

Heterogeneous Cooperative Spectrum Sensing Test-Bed Using Software-Defined Radios

Kuldeep S. Gill, Alexander M. Wyglinski
Wireless Innovation Labortary
Department of Electrical and Computer Engineering
Worcester Polytechnic Institute, Worcester, MA
Email: ksgill@wpi.edu, alexw@wpi.edu

Abstract—In this paper we implement a cooperative spectrum sensing test-bed using software defined radios with different sensing capabilities, e.g., sampling rates, RF characteristics, etc. Normalized energy detection is used for spectrum sensing due to its low implementation complexity. The proposed heterogeneous spectrum sensing test-bed is implemented using USRP N210s and RTL-SDRs within a controlled indoor laboratory environment. All signal processing is performed using GNU Radio and post processing is conducted using MATLAB. Sensor units (SUs) are designed to generate the local test statistic L and transmit it to a Fusion Center for decision making. The Fusion Center (FC) is a base station that decides whether signal is present or not based on the data from all sensor units. We examine both soft and hard data fusion techniques and compare their performance in a practical fading channel scenario.

Keywords—Fusion Center, Cooperative Spectrum Sensing, Cognitive Radios, Normalized Energy Detection (ED)

I. INTRODUCTION

There has been a significant increase in the study of cognitive radios for efficiently utilizing the electromagnetic spectrum. It has been observed that the spectrum occupancy is not uniform across all frequency bands, resulting in numerous spectral white spaces [1]. In order to more efficiently utilize the spectrum, dynamic spectrum access (DSA) has been proposed in [2] and [3]. To opportunistically access the idle channel, spectrum sensing is considered to be a significant technology enabling DSA. Although several spectrum sensing techniques have been proposed in the open literature, energy detection is widely used due to its low implementation complexity [4].

It is very challenging to get an accurate estimate using a single-sensor system under a practical fading environment based on energy detection. Various non-idealities such as shadowing, multipath and fluctuating noise variance can make it difficult to detect the primary user [5] [6]. Cooperative spectrum sensing can mitigate the effects of multipath and shadowing by utilizing the spatial and temporal diversity of a multiple radio network [7] [8]. In cooperative spectrum sensing, each sensor node collects the spectral data and transmits it to a fusion center (FC) for decision making. Figure 1 shows how a heterogeneous sensor network exploits the spatial diversity.

Both soft data fusion and hard data fusion have been extensively studied [9] [10] [11], with several algorithms being implemented for each scheme. In a hard decision approach,

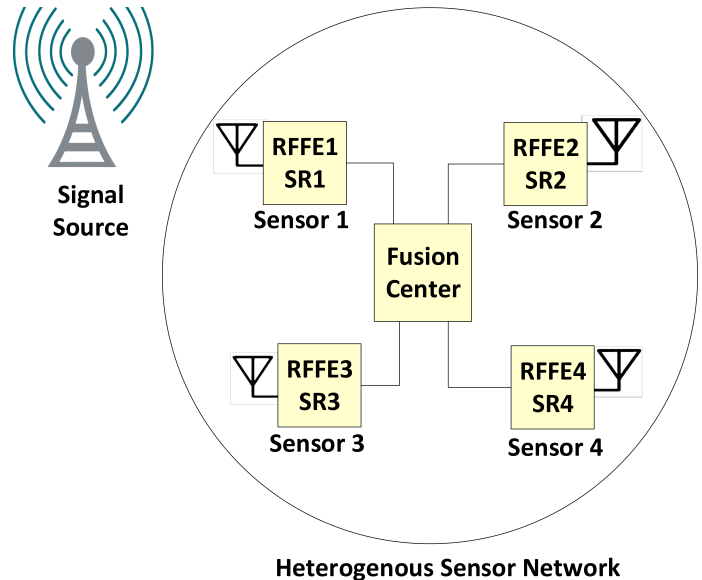


Figure 1: Heterogeneous sensor network employing cooperative spectrum sensing. RFFE i and SR i represents different sampling rates and front end for the SDR units.

each local decision statistic from sensor node is transmitted to an FC via overhead channels. The FC merges the sensing data and makes a global decision based on various algorithms such as majority rule, OR rule and AND rule [12]. For a soft decision scheme, each SU sends its local sensing data to the FC, which makes decision based on a global test statistic G . Soft decision combining improves the cooperative gain but it also possesses several limitations. With an infinite bandwidth, the real floating values can be transmitted to the FC, which can lead to a reliable decision mechanism. However, due to bandwidth constraint we have to quantize the data and this leads to error in the energy values. In hard decision combining, we can just transmit the decisions of the sensor nodes to the FC which can be binary values with "1" indicating that signal source is present and "0" indicating that a signal source is absent.

In this paper, we implement cooperative spectrum sensing with normalized ED using both soft data fusion and hard data fusion on available software defined radios. For soft data

fusion, Maximum Normalized Energy (MNE) and Equal Gain Combination (EGC) are implementation. Hard data fusion is also implemented using majority rule, AND, and OR approaches. In this paper, we employ USRP N210s [18] and RTL-SDRs [17] for the implementation of the heterogeneous sensor network, with each device intentionally configured with different sampling rates to model potential real-world scenarios involving spectrum sensing. Since the Realtek RTL2832U SDR dongles cannot be used for transmission, the USRP N210 units are used instead to transmit decision statistics via overhead channels keeping the operating values the same for all SDR systems. All real-time measurements are performed using GNU Radio, which is an open source environment for software radios [16]. Finally, the results are processed in MATLAB which acts as a FC and makes the decision based on the global test statistic for both hard and soft data fusion mechanism.

This paper is organized as follows: In Section II, we present the theoretical model for soft and hard decision combining techniques using Normalized ED in a cooperative spectrum sensing environment. In Section III, the experimental setup for the paper is described and in Section IV the results are presented for cooperative spectrum sensing for soft and hard data fusion. Finally, we conclude the paper with Section V, where we discuss the future work for the research.

II. NORMALIZED ENERGY DETECTION FOR COOPERATIVE SPECTRUM SENSING

One popular form of spectrum sensing is energy detection since it possesses a very low implementation complexity [4]. The energy detection scheme detects the presence or absence of a signal source based on its intercepted energy signature. If the energy of the signal is higher than a certain threshold, this indicates that the channel is occupied. The ED can be modeled by the equation:

$$y(n) = \begin{cases} w(n), & \mathbf{H}_0 \\ s(n) + w(n), & \mathbf{H}_1 \end{cases} \quad (1)$$

where $y(n)$ represents the received signal, $s(n)$ represents the signal source PU, and $w(n)$ is the white Gaussian noise $w(n) \sim N(0, \sigma_n^2)$. \mathbf{H}_0 describes the hypothesis when there is no signal present, while the hypothesis \mathbf{H}_1 is the presence of signal.

The decision whether the signal is present or absent is decided by evaluating a local test statistic L to see whether it is above or below certain fixed threshold τ . The local test statistic L , which is the complex-magnitude squared of the FFT samples, is compared with τ using equation:

$$L = \sum_{n=1}^M |y(n)|^2 = \begin{cases} < \tau, & \mathbf{H}_0 \\ > \tau, & \mathbf{H}_1 \end{cases} \quad (2)$$

where $|y(n)|^2$ is the energy of a specific FFT bin and $n=1,2,3...M$ are the number of samples received.

The probability of false alarm P_{fa} and probability of detection P_d are given by:

$$P_f = Q\left(\frac{\tau - M(2\sigma_n^2)}{\sqrt{M}(2\sigma_n^2)}\right), \quad (3)$$

$$P_d = Q\left(\frac{\tau - M(2\sigma_n^2)(1 + \gamma)}{\sqrt{M}(1 + 2\gamma)(2\sigma_n^2)}\right). \quad (4)$$

In cooperative spectrum sensing, each sensor node transmits the local sensing data to the fusion center for signal source detection. The local sensing data has to be quantized, thus yielding quantization errors. To minimize the quantization error in local test statistic L and to reduce the effect of noise variance, the energy of the received signal $y(n)$ is normalized [13]. The local test statistic L for the r^{th} sensor node is given as:

$$L_r = \frac{1}{M_r \sigma_{n,r}^2} \sum_{r=1}^{M_r} |y(n)|^2 \quad (5)$$

where M_r is the number of samples used to estimate the power of the signal source in the node, $\sigma_{n,r}$ is the noise power variance.

In Eq (1) $s(n)$ is considered as a deterministic signal and $w(n)$ is a Gaussian random variable with a variance of σ_n^2 . Based on CLT, L_r will have a following distribution [7]:

$$L_r = \begin{cases} N(1, \frac{1}{M_r}), & \mathbf{H}_0 \\ N(\gamma_r + 1, \frac{1 + 2\gamma_r}{M_r}), & \mathbf{H}_1 \end{cases} \quad (6)$$

where γ_r is the received SNR of the r^{th} SU. The local decision statistic L_r is quantized before transmission due to the bandwidth constraint, and this can lead to quantization errors. The values of L_r received by FC can be modeled as:

$$\beta_r = L_r + w_{q,r}, \quad (7)$$

where β_r is the decision statistic received by the FC and w_q is the noise added to the signal due to fading and quantization error. In [14], the w_q is modeled as a Gaussian noise with zero mean and σ_q^2 variance.

In this paper, we are using MNE and EGC cooperative spectrum sensing techniques for soft data fusion. In MNE based cooperative sensing, the FC selects the test statistic β with the largest value and makes the decision based on it. For the EGC scheme, we average out the B values from all the sensor nodes and creates a global test statistic which is later used for detection. The following sections describe these detection techniques in detail.

A. Maximum Normalized Energy Based CS Scheme

The local test statistic in each sensor node is given by Eq.(3), where r represents the number of sensing nodes. For this paper, we are using four sensor nodes equipped with different sensing abilities such as the sampling rates and noise floor. Therefore, the global test statistic G can be modeled by:

$$G_{MNE} = \max\{\beta_r\}, \quad (8)$$

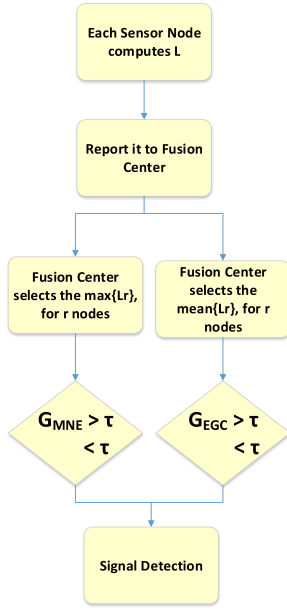


Figure 2: Flowchart describing Maximum Normalized Energy (MNE) and Equal Gain Combination (EGC) scheme for cooperative spectrum sensing studied in this work.

The P_{fa} and P_d values for the MNE-CS is given by: [12],

$$P_{fa} = 1 - \prod_{r=1}^R \left(1 - Q \left(\frac{\tau - 1}{\sqrt{\frac{1}{M_r} + \sigma_{q,r}^2}}} \right) \right), \quad (9)$$

$$P_d = 1 - \prod_{r=1}^R \left(1 - Q \left(\frac{\tau - 1 - \gamma_r}{\sqrt{\frac{1 + 2\gamma_r}{M_r} + \sigma_{q,r}^2}}} \right) \right). \quad (10)$$

where τ is the global threshold for MNE, M_r is the number of samples for r^{th} sensor node, and $\sigma_{q,r}$ is the noise variance for the received local test statistic. The algorithm for MNE-CS is illustrated by the flowchart in Figure 2.

B. Equal Gain Combining CS Scheme

For EGC, the global decision statistic is the mean of the β values for all the sensor nodes. It has been shown in [15] that the EGC scheme performs better than the MNE scheme in a noisy channel. The EGC scheme can be modeled by:

$$G_{EGC} = \frac{1}{M} \sum_{r=1}^M \beta_r, \quad (11)$$

where G_{EGC} is global test statistic of EGC scheme. The P_{fa} and P_d values for the EGC-CS scheme are given by:

$$P_{fa} = Q \left(\frac{\tau - 1}{\sqrt{\frac{1}{R^2} \sum_{r=1}^R \left(\frac{1}{M_r} + \sigma_{q,r}^2 \right)}} \right), \quad (12)$$

$$P_d = Q \left(\frac{\tau - \frac{1}{R} \sum_{r=1}^R (1 + \gamma_r)}{\sqrt{\frac{1}{R^2} \sum_{r=1}^R \left(\frac{1 + 2\gamma_r}{M_r} + \sigma_{q,r}^2 \right)}} \right). \quad (13)$$

The algorithm for EGC-CS is also illustrated by the flowchart in Figure 2.

C. Hard Data Combining Scheme

For hard data fusion, the noise w_q can be neglected since the sensor nodes can just transmit their decision statistic in an efficient way, where the floating values are not required. For example, the SUs can just transmit "1" and "0" depending on whether the primary user is present or absent. Furthermore, in the Fusion Center the decision can be made by using the OR, AND, or majority rule algorithms.

For the AND decision rule, the FC performs the logical AND operation for all the local decisions and conducts the detection. Similarly, for the OR rule, the logical OR operation is used to decide whether the signal is present or not. Finally, the majority rule conducts majority vote and decides based on it. The P_d for AND, OR and Majority Rule for $R=4$ sensor nodes is given by [15].

$$P_{d,AND} = (P_d)^4$$

$$P_{d,OR} = 1 - (1 - P_d)^4 \quad (14)$$

$$P_{d,MJR} = 6P_{davg}^2(1 - P_{davg})^2 + 4P_{davg}^3(1 - P_{davg}) + P_{davg}^4$$

where P_{davg} is the average probability of detection of the sensor units. Similarly, we can calculate the P_{fa} for all three schemes by replacing P_{davg} by P_{faavg} in Eq (14).

III. PROPOSED EXPERIMENTATION TEST-BED USING USRP AND RTL-SDR

The measurements are performed using software-defined radios (SDRs) and the post processing is conducted on desktop computers. The desktop computer consists of i7 Intel processor with eight cores and 3.41 GHz clock cycle running Ubuntu 16.04. The sensor node network is implemented using RTL-SDR dongles and Ettus Research USRP N210 on GNU Radio Software platform. The measurements are analyzed in MATLAB and measurement plots are generated. Figure 3 consists of three RTL-SDRs and two USRP N210s. One USRP N210 in the middle acts as a primary user and other SDRs are sensor nodes. All the SDRs were placed in the lab atleast 5-6 meters away from the primary user.

These sensor nodes collect the spectral data, normalize it and then transmit it to the FC for the detection. For soft data fusion, the data is quantized in the local sensor nodes before it is transmitted to FC due to the limited bandwidth of the overhead channel. The delays caused by different sensor nodes is ignored, as it would require extra computational complexity and it is out of the scope of this paper.

The USRP N210 transmits a DQPSK modulated signal with 4 samples per symbol with the alpha factor of the root raised

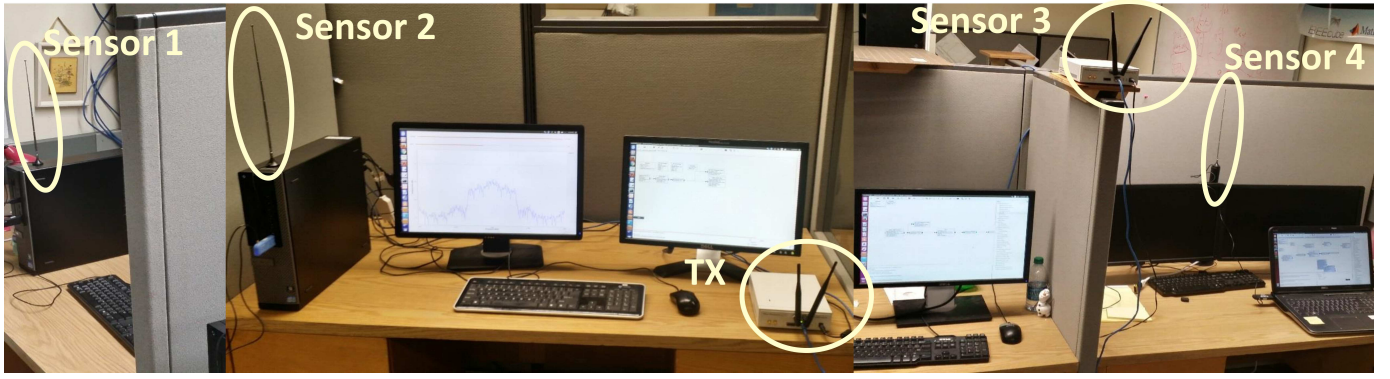


Figure 3: Experimental Test-Bed For Cooperative Sensing in Heterogeneous Network. Sensors 1, 2 and 4 are RTL-SDR units, sensor 3 is USRP N210 and TX is another USRP N210 unit which is used as a signal source for this work.

cosine filter set to 0.35. The transmitter gain and amplitude are varied to get different SNR values for each node.

The sensor nodes collect the data for the equivalent of 300,000 energy samples, and each measurement is conducted three times to eliminate any irregularities. The noise variance σ_n^2 for each SU is estimated by running each sensor node without any transmission at 450 MHz. The flow-graph is executed multiple times to get a better estimate of noise variance.

Once the data is received from all the sensor nodes, Probability of detection is calculated for different received SNR values for all the sensor nodes. To properly evaluate the performance of each of the cooperative spectrum sensing techniques, the average P_d is calculated for each scheme.

IV. MEASUREMENTS AND RESULTS

A. Transmitter Setup For CS Measurements

To evaluate the performance of the cooperative spectrum sensing, the USRP N210 is used as a transmitter where its gain and amplitude are varied. Figure 4 shows the flow-graph used for the transmitter.

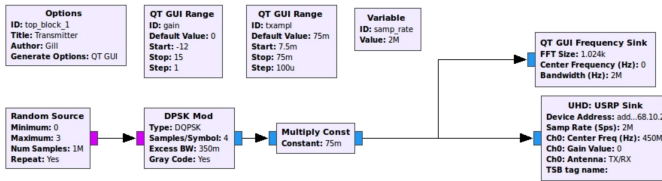


Figure 4: GNURadio Flowgraph For Transmitter Running on USRP N210.

All four sensor nodes have different sampling rates to truly model the heterogeneous environment. The USRP N210 which is also used as a 4th sensor node has a very low noise floor compared to the three other and hence can detect a signal with very low SNR. This is a challenging factor for data fusion when the nodes have different operating parameters and FC has to make optimal decisions by combining this varying data. And due to their spatial diversity the node closest to

the transmitter will have different SNR compared to the other nodes. All these factors impact the data combining at FC. The GNURadio flow-graph for the sensor nodes is shown in the Figure 5. The same flow-graph is used for all sensor nodes with different operating parameters. For USRP N210 node, we replaced the RTL-SDR source with UHD:USRP Source gnuradio block.

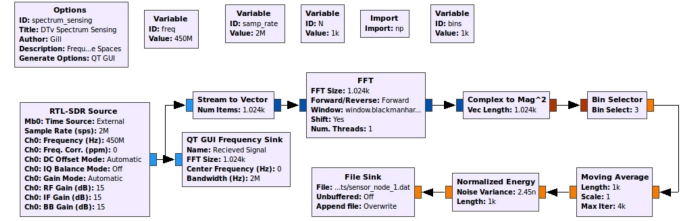


Figure 5: GNURadio Flowgraph For USRP and RTL-SDR sensor nodes.

The central frequency is kept at 450 MHz and the operating parameters of each sensor node is provided in the table. The values of the transmitter amplitude and gain are varied to get the different sets of SNR values which are used for computing P_d values for each node. The plots are generated in MATLAB by using the data files from gnuradio platform.

Table I: Operating Characteristics of Sensor Nodes

Nodes	F_s	Gain	FFT Size	Bin Size
RTL-SDR-1	1.1 Msps	10 dB	512	2.148 KHz
RTL-SDR-2	1.8 Msps	10 dB	512	3.515 KHz
RTL-SDR-3	2.4 Msps	10 dB	512	4.687 KHz
USRP N210	7.2 Msps	10 dB	512	14.062 KHz

The Figure 6 shows the $P_{d,avg}$ versus SNR_{avg} for all four sensor nodes with operating parameters mentioned in Table I. It can be seen that OR performs the best while AND performs the worst in a fading channel. The SNR_{avg} was computed by taking the mean of all the SNRs for the sensor nodes. The SNR was varied for each sensor node by varying the transmitter amplitude and gain in the gnuradio flowgraph.

The Figure 7 shows the ROC characteristics for the hard decision combining at two different SNR_{avg} for all three hard

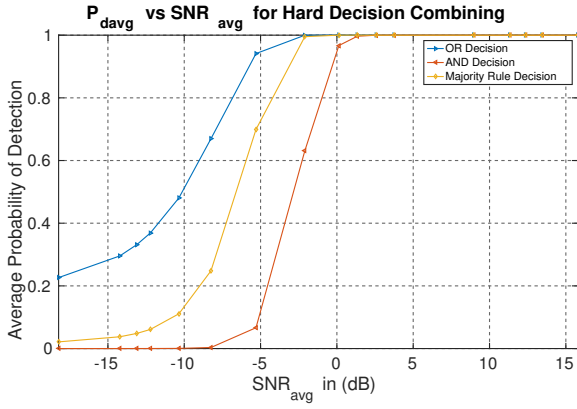


Figure 6: Probability of Detection versus SNR_{avg} For Hard Decision Combining.

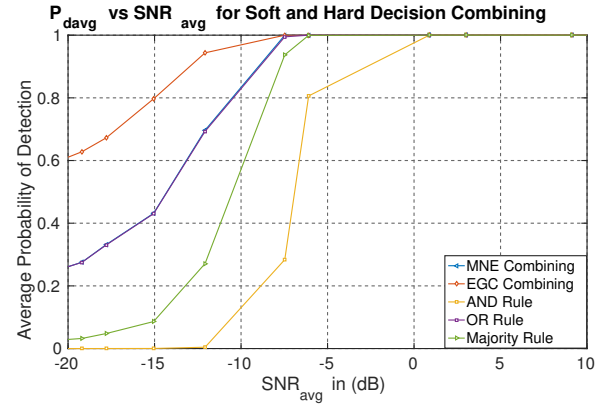


Figure 8: Probability of Detection versus SNR_{avg} For Soft and Hard Decision Combining.

decision combining schemes. The Figure 8 shows the P_{davg}

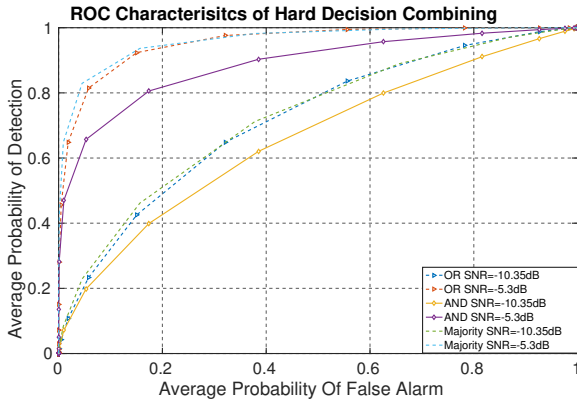


Figure 7: ROC Characteristics for Hard Decision Combining with Different SNRs.

versus SNR_{avg} for both soft data and hard data combining schemes. Furthermore, it is evident from the plot that soft decision combining performs better than hard decision in a real fading channel. Nevertheless, we also observe that if the SNR values are higher, then all the schemes converges to the same values.

V. CONCLUSION

In this paper, we conducted an experimental study for cooperative spectrum sensing using normalized energy detection for both soft and hard decision combining techniques. It was found that the soft fusion schemes works better than hard decision for real fading environment with low SNR values. For higher values, all schemes converged to the same decision which led us to conclude that hard fusion schemes pays better when the environment is less noisy due to their low complexity as compared to soft fusion. For future work, it is worth exploring an increase in the number of nodes and adding mobility for the testing the performance of heterogeneous networks in a time-variant channel.

REFERENCES

- [1] A.Wyglinski, D.Pu "Digital Communication Systems Engineering with Software-Defined Radio"
- [2] I.F.Akyildiz, W.Y.Lee, M.C.Vuran, and S.Mohanty, "NeXt Generation/Dynamic Spectrum Access/Cognitive Radio Wireless Networks: A Survey, Computer Networks, Vol.50, No.13, Sept 2006, pp.2127-2159
- [3] Q.Zhao and B.M.Sadler, "A Survey of Dynamic Spectrum Access, IEEE Signal Processing, Vol.24, No. 3, May 2007, pp.7989.
- [4] Harry Urkowitz, "Energy Detection of Unknown Deterministic Signals", Proceedings Of The IEEE, Vol.55, No.4, April 1967
- [5] D.Cabric, S.M.Mishra, and R.W.Brodersen, "Implementation issues in spectrum sensing for cognitive radios, Proc.38th Asilomar Conf. Signals Systems, Computers, pp.772-776, 2004.
- [6] R.Tandra and A.Sahai, "Fundamental limits on detection in low SNR under noise uncertainty", Proc. of the Wireless Communications Symposium on Signal Processing 2005, June 2005.
- [7] S.M.Mishra, A.Sahai, and R.W.Brodersen, "Cooperative sensing among cognitive radios", in Proc. IEEE Int. Conf. Commun., Jun. 2006, pp. 1658-1663.
- [8] A. Ghasemi and E.S. Sousa, "Impact of User Collaboration on the Performance of Sensing-Based Opportunistic Spectrum Access", Proc. IEEE VTC Fall, Sept. 2006, pp. 1-6.
- [9] J. Ma, G. Zhao, and Y. Li, "Soft combination and detection for cooperative spectrum sensing in cognitive radio networks", IEEE Trans. Wireless Commun., vol. 7, no. 11, pp. 4502-4507, Nov. 2008.
- [10] B.Shen, T.Cui, K.Kwak, C.Zhao, and Z.Zhou, "An optimal soft fusion scheme for cooperative spectrum sensing in cognitive radio network", in Proc. IEEE Wireless Commun. Netw. Conf., Apr. 2009, pp.15.
- [11] H.Rif-Pous, M.J.Blasco, and C.Garrigues, "Review of Robust Cooperative Spectrum Sensing Techniques for Cognitive Radio Networks, Springer Science+Business Media, LLC, pp. 175-198, Nov 2011.
- [12] Y.H.Zeng, Y.C.Liang, S.K.Zheng, and E.C.Y.Peh, "Optimal cooperative sensing and its robustness to decoding errors", in Proc. IEEE Int. Conf. Commun., Jun. 2011, pp.15.
- [13] Guosheng Yang and et.al. "Cooperative Spectrum Sensing in Heterogeneous Cognitive Radio Networks Based on Normalized Energy Detection", IEEE Transactions on Vehicular Technology, Vol.65, No.3, March 2016.
- [14] Y. Zeng and Y. chang Liang, "Eigenvalue-based spectrum sensing algorithms for cognitive radio, Communications, IEEE Transactions on, vol.57, no.6, pp. 1784-1793, June 2009.
- [15] S.Nallagonda, A.Chandra, S.D.Roy and S.Kundu, "Performance of Cooperative Spectrum Sensing in Hoyt Fading Channel under Hard Decision Fusion Rules", IEEE Int. Conf on Comp. and Dev. for Commun., 2012.
- [16] GNU Radio, "http://gnuradio.org/"
- [17] RTL-SDR, "http://www.rtl-sdr.com/"
- [18] USRP, "https://www.ettus.com/product/category/USRP-Embedded-Series/"