Towards A Large-Scale Cognitive Radio Network Testbed: Spectrum Sensing, System Architecture, and Distributed Sensing

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Abstract— **This paper presents a comprehensive review of the cognitive radio network (CRN) testbed built at TTU. Our goals are (1) to use our CRN testbed as a data acquisition tool; (2) to use random matrix theory to model the collect data and apply the new models in the context of quantum information. We attempt to achieve a balance between experimental work and theoretical work. We first spell out the vision and concrete tasks for our research in the near future. Second, we review our latest results in an more accessible manner than the conference version.**

Index Terms— **Cognitive Radio Network, Spectrum Sensing, Distributed Sensing**

I. Introduction

"Big Data" [1] refers to datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze. Big Data is envisioned as the next frontier for innovation, competition, and productivity. This paper is motivated to spell out the vision and some recent results in the context of next generation cognitive radio network (CRN) [2].

Three analytical tools are central to the CRN: (1) large random matrices; (2) convex optimization; (3) game theory. The unified view is the so-called "Big Data"—high-dimensional data processing. Due to the unique nature of cognitive radio, we have an unparalleled challenge—having too much data at our disposal. In the today's digital age, making sense of the data in real-time is central to not only the major players like Facebook, Google and Amazon, but also our telecommunication vendors. For the solutions to the Big Data problem to become successful, however, there are still many hurdles. For one thing, the current tools are inadequate. Our research is motivated for this need. The testbed is used as a tool for data collection. On the other hand, an analytical tool of using large random matrices is proposed to analyze the big data collected using such a network testbed. To our best knowledge, very little (probably none) work has been done using this hybrid approach.

Compared with the previous systems, the CRN contains radios that are highly programmable; their modulation waveforms are changing rapidly and their frequencies are agile; their radio frequency (RF) front-ends are wideband (up to several GHz). In addition to the highly programmable nature of their physical layer functions, a CRN radio senses the spectrum at a unprecedentedly low signal-to-noise-ratio (SNR) (e.g. -21 dB required by the FCC). To support this fundamental spectrum sensing function, the system allocates computing resources with the ultimate goal of real-time operations. From another view of point, this radio is a powerful sensor with almost unlimited computing and networking capabilities. Through the combination of these two views, communications and sensing are merged into one function that transmits, receives, and processes programmable modulated waveforms. Real-time distributed computing is embedded in these two functions.

It is believed that we lack a coherent network theory that is valid for numerous applications. Rather, the state-of-the-art network is designed for special needs, when a new need arises, the network must be redesigned. Costs are wasteful due to the lack of a network theory. The cognitive radio poses unique challenges in networking. Another motivation for this paper is to build a testbed that will collect more empirical data. Only when sufficient empirical experience is accumulated, good network models can be established and thus the exact network science.

Wireless technology is proliferating rapidly; the vision of pervasive wireless computing, communication, sensing and control offers the promise of many societal and individual benefits. Cognitive radios, through dynamic spectrum access, offer the promise of being a disruptive technology. Cognitive radios are fully programmable

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wireless devices that can (1) sense their environment and (2) dynamically adapt their transmission waveform, channel access method, spectrum use and networking protocols. It is anticipated that cognitive radio technology will become a general-purpose programmable radio that will serve as a universal platform for wireless system development, as microprocessors have served a similar role for computation. There is, however, a big gap between having a flexible cognitive radio, effectively a building block, and the large-scale deployment of cognitive radio networks that dynamically optimize spectrum use. Testbeds are built to partly fill this gap.

One goal is aimed towards a large scale cognitive radio network; in particular, we need to study novel cognitive algorithms using quantum information and machine learning techniques, to integrate FPGA, CPU and graphics processing unit (GPU) technology into state-of-the-art radio platforms, and to deploy these networks as testbeds in real-world university environment. Our applications range from communications to radar/sensing and Smart Grid technologies. Cognitive radio networking/Sensing for unmanned aerial vehicles (UAVs) is also very interesting and challenging due to its high mobility. Synchronization is critical. UAVs can be replaced with robots.

One task will pursue a new initiative of CRN as sensors and explore the vision of a dual-use sensing/communication system based on CRN. The motivation is to push the convergence of sensing and communication systems into a unified cognitive networking system. CRN is a cyber-physical system with the integrated capabilities of control, communications, and computing.

Due to the embedded function of cooperative spectrum sensing in CRN, rich information about the radio environment may be obtained. This information *unique to CRN* can be exploited to detect, indicate, recognize, or track the target or intruder in the covered area of a CRN. The data for this kind of information system are intrinsically high-dimensional and random. Hence, we can employ quantum detection, quantum state estimation, and quantum information theory in our new initiative using CRN as sensors. In this way, the sensing capability of CRN can be explored together with great improvement in performance.

Roughly speaking, a cognitive radio has two fundamental functions [2]: (1) spectrum sensing; (2) radio resource management. In-networking (distributed) computing is required for supporting these two functions. The central problem is so-called Big Data [1]—-in analogy with big data sets encountered in Facebook, Amazon, and Netflix etc. Spectrum sensing requires huge data vectors are recorded. How do we make sense of these data? First, a novel paradigm of quantum information exploiting long data vectors is proposed for spectrum sensing. The performance of quantum detection in the example below has achieved 8 dB better that of the classical GLRT! This new capabilities are critical to anti-jamming communications. Second, sample covariance matrices are used as the starting point; they are modeled as large random matrices. Random matrix theory [2], [3] are chosen as the mathematical tool.

II. Ethernet Connection between Hardware Platform and MATLAB

Ethernet is widely used in telecommunication computing platforms, especially in multi-blades platforms that require carrier grade computing capacity.

MATLAB supports transmission control protocol (TCP) / internet protocol (IP) for data exchange, with built-in toolbox or third-party software package. Instrument Control Toolbox, provided by Mathworks Inc., is one of the widely used toolboxes enabling MATLAB and Simulink to support TCP/IP communications. Another similar toolbox called TCP/UDP/IP toolbox [4] is in light weight and still reliable. It provides Socket APIs for TCP or user datagram protocol (UDP) communications. Although this toolbox is developed by a third party, it is easy to be integrated into MATLAB.

We use WARP to acquire radio data and implement functional modules of wireless physical layer, like modulation and demodulation. WARP is a full-functional hardware platform in which the Ethernet is used for communicating with MATLAB on personal computer (PC) server. On the WARP Board a 10/100/1000 Mbits Ethernet device is provided [5]. The system on chip (SOC) is implemented in the on-board Virtex-4 FPGA where Xilinx Tri-Mode EMAC Ethernet IP core can be integrated to support Gigabit Ethernet [5]. TCP/IP protocols can be supported by integrating a third-party TCP/IP stack or a self-developed protocol stack, with optimal design on data memory/first-in-first-out (FIFO).

We propose a simple working model to implement the computing transaction base on the architecture described above:

1) Static IP addresses are configured on both WARP hardware platform and PC server. Meanwhile, a static route entry needs to be set at PC server.
2) In MATLAB, a TCP or UDP socket is created by the TCP/UDP/IP toolbox [4], to keep listening the input TCP/UDP message at a specified port. UDP is used in our experiment due to less time cost than that of TCP.
3) The computing request is initiated at WARP and sent to MATLAB with user data via UDP stack over the Ethernet interface. A randomly generated identification (ID) is used to label this computing transaction.
4) Once MATLAB receives the UDP data sent from WARP over the specified port, it extracts the data from the UDP packet and sends out a response, tagged with the transaction ID, to WARP over the specified UDP port.
5) The time cost is measured at WARP once it receives the response with expected transaction ID.

Our measurement is focused on the time delay on data exchange. In MATLAB, no actual processing algorithm

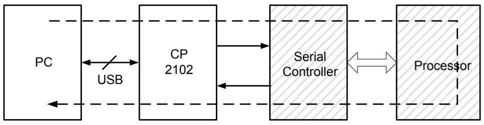


Figure 1. Schematic of the evaluation system.

is performed. The test results show that 5 ms is the cost to transfer one full-length UDP packet of 1480 bytes to MATLAB and get the response. With increasing number of user data packets, the time cost increases approximately linearly, e.g., 6 UDP packets cost about 28 ms. The throughput of the data exchange is around 2 Mbps. There is still much space to improve the performance, as our current TCP/IP implementation based on WARP is not optimal. For example, current Ethernet IP core in the Virtex-4 SOC is designed to work in polling mode which has worse performance than interrupt mode.

The serial port connection between FPGA and MATLAB is also explored as the other option to integrate the off-board computing engine [6]. Fig 1 shows the schematic of the implementation. Instead of the basic RS-232 serial communication, a USB-to-universal-asynchronous-receiver/transmitter (UART) is used to support higher data rate up to 912600 bps. Although this data rate is acceptable in many applications, this kind of connection method is better used when Ethernet is not available. Ethernet is an universal communication interface in most of the embedded system, with better reconfigurability and competitive performance.

The integration of the off-board computing with standalone on-board processing is also pervasive in typical Software Defined Radio (SDR), like the USRP/GNURadio [7]. In the SDR system, the front-end only performs the RF functions and some fixed functions like, ADC, DAC, and up-conversion/down-conversion, etc., while most of the base-band communications physical layer is running over the software on the general purpose processor [8], [9]. This kind of architecture provides better flexibility to introduce configurable physical layer and data link layer. And the complex and novel application algorithms are easier to be integrated [10]. However, compared with the architecture of WARP + PC, the normal SDR system needs to implement both the time critical communication tasks and the additional data processing algorithms on the same general purpose processor (GPP). The additional computing and timing overhead in the SDR system needs to be considered in selecting the network node platform corresponding to different network applications.

III. Cognitive Radio Network as Sensors: Experiments and Lessons

Our research on the distributed sensing is now exploiting the evolving large scale cognitive radio network testbed. The concept of the cognitive radio network as sensor network naturally derives from the spectrum sensing functionality of the cognitive radio network. The convergence of the distributed sensing with the cognitive engine enables the adaptive waveform design, intelligent processing of sensing information, etc. The referenced system interface and architecture are well described in IEEE 1900.6 [2], [11] as Fig. 2.

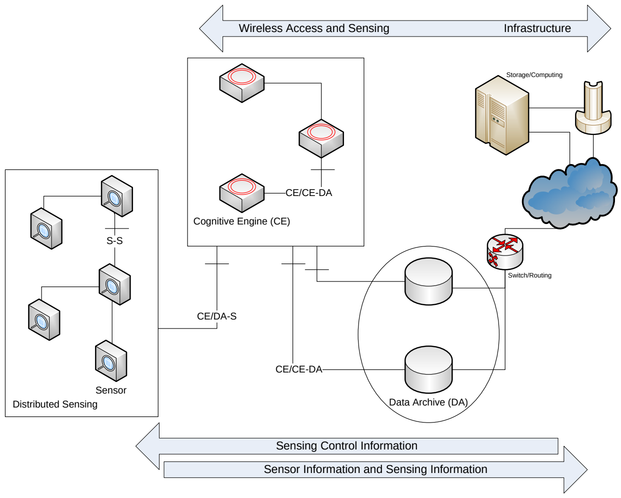


Figure 2. Sample topology of an IEEE 1900.6 distributed RF sensing system.

A series of experiments have been performed with the motivation of cognitive radio network as sensors [12]–[14]. This section reviews the experimental results and the corresponding lessons, to disclose the challenges and directions towards the large scale cognitive radio network.

Distributed cognitive sensing has materialized by intrusion detection using machine learning, joint spectrum sensing and localization [15], distributed aspect synthetic aperture radar, wireless tomography [16]–[18], closed-loop wide-band cognitive sensing [6], mobile crowdsensing [19], and so on. The following experiments are really initial results to demonstrate the motivated applications.

1) Through Tree Target Detection: As the effort towards distributed cognitive sensing, the through tree target detection experiment with single transmitter and receiver is performed. MATLAB is used as waveform design tool. WARP platform and a digital phosphor oscilloscope (DPO) are used as signal transmitter and receiver respectively. The experiment architecture is shown in Fig. 3. Multi-frequency signal is used to sound the target.

When there is no target, the corresponding power spectrum density (PSD) of the received signal is displayed at DPO as Fig. 4 (a). If there is a target behind tree, the corresponding PSD at the receiver is shown in Fig. 4 (b). The amplitude perturbation caused by the presence of target can be easily identified from the comparison between Fig. 4 (a) and Fig. 4 (b). Although the experiment is just composed of the single transmitter and receiver, it still unveils the potential of the feasibility for the localization functionality of the sensing network over cognitive radio network.

2) Intrusion Detection by Machine Learning: Passive target intrusion detection is a very important application in distributed cognitive sensing. In the complex radio

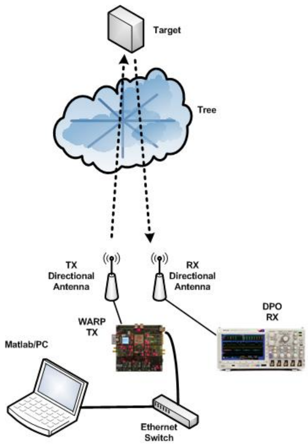
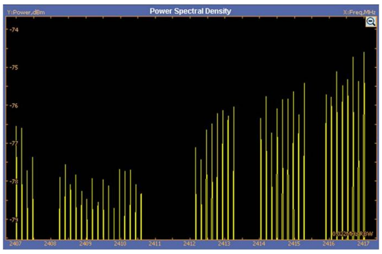
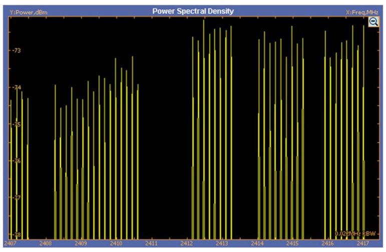


Figure 3. Experiment architecture for through tree target detection. [12]



(a) Power spectrum density of the received multi-frequency signal, without target



(b) Power spectrum density of the received multi-frequency signal, with target

Figure 4. Power spectrum density of the received multi-frequency signal. [12]

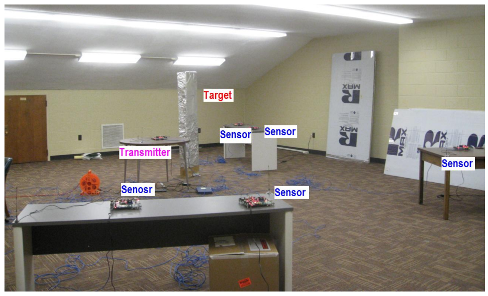


Figure 5. The experiment scenario for passive target intrusion detection using machine learning. [13]

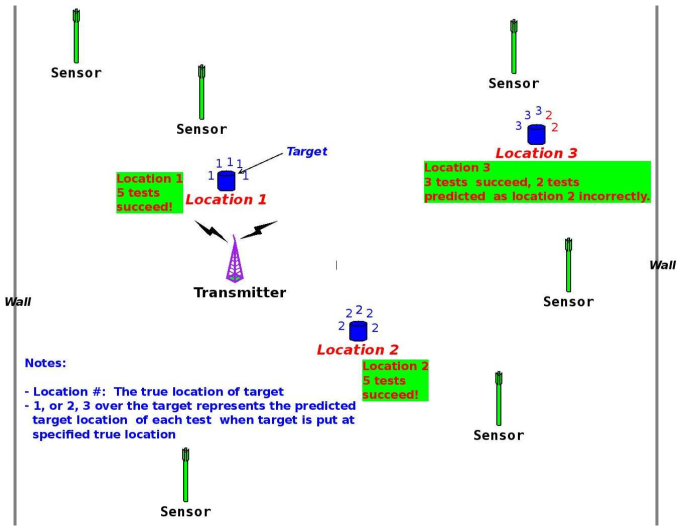


Figure 6. The preliminary results for passive target intrusion detection using machine learning. [13]

environment, for example indoor office environment or ground clutter, it is hard to detect and locate the target by simple radio propagation theory due to the multi-path phenomena. Hence, we explore machine learning algorithms, like multi-class support vector machine (SVM), for passive target intrusion detection and localization.

A database with mass data is built. These data correspond to the information about the radio environment when the potential targets are in different locations. These data are used to train the classifier. Then, if some target intrudes into the surveillance area, the recorded information about the radio environment is sent to the pre-trained classifier. In this way, the intrusion can be detected and the location of the target can be found. Thus, the perturbation is implicitly used by multi-class classification.

The experiment scenario is shown in Fig. 5. One WARP platform is used as the radio transmitter to sound the environment. The other six WARP platforms are exploited as the radio receivers to record signal about radio environment. NC-OFDM is applied. Multi-class SVM using one against all strategy and Gaussian kernel is exploited as the classifier. The preliminary localization results are shown in Fig. 6. These results show the potential and prospect of intrusion detection using machine learning.

Some potential improvements are expected in future work for this machine learning based localization. Firstly, more sensors are to be involved in to improve the accuracy. Secondly, intensive computing on the collected big data requires stronger computing engine with minor delay to achieve real time localization. In addition, the hardware/software platform should be flexible such that the advanced algorithms such as machine learning and convex optimization can be integrated seamlessly and quickly.

3) Variance-based Moving Target Tracking: We have demonstrated the localization and tracking of a moving target by monitoring the variance of received signal strength (RSS) measurements taken by a network of USRP platforms. It is assumed that the signal of opportunity is transmitted from one USRP platform. All the other USRP platforms serve as sensors. Because the moving target causes the attenuation and perturbation of signals between the transmitter and receivers. Thus, the variance of the signal strength can be used to indicate the presence of the target. The location of the target is

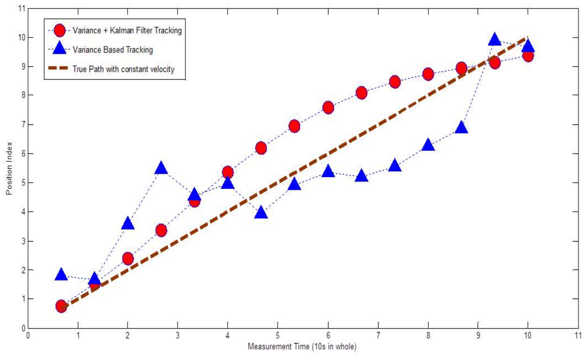


Figure 7. The preliminary results for variance-based moving target tracking. [14]

based on the location of each sensor and the variance of the corresponding received RSS. The tracking results are shown in Fig. 7.

The similar variance-based motion tracking method has been proposed in [20], [21], implemented on narrow-band system. Our research goal is to build the a dual-use sensing/communication network with dynamic spectrum access [14]. Also, our experiment achieves the real time tracking capability by exploiting the SDR platform with more flexibility. The algorithm development is also faster due to the well designed software architecture of GNU-Radio. However, with sensing nodes increasing, there are still some bottlenecks caused by the big data exchanging and full occupation of the computing resource. The system performance and availability are impacted by these bottlenecks.

IV. Testbed for Large Scale Cognitive Radio Network: Challenges and Enabling Technologies

Our past experiments demonstrate the application of CRN for the sensor networks. The results of these experiment are encouraging. However, The results also disclose the imperative demands on the large scale cognitive radio network. More attractive services can be introduced into the large scale CRN. Also the performance of the services can be improved significantly by exploiting the big data collected from this large scale cognitive radio network.

Taking the the sensing service as example, the capacity and performance of a single sensor heavily depend on the hardware configuration of the sensor platform, such as radio frequency bandwidth, CPU processing capability, memory size, FPGA capability, etc. But a kind of distributed sensing based on large scale cognitive radio network can significantly mitigate the weakness of a single sensor or small scale sensor network. The deployed large scale cognitive radio network expands the sensing capability of the single sensor in both space and radio frequency domains, especially when the cognitive radio technology is enabled within the network. Besides, the network usage can relax the hardware requirement for each sensor. Thus we can configure the network with flexible divergence regarding different sensing requirements.

Inspite of the benefits from the large scale cognitive radio network, many challenges emerge when bringing such network to a feasible fact. In the rest of this section, the following aspects are discussed regarding the challenges and the corresponding enabling technologies in vision: network architecture, communications and waveform diversity, computing and control, finally, the SDR based implementation architecture.

A. Network Architecture

Wireless network is usually established in two modes: ad-hoc or infrastructure based. Similarly, the cognitive radio network can also be considered to be deployed in either of the two ways [22]. In the infrastructure based CRN, the centralized node acts as the base station, which collects spectrum sensing information from the CR user (including iteself) and performs resource allocation, etc. In the ad hoc CRN, all the CR users are with the same cognitive radio capabilities such as the decision making [22].

However, it is more feasible to build the large scale cognitive radio network over a hybrid, heterogeneous and hierarchical architecture, as shown in Fig. 8. Although some applications of CRN, like the mobile distributed sensing, are applicable to adopt ad hoc network configuration. But, the ad hoc network capacity is tightly related with the network diameter and the node distribution [23], [24]. Also, compared with the traditional ad hoc wireless network, the ad hoc CRN faces more challenges in the radio resource allocation, topology control, relaying and the primary user protection, etc [22]. Thus, the scalability would be a challenge when extending the size of the CRN significantly while keeping the performance of the network. On the other hand, the ad hoc network configuration usually requires the nodes to be homogeneous. As we have different wireless platforms with distinct capabilities, it is a better way to converge these platforms in heterogeneous manner for different applications.

As in Fig. 8, according to our achieved testbed experience, we propose the large scale cognitive radio network consisting of software defined radio (SDR) platforms, like universal software radio peripheral (USRP), wireless open access research platform (WARP), etc., and also our latest wideband cognitive sensing platforms as well as multiple input multiple output (MIMO) wideband communication systems. WARP platform has powerful FPGA to support real-time applications and real time signal processing.

This hierarchical network is composed of clusters. The homogeneous nodes developed on similar platform form the cluster as the subnet which could be configured in ad hoc mode or infrastructure based mode. The size of each cluster could be not so large. The nodes distribution within the cluster could be limited and not very dense. However, the size of the whole network can be extended easily and significantly by connecting all the clusters to wired infrastructure. A cluster head is assigned for each

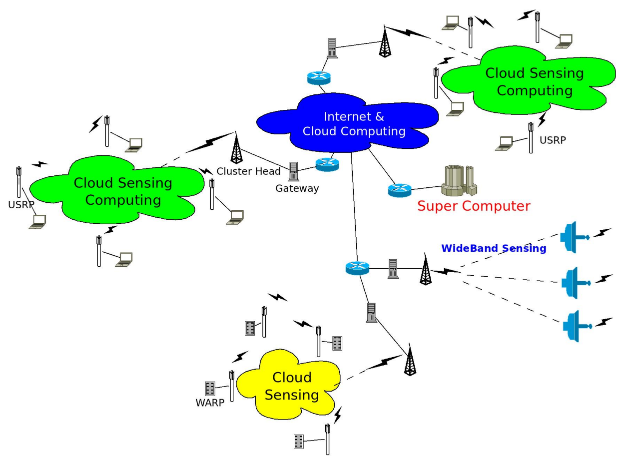


Figure 8. Overall architecture of the testbed for large scale cogntive radio network.

cluster. This cluster head is developed on a platform with higher capability than that of nodes within the cluster. It has three functions but not limited to: 1) Exchanging data/control information between clusters, 2) Radio resource management and cluster control, 3) Performing the collective task in the distributed computing within the cluster.

In addition, the capabilities of all the clusters can be expanded through exploiting the cloud computing. These additional computing resources can be provided by Internet or some other super computers connected to our hierarchical network.

B. Waveform diversity for communications and sensing

The challenges of the communication system within the proposed hierarchical large scale cognitive radio network mainly lie in the wireless clusters. Unlike the licensed primary user, the cognitive user is featured with dynamic spectrum access. Also, the cognitive radio node within our network is expected to perform both wireless communication and sensing tasks. Thus, the waveform diversity combined with the OFDM technology is the solid base of the physical layer for the large scale cognitive radio network.

Waveform diversity is a key research issue in the current wireless communication system, the radar system, and the sensing or image system. Waveform should be designed or optimized according to the different requirements or objectives of system performance and should be adapted or diversified dynamically to the operating environment in order to achieve a performance gain [25]. For example, the waveform should be designed to carry more information to the receiver in terms of capacity. For navigation and geolocation, the ultra short waveform should be used to increase the ranging resolution. For multi-target identification, the waveform should be designed so that the returns of radar signals can bring more information about targets back. Waveform diversity will also play an important role in the dual-use communication/sensing system, e.g., the large scale cognitive radio network. OFDM waveform will be the competent candidate.

OFDM is the core technology in wideband communication. The OFDM waveform has also been used in the radar society [26]–[29]. The advantages of using OFDM for radar tasks have also been summarized in [30]. Digital generation, inexpensive implementation, pulse-to-pulse shape variation, interference mitigation, noise-like waveform for low probability of intercept/detection (LPI/LPD), and so on are the benefits of the OFDM waveform [30]. Similarly, the research about the joint OFDM-based radar and communication system has been carried about in Karlsruhe Institute of Technology, Germany [31]–[35]. Range estimation, angle estimation, and Doppler estimation are extensively studied.

For the OFDM-based dual use communication/sensing system, there are three basic strategies to design waveform. The first strategy is to embed radar sounding signal or sensing task into communication waveform. When the communication is executed, the sensing task will also be performed. The second strategy is to put the communication payload data into the radar sounding signal. The small amount of data can be exchanged among radar stations or sensor nodes. The idea of the third strategy is borrowed from OFDMA, which means different tones of OFDM waveform are assigned to different communication and radar tasks. In this way, joint and multi-objective optimizations are needed with consideration of energy consumption, spectral shaping, performance requirement for each task, inter-task interference suppression, and so on.

C. Computing and control

In our experiments of machine learning based localization, and the variance based moving target tracking, it is expected that the performance of the experiments can be improved with extending the sensing network to large scale cognitive network. However, involving more sensing nodes always brings the overhead of both the radio resource and computing resource. In the real time tracking experiment, the whole system even stops working when too many sensors are introduced into the sensing network. The congestion of the collected data between the centralized computer and the sensor nodes is the bottleneck. In such situation, the distributed and collaborative computing within nodes of the wireless cluster is necessary. Instead of just transferring all the collected data to the centralized computer server, the computing tasks would be well designed and balanced among the networks nodes as possible as it can. Only those intermediate resulting data of the computing at the network nodes is transfered to the centralized server. The overhead from both the network traffic and the computing delay is decreased.

The design challenges for this kind of wireless in-network computing are well discussed in [36]. Different with traditional wired distributed computing, the research

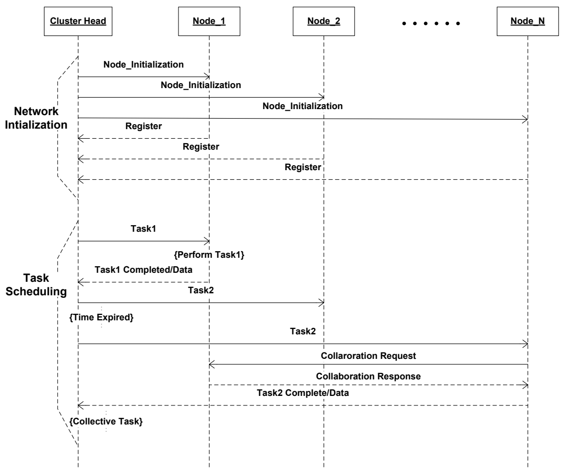


Figure 9. Example of task scheduling within clusters.

and design challenges for wireless distributed computing are from these aspects:

1) Communication network design: Due to the channel uncertainty, the efficient and stable MAC layer is required. The computing data needs to be exchanged among the network nodes robustly. Proper routing, relaying, buffering can also be considered to improve the reliability of the message passing.

2) Synchronization: For certain distributed computing algorithm, the synchronization among tasks on different nodes are necessary. This synchronization is established at the process/event level [37]. On the other hand, the clock level synchronization is required when the timestamps of the network data are needed. For the sensing network, the collected data is similar to the snapshot of the network state. Thus the data fusion of all the nodes requires the fairly accurate time synchronization. Usually, the global reference clock and the GPS receiver can be merged into the network nodes.

3) Network Control: The network control, for purpose of optimally cooperating the computing resources, includes the topology control, resource management, tasks scheduling, and working load balance. The wireless distributed computing over the cognitive radio network could suffer from the dynamic spectrum access. The topology stability and the nodes availability could be changed more frequently than the traditional wireless network. We propose to adopt the centralized network control than distributed manner, in the current research stage, for easier control with predicted behavior. Fig 9 shows a simple example in which the cluster head performs the centralized control of computing tasks assigned to the network nodes. The task scheduling is based on the event/process synchronization.

For the large scale cognitive radio network and cognitive radio network as sensors, the large scale optimization can be explored to address the related issues, e.g., high-fidelity wireless communications, various sensing tasks, resource management, load balancing, task distribution,

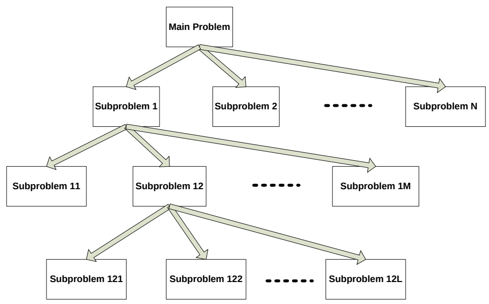


Figure 10. Multi-level Decomposition [40].

and so on. Optimization stems from human instinct. Through optimization, we can achieve the best performance we expect. However, the scalability is one of challenges in optimization theory, which means it is hard to handle the optimization problem with thousands of or millions of variables. Grid and cluster computing has been used to solve the large scale optimization problems [38]. The parallel implementations of various solvers to optimization problems on grids and clusters have been presented [38]. Thanks to the in-network computing capability and the strong computational power of the whole network, it is straightforward to deal with the large scale optimization problem in a distributed fashion using all the available resources provided by cognitive radio network.

Layering as optimization decomposition [39] was first proposed to solve the network design issue. However, it is one of the general and analytic methodologies to solve the large scale optimization problem. A large scale problem can be divided into many sub-problems that can be distributed to multiple tasks. The decomposition of the large scale optimization problem can be based on Lagrange duality. Multi-level decomposition shown in Fig 10 can be supported [40]. Alternating direction method of multipliers (ADMM) is another way to deal with large-scale statistics, machine learning, and optimization problems [41]. It takes the form of a decomposition-coordination procedure, in which the solutions to small local sub-problems are coordinated to find a solution to a large original problem [41]. An ADMM algorithm for a class of total variation regularized estimation problems has recently been studied in [42]. MapReduce is the third way to support distributed computing for large data sets on clusters of computers. MapReduce is a patented software framework introduced by Google in 2004 [43] [44]. "Map" step performs the division of input and "Reduce" step combines the results to get the output. MapReduce can easily make the traditional algorithms scalable.

D. SDR based implementation architecture

The large scale cognitive radio network requires the network node to be intelligent enough with computing, communication, control, and sensing capability. Meanwhile, the development on the platform should be fairly easy to meet the requirement of fast prototyping of the advanced algorithms, quick network configuration.

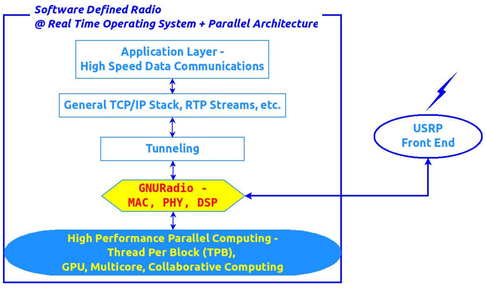


Figure 11. Software architecture over GNURadio working with USRP.

For USRP/GNURadio, the well defined SDR architecture is very helpful to combine the upper layer software including TCP/IP/MAC and the physical layer, as shown in Fig. 11. The tunneling virtual device is used to bridge the GNURadio physical layer with the existing upper layer stack embedded in the Operation System (OS) like Linux [7], [45]. Thus the GNURadio based physical layer can be decoupled with the application layer. The services and control can be added into such SDR based platform flexibly. It is feasible to implement the separated data plane and control plane on a single SDR platform [46], [47].

The real-time configurable OFDM waveform can be implemented under such flexible SDR architecture to meet the dynamic spectrum access requirement for cognitive radio network. On the other hand, the combination of the SDR with the parallel computing architecture will also bring big benefit for the "big data". There are two flavors of parallel computing to be integrated within our testbed of large scale cognitive radio network. At each USRP/GNURadio node, the thread-per-block signal flow will naturally work in a parallel manner when the software is running over multi-core architecture. Also, the general-purpose computing on graphics processing units (GPGPU) will be utilized for high speed signal processing algorithms [48].

As the signal processing application of USRP/GNURadio can be developed using general programming language, the rich software libraries of the convex optimization and machine learning can be easily integrated [46], [49], [50].

The software architecture for rapid prototyping of the applications over SDR is also a challenging but helpful research area from the computer engineering perspective. Some existing cognitive radio network testbeds [51], [52] provide the middle-ware [53]–[55] based software framework for the testbed users to develop the applications easily.

E. UAV - extend to dynamic large scale cognitive radio network

The static cognitive radio network can be extended to a dynamic cognitive radio network as shown in Fig 12. UAV can be incorporated into cognitive radio network. The key point of the dynamic cognitive radio network is that UAV has the mobile capability. UAV can at least search for the available spectrum in different locations intelligently. The movement of UAVs can change the existing network topology. However, this change is still under some level of control. The dynamic cognitive radio network can undoubtedly achieve autonomous network resiliency in the crowded radio environment. If the relay node is out of the communication range or there is no available spectrum for the relay node to use, UAV can intelligently change its location to maintain the connectivity of wireless communication. In order to shoot for this kind of smart and dynamic network, the movement control, the movement overhead, the movement benefit, and the movement restriction should be mathematically incorporated into the network design. Performance analysis of 802.11a wireless links from UAV to ground nodes has been presented in [56]. Wireless relay communications with UAV has been discussed in [57]. UAV relay network to support WSN connectivity has been reported in [58].

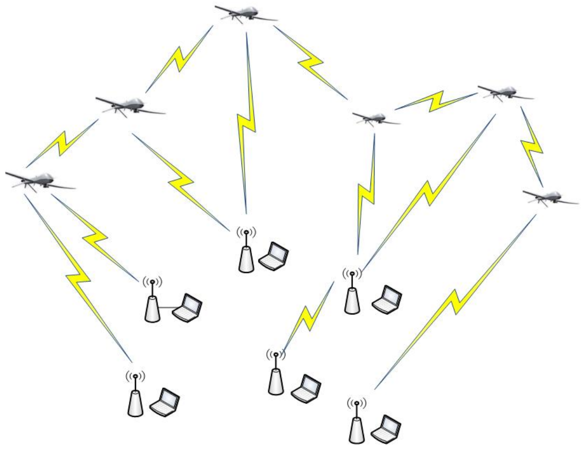


Figure 12. Dynamic cognitive radio network using UAVs

Meanwhile, the capability of cognitive radio network as sensors can also be greatly enhanced. The development of UAV system has gained a lot of attentions throughout the world. The importance and significance of this kind of system in aerial activities have grown continuously [59]. Also, UAV systems are greatly preferred in operations where the tasks are dangerous, tedious, and impossible for human pilots [59]. For example, radio source localization by a cooperating UAV team has been presented in [60]. Source localization is formulated as a stochastic distributed estimation problem. UAV is exploited to improve the observability in terms of the Fisher information matrix of the corresponding estimation problem [60]. An automatic flight control algorithm that exploits network mobility and allows an autonomous UAV team to react cooperatively is developed to determine the location of a radio emitter [60]. Besides, UAV can also serve as mobile data sink. For example, UAV is used to collect data from low-power wireless sensors [61].

F. Intrusion and Anomaly Detection in CR-based Smart Grid Network:

The salient features of CR, namely, frequency agility, transmission speed, and range, are ideal for application to the Smart Grid [62], [63]. In this regard, a CRN can serve as a robust and efficient communications infrastructure that can address both the current and future energy management needs of the Smart Grid. The CRN can be deployed as a large scale wireless regional area network (WRAN) in a Smart Grid. In this manner, a CRN testbed for the Smart Grid would serve as an ideal platform to not only address various issues related to the Smart Grid, such as security, information flow and power flow management, etc., but also reveal more practical problems for further research. From both the power and information flow standpoint, it is imperative to detect any abnormalities in the received data, before processing. These abnormalities could result from intentional intrusion by unauthorized personnel, smart meter miscalibration or failure, in addition to communication errors due to noise, network congestion, or outages. Recently, anomaly detection algorithms for astronomical data was presented in [64], [65]. These algorithms can be readily applied to the CRN based Smart Grid for intrusion and anomaly detection.

V. Modeling of the CRN with Large Random Matrices

At this point, it is assumed that a CRN testbed is at our disposal. The nature questions arise. How do we configure our network tested to collect data? What information can we infer from the collected data? Very little work is known in the literature to answer the two basic questions.

With data acquisition and storage now easy, today's statisticians often encounter datasets for which the sample size, n, and the number of variables, p, are both large [66]: in the hundreds, thousands, millions and even billions in situations such as web search problems. This phenomenon is so-called "big data". The analysis of these datasets using classical methods of multivariate statistical analysis requires some care. In the context of wireless communications, network becomes more and more dense. Spectrum sensing in cognitive radio collects much bigger datasets than the traditional MIMO-OFDM, and CDMA systems.

Assume we have a number of USRP2 nodes $p = 100$; the sample size of n can be collected. The maximum sampling rate is 25 Mega samples per second (16bit length for each sample). The collected data can be viewed as an ensemble of large random matrices. When only noise is present, the output of the receiver for the $i-$th sample of the $j-$ node is X_{ij} where X_{ij} i.i.d. standard normal variables of $n \times p$ matrix $\mathbf{X}$ defined as

$$\mathbf{X} = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1p} \\ X_{21} & X_{22} & \cdots & X_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ X_{n1} & X_{n2} & \cdots & X_{np} \end{bmatrix}_{n\times p}. \quad (1)$$

The sample covariance matrix is defined as

$$\mathbf{S}_n = \left(\frac{1}{n} \sum_{k=1}^{n} X_{ik} X_{jk} \right)_{i,j=1}^{p} = \frac{1}{n} \mathbf{X}\mathbf{X}^H, \quad (2)$$

where n vector samples of a $p-$dimensional zero-mean random vector with population matrix I and H standards for conjugate transpose (Hermitian) of a matrix.

A. Basic connection and paradigm shift

The classical limit theorem are no longer suitable for dealing with large dimensional data analysis. The classical methods make implicit assumption that p is fixed and n growing infinitely large,

$$p \ \text{ fixed}, \quad n \to \infty. \quad (3)$$

This asymptotic assumption (3) was consistent with the practice of statistics when these ideas were developed, since investigation of datasets with a large number of variables was very difficult. A better theoretical framework—that is, large p— for modern datasets, however, is the assumption of the so-called "large n, large p" asymptotics

$$p \to \infty, n \to \infty, \quad \text{but} \quad \frac{p}{n} \to c > 0. \quad (4)$$

where c is a positive constant

There is a large body of work concerned with the limiting behavior of the eigenvalues of a sample covariance matrix $\mathbf{S}_n$ when p and n both goes to ∞; see (4); A fundamental result is the Marchenko-Pastur equation, that relates the asymptotic behavior of the eigenvalues of the sample covariance matrix to that of the population covariance in the "large n, large p" asymptotic setting. We must change points of view: from vectors to measures.

One of the first problems to tackle is to find a mathematically efficient way to express the limit of a vector whose size grows to ∞. (Recall that there are p eigenvalues to estimate in our problem and p goes to ∞). A fairly natural way to do so is to associate to any vector to a probability measure. More explicitly, suppose we have a vector $(y_1, ..., y_p)$ in $\mathbb{R}^p$. We can associate to it the following measure:

$$dG_p(x) = \frac{1}{p} \sum_{i=1}^{p} \delta_{y_i}(x).$$

G_p is thus a measure with p point masses of equal weight, one at each of the coordinates of the vector. The change of focus from vector to measure implies a change of focus in the notion of convergence—weak convergence of probability measure.

In wireless communications, an excellent book by Couillet and Debbah (2011) [3] has just appeared, joining Tulino and Verdu (2004) [67] as two major books. The aim of [2]—about 110 pages on large random matrices—is to introduce the relevance of random matrix theory in the context of cognitive radio, in particular spectrum sensing. Our treatment is more practical than those of two books, although some theorems are also compiled in our book. But no proofs are given. We emphasize how to apply the theory, through a large number of examples.

B. Sample Covariance Matrix

The study of sample covariance matrix is fundamental in multivariate analysis. With contemporary data, the matrix is often large, with number of variables comparable to sample size (so-called "big data") [68]. In this setting, relatively little is known about the distribution of the largest eigenvalue, or principal component variance. A surprise of the random matrix theory, the domain of mathematical physics and probability, is that the results seem to give useful information about principal components for quite small values of n and p.

Let $\mathbf{X}$, defined in (1), be an $n \times p$ data matrix. Typically, one thinks of n observations or cases $\mathbf{x}_i$ of a $p-$ dimensional row vector which has covariance matrix $\mathbf{\Sigma}$. For definiteness, assume that rows $\mathbf{x}_i$ are independent Gaussian $\mathcal{N}(0, \mathbf{\Sigma})$. In particular, the mean has been subtracted out. If we also do not worry about dividing by n, we can call $\mathbf{X}\mathbf{X}^H$ a sample covariance matrix defined in (2). Under Gaussian assumption, $\mathbf{X}\mathbf{X}^H$ is said to have a Wishart distribution $\mathcal{W}(n, \mathbf{\Sigma})$. If $\mathbf{\Sigma} = \mathbf{I}$, the "null" case, we call it a white Wishart, in analogy with time series setting where a white spectrum is one with the same variance at all frequencies.

Large sample work in multivariate analysis has traditionally assumed that n/p, the number of observations per variable, is large. Today, it is common that for p to be large or even huge, and so n/p may be moderate to small and in extreme cases less than one.

C. Spectrum Analysis of Large Random Matrices

The first application of random matrix theory we consider is cooperative spectrum sensing in a large cognitive radio network. The most remarkable fact is that in many cases the eigenvalues of matrices with random entries turn out to converge to some *fixed distribution*, when both the dimensions of the signal matrix tend to infinity with the same order [69]. For Wishart matrices, the limiting joint distribution called Marchenko-Pastur law has been known since 1967 [70]. Then, most recently, the marginal distribution of single ordered eigenvalues has been found. By exploiting these results, we are able to express the largest and the smallest eigenvalues of sample covariance matrices using their asymptotic values in closed form . The closed-form, exact expression for the standard condition number (defined as the ratio of the largest to the smallest eigenvalue) is available. Hence, spectrum sensing using the ratio $\lambda_{max}/\lambda_{min}$ can be pursued. These algorithms can be tested in our testbed.

The asymptotic limiting results for infinitely large matrices are often valid for finite-size matrices. The real power of large random matrices lies in that such an approximation is stunningly precise. If the matrices under consideration are larger than 8×8, those asymptotic results are accurate enough, when compared with simulated Monte Carlo results.

Let us consider two common examples: (1) Marchenko-Pastur law for sample covariance matrices; (2) the law for information plus noise matrix model. We compare these theoretical predictions with Monte Carlo simulations, using the data for CRN collected in our Lab.

Marchenko-Pastur Law [70] Consider a $p \times N$ matrix $\mathbf{W}$, whose entries are independent, zero-mean complex (or real) random variables, with variance $\frac{\sigma^2}{N}$ and fourth moments of order $O\left(\frac{1}{N^2}\right)$. As

$$p, N \to \infty \quad \text{with} \quad \frac{p}{N} \to \alpha, \tag{5}$$

the empirical distribution of $\mathbf{W}\mathbf{W}^H$ converges almost surely to a nonrandom limiting distribution with density

$$\begin{array}{c} f(x) = \left(1 - \alpha^{-1}\right)^{+} \delta(x) + \frac{\sqrt{(x-a)^{+}(b-x)^{+}}}{2\pi\alpha x}, \\ a = \sigma^2 (1 - \sqrt{\alpha})^2, b = \sigma^2 (1 + \sqrt{\alpha})^2. \end{array} \tag{6}$$

The Additive Spiked Model If signals exist, the additive spiked model can be exploited. The additive spiked model (or information plus noise model) [71] is

$$\mathbf{Y}_N = \mathbf{B}_N + \mathbf{W}_N \tag{7}$$

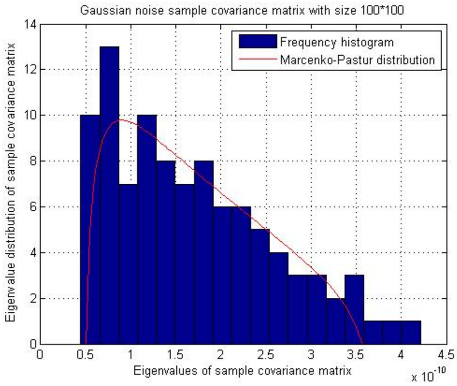
where $\mathbf{B}_N$ is a deterministic rank-K matrix such that $\lambda_{k,N} \to \rho_k$ for $k = 1, ..., K$, and $\mathbf{W}_N$ is a $L \times N$ random matrix with independent $\mathcal{CN}(0, \sigma^2/N)$ elements. When $L, N \to \infty$, in such a way that $c_N = \frac{L}{N}$ converges to a non-zero constant, denoted as c_*. Let $i \leq K$ be the maximum index for which $\rho_i > \sigma^2 \sqrt{c_*}$. Then, for $k = 1, ..., i$,

$$\begin{array}{ll} \mathcal{H}_0 : & \lambda_{i+1,N} \underset{N \to \infty}{\overset{a.s.}{\to}} \sigma^2 \left(1 + \sqrt{c_*}\right)^2, \\ \mathcal{H}_1 : & \lambda_{k,N} \underset{N \to \infty}{\overset{a.s.}{\to}} \gamma_k = \frac{\left(\sigma^2 c_* + \rho_k\right)\left(\sigma^2 + \rho_k\right)}{\rho_k} > \sigma^2 \left(1 + \sqrt{c_*}\right)^2. \end{array} \tag{8}$$

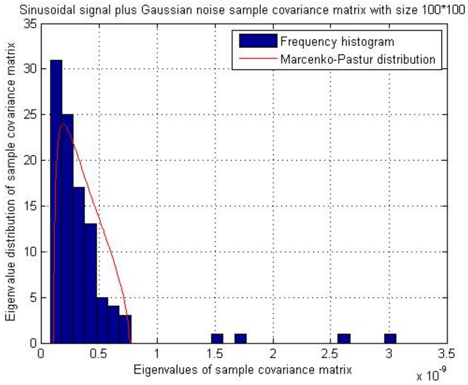
where $\mathcal{H}_1$ denotes the presence of signal(s), while $\mathcal{H}_0$ the absence of signal(s). Here "a.s." means convergence "almost surely". Eq. (8) is illustrated below.

We use our measured data to verify the validation of the Marchenko-Pastur law for modeling the CRN. There are five USRP platforms serving as sensor nodes. The data acquired from one USRP platform are segmented into twenty data blocks. All these data blocks are used to build large random matrices. In this way, we emulate the network with 100 nodes. Fig. 13 shows the spectrum with and without signal.

If there is no signal, the spectral distribution of noise sample covariance matrix is shown in Fig. 13(a) which follows, as expected, the Marchenko-Pastur law of (6). When signal exists, the spectral distribution of sample covariance matrix of signal plus noise is shown in Fig. 13(b). As predicted from (8), a dense bulk spectrum that corresponds to white Gaussian noise co-exists with some—specifically four–isolated eigenvalues. The experimental results are in good agreement with the theoretical prediction. The support of the eigenvalues is finite. The theoretical prediction offered by the Marchenko-Pastur law can be used to set the threshold for detection. This initial result is encouraging us to pursue this direction systemically. Preliminary results obtained in our Lab also show that the observation of Fig. 13 is valid for SNR as low as -20 dB for practical observation time.



(a) noise sample covariance matrix.



(b) sample covariance matrix of signal plus noise.

Figure 13. Spectral distribution.

Several promising techniques will be pursued to use large random matrices for modeling the CRN.

1) **Deterministic equivalents** Deterministic equivalents for certain functions of large random matrices are of interest. The most important references are [72]. There exists a deterministic equivalent $\mathbf{T}_N(z)$ to the empirical Stieltjes transform of the distribution of the eigenvalues of $\mathbf{Y}_N\mathbf{Y}_N^T$. It is also proved that $\mathrm{Tr}\,\mathbf{T}_N(z)$ is the Stieltjes transform of a probability measure. We propose to use this deterministic equivalent as a starting point to analyze the large data sets collected in the Lab.
2) **Universal correlations and power-law tails** The global spectral density or individual eigenvalues of financial covariance matrices are best modeled by introducing correlations among matrix elements that lead to a power-law decay [73].
3) **Spectrum of Kernel random matrices** Uncertainties caused by A/D sampling and power amplifiers can be modeled as non-linear functions. We propose smooth [74] and non-smooth kernel functions [75] to model these devices.

Failure Localization: Random matrix theory will be applied to local failure localization of large dimensional systems in the proposed work. These failures include sensor failure, link failure, and so on. These failures can be easily identified through the perturbation matrix as well as its eigenvector properties. The limiting distribution of the largest eigenvector in the spiked model for Gaussian sample covariance matrices has been shown in [3], [76]. Meanwhile, the effect of matrix perturbation on singular vectors can be found in [77].

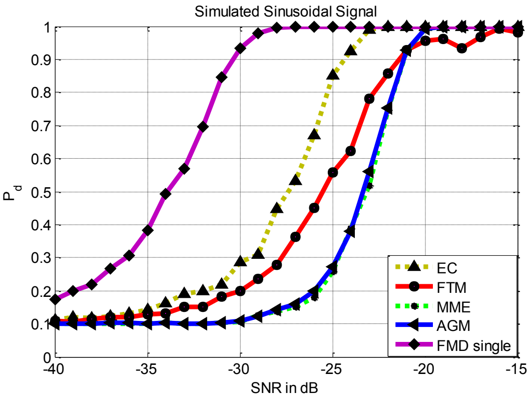
Besides, we can also monitor the sudden parameter change in the large-scale cognitive radio network. These sudden parameter changes can be analyzed through random matrix theory. We can infer and extract information from sudden parameter change for intrusion detection, anomaly detection, moving target tracking, network tomography, and so on. For intrusion detection or moving target tracking, the perturbations of the received signal matrices are different due to the different locations of target of interest and the mobility of target. By random matrix theory, we can detect the different perturbations and extract the corresponding features which can be used to identify and locate the target. In homogeneous network, the sudden parameter change may lead to similar amplitudes of the extreme eigenvalues [3]. Thus, leading eigenvector or leading subspace may be more sensitive to the change and perturbation than the extreme eigenvalue. Network tomography is the study of a network's internal characteristics using information derived from external observations. A cognitive radio network is a large complex system with so many nodes. Measured continuous data flows from all the nodes can be used to build a large random matrix from which we can infer the properties and traffic flows in cognitive radio network. These properties include data loss, link delay, routing state, and network fault.

VI. Spectrum Sensing Exploiting Quantum Information Theory

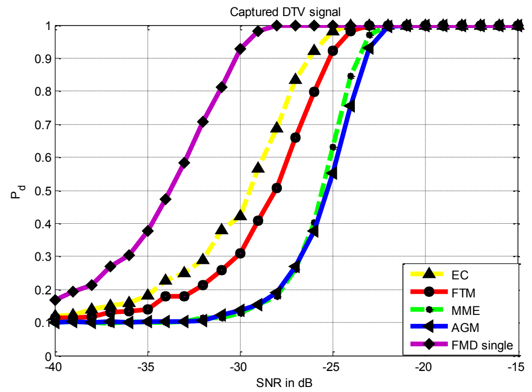
Spectrum sensing in the low signal-to-noise ratio (SNR) situation is a unique challenge in cognitive radio network. Our goal is to propose new algorithms that work for the SNRs as low as possible. The GLRT is promising for spectrum sensing. Its kernel version, Kernel GLRT [78], performs well, in contrast to Kernel PCA [78]. Leading eigenvectors can be used features for spectrum sensing [79], [80]. Robust PCA [81] can be also used.

A novel framework for hypothesis detection has been discovered to exploit the quantum information of noncommutative random matrices. This novel formalism—that was first proposed in [82], [83]— has led to algorithms that work at unprecedentedly low SNRs. For SNRs as low as -30 dB—in sharp contrast with -22 dB (for the state-of-the-art algorithms below), those novel algorithms have a detection probability of higher than 90%. This is practically important when a jamming signal or strong interference is present. A whole chapter of [2] is dedicated to this topic. Our objective here is to explore those novel algorithms in the context of testbeds: FGPA implementations will be used.

If the "state" matrices (defined as true covariance matrices requiring infinite lengths of data vectors) are communicative, the quantum hypothesis testing is equivalent to



(a) Simulated narrowband signal.



(b) Measured DTV data

Figure 14. Probability of detection.

the classic generalized likelihood ratio test (GLRT) [84]—related to Shannon's information. The two alternative sample covariance matrices (only requiring finite lengths of data vectors) are, however, *noncommunicative*—related to Von Neumann quantum information [85]–[90]. Functions of (sample covariance) matrices for detection (FMD) may be used [82], [83]. We essentially deal with two random matrices. Here, the macroscopic statistical properties of the algorithms are similar to the quantum system. We are not dealing with the microscopic level of quantum mechanics. Quantum information or noncommunicative probability is a better description for the formalism. The performance of quantum detection in the example below has achieved 8 dB better that of the classical GLRT!

Our hypothesis testing problem can be formulated in the following form:

$$\begin{array}{l} \mathcal{H}_0 : \mathbf{A} = \mathbf{I} + \mathbf{X} \\ \mathcal{H}_1 : \mathbf{B} = SNR\,(\mathbf{I} + a\sigma) + \mathbf{I} + \mathbf{Y} \end{array} \tag{9}$$

where $\mathbf{X}$ and $\mathbf{Y}$ are two random matrices, $\mathbf{I}$ identity matrix, σ a low rank deterministic signal matrix and a scaler parameter. The hypothesis testing problem can be viewed as a problem of partial ordering of two sample covariance matrices $\mathcal{H}_0 : \mathbf{A}$ and $\mathcal{H}_1 : \mathbf{B}$. Matrix inequalities are the basis of the proposed formalism. Often, Hermitian matrices are objects of study. The positivity of these matrices is required for many recent results developed in quantum information theory [85]–[90]. The fundamental role of positivity of covariance matrices is emphasized here.

The preliminary results are shown in Fig. 14. The proposed algorithm is compared with several state-of-the-art algorithms: estimator-correlator (EC) based on GLRT [84], together with arithmetic-to-geometric mean (AGM) [91], feature template matching (FTM) [79], maximum-minimum eigenvalue (MME) [92]. A DTV signal (field measurements) captured in Washington D.C. will be employed for the simulation in this subsection. The number of total samples is 100,000. Probability of false alarm is fixed with $P_{fa} = 10\%$. For a simulated sinusoidal signal, the parameters are set the same. The proposed method can greatly improve the performance of spectrum sensing in the extremely low SNR situation (such as -30 dB).

VII. Conclusion

At the writing of this paper, TTU has two CRN testbeds: (1) one based on 8 WARP nodes; (2) one based on 11 USRP2 nodes. In the near future, the targets are to increase the numbers of nodes, respectively, to 16 WARP nodes and 100 USRP2 nodes. We have made some progress, as described by the surveyed recent results obtained at TTU. Networking for highly-mobile nodes like UAVs remains a challenge—this motivates us for the core network development. Another direction is to increase the numbers of nodes (as mentioned above). It is believed that the current architecture is scalable, since we have designed it with supporting a large number of nodes in mind as the final goal.

In the next stage, the emphasis is to use the expertise of the CRN as a data acquisition tool; for example, DARPA's Advanced RF Mapping (RadioMap) program [93] seeks to provide real-time awareness of radio spectrum use across frequency, geography and time. With this information, spectrum managers and automatic spectrum allocation systems can operate much more efficiently, reducing the problems caused by spectrum congestion. With better understanding of spectrum use, unexpected transmissions can be detected locally, enabling better mitigation of interference problems. The program plans to provide this information in part by using radios deployed for other purposes, like data and voice communications systems. The program aims to develop ways to use the capabilities of modern radios to sense the spectrum when they are not communicating.

Another focus is to develop mathematical tools to process the high-dimensional Big Data. In particular, it is our belief that large random matrices may be used for such a purpose. Quantum information, rather than the classical Shannon information, can be extracted during this data processing.

Acknowledgment

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