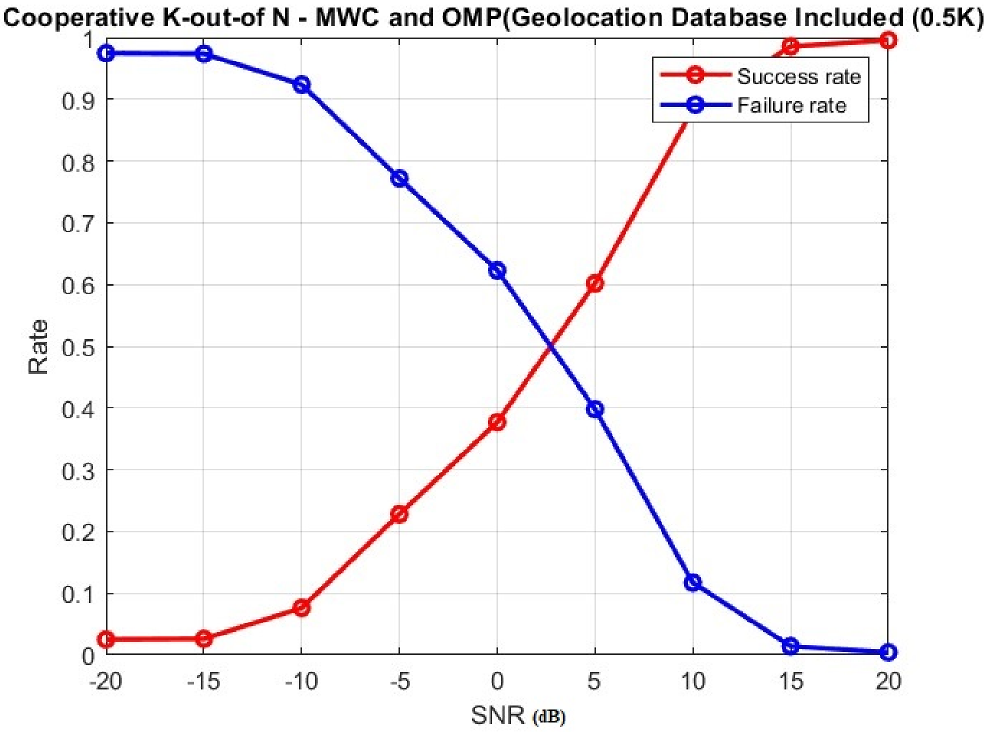


Figure 5.3: The Success Rate of Detection for K out of N rule

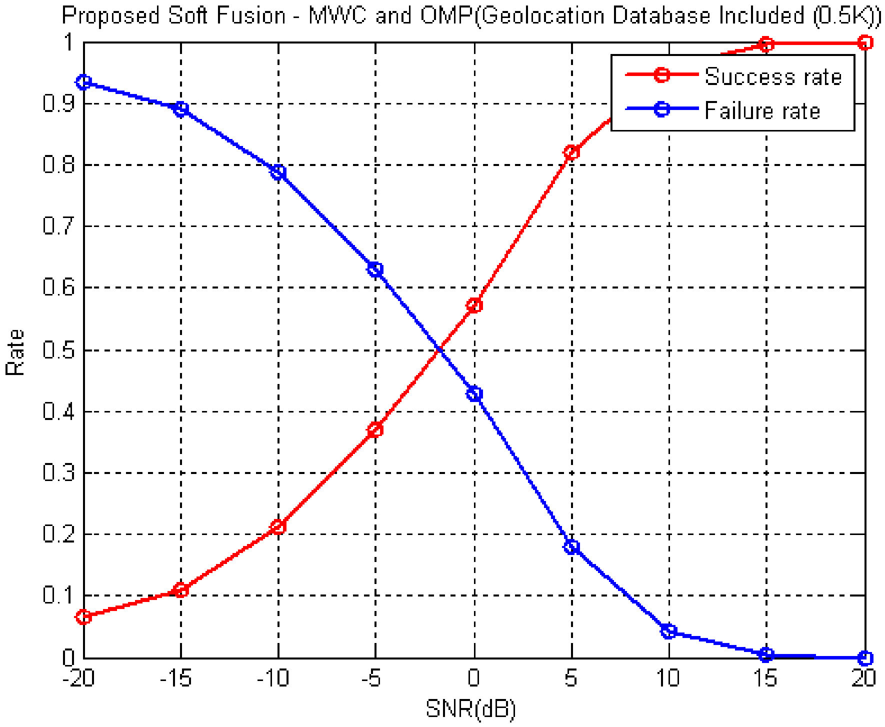


Figure 5.4: The Success Rate of Detection for proposed soft fusion rule

Chapter 6

Advantages

The hybrid approach of sub-nyquist wideband cooperative spectrum sensing, which relies on modulated wideband converters and prior data from the geolocation database reduces the amount of computation iterations and time needed to recover the spectrum support. This method enhanced the spectrum utilization and white space detecting performance. Cooperative spectrum sensing using the soft fusion rule performs better than the hard fusion rules. If several cognitive radio users collaborate with one another as they do in cooperative spectrum sensing, all the limitations of the transmitter-based detection technique can be eliminated. To combat the effects of fading and shadowing, cooperative spectrum sensing employs the spatial diversity principle. Because different cognitive radio users work together, cooperative spectrum sensing has a high value for detection effectiveness. Cooperative spectrum sensing(CSS) is the best method for evaluation of white space when multiple secondary user work in the collaboration. All local nodes scan the licensed band and give their decision to central fusion center. Central fusion center then aggregate the local nodes decision by soft fusion or hard fusion rules and give the final conclusion whether white space is available or not. Cooperative spectrum sensing enhances the spectrum detection efficiency by reducing the effect of fading and shadowing using spatial diversity and also reduced noise uncertainty problem. The simulation result in this article shows a relative comparison between various soft fusion and hard fusion rule. Soft fusion rule has high value of the detection efficiency in comparison of the hard fusion scheme at the cost of bandwidth.

Chapter 7

Future Scope

In spectrum sensing, machine learning is used to extract a feature vector from a pattern and classify it into a hypothesis class that either indicates the absence or existence of PU activity. Spectrum sensing cannot accurately establish the PU status based on the current sensing slot alone since fading and shadowing can make it difficult to estimate the channel condition. However, spectrum sensing based on machine learning has the ability to implicitly learn the surrounding environment. Another benefit of machine learning-based spectrum sensing is that it may accurately identify PU activity without the need for prior environmental knowledge. So as a future scope we suggest to incorparate machine learning based fusion rules.

Chapter 8

Conclusion

This work suggests a less complicated joint sub-nyquist cooperative wideband spectrum sensing method for white space devices. Less complex wideband spectrum sensing is made possible by the OMP algorithm and modulated wideband converter. To simplify computation and boost detection performance, prior data from a geolocation database is integrated. Each secondary user scans a permissible band and informs the central fusion centre about their decision. The cooperative spectrum sensing can be perform in three ways in centralize, coordinated cooperative model central fusion center will be responsible to give concluded result each secondary report to central fusion center. In the another centralize uncoordinated model there is no fusion center every secondary user share their decision to another secondary using multiple clustering algorithm. In third type of cooperative model that is uncoordinated decentralize there is no coordination between secondary user. The fusion centre will combine local node decisions made using various fusion rules to determine whether or not white space is available. The novel fusion rule performs better when compared to hard fusion rules like the OR rule, AND rule, and K out N rule. Apparently, it decreases the amount of computation time and iterations needed to recover the spectral support. It also enhanced the efficacy of white space detection and spectral utilization. This technique so works better for small, low-power cognitive devices.

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