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High-Fidelity Spectrum Characterization with Low-Cost Sensors

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Abstract

With the increasing use of wireless technologies, we see a heavy use of the spectrum at certain frequencies whereas it is underutilized at other frequencies. We need to utilize the currently underutilized spectrum. Hence, a paradigm called Dynamic Spectrum Access arises. Dynamic Spectrum Access looks for opportunity to utilize this underutilized spectrum by allowing devices to opportunistically access spectrum that is not actively used. DSA, however, requires spectrum sensing and spectrum characterization across time, space, and frequency for opportunistic devices to know where to operate. Spectrum sensing is the process of collecting power level traces from the radio-frequency spectrum, whereas spectrum characterization determines how many transmitters occupy a given spectrum and what are their temporal and frequency characteristics. Traditional spectrum sensing and characterization is performed with expensive sensors, which renders the task economically-infeasible. Our project introduces a low-cost alternative, which is more mobile and cost efficient. A typical issue with low cost sensors is that the scans from the low-cost sensor are of lower quality compared to scans from a higher-cost alternative. In this end, we compare the characterizations of the spectrum from the low cost sensor to the high-cost sensor across time, frequency, and space. We conduct granularity, sensitivity,transmitter pattern, and mobility experiments to compare the scans of the two sensors in different scenarios. We analyze the two characterizations from the two sensors in a controlled setting to see if the scans of the two are comparable. From the mobility and granularity experiments, we observe that scans from the low-cost sensors are comparable to the scans from the high-cost sensors. However, as expected, we do see lower sensitivity in the low-cost sensor. Comparing the two scans will help us form a better picture of the kind of

infrastructure we can build using the two sensors that is both economically feasible and can give us high-fidelity scans.

Table of Contents

List of Figures

List of Tables

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Chapter 1

Introduction

1.1 Motivation

Today our need for wireless network capacity has expanded tremendously with the increasing use of wireless and cellular data. Since the advent of smart phones and tablets, we see that there has been a tremendous growth in traffic. AT&T reported that traffic has increased by 20,000% since the iPhone debuted in 2007. From a report in 2011, it can be seen The iPhone uses 24 times as much spectrum as an old-fashioned cell phone, and the iPad uses 122 times as much. For a consumer this means calls get dropped, data speed get slow, and cost of cellular data increases [2]. This leads to a phenomenon called ”the spectrum crunch”,which is further aggravated by the growth in mobile data and an increasing number of applications in fields like telemedicine, autonomous cars/drones and mobile virtual/augmented reality.

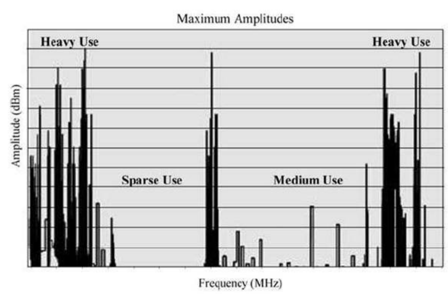


Figure 1.1: Spectrum Utilization Across Frequencies [1]

Most of the spectrum today has been allocated to different technologies. Nowadays we use frequency spectrum for cellular networks, wireless networks, military communications, FM, TV bands etc. This allocated spectrum is assigned to different companies. For example, the cellular band is assigned to companies like AT&T, Verizon, and Sprint.

However, today we face a problem where allocated spectrum is not being used to its full potential. In Fig 1.1, we see the spectrum utilization at different frequencies. Here the x-axis is the frequency(Hz) and the y-axis is the amplitude of signals observed in a given band. Higher amplitudes are an indication of more transmitter activity. We can observe that are frequencies where we see heavy use of spectrum whereas some other frequencies have very low use of spectrum. There is an under utilization of spectrum especially under the 3 GHz range. This is a waste of precious finite resources that mandates a rethink of current spectrum allocation practices and a corresponding redesign of spectrum policy and technology. The latter has brought together the government, industry, and academia to devise a new approach to spectrum use.

This leads to a new paradigm called Dynamic Spectrum Access(DSA) which looks for opportunity to occupy the underutilized spectrum that is not currently being occupied in this allocated spectrum. Currently, most devices operate at an assigned frequency. The need of the future networks is to be able to dynamically and opportunistically choose their operating frequencies. Devices need to be **agile** to be able to move from one frequency to another. Future devices should be able to form communication links on any radio frequency that is not actively used.

However, for devices to know to move frequencies opportunistically, they need to have a deep understanding of spectrum utilization across time, frequency and space. For this, DSA requires **spectrum sensing** and **characterization**.

1.2 Low Cost Spectrum Sensing and Characterization

Past research on spectrum sensing takes two approaches: direct and indirect sensing. In direct sensing, communicating devices are also tasked with identifying idle spectrum for operation.Indirect sensing makes use of a dedicated spectrum infrastructure which looks for an opportunity on behalf of the communicating devices. We will further look into this in *section 3.2*. The joint work of government, academia and the industry has determined indirect sensing.[[3] [4]] Thus, our work focuses on the design of a low-cost, high-fidelity spectrum measurement infrastructure, which will provide high fidelity scans that can be characterized across time, frequency, and space. The ability of these scans to be characterized depends on the scans collected. Most options for spectrum sensing currently are high-cost, and are thus not economically and geographically scalable. This brings in a need for lower cost sensors that can scan across time, frequency, and space. However, some issues with lower-cost sensors is that the scans are sparse, have low sensitivity i.e they cover a smaller geographical range, and have low granularity.

We propose a system with high fidelity scans that can be characterized for DSA but is also economically feasible. For this we need a deeper understanding of the benefits and limitations of mixed infrastructures on spectrum characterization. Additionally, we also need to analyze how a low-cost sensor will compare to a high cost sensor to better understand the trade offs of using a low cost sensor vs a high cost sensor. We do this by collecting spectrum scans in a controlled environment and comparing the characterizations from a low-cost sensor to a high cost sensor. We perform sensitivity, granularity, transmitter pattern, and mobility experiments to emulate different scenarios and evaluate the known limitations of a low-cost sensor. We propose a framework that allows us to quantify the accuracy of spectrum characterization. Our framework features key metrics such as bandwidth, active time and cycle of active detected transmitters. We apply our framework on scans collected in a controlled environment and draw conclusions about the feasibility of spectrum characterization from low-cost sensors.

Chapter 2

Related Works

Early work on spectrum management infrastructures [5, 6, 7] uses high cost stationary sensors such as the CRFS RfEye [5, 6, 7] or USRP [6, 7]. While they do give high quality and persistent scans, they do not scale well for ubiquitous sensing. There is some work done with both low-cost sensors and high-cost sensors. Current implementation from Nika et. Al [8] explores the feasibility of using a $20 RTL-SDR with a smartphone for crowd-sourced spectrum monitoring. Work from Zhang et al.[9] includes using a system called Snoopy that translates a mobile phone into a RF spectrum analyzer using a WiFi NIC card. Work done by Chakrobarty et. al.[10] also talks about the advantages of crowd sourcing for collecting scans from a low-cost sensor. They compare such a system to an app like Flight Aware, which uses a low-cost commodity RF sensor hardware to capture signals from airplanes flying overhead. It creates a system of efficient spatial interpolation of RF signals and optimized selection of sensors. They explore the possibility of creating a heterogeneous system. Previous works in crowd sensing shows us that while crowd sensing can provide a high density of scans, scans collected from crowdsensing can be poor quality. This is further aggravated by the large variety of the consumer electronics and the measurement artifacts they introduce. Moreover, consumer electronics' chipsets only cover ISM and cellular bands, which makes then infeasible for wideband sensing. Previous work suggests external augmentation of consumer electronics' RF frontend by RTL-SDR [8] or down-converters [9]. However, this makes a device bulky and not really feasible to be carried around for crowd sensing.

Zhang et. al also use a vehicular spectrum measurement [9] to collect their scans. The vehicular system combines crowd sensing and Snoopy. This combines the benefits of stationary and crowd-sourced spectrum sensing by providing a high spatial coverage and a uniform, persistent scan quality. However, we observe that with the current FCC rules this is not feasible. There is also a large deployment cost and large volume of measurements.

Hence, from previous implementations such as crowdsensing and vehicular scans, it can be inferred that a *a homogenous sensor infrastructure will not meet the needs of future spectrum management* for high scan resolution and learning. Hence, there is a need to have a system that gives high fidelity scans for characterization but is also economically feasible. High-cost sensors can produce fine-granularity scans but the cost of the infrastructure drastically increases as spatial coverage requirements increase. Low-cost sensors are economically efficient but they have low resolution, sensitivity, and are sparse, resulting in poor data quality. Hence, drawing from the strengths of these extremes and envision a hybrid infrastructure that features a mix of mobile, static, low- and high cost sensors.

Chapter 3

Background

3.1 Spectrum measurement objectives

Different spectrum measurement objectives pose different requirements on measurement algorithms and infrastructures for Dynamic Spectrum Access. For example, if the goal of measurements is to simply capture the idle and occupied time-frequency blocks, then lightweight characterization can be performed at the sensors, and raw spectrum traces can be discarded. On the contrary, if the goal is detailed analysis of number of transmitters and their time-frequency usage patterns i.e where and when they are idle and occupied, then sensor-side characterization might not be feasible. This requires migration of spectrum scans to a centralized server for processing. Hence, if the goal is validation of analytical methods and Dynamic Spectrum Access (DSA) protocols, then there is a need for longitudinal sensing, centralization and storage of spectrum traces.

A recent survey on spectrum measurement objectives [11] identified a wide range of priorities. Spectrum measurements (i) should help incumbents and secondary users to make real-time decisions for spectrum use, (ii) should support validation of analytical methods and protocols, (iii) should assist in spectrum enforcement and (iv) should be able to serve multiple objectives. Thus, there is a need for a spectrum measurement infrastructure that can provide continuous spatial coverage of spectrum measurements, store spectrum scans longitudinally and characterize the spectrum occupancy including number of transmitters, their temporal and frequency characteristics and the opportunity they grant for secondary spectrum access.

3.2 Infrastructure modalities

Direct and Indirect Sensing. Past research on spectrum sensing and characterization takes one of two approaches: (i) *direct* and (ii) *indirect*. In the *direct* approach, communicating devices (i.e client and base station) are also tasked with identifying a common working frequency. The *indirect* approach, in turn, makes use of a dedicated spectrum infrastructure to measure and characterize the spectrum. Communicating devices query these dedicated infrastructures in order to obtain an operation frequency for opportunistic access. The benefit and drawbacks of these approaches can be discussed across several key criteria including (i) scalability, (ii) economic feasibility, (iii) sensing and characterization accuracy, (iv) communication overhead and (iv) applicability.

	Direct	**Indirect**
Scalability	**Y**	**N**
Economic	**Y**	**N**
Accuracy	**N**	**Y**
Overhead	**N**	**Y**
Applicability	**N**	**Y**

Table 3.1: Pros and cons of *direct* and *indirect* spectrum sensing and characterization.

Table 3.1 provides a summarized comparison of the two types of spectrum modalities across these criteria. The direct comparison works well with the scalability and geographical distribution of the communication network, as each device will participate in sensing. It is also the more economically-feasible option. However, direct sensing is plagued with low accuracy, high overhead , and low applicability. In terms of accuracy the differences in heterogeneous sensing devices lead to variable quality of the spectrum scans [8, 12, 10, 13], which has an adverse impact on the accuracy of spectrum characterization. As a result, communicating devices may be unable to find a common operating frequency. Furthermore, direct sensing results in additional time, protocol and communications overhead, which effectively reduces the time devices are left with to perform useful communication. The latter may have a detrimental impact on network performance and user experience. Last but not least, direct sensing has limited applicability. While it is geared to serve DSA technology, it is not well-suited for DSA policy and spectrum enforcement that require longitudinal, detailed and preemptive spectrum characterization. Indirect spectrum measurements solve the limitations of direct sensing by ensuring high accuracy and applicability, and low overhead of spectrum measurements. Key drawbacks of indirect spectrum sensing, however, are related to scalability and economic feasibility, as dedicated infrastructures require careful design to be able to inform ubiquitous opportunistic access and are associated with a large additional cost for deployment and maintenance. Researchers and practitioners in next generation spectrum access agree that the benefits of indirect spectrum sensing outweigh its drawbacks, and thus, opportunistic spectrum access should be supported by dedicated spectrum sensing and characterization infrastructures [14]. Hence, most new policy enforcements as henceforth, our work works towards indirect sensing.

3.3 Key tradeoffs

Sensor cost	Instant Bandwidth	Sampling Rate	Noise Figure
Low-cost (RTL-SDR)	3.2MHz*	2MSps	8-13dB**
Mid-cost (USRP N210, WBX)	40MHz	25MSps***	5dB

*Stable at 2MHz; ** Dependent on host configuration; *** Limited by host bandwidth

Figure 3.1: Key Tradeoffs of High Cost vs Low Cost

Low-cost sensors often have sparse scans, have low sensitivity, and low granularity i.e they detect across a smaller range and they drop more samples than a high-cost sensor. As seen in Fig 3.1, the sampling rate of a low-cost sensor is 2 Mhz, which is much lower than that of a high-cost sensor. This means that the number of samples it can carry per second is much lower for the low-cost sensor, which has a direct impact on the granularity of data and leads to sparse wideband spectrum scans. It also has a higher noise figure (number by which performance of a radio or amplifier can be specified) than that of a high-cost sensor.

Nevertheless, low-cost sensors are much lower in price than a high-cost sensor; i.e. $20 for a low-cost sensor compared to $2000 for mid- and hundreds of thousands of dollars for a high-end sensor. High-cost sensors are also location prohibitive. Due to their disadvantages, they are usually placed more sparsely geographically.

Hence, there is a need for an infrastructure which is both economically feasible and can give high-fidelity scans for spectrum characterization. As we saw from other related works (Chapter 2), it looks to be that this infrastructure needs to be heterogeneous with a balance of low-cost and high cost sensors.

Chapter 4

Methodology

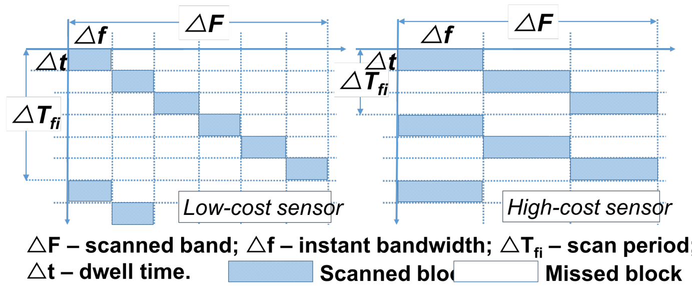


Figure 4.1: Sensor capabilities vs. cost.

The goal of our research is to investigate the feasibility of a hybrid cost and mobility sensing infrastructure. Thus, we carry out a controlled study of spectrum characterization outcomes by low- and mid-end spectrum sensors. We specifically focus on a few experimental scenarios including effects of sensor sensitivity, effects of sensor granularity, and effects of sensor mobility.

Evaluating characterization outcomes in the above scenarios provides critical insights into spectrum measurement infrastructure design, which we describe in chapter 4.

Effects of sensor cost. The goal of spectrum measurements is to collect representative scans from a target frequency band ΔF. ΔF is typically in the order of GHz, however, a spectrum sensor is only able to scan a few MHz at a time. In order to cover the target wideband spectrum (30MHz-6GHz [14]), spectrum measurement infrastructures such as Microsoft's Spectrum Observatory [6], utilize sequential scanning of consecutive bands as illustrated in Fig. 4.1. The key limitation of sequential scanning is that any given frequency chunk f_i is scanned in discrete times t_j, as opposed to being scanned continuously as in the case of a higher cost sensor. This causes some time-frequency blocks to be missed, which may lead to omission of important transmitter characteristics. Two key spectrum scan properties affect the impact of sensors on the measurement outcomes: (i) *scan periodicity*, or how often do we get data from a given spectrum chunk and (ii) *scan quality*. These two factors, in turn, depend on the scan configuration and the capabilities of the employed spectrum sensors.

The periodicity and quality of spectrum data collection are determined by the scan configuration and the sensor capabilities. In terms of configuration, the desired dwell time and FFT size determine the utility and quality of scan data. In terms of sensor capabilities, fundamental limiting factors are the instantaneous bandwidth, sampling rate and sensitivity (as determined by the noise figure). These capabilities vary drastically with the cost of the sensor. Apart from the software defined radio (SDR), the processing power of the sensor also plays a critical role in how fast data can be processed (i.e. PSD estimation) and stored.

To quantify the *scan periodicity* of a spectrum chunk f_i, we define the *scan period* ΔT_{f_i} as the time between recurring scans of f_i. ΔT_{f_i} depends on sensor capabilities and scan configuration as follows: $\Delta T_{f_i} = (\Delta t * \Delta F/\Delta f) + t_{proc}$, where Δt is dwell time, Δf is the sensor's instantaneous bandwidth and t_{proc} is a delay that factors in the processing overhead (e.g. time to calculate the FFT). Our evaluation demonstrates that the overhead in wideband sequential scanning by a low-cost sensor can be substantial as the computation load increases. From a prior study, we see that the processing requirements of FFT calculation is proportional to the FFT size N. As the processing demand increases, the tune-to-record time grows rapidly from $200ms$ at $N = 256$ to $6s$ at $N = 4096$.

The *quality* of spectrum data in a scanned block can be quantified by its (i) time-frequency *granularity* and (ii) *dynamic range*. The frequency granularity, of a scanned band f_i can be expressed as $f_i^n = \Delta f/N$, where N is the desired FFT size, $f_i^n, n \in \{1, \ldots, N\}$ is the size of a frequency bin and Δf is the sensor's instantaneous bandwidth. The temporal granularity of spectrum data is determined by the number of sweeps J that can be completed in a frequency chunk f_i for a given dwell time Δt. The time to complete a single sweep $t_j, j \in \{1, \ldots, J\}$ is dependent on the sensor capabilities as follows: $t_k = (N/f_s) + t_{proc}$, where f_s is the sensor's sample rate. As Fig. 4.1 shows, the processing overhead of a sensor can significantly impact the temporal granularity of spectrum data. Along with granularity, the dynamic range of the sensor plays a key role in spectrum data quality. It depends on the sensitivity of the sensor, which is influenced by the quality of the receiver RF chain. Previous work [8] observed that the noise figure of low-cost RTL-SDR is 8-13dBm higher than that of mid-cost USRPs. This limits the capabilities of RTL-SDRs to sense low-power transmissions.

Effects of sensor mobility. Sensor mobility increases the spatial coverage of spectrum scans, however, it also increases the scan period and reduces the data quality. Let us consider a mobile sensor that traverses a fixed route L of length d meters with speed s meters per second and scans the full target band ΔF at discrete locations $l_i, i \in \{1, \ldots, |L|\}$ along the route. The scan period of a frequency chunk f_i at location l_i will then be $\Delta T_{f_i}^{l_i} = d/s + \Delta T_{f_i}$. Intuitively, the scan intermittency of a band f_i increases due to sensor mobility, which further increases the chance of missed transmitter characteristics. Mobility also impacts the spectrum scan quality, as it introduces variability of the signal level at which transmitters are sensed as the sensor moves towards and away from these transmitters.

We perform a study of the effects of sensor cost on spectrum learning outcomes in a controlled scenario. We are particularly interested in (i) the impact of distance between transmitter and sensor and (ii) sensing duration on spectrum learning outcomes. We also perform experiments at different FFT sizes to observe the behaviour of the two sensors at different FFT sizes. We also test the mobility property of sensors in a controlled setting.

4.1 Key Characterization Metrics

Our sensors collect transmissions from the transmitter which are either periodic or aperiodic (depending on the experiment). To characterize these transmissions collected from the transmitter, we evaluate our transmission into the following metrics:

1. *Gap*: The gap is the idle time period between two transmissions. We calculate this as the time between the beginning of the transmission and the end of the previous transmission.

2. *Cycle*: The cycle is the time from the beginning of the current transmission to the beginning of the next transmission.

3. *Duration*: The duration is the time a transmission is transmitted for. This is measured from the beginning of the transmission to the end of the transmission

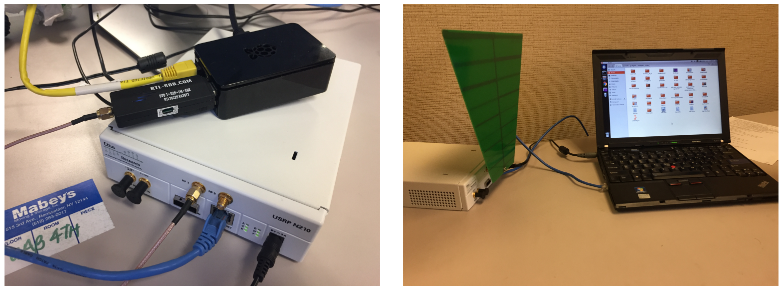
4. *Bandwidth*: Bandwidth indicated the occupied frequency. It is the frequency that the transmission is transmitted over.

We use this gap, cycle, duration, and bandwidth metrics and compare them for the low-cost and high-cost sensor. This indicates if the characterizations from the scans of the sensors could be comparable.

Chapter 5

Experimental Setup

5.1 Hardware Setup



(a) sensors (b) controlled transmitter

Figure 5.1: Experimental Setup

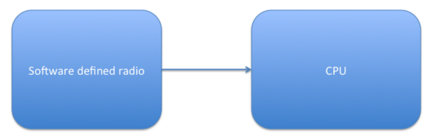
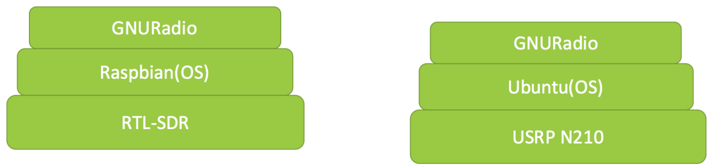


Figure 5.2: Hardware Design

A Software-defined radio is comprised of a radio and a processing unit (ref to figure 5.2). The radio is the sensor we use to collect our traces whereas the processing unit is a computer like a laptop. Our experimental setup is seen in figure 5.1.

As seen in our experimental setup, our experiments have two sensors for comparison: the low cost sensor and the high cost sensor. They both have one antenna to reduce experimental variability. The low-cost implementation we used was the RTL-SDR in conjunction with the Raspberry Pi. The RTL-SDR costs around $ 20. The sampling rate of a RTL-SDR is 2 MHz. For our higher cost sensor to compare with the RTL-SDR, we are using the USRP N210 from Ettus Research with a laptop. Its maximum sampling rate is 32 MHz whereas its stable sampling rate is 22 MHz. We are also using the USRP N210 to evoke controlled transmissions. To collect our traces, we are connecting our RTL-SDR to a Raspberry Pi. This device runs a linux platform called Raspbian and it receives the traces from the RTL-SDR. Raspberry Pi is an ideal candidate for a low-cost sensor since it is readily available. has a linux platform, is mobile, and is extremely low-cost ($35). Raspberry Pi 3(one of the devices we use for our experiment) includes a quad-core ARM Cortex-A53 CPU running at 400 MHz and 1 GB ram.

5.2 Software Setup



(a) RTL-SDR stack (b) USRP stack

Figure 5.3: Hardware/Software Stack

As seen in figure 5.3, apart from using the RTL-SDR and USRP as the hardware components of the sensor, we are using Raspbian as the operating system for the RaspberryPi and Ubuntu(Linux) as the operating system for the laptop.

We are using the Gnuradio[15] Open Source library for the software components of our sensors. We used blocks provided by GnuRadio to configure our transmitter and receiver. By using and modifying various available blocks in Gnuradio, we set up multiple transmitters environments for our experiments. For example, configuring the Gnuradio library allowed us to get periodic and random transmitter pattern. After getting raw data, it needs to be processed according to fft-size and other parameters. Gnuradio also provided us with the tools to modify our files as required and generate a visualized version of the data. We are generating binary file from raw data which will be used further for either getting metric of PSD values or generating heatmaps to see ongoing transmission traces. For characterization of data to find the transmitters in the transmission from collected data we are using MATLAB for better and fast visualization and processing.

After collecting the traces, we are using AirView to characterize our data according to time, frequency, and space. We also created Java programs to get the required information like gap, bandwidth, cycle, and from this characterized data. We using Python and its MatPlotLib, Numpy libraries for data analysis and to create our graphs.

5.3 Spectrum Scan Characterization

To perform our characterizations, we are utilizing AirView, the Honors Project of Tim LaRock(Spring 2016). This project is a mechanism for spectrum sensing and characterization that allow real-time and batch processing of spectrum scans to reveal an essential mix of characteristics such as number of occupants, their temporal and frequency usage patterns, mobility and their eligibility to operate. It operates on spectrum scans comprised of power spectrum density (PSD) measurements over frequency and time. For single-sweep spectrum analysis, AirView employs wavelet decomposition of PSD to separate transmitter edges from the noise floor.

The accuracy of such a method hinges on the careful selection of its parameters, including binary tree scales for multiscale product calculation and a threshold scaling coefficient. Hence, these values have to picked carefully for all the scans taken. This was one of the challenges we faced while characterizing our spectrum scans.

Chapter 6

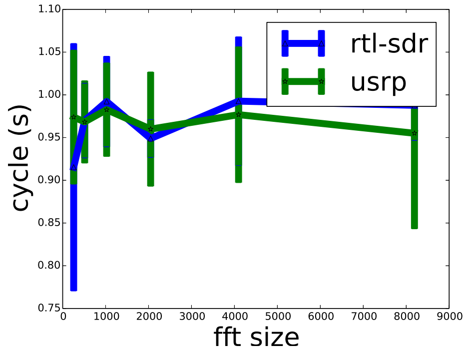
Evaluation

To characterize scans from both the low-cost sensor and high-cost sensors across time, frequency, and space and compare the scans from the two.

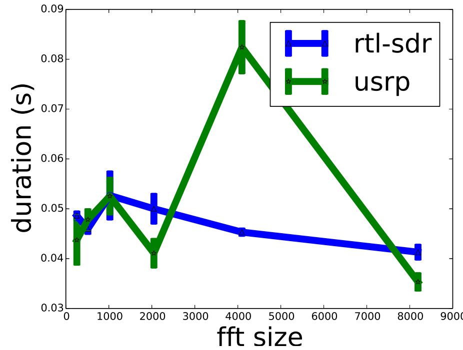
We begin our experiments in a controlled setup, to be able to control the transmitter characteristics like the pattern it sends transmissions in and transmitter properties like its gain. We also want to be able to control sensors' configuration and mobility in a controlled environment. We utilize real transmitters and sensors based on a range of SDRs (RTL-SDR, USRP N210, and USRP B210) and host platforms(e.g embedded RaspberryPi and laptops). We program the transmitters to emit a diverse set of benchmark patterns in order to evaluate the *the effects of transmitter count and dynamics on learning outcomes.* We sense these transmitters with a mix of cost/mobility sensors and while varying their sensing configurations in order to evaluate the *effects of sensor type and configurations on learning outcomes.* Specifically, we evaluate the effects of the following factors on spectrum characterization outcomes:

1. *Effects of spectrum data granularity (f_i^n and t_k).* We varied the FFT size N of both sensors, while sensing the periodic transmissions from the transmitter. Through this experiment, we studied and compared the effect of different FFT sizes on the two sensors. We set one of the USRPs as a transmitter and collected traces at FFT sizes 256, 512,1024,2048,4096,and 8092. We set the sampling rate of the sensors to be 2M.

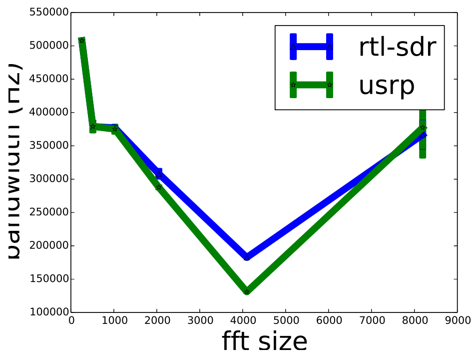
   Our results are presented in figure 6.1. The x-axis is the FFT size i.e 256, 512, 1024, 2048, 4096, 8092 and y-axis are the measurement metrics: gap, cycle, bandwidth, and duration. We observe that the gap and cycle for the two are comparable. One outlier we can observe is the 256 ft RTL-SDR trace has a large standard deviation. We see that the bandwidth and duration is comparable too. However, we see an outlier at 4096 FFT. We see that the bandwidth for both the low-cost and high-cost sensors at 4096 FFT dips. We also see a spike in the high-cost sensor data at 4096 FFT. This could be due to a sensor inconsistency or an inconsistency in transmitter behavior. The sensors could not have collected the traces properly. However, it is more likely that the transmitter malfunctioned for this FFT size. Hence, overall we see that the measurement metrics for both the sensors are comparable at



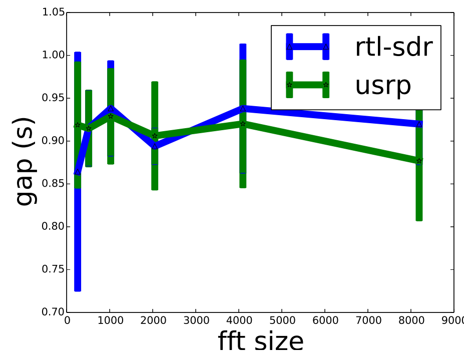
(a) Cycle



(b) Duration



(c) Bandwidth



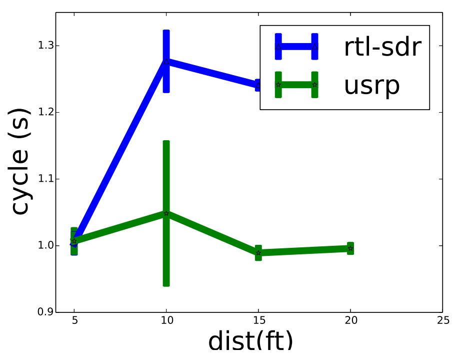
(d) Gap

Figure 6.1: Results from Granularity experiment

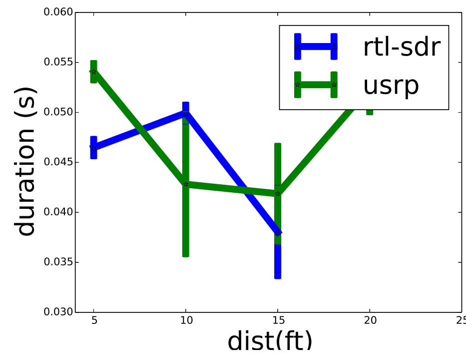
different FFTs.

2. *Effects of sensor sensitivity* The noise figure of different sensors determines their sensitivity to transmitters at different SNR (Signal to Noise Ratio). We will compare the learning outcomes of a low-cost, the less sensitive sensor, to a high-cost sensor, the more sensitive sensor for a given transmitter pattern with varying SNR. We will ensure the same scan period, granularity(1024 fft) ,and sampling rate to 2M in order to focus only on the effects due to sensitivity.

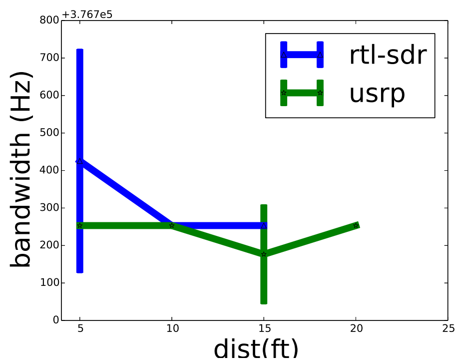
   For this experiment, to look at the effects due to sensitivity, we placed the sensors at a distance of 5 ft, 10 ft, 15 ft , and 20 ft to observe the sensitivity of the two transmitters.



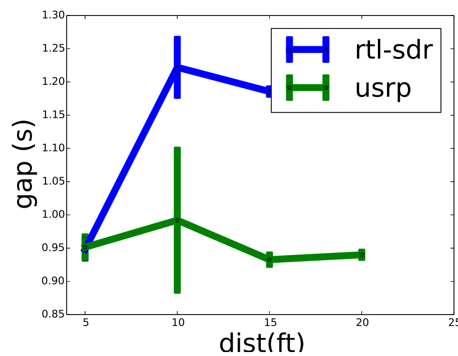
(a) Cycle



(b) Duration



(c) Bandwidth



(d) Gap

Figure 6.2: Results from Sensitivity experiment

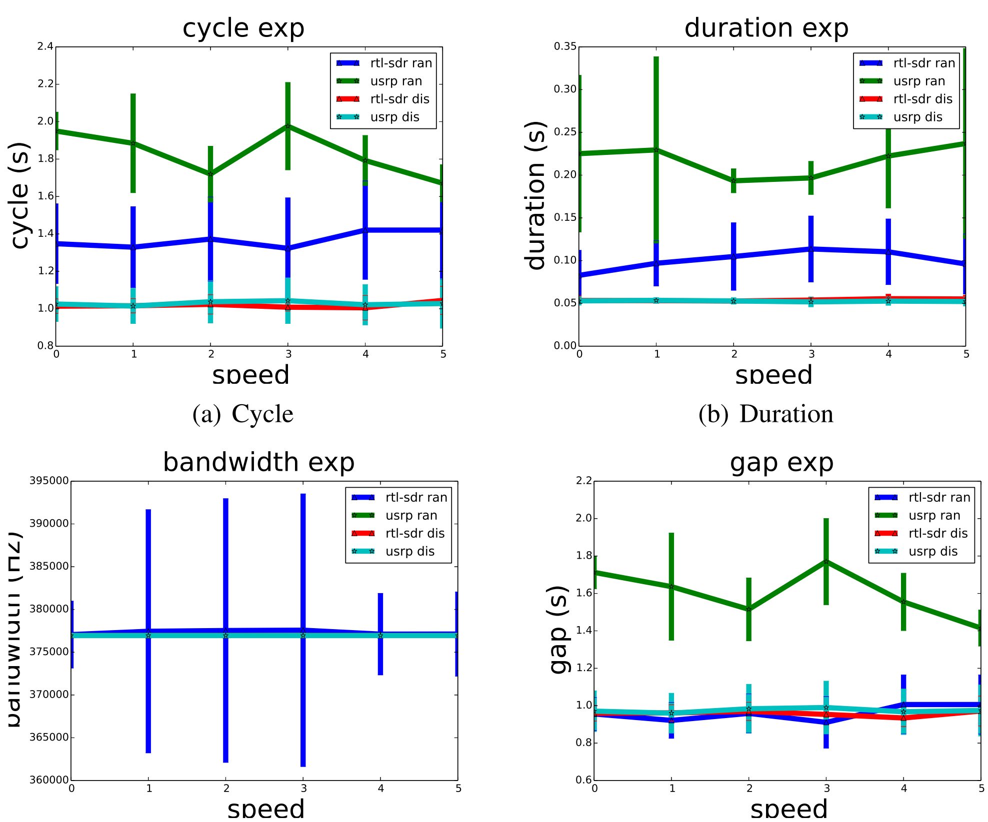
In the above graphs (Fig 6.2), the x-axis holds the distance i.e 5 ft, 10 ft, 15 ft, and 20 ft and the y-axis has the measurement metrics i.e cycle, duration, bandwidth, and gap. The transmitter has a periodic pattern. We see that the bandwidth and duration are similar. We see that the gap and henceforth, the cycle are much larger at 10ft and 15ft than the USRP at the same distances. This is because, as a result of RTL's reduced sensitivity at longer distances, the perceived duration for the RTL-SDR is much smaller than the USRP. Hence, the gap detected is much larger. We see some outliers at 10 ft for duration where the duration for the low-cost sensor is higher than the high-cost sensor.

Since the RTL-SDR has low sensitivity, we lose traces at 20 ft. We see the low-cost sensor loses sensitivity as the sensor gets farther away from the transmitter.

3. *Effects of sensor mobility.* As detailed, sensor mobility increases the scan period $\Delta T_{f_i}^{l_i}$,

which impacts characterization outcomes. To study the effects of mobility, we will emulate sensor mobility by periodically halting the sensing activity for a predefined time window (effectively emulating the sensor moving away from location l_i). We configured our low-cost sensor and high-cost sensor to be mobile at different speeds by halting the sensing activity for different time periods. We set the transmitter patterns to aperiodic and periodic to benchmark the effects of mobility on spectrum characterization.

One USRP device transmitted the signal in random and discontinuous pattern. The other two setups(RTL and USRP) collected the traces of ongoing transmission. To emulate mobility we repetitively clipped portions of the collected scan, effectively causing a halt in the sensed trace. By decreasing the size of the clipped portion we emulate an increase in the sensors moving speed.



(a) Cycle (b) Duration

(c) Bandwidth (d) Gap

Figure 6.3: Results from Mobility experiment

In the figure 6.3, the x axis is the different speeds (with 0 being stationary) and the y axis is the different measurement metrics gap, cycle, bandwidth, and duration. Here we can observe characterization for the RTL(low-cost) and USRP(high-cost) for random and discontinuous transmission patterns.

From the graphs, we see that the bandwidth is similar across all the traces collected. We see that there is a large standard deviation for the bandwidth collected. However, the bandwidth remains constant at different speeds. For the duration, we see that RTL at a random pattern, USRP and RTL at a discontinuous transmission pattern are similar. We see this duration remains similar at different speeds. Both the gap and duration are higher for the random transmission pattern. This is expected since the random transmission pattern have variable gaps and durations.

Chapter 7

Conclusion

As we are using more technology, we see that the spectrum is coming to a capacity crunch at several frequencies. While some frequencies are being used to their full capacity, others are being sparsely used. There is a need to use the unused allocated spectrum. This leads to a new paradigm called Dynamic Spectrum Access(DSA) which looks for opportunity to occupy the underutilized spectrum that is not currently being occupied in this allocated spectrum. However, for Dynamic Spectrum Access to use this opportunity, it needs spectrum sensing and characterization across time, frequency, and space.

Most of the current option for spectrum sensing and characterization are high-cost. We want to look at low-cost options and compare the characterizations of the low-cost and high-cost sensors.

For looking at the characterizations, we can see that the characterizations are comparable for different fft sizes apart from a irregularity for 4096 fft size. We also see similar results for both mobile and stationary transmissions for mobile sensors for both periodic and aperiodic transmission patterns. However, in the case of our sensitivity experiment, where we look at characterizations at different distances, we see that low-cost sensors have lower sensitivity and tend to have lower perceived duration at larger distances.

We see that to have an economically feasible infrastructure with high-fidelity spectrum scans, a heterogeneous infrastructure seems to be the better option. However, to use low cost sensors to create our infrastructure we can increase the density of these sensors to overcome the drawback of low fidelity.

7.1 Future Work

Our future work includes doing more experiments with uncontrolled transmitters. This includes transmitters in the area like cellular towers. We aim to characterize these scans from these real world scenarios to really understand the behavior of the two sensors in the real world.

As a part of our analysis, we discovered that the scan imperfections of low-cost sensors sometimes manifest themselves as deceitful transmitter behavior: where one would expect the transmitter to be active the spectrum appears idle. We call such deceitful behaviour sensor-induced scan artifacts. As a part of our future work we will investigate how the occurrence of such artifacts is related to the sensor properties. We will, in turn, develop mechanisms that can automatically differentiate between true transmitter behavior and sensor-induced artifacts.

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