

# Local and Low-Cost White Space Detection

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**Abstract**—White spaces are portions of the TV spectrum that are allocated but not used locally. If accurately detected, white spaces offer a valuable new opportunity for high speed wireless communications. We propose a new method for white space detection that allows a node to act locally, based on a centrally constructed model, and at low cost, while detecting more spectrum opportunities than best known approaches. We leverage two ideas. First, we demonstrate that low-cost spectrum monitoring hardware can offer “good enough” detection capabilities. Second, we develop a model that combines locally-measured signal features and location to more efficiently detect white space availability. We incorporate these ideas into the design, implementation, and evaluation of a complete system we call Waldo. We deploy Waldo on a laptop in the Atlanta metropolitan area in the US covering 700 km<sup>2</sup>. Our results show that using signal features, in addition to location, can improve detection accuracy by up to 10x for some channels. We also deploy Waldo on an Android smartphone, demonstrating the feasibility of real-time white space detection with efficient use of smartphone resources.

## 1. Introduction

In 2008 the FCC issued a ruling that allows the unlicensed opportunistic usage of unused portions of the UHF and VHF spectrum [6], referred to as TV *white spaces*. This ruling triggered research and development of white space standards, protocols, and prototypes [12], [23], [46] due to the good propagation characteristics of signals at those frequencies, and the abundance of white space bandwidth in many settings [12]. When using white spaces, it is critical to keep spectrum incumbents *safe*, by avoiding interference with licensed transmissions from the primary spectrum incumbents. When safety is assured, *efficiency* becomes important, so that as many white spaces can be detected as possible.

The approach preferred by the FCC for white space detection is the use of a spectrum occupancy database. These databases are trusted, centralized entities that store information about the location of primary incumbents and use propagation models to infer geographic regions that are within incumbent transmission range. Users querying the database are given permission for opportunistic use of white space spectrum only in locations that are outside

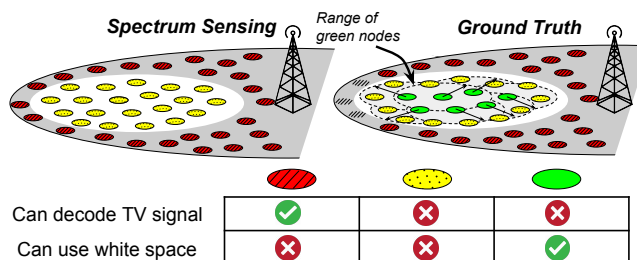


Figure 1. A “pocket” of white space represented by the white area with the grey area representing places where TV signal is decodable. Spectrum sensing dismisses the pocket by considering all nodes in it to be hidden nodes. The ground truth is that green (solid) nodes, that are far enough from red (striped) nodes not to cause harmful interference, should be able to use the white space.

all estimated incumbent regions. The spectrum databases approved by the FCC all use the same propagation model (R6602 [24]) and are subjected to rigorous testing to ensure they avoid interfering with incumbents. While this approach ensures safety, spectrum databases constructed using this propagation model have significant *overprotection* errors that limit coverage and reduce efficiency, meaning they deem locations to be within incumbent range when they are not. This overprotection reduces the opportunities for white space use, reportedly up to 71% [52].

A second approach to white space detection involves local sensing to determine whether the desired spectrum is used by an incumbent, without relying on a database. As depicted in Figure 1, local sensing has the potential to improve efficiency by detecting “pockets” of channel availability, produced by terrain variations and obstacles, that can be missed by generic propagation models. The problem with this approach, however, is that local sensing at a device is subject to *underprotection* errors when the device falls in a hidden node scenario. This can happen, for example, if an obstacle prevents the device from detecting the full-strength TV transmission signal, yet the channel is in use within the region. To reduce the risk of such errors, the FCC requires that devices using local spectrum sensing avoid channels they detect at a lower power (-114 dBm) than the minimum decodable TV signal power (-84 dBm) [9]. With this low power requirement, local spectrum sensing also results in overprotection, up to 2x of the actual

coverage area [30]. Moreover, spectrum analyzers capable of detecting at the lower power threshold are expensive (\$10-40K) [33].

The growing importance of efficiency as a metric has sparked recent research aiming to provide more accurate approaches without compromising safety. The importance of efficiency becomes evident when considering the obvious shortage of white space opportunities in urban areas when employing over-protective approaches [45]. This shortage is further exacerbated by the RF smog urban areas typically suffer from within the ISM band [28]. Such shortage, along with the better propagation and power efficiency characteristics white spaces possess compared to the ISM band [12], makes improving channel detection accuracy a major objective. Recent work tackles this problem by either using more accurate propagation models, validated with large scale measurements [38], or augmenting measurements with databases [18], [44], [52]. These approaches rely on constructing a model that better captures signal propagation in a specific area, thus mitigating errors in generic propagation models. However, these approaches rely on -114 dBm sensing which requires expensive equipment, rendering them practically infeasible.

In this work we ask the following question: *Can low cost spectrum sensing be used as the basis for a white space detection system that rivals or improves upon spectrum databases and existing spectrum sensing solutions?* At first glance the answer would seem to be no. Low cost spectrum monitoring hardware is not capable of detecting at the required -114 dBm level. However, through extensive measurements, we show that low cost sensors are capable of detecting at the -84 dBm level. We also show that -84 dBm is sufficient as the basis of a detection scheme when used in combination with readings from other nearby sensors on the same channel. With appropriate algorithms, collective data can be used to more efficiently detect white spaces, with comparable protection for incumbents, compared to spectrum databases or high fidelity single location measurements. We are essentially capable of identifying the green (solid) nodes in Figure 1 that can use white spaces, which spectrum sensing would dismiss by considering them hidden nodes.

After conducting a measurement study to evaluate two different low cost sensors, we turn to their use in our Waldo (White space Adaptive Local DetectOr) System. Waldo relies on crowdsourcing local spectrum measurements, performed by low-cost sensors, to a central repository where location-based models for white space availability can be constructed. White space devices access the repository by providing location and signal features to obtain information on whether a channel is available for opportunistic use. Waldo thus combines elements of local spectrum sensing with elements of a modeling-based central database, introducing a balance between *sensing* and *sensibility*.

We conduct an evaluation of Waldo using a laptop to show that our proposed approach can outperform conventional state-of-the-art in white space detection by up to 10x in terms of accurately detecting white spaces. We

demonstrate the practical feasibility of the proposed system by deploying it on an Android phone and show that realtime results can be produced with a small resource footprint, using 2.35% of the processing power on average.

Overall, we make the following contributions:

- We present a large scale measurement study comparing the sensitivity of two low-cost sensors and benchmarking their white space detection performance as compared to a high-cost spectrum analyzer.
- We propose a new approach for white space detection that combines the centrally coordinated, location-based nature of spectrum database, along with the realistic view and local nature of spectrum sensing. We present the design and implementation of Waldo, a system that embodies the new white space detection approach.
- We analyze the performance of the proposed system using the data collected in the measurement study. We also evaluate the deployment of such a system on a typical Android phone in terms of processing overhead and responsiveness.

The remainder of the paper is organized as follows. Section 2 presents a study showing the feasibility of the proposed system using low-cost sensors. The details of Waldo are then presented in Section 3 and evaluated in Section 4. An implementation of Waldo on an Android phone is presented in Section 5. Section 7 provides an overview of related work and the paper is concluded in Section 8.

## 2. Viability of Low-Cost Sensors

We explore the accuracy of two low-cost sensors for white space detection. In particular, we define clear bounds on the “usefulness” of low-cost spectrum sensors represented by a USRP B200 as a high-end sensor, costing \$686<sup>1</sup>, and an RTL-SDR TV dongle as a low-end sensor, costing \$15. A “good enough” sensor should possess sufficient sensitivity to detect white spaces while maintaining efficiency and safety. We briefly define each of these factors [38]. *Sensitivity* is a measure of the lowest signal strength distinguishable from the noise floor. *Safety* is defined as minimizing interference with spectrum incumbents by reducing false positive detection decisions. *Efficiency* is the maximization of the detected white space opportunities by reducing false negative detection decisions. We validate our findings by comparing low-cost sensors to a high end spectrum analyzer through a large scale measurement campaign conducted in the Atlanta metropolitan area in the US.

### 2.1. Setup and Methodology

**Data Collection:** The measurement collection setup is depicted in Figure 2. A typical sensing node in the envisioned system should have only one sensor. However, our

1. Note that USRP is a versatile piece of equipment with RF coverage from 70 MHz to 6 GHz which is much more than needed for the sensing tasks we use it for. A more specialized card should have a lower cost.

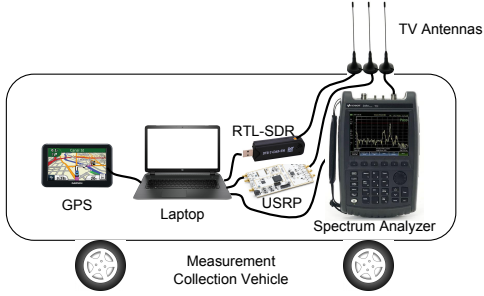


Figure 2. War driving setup.

war driving setup has three different sensors (i.e., RTL-SDR [3], USRP B200 [5], and FieldFox N9917-A spectrum analyzer [2]). The USRP and the RTL-SDR were calibrated using an Agilent E4422B signal generator to compute a linear function that maps different input levels to their corresponding output readings of conventional energy detectors [16]. The calibration was performed via a wired connection, to develop a baseline for the sensitivity of the sensors.

In our setup, all sensors are connected to a laptop. Each sensor is connected to an omnidirectional antenna with 0 dB gain. Antennas are mounted on top of a minivan vehicle (i.e., antenna height around 2 meters above ground level). The RTL-SDR is connected through a USB 2.0 port, the USRP through a USB 3.0 port, and the spectrum analyzer through an Ethernet connection. Readings are collected from all devices simultaneously using a python script that relies on GNUradio v3.7.5 [16] for the USRP and the RTL-SDR, and Standard Commands for Programmable Instruments (SCPI) for the spectrum analyzer. Each collected reading is tagged with a GPS coordinate reported by a Garmin GLO GPS receiver.

Readings are collected continuously through data collection drives that cover around 800 km with a total area of around 700 km<sup>2</sup> (Figure 3). Empirical data from earlier work suggest that the correlation between shadowing effects at two points is described by  $R(d) = e^{-ad}$ , where  $d$  is the distance between the two points and  $a$  is an environment parameter [29]. Hence, good detection accuracy between collaborative nodes can be achieved in urban areas if the separation distance between two measurement points is larger than 20 meters [27]. In our setup, readings collected for a certain channel are always separated by more than 20 meters.

**Collected Data:** One of our goals is to show the robustness of the calibration process. We used several RTL-SDR devices for data collection which also implies that the generated calibration parameters are not unique for a certain device. Furthermore, we gathered two sets of measurements collected several months apart and we used the same calibration factors for both sets. We collected a total of 5282 readings per channel per sensor for nine channels and three sensors. Each collected reading is comprised of GPS location, signal strength reading, and 256 In-phase/Quadrature (I/Q) samples. Signal strength reading are generated using

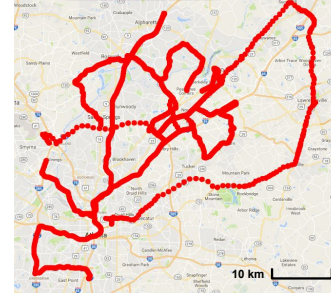


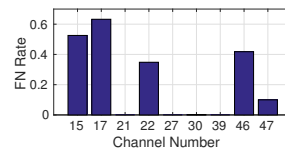
Figure 3. War driving path within Atlanta metropolitan area, USA covering 700 km<sup>2</sup>.

**Algorithm 1** Determines if a location is not safe for white space operation based on collected measurements at that location and nearby locations (i.e., a node is safe otherwise).

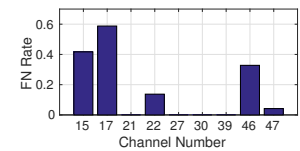
```

1: procedure LABELDATASET ()
2:   for all Node  $n$  in Dataset do
3:     if  $Power(n) > -84$  dBm then
4:        $SetNotSafe(n)$ 
5:     for all Node  $n'$  in Dataset do
6:       if  $Dist(n, n') \leq 6$  km then
7:          $SetNotSafe(n')$ 

```



(a) Not accounting for antenna correction factor



(b) Accounting antenna correction factor

Figure 4. False negative rate of Google spectrum database as compared white spaces detected through spectrum analyzer measurements. Accounting for antenna correction factor reduces the number of detected white spaces, however, the error of spectrum databases remains high.

an energy detector that takes the 256 I/Q samples as input and generates signal power in dBm.

In order to minimize noisy readings and lower the noise floor during spectrum sensing measurements, we use a similar approach to spectrum sensing as in V-Scope [52]. Essentially, instead of measuring the signal power over the whole 6 MHz bandwidth of each channel, we focus on the narrowband surrounding the pilot frequency. The pilot of a digital TV channel is required to be 11.3 dB lower than the total power of the channel. In this paper, we add 12 dB to the power of the pilot that is obtained after the calibration function mapping. For safety and efficiency analysis, all nine channels are considered. However, for the system performance evaluation only seven channels are used. This is because the remaining two channels were completely occupied by incumbents in all of our measurements which makes them uninteresting for the system's performance evaluation.

**Data Labeling:** FCC regulations for protecting incumbents define the protected contour of a TV station as the

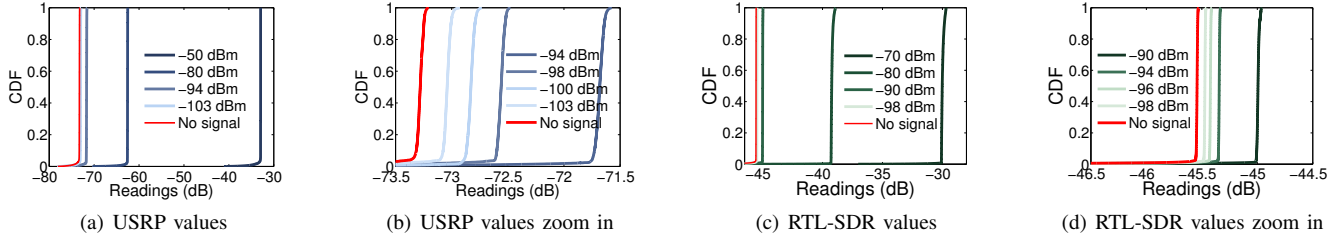


Figure 5. CDF of USRP and RTL-SDR readings for different inputs generated by a calibrated signal generator. RTL-SDR sensitivity allows it to detect signal levels down to  $-98$  dBm. USRP is more sensitive and able to detect readings down to  $-103$  dBm.

area where the received signal strength is more than  $-84$  dBm [6], [37]. Protection of TV receivers from White Space Device (WSD) operation requires a further separation distance that depends on the antenna height and transmission power of the WSD (e.g., 6 km for portable devices [7]). We use this definition to label our data as either safe or not safe for white space operation (Algorithm 1). We label a location as safe for white space operation if the nearest reading with  $RSS \geq -84$  dBm is more than 6 km away. Otherwise, it is considered not safe. *This labeling approach is biased towards the protection of the spectrum incumbents as noisy readings higher than the  $-84$  dBm threshold affect all readings within 6 km radius.* The effect of noisy readings inaccurately below the  $-84$  dBm threshold is mitigated by surrounding readings that are not noisy. It is also important to note that the conservativeness of this approach can be controlled by decreasing the threshold.

We realize that using the  $-84$  dBm without compensating for typical TV antenna heights of approximately 10 meters can lead to erroneous decisions regarding the presence of TV stations. In particular, not having high enough antennas during measurements can lead to false views of the absence of TV stations. Hence, we account for using antenna heights of 2 meters, with a difference of  $h_m = 8$  meters from the 10 meters assumed in regulations, using the antenna correction factor  $a(h_m)$  of Hata's urban area propagation model  $a(h_m) = 3.2(\log 11.5h_m)^2 - 4.97$  [31]. This yields a 7.5 dB correction factor that should be added to  $Power(n)$  in Algorithm 1. We add the correction factor uniformly to all RSS values used in labeling points as safe or not safe. Adding a uniform antenna correction factor means that most readings which would have been considered noise otherwise, are too close to the  $-84$  dBm threshold. This increases the probability of false detection of TV channels by a spectrum sensor which adds to the approach's safety. Figure 4 shows the effect of antenna height on the availability of white spaces which databases cannot detect.

The antenna correction factor is a constant added uniformly to all readings, which does not contribute to the complexity needed to model white space behavior by our proposed approach or approaches we compare to. Hence, without loss of generality of the proposed approach, we focus on scenarios where we measure white space detection at ground level rather than at 10m and report some results for accounting for antenna correction factor. This paper is a

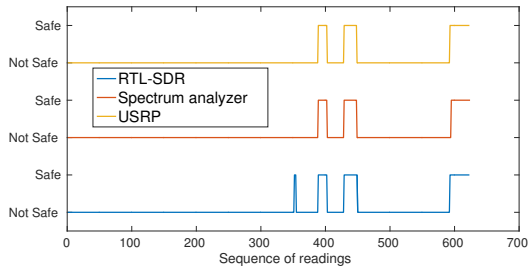
first step in this direction of using low-cost sensors in white space detection using both signal measurements and location information. A full operational system will require further testing in multiple locations and using a wider variety of low-cost sensors and better modeling of factors (e.g., the antenna correction factor).

## 2.2. Low-Cost Sensor Performance

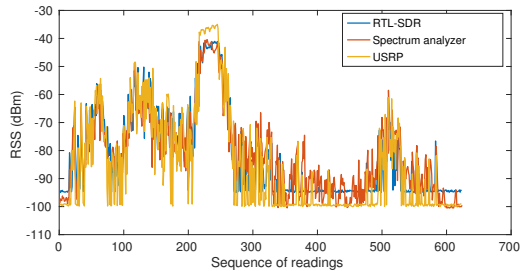
**Sensitivity analysis:** We compare the sensitivity of RTL-SDR and USRP in detecting a signal from a wired input signal with known power. This analysis compares the absolute sensitivity of both sensors. Figure 5 shows the CDFs of the reported readings of both sensors for different input power levels. As the CDF of the reported readings get closer, distinguishing two input levels becomes harder. For the RTL-SDR, the CDF shows little variability, however, the USRP results show some variability which increases chances of confusing two input levels for the USRP. This stability of RTL-SDR was validated on two different pieces of hardware to ensure that it is not a singularity in a single sensor. Similar results were produced when the RTL-SDR was connected to the Android smartphone. As expected, the sensitivity of the RTL-SDR is less than the sensitivity of the USRP. The RTL-SDR produces a CDF for any input signal level below  $-98$  dBm nearly identical to CDF of readings collected when no signal is supplied (Figure 5(d)). On the other hand, the USRP can detect a signal down to  $-103$  dBm as indicated in Figure 5(b).

**Safety and efficiency analysis:** For this study, we consider results obtained by the spectrum analyzer to be the ground truth of white space detection<sup>2</sup>. We follow Algorithm 1 for labeling detection decision. We compare the detection decisions made by the spectrum analyzer to the decisions made by the RTL-SDR and USRP. Figure 6 depicts the comparison for one channel. We count misdetections (i.e., false negatives) by the low-cost sensors for all channels as a measure of efficiency. Our results show misdetection rates of 39.8% and 20.9% for RTL-SDR and USRP respectively. We count the false alarms (i.e., false positives) by the low-cost sensors as indicators of safety. The results show false alarm rates of 0.8% and 5.2% for RTL-SDR and USRP respectively. These results show that both low-cost sensors can detect white spaces ignored by

2. Spectrum analyzer data is used only for validation not labeling.



(a) Comparison between white space detection decision.



(b) Comparison between recorded RSS values.

Figure 6. Comparison between USRP, RTL-SDR, and spectrum analyzer detection capabilities showing both detection decisions (i.e. labels) and RSS readings. Correlation between the measurements from all devices is evident.

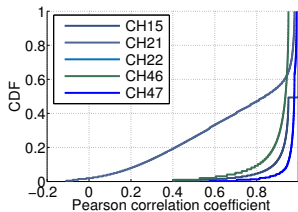


Figure 7. CDF of Pearson's correlation coefficient between RTL-SDR labels and USRP labels.

current approaches. Yet, RTL-SDR lacks the sensitivity to have as high efficiency as spectrum analyzers. On the other hand, both sensors have high safety which results from our approach that allows one reading above  $-84$  dBm to affect the decision of all readings within a 6 km radius of it.

**Comparison of RTL-SDR and USRP detection accuracy:** Despite the difference in sensitivity between the RTL-SDR and the USRP, both sensors produce nearly identical white space detection decisions. Figure 6 shows a visualization of data collected for all sensors for channel 47 showing their class (i.e. safe or not safe) and the received signal strength. The figure shows that all sensor produce almost identical results. Figure 7 summarizes the results for the rest of the measured channels showing that the median of correlation coefficient between the labeling of both sensors is above 0.9 for all cases. The one channel with an anomalous behavior (i.e., channel 21) is where the RTL-SDR has a higher misdetection rate due to its lower sensitivity.

**Conclusion:** With high density<sup>3</sup> spectrum measure-

3. Different sensors, including spectrum analyzers, produce similar error at densities higher than 15 measurements per  $\text{km}^2$  [22].

ments, low-cost sensors can detect white spaces with high safety (i.e., 0.8% false alarms for the RTL-SDR) and reasonable efficiency (i.e., 39.8% misdetections for the RTL-SDR) compared to spectrum analyzers. Hence, labeling signal measurements, using the aforementioned technique, requires low sensitivity of only  $-84$  dBm while producing high safety and reasonable efficiency. We rely on this finding to build a white space detection system that relies solely on measurements collected by low-cost sensors, yet maintains the safety and improves on the efficiency of the state-of-the-art detection systems.

### 3. Waldo

We present the details of Waldo, a spectrum-sensing-based system that combines signal features with location information to improve accuracy of white space detection. The system relies on low-cost sensors allowing Waldo to reduce the cost of white space detection. It also allows for local decision as compared to spectrum databases that require out of band connectivity to the database for each lookup.

It is important to clarify a couple of non-goals. *Waldo does not present novel statistical models for capturing signal propagation characteristics.* It rather aims at producing low-overhead accurate models based on **standard classifiers**. Moreover, *Waldo does not present new signal features.* It aims at fusing location information with spectrum measurements to improve sensing accuracy and reduce its cost.

#### 3.1. System Overview

Figure 8 provides an overview of the system's flow of operations. The system has two components: 1) a central spectrum database, and 2) mobile White Space Devices (WSDs). Waldo works in two phases:

1. An offline phase, during which the central spectrum database collects location-tagged spectrum measurements from crowd-sourcing devices [40], [53] or low-cost dedicated infrastructure (e.g., sensor-mounted public transportation [52]). These measurements are used to construct local models representing white space availability at different large areas.
2. An online phase, during which a WSD downloads the model for the area where it is located. The WSD uses the model to detect white spaces by feeding it location-tagged measurements it collects locally. The location-tagged measurements are uploaded to the database to improve the model.

The *Model Constructor* module processes collected data and produces parameters of a classification model (§3.2). When a WSD needs to use white space channels, it first checks whether it already has a *White Space Detection Model* covering its current location. If it does, the WSD uses the available model to estimate the available white spaces, locally, by feeding the *White Space Detector* signal readings and location information into the model (§3.3). If no model is available for the device's current location, it is required to

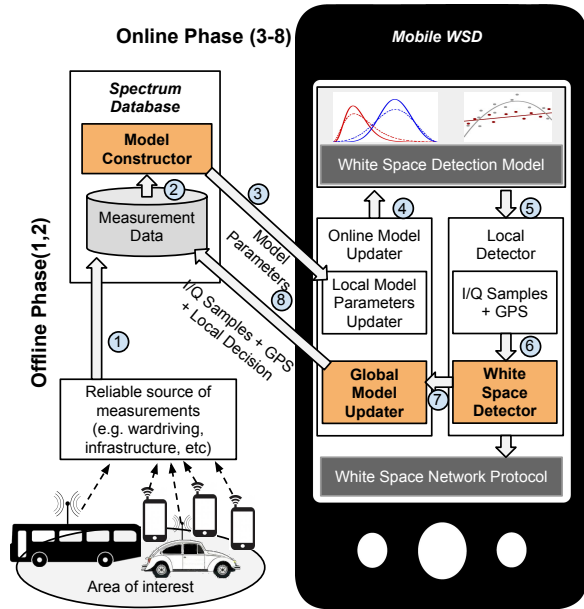


Figure 8. Waldo flow of operations.

connect to Waldo’s spectrum database to obtain the model’s information using its *Local Model Parameters Updater*. A WSD is expected to connect to the central database in this case through the same means it connects to a conventional spectrum database. However, an important distinction is that when a WSD connects to Waldo’s spectrum database, it downloads a lightweight model that can be used to infer data for large areas with higher accuracy, as opposed to the conventional databases that requires frequent queries.

Once a WSD is connected to the Internet through a white space network, it can update Waldo’s spectrum database with location-tagged measurements using the *Global Model Updater* (§3.4). A clear motivation for this exchange of information is that devices can obtain more channels by having more accurate models.

### 3.2. Model Constructor

The *Model Constructor* module builds a binary classifier that determines if TV band channels are safe or not safe for white space operation. In order for Waldo to operate, a dataset of signal samples covering all channels of interest within a certain area should have been collected by trusted entities which can be network users or low-cost infrastructure. Collected data are labeled centrally using Algorithm 1. The model construction process is performed at the spectrum database based on the labeled data using the following approach. The steps of the model construction are summarized in Figure 9.

**Localities Identification:** A binary classifier can be trained using all data collected, which can cover hundreds of kilometers square or more which allows producing small number of models, hence, requiring less communication between WSDs and the database. However, having one model for a large area can reduce the accuracy of the

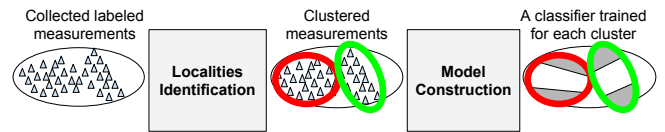


Figure 9. Breakdown of model construction steps.

classifier compared to more localized models that cover smaller areas. We strike the balance by partitioning the area based on the density of collected readings. Contiguous areas of covered by measurements should be grouped together to avoid misclassifications due to missing readings. We show that best performance for our area of interest (i.e., 700 km<sup>2</sup>) is attained using a small number of clusters (i.e., three clusters) (§4).

We cluster co-located readings using k-means clustering and generate a classification model for each cluster separately (i.e., local clusters). It should be noted that clusters that are all safe or all not safe enhance the efficiency of the model. Hence, a fine grain model can help make models more efficient by being binary (i.e. either always safe or always not safe).

**Model characteristics:** WSDs using Waldo download the classifier for each new area they enter. This requires classifiers that can be efficiently represented to reduce the overhead of downloading the classifier. Hence, having a small number of parameters and coefficients is an important characteristic of a classification algorithm that is Waldo-friendly. Such algorithms include SVM, Bayesian classifiers, decision trees, and regression analysis-based classifiers [17].

Although we collected a comprehensive dataset of spectrum information, the datasets collected through our study as well as similar studies tend to follow main roads and/or highways [38], [44], [52]. This makes the collected data sparse and susceptible to overfitting. For instance, our experiments with decision trees showed a maximum error of 1% which can be a result of an overfitting to the current dataset, as standard decision trees are usually outperformed by SVM [17]. Hence, we choose to demonstrate Waldo using two standard models that are suitable for the nature of the collected dataset: SVM and Naive Bayes. Both selected models are represented in a compact way and SVM is known to be less susceptible to overfitting [35].

**Signal Features:** Selecting signal features that best discriminate between a white space and an occupied channel is an important step to ensure the accuracy of the model. Conventional spectrum databases use only one feature (i.e. location) to classify a channel as a white space. Waldo uses signal characteristics of that channel as well as location. We consider several signal features in both the time domain (e.g. I/Q samples statistics) and the frequency domain (e.g. Discrete Fourier Transform (DFT) bins mean, DFT bins individual values, and DFT bins variance). We select features based on their discriminability between the two cases for white space (i.e. safe or not safe for white space operation).

We tested statistical difference between the case of white space availability for different features through analysis of variance (ANOVA). Three features exhibited significant

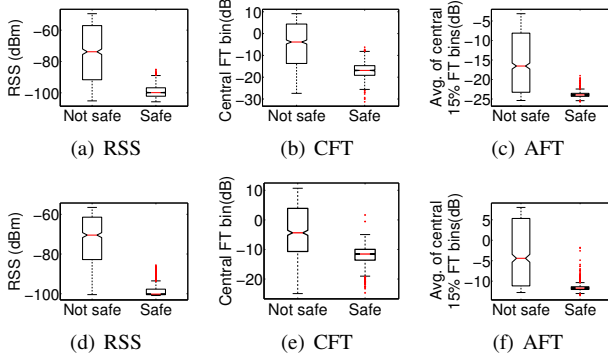


Figure 10. Boxplots for the value of three signal features for the two cases of Safe/Not safe showing USRP results (top row) and RTL-SDR results (bottom row) for channel 47.

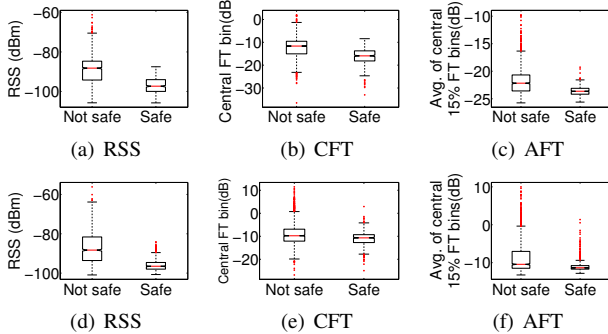


Figure 11. Boxplots for the value of three signal features for the two cases of Safe/Not safe showing USRP results (top row) and RTL-SDR results (bottom row) for channel 30. All features exhibit statistical difference between the two cases of occupancy which is clear visually for RSS and AFT.

discriminability: received signal strength (RSS), central DFT bin (CFT), and the average of the central 15% of the DFT bins (AFT). Figures 10 and 11 shows the values of those features for two different channels for both the USRP and the RTLSDR for channels 47 and 30, respectively. It is clear from the figures that the three selected features are sensitive to the presence of a TV signal even if it is near the noise floor (i.e. low RSS values). All three features were scored based on ANOVA calculations with a  $P$  value of almost zero for all selected features on all channels. The rest of the tested features score  $P > 0.1$  for at least one channel which discouraged us from exploring them further. We acknowledge that there is room for more research in detecting better signal features that can enhance detection accuracy.

### 3.3. White Space Detector

The main challenge faced by WDS using Waldo is overcoming the noisy nature of the low-cost hardware. This noisy nature is only exacerbated when the gain parameter of the devices is increased to enhance its sensitivity. One of the main functionalities of the *White Space Detector* is to overcome the effect of noise and reach a stable classification decision. We use smoothing through moving average to filter

out noise readings. Furthermore, outliers falling outside the 5<sup>th</sup> and 95<sup>th</sup> percentile of the data are filtered out. The average of the data is then used when the span of the 90% confidence interval is smaller than a sensitivity parameter  $\alpha$  (dB). We apply this selection process with a parameter  $\alpha$  so as to ensure that the value used fully represents the actual state of the channel. We presents the effect of the parameter  $\alpha$  on the delay of producing decisions (§5).

### 3.4. Model Updater

The two main challenges facing a large scale deployment of Waldo are: 1) collecting enough data to bootstrap the system, and 2) coping with changes in the environment that affect signal propagation. The *Global Model Updater* module is responsible for solving those two problems by allowing WSDs that use Waldo to submit portions of their readings that exhibit noise level that meet some criteria  $\alpha'$ . Each device uploads the readings it used to make the local decision which we find to be in the range of a few hundred kilobytes to 1 Megabyte depending on the convergence time which is a small amount of data to upload to the database.

The problem of ensuring the accuracy of updates and security of Waldo against malicious contributors is a serious aspect of the system design that needs addressing. Earlier work [26] discusses security of collaborative sensing systems and uses an approach that relies on correlating nearby readings from different contributors along with signal propagation characteristics to detect malicious contributions. Such approach can be directly used to secure Waldo.

## 4. Waldo Evaluation

In this section, we present an evaluation of Waldo where we show the effect of different systems parameters. We also compare Waldo to the state of the art.

### 4.1. Evaluation Methodology

We use the dataset we collected over 700 km<sup>2</sup> in Atlanta metropolitan area in the US from both a USRP and an RTL-SDR, as described in (§2.1). We start by showing the effect of adding signal features on the accuracy of classification, as compared to using only location. This provides a comparison between Waldo and the family of measurement-augmented spectrum databases. This family of approaches construct their models from local measurements, then use only location for classification using different analytical models (e.g. KNN, Kriging interpolation, or linear interpolation [10], [49] and regression analysis [52]). We implemented both components of Waldo in 700 lines of code using Java and OpenCV's Machine Learning Library [13] which is portable to Android (§5). We label all collected readings using Algorithm 1. Those labels are then used to train the two models. Our evaluation is based on 10-fold cross validation where we use randomly selected 90% of data to train the classifiers to classify the remaining 10% and repeat

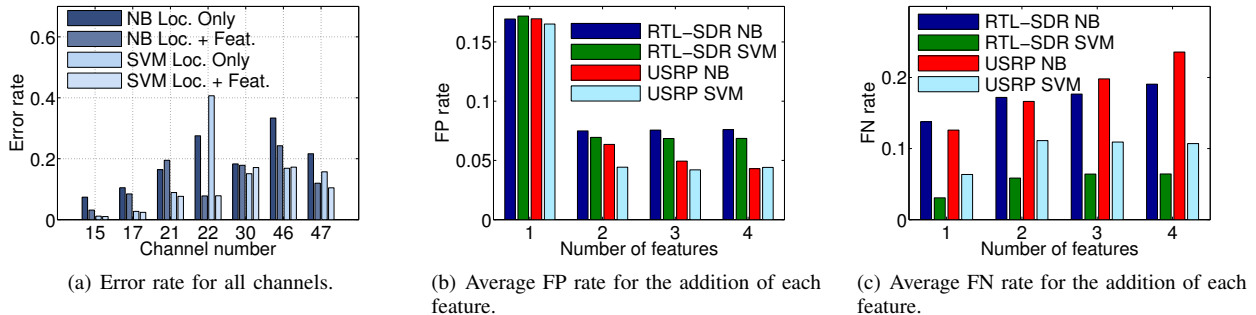


Figure 12. Error rate, FP rate, and FN rate for classification using location only and location with signal features. (a) Adding signal information always improves error rate. (b) USRP has higher sensitivity compared to the RTL-SDR. (c) RTL-SDR has less noise showing better specificity and hence less FN rate.

that process ten times to cover all data. We use only 10% as the testing data because the continuous update of the Waldo’s database ensures that training data will always be far greater than testing data.

## 4.2. Evaluation Metrics

We use three metrics to analyze the detection performance: the false positive (FP) rate, the false negative (FN) rate, and the Error rate. We use the same definitions of the metrics used in earlier work [38], [52]. False positives refer to cases where the system declares a channel vacant while it is occupied which reflect safety (i.e., should be kept close to zero). False negatives refer to cases where the system declares a channel occupied while in fact it is vacant which reflect efficiency (i.e., the metric we want to minimize). We also use the Error rate, which provides a single value to measure the effectiveness of the detection system, by reporting the total rate of errors, both positive and negative.

## 4.3. Performance of Waldo

We measure two aspects of the system for both the USRP and RTL-SDR. We believe this comparison can highlight ways for improving certain aspects of the hardware (e.g. sensitivity over specificity).

**Effect of adding signal features:** Figure 12(a) is a summary of our findings. It shows a comparison, for all channels, between NB and SVM with only location, and with location as well as signal information (i.e., RSS and CFT) as features. Figure 12(a) presents results obtained from only USRP measurements. The insight here is that adding signal features have a worst case that produces error rates similar to location-only models, while having the potential for enhancing the accuracy by up to 5x in the best case (i.e. performance on channel 17).

The true power of adding signal features becomes clearer in Figures 12(b) that compares FP rates for different numbers of features, averaged over all channels. Using one feature, which refers to using only location, provides the worst FP rate (i.e. worst in terms of safety). Signal features are added in the following order: RSS, CFT, then AFT.

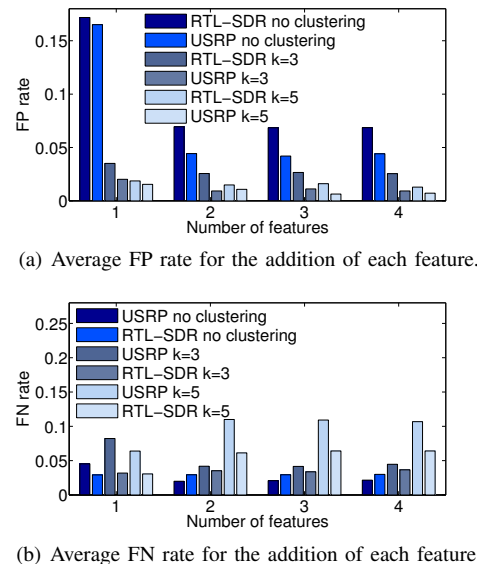


Figure 13. FP rate and FN rate for different values of number of  $k$  clusters (i.e., number of local models) for different number of features.

As features are added, FP rate (i.e. safety) improves. This behavior is consistent between different models and sensors. This result reflects the ability of this new generation of models to better capture the presence of the signal. Figure 12(c) shows the effect of adding features on FN rate. We observe that FN rate is slightly sacrificed. The figure also demonstrates the evident superior performance of SVM as compared to NB, especially in FN rate. Higher FN rate are produced by NB because signal features that represent signals that are too weak (i.e. signal near the border of a TV stations coverage area) can be confused by a probabilistic model with noise (i.e. no signal).

It is important to note that the USRP almost always has a better FP rate than the RTL-SDR. The difference in performance reflects the USRPs superior sensitivity (cf. §2.2). This sensitivity increases the probability of detecting incumbent signals which reduces the FP rate and increases FN rate due to higher probability of false detections. We stress that both sensors still produce comparable results and show similar trends that are far better than relying on location-only models.



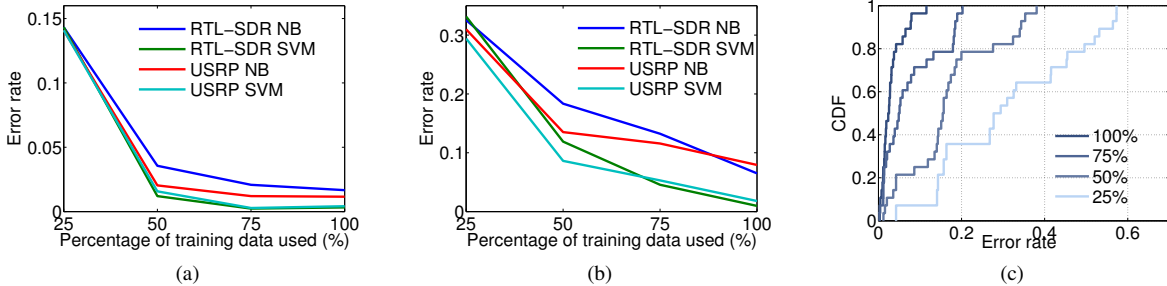
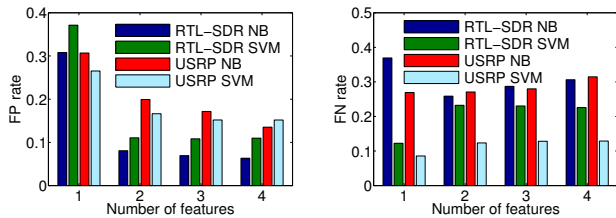


Figure 14. Effect of incremental increase of training dataset: In (a) and (b), channels 15 and 30, respectively, show clear incremental improvements. (c) error rate CDF for all channels as the training dataset increases.



(a) Average FP rate for the addition of each feature. (b) Average FN rate for the addition of each feature.

Figure 15. FP rate and FN rate with compensation for antenna height showing similar performance as in Figure 12.

**Effect of local models:** Figure 13 demonstrates the effect of varying the clustering size for local models. Clusters of measurements are determined based on the location of those measurements to allow for the construction of localized models. We choose small values for the number of clusters,  $k$ , to ensure that the generated local models still cover large areas. Furthermore, we aim at avoiding overfitting the data. It is clear that more local models can significantly enhance FP rate while slightly harming the FN rate, especially when moving from one model to three. The figure also reflects that the effect of adding signal features on the system’s performance is still maintained.

**Effect of updating the training dataset:** Figures 14(a) and 14(b) show the effect of increasing the size of the training set for a model trained with two signal features in addition to the location using a clustering parameter of  $k = 5$ . We select a random 10% of the data as testing data; we use the remaining 90% of the data to continuously update the training data by adding 11.11% of the remaining data at each step. Adding more training data improves classification accuracy. Figure 14(c) shows that adding more data consistently improves the system’s performance when averaged over all cases. The CDF of the error rate is generated considering all channels for all classification cases (i.e. using a different number of features with different sensors).

Although the dataset collected is not large enough to carefully study the effect of updating the training dataset, it is important to show that continuous updates can significantly enhance Waldo’s accuracy. This opens the door for developing more sophisticated algorithms and enhancing the detection accuracy once such large datasets are available.

**Effect of adding antenna correction factor:** The addi-

System	V-Scope	Waldo USRP	Waldo RTL-SDR
FP	0.3632	0.0441	0.0685
FN	0.2029	0.1068	0.0640

TABLE 1. A QUANTITATIVE COMPARISON BETWEEN THE SAFETY AND EFFICIENCY OF WHITE SPACE DETECTION SYSTEMS.

tion of the correction factor makes all readings collected for some channels (i.e. channels 21, 30, and 46) as not safe for white space operation. We report results for the remaining channels (i.e. channels 15, 17, 22, and 47). Figure 15 shows that adding the antenna correction factor doesn’t affect the trends reported for Waldo without it, which is expected being simply a constant factor added uniformly to all readings (§2.1). Hence, for the rest of this section we report only results generated without adding the antenna correction factor.

#### 4.4. Comparison with Earlier Work

There are three directions that are currently adopted by the research community as potential approaches for white space detection: 1) spectrum sensing [33], [51], 2) spectrum databases [30], [34], [38], and 3) measurement-augmented spectrum databases [10], [11], [18], [49], [50], [52].

We have shown in Figure 4 that using Waldo can detect more white spaces opportunities compared to conventional spectrum databases, (i.e. Google’s spectrum database [1]). We found spectrum databases to produce around 2% FP rate which is comparable to Waldo’s 4% averaged over all channels. We note that while the error in Waldo was similar in all channels, the FP rate of the database was around 14% in one channel and zero for the rest of the channels.

Comparing Waldo to spectrum sensing is fairly straightforward as they share in common the reliance on the local view of the spectrum. A fundamental difference between both approaches is that spectrum sensing relies only on its sensory readings without attempting the usage of any other context information. This forces spectrum sensing to rely on low sensing thresholds which makes spectrum sensing infeasible in most scenarios due to equipment cost and size. Waldo incorporates contextual information (i.e. a model that ties signal features at a certain location to white space availability). This difference in approaches allows Waldo to detect white spaces that are ignored by sensing-only approaches. It also allows Waldo to use low-cost sensors.

Detection Method	Spectrum sensing	Spectrum databases	Measurement-augmented DB	Waldo
Source of information	Local information	Universal models	Locally constructed models	Local information + locally constructed models
Safety	Very High	Very High	High	High
Efficiency	Moderate	Low	High	Very high
Operational overhead	High	Moderate	Moderate	Low

TABLE 2. A QUALITATIVE COMPARISON BETWEEN DIFFERENT WHITE SPACE DETECTION APPROACHES.

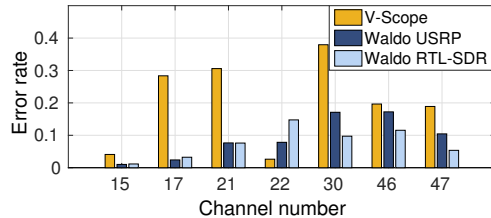


Figure 16. A comparison of error rate between *V-Scope* and Waldo.

We compare Waldo to a measurement-augmented databases represented by *V-Scope* [52]. We implemented the *measurements clustering* and the *propagation model fitting* modules presented in [52]. *V-Scope* extends spectrum databases that predict white space availability using universally constructed propagation models, by learning the parameters of the propagation model from locally collected measurements. We compare spectrum databases and *V-Scope* to Waldo’s performance for the USRP and the RTL-SDR using SVM with two features (i.e. RSS and CFT) and **no clustering**. The goal of removing the clustering step is to focus on the value of adding signal features to location for white space detection.

Table 1 compares the FP and FN rates for Waldo and *V-Scope* averaged over all channels. Waldo outperforms *V-Scope* by up to 8.2x in terms of FP rate and up to 3x in terms of FN rate. Waldo’s higher efficiency and safety are due to its ability to capture the shape of the coverage area by combining both signal features and location. On the other hand, *V-Scope* tries to predict the signal levels at a certain node based on the identified propagation characteristics at the area of interest. Hence, *V-Scope* does not take into account the nature of each specific point which can lead to errors. Figure 16 shows the error rate on different channels. Waldo performs better than spectrum databases in all cases and better than *V-Scope* by up to 10x. We note that even with adding the antenna correction factor, Waldo retains its superior performance.

## 5. Waldo on Android

We present the implementation and evaluation of a prototype of the proposed system on an Android phone. Our goal is to demonstrate the feasibility of our system in realistic mobile setup with respect to responsiveness, CPU overhead, and model download overhead.

**Implementation details:** The system was implemented by extending the *RFAnalyzer*<sup>4</sup> Android app which allows

4. The application is developed by Dennis Mantz. It requires an Android RTL-SDR driver by Martin Marinov.

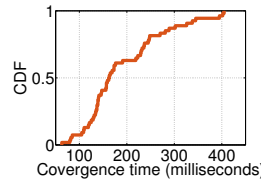


Figure 17. CDF of time it takes for the sensor to construct a 90% confidence interval of RSS with a 0.5dB span.

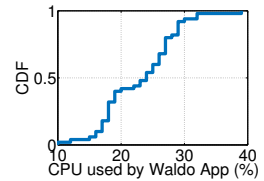


Figure 18. CDF of percentage of CPU used by Waldo App at peak periods when white space detection is activated.

for recording I/Q samples obtained from the RTL-SDR while connecting it to the phone using a Micro-USB-OTG-to-USB 2.0 Adapter. In order to ensure the optimization of the classification implementation used, we use the ML library of OpenCV4Android as its implementation is already optimized and written in native code for Android. The application implements the architecture presented in Figure 8.

The model uses GPS coordinates to determine the classifier parameters to download. When the needed model is available on the phone, the application sends the most recent I/Q samples along with the current GPS reading for feature extraction and classification. This process is then repeated every 60 seconds [6]. We consider a central server that obtains all measurements for the area of interest. This server trains the two classifiers and produces a configuration file that is sent to the mobile device.

**CPU overhead:** As for the implementation’s footprint on the device’s resources, Figure 18 shows a CDF of the application’s utilization of the device’s CPU. It should be noted that these utilization percentages represent peak times which are supposed to run once a minute for a total of 5.89 seconds. Hence, this utilization percentage has an average of only 2.35% when normalized over the whole minute.

**Model download overhead:** An initial factor of its design is the size of the model that represents the area of interest. OpenCV’s Machine Learning Library produces a descriptor file that has the parameters of each of the models. The size of the generated file is around 4 kB for NB and 40 kB for SVM. Hence, Waldo’s administrator can choose to optimize the system’s performance by carefully choosing the model. Choosing a model presents a tradeoff between accuracy and bootstrapping overhead (i.e. overhead of sending a model descriptor per channel). It should be noted that the size of the generated configuration file is comparable to the size of a typical white space query to a spectrum database, which is typically sized at a few kB [14]. However, a single white space query represents one location, while a model’s configuration file typically covers an area of tens of kilometers squared.

**Responsiveness:** We conducted several experiments to benchmark the time it takes the system to converge to a high confidence decision under different values for the sensitivity parameter ( $\alpha$ ), which represents the span of the 90% confidence interval of collected readings. To our surprise, for different values of  $\alpha$  between 0.5 dB and 5 dB, the convergence time does not change for stationary measurements, where the device is placed in the same location through the experiment. The convergence time for stationary experiments is presented in Figure 17, with an average of 0.19 seconds. We note that such convergence time can result in a total of 5.89 seconds of processing for all 30 channels which exceeds IEEE 802.22's guidelines that require sensing to be performed in only 2 seconds. However, improvements in hardware development for white spaces (e.g. FFT at the hardware level [53]) can significantly decrease Waldo's processing time. Furthermore, not all 30 channels are occupied everywhere, and clearly vacant channels, with no operational station anywhere in the area, can be cached and not scanned by Waldo. On the other hand, as predicted for low-cost sensors, the convergence time varied greatly for mobile experiment with a minimum of 0.3 seconds with a large percentages of no convergence. In mobility cases, larger values of  $\alpha$  can be used or the decision can be made for values at the 5<sup>th</sup> percentile and the 95<sup>th</sup> percentile with their decision NORed to favor decisions declaring the channel not safe.

**Conclusion:** CPU overhead was found to be almost negligible compared to typical CPU utilization figures [21], [25] with performance improving if GPU is used [21]. Model exchange overhead was found to be more efficient than current spectrum databases. Energy consumption of RTL-SDR-based spectrum sensing was studied in [14] and was found to be sometimes comparable to the energy consumption of queries to spectrum databases. Responsiveness of Waldo on Android was found to be 2.9x the time required by regulations and standards. The larger delays are a result of the noisiness of the low-cost sensors which also favors in most cases safety rather than efficiency in detection decisions. This noisiness can be significantly reduced with the development of better sensors [53] and carefully designed antennas.

## 6. Discussion

**Regulations:** An important issue for the realization of Waldo deployment is having updates in the FCC rules that acknowledge the lack of decodable signal as the main definition of a white space. It will also require providing a certification process for low-cost sensing devices. We feel optimistic about the feasibility of those amendments to regulations because Waldo already conforms with regulations with respect to the protection of TV band incumbents. Due to the continuous effort in improving white space detection approaches, the FCC has been reducing its restrictions to accommodate new research findings. Some of the improvements include relying on standalone databases instead of sensing and databases [6], [7], improving sensing thresholds

for wireless microphones from -114 dbm to -107 dbm [6], [7], and reducing the required separation distance for portable WSDs from 6km to 4km and finally to 1.7km [7], [8], [9].

**Applications of Waldo :** We believe that its applications go beyond being a standalone white space detection system. For instance, it can be used cost-efficient amending of propagation models' estimations used in spectrum databases [52]. Furthermore, it allows for a feasible large scale infrastructure that can be used for determining protected areas of primary spectrum users and monitoring cross interference between white space networks and spectrum incumbents (e.g., more affordable approach to work like [33], [47]). This approach can also be used as a standalone solution in extreme cases in rural areas where no internet connection and nodes are trying to communicate locally over large distances. Finally, we believe that the availability of data generated by this approach will enable innovation in the development of white space systems and regulations.

**Advancements in hardware capabilities:** The flexibility of Waldo, in terms of reliance on the spectrum database, is largely affected by the accuracy of the model and the amount of processing that can take place at the sensing node. Several advancements in both sensing devices [53] and phone capabilities can significantly enhance the potential usefulness of Waldo. Recently several new pieces of work suggest using RTL-SDR and similar cheap RF interfaces for spectrum monitoring for TV band, WiFi, and LTE purposes [20], [41], [53]. A comparison between different low-cost devices to chart difference in overhead and energy consumption was presented in [21]. The main target of this research direction is to develop and utilize cheap hardware to monitor the utilization of different portions of the spectrum. Advancements in this direction introduces new, more accurate, sensing hardware that Waldo can leverage to improve its overall performance.

**Compensating for antenna height:** In this paper, we presented results that show that Waldo maintains its high performance even when subjected to a constant antenna correction factor. Our goal was to avoid two paths typically followed in earlier work: 1) using -114 dBm as a threshold which implicitly compensates for such cases [18], [50], [52], and 2) comparing Waldo to propagation models that produce results for receiver antenna heights with the same value at which the data was collected (i.e. around 2 meters) [10]. This allows us to maintain the system's feasibility and provide a realistic comparison between Waldo and spectrum databases. However, the addition of a correction factor that is drawn from universal models motivates a separate and more directed study towards finding better ways to account for antenna heights. One approach can be considering reporting altitudes when WSDs update the model which can make use of cases when devices are in multistory buildings. However, such a study is out of the scope of this paper.

**Measurement collection and utilization:** Bootstrapping this system is an important issue. We believe that it should initially rely on trusted entities that perform war driving, then once a trusted model is constructed it can be updated

(Section 3.4). We also see, for large deployments of Waldo, a continuous realtime stream of spectrum scans that can be used to monitor and localize both primary and secondary networks [52].

## 7. Related Work

**Spectrum databases:** FCC regulations require the usage of propagation models to estimate the coverage area of TV towers. The efficiency and safety of several propagation models have been studied (e.g., FCC’s R6602 propagation curves [18], [52], Longely-Rice [44], Egli, and free-space models [38]). Propagation models have been repeatedly found to be safe, yet not efficient with a variance that depends on the model used. For the spectrum database’s safety and simplistic implementation approach, several systems have been presented to build such databases. Building such databases requires the efficient handling of storage of modeled coverage areas [30], [34], [38]. Several commercial databases are now available that are certified by the FCC (e.g., Google’s Spectrum database [1] and SpectrumBridge [4]).

**Measurement-augmented databases:** To improve on the efficiency of spectrum databases, it was recently proposed to rely on customized propagation models and real-time readings from spectrum analyzers rather than propagation models. WISER [50] pioneered this direction incorporating real-time readings from strategically placed sensors to allow for better indoor white space detection. V-Scope [52] further extended the idea to use collected spectrum measurements to construct area-specific propagation models. The work in [18] optimizes the operation of V-Scope-like systems by selecting locations for measurement collection based on the likelihood of standard model errors. Measurement-augmented databases are also used to coordinate usage of detected white spaces which requires less sensitivity from participating sensing devices [19].

Waldo shares with database-based systems the reliance on models and draws inspiration from measurement-augmented databases to rely on real-time measurements. Waldo relies on the same regulations to define white spaces, however, it follows a different path to white space detection. Waldo relies on both a device’s location and its view of the spectrum which was shown to improve the accuracy of white space detection. Moreover, Waldo relies on low-cost sensors for the construction of its model.

**Spectrum sensing:** While spectrum sensing was identified as a key technology for Dynamic Spectrum Access (DSA) early on [32], we are yet to see a satisfactory sensing-only system [42]. Energy detection is the most basic and intuitive approach for spectrum sensing [15]. This approach relies on the detection of signal strength at -114 dBm. Improvements on the accuracy of spectrum sensing include detection of signal features (e.g., matched filter detection). Cooperative sensing, which is a well studied topic, further improves on the performance of single-node sensing by either reducing sensing time or reducing inaccuracies [36], [51]. Waldo is highly related to cooperative sensing in the

sense that we rely on different sensory nodes to avoid erroneous decisions. Waldo combines spectrum sensing (i.e., where the input is sensory readings) along with signal modeling (i.e., where the input is location) to allow for low-cost sensing that is more accurate than typical modeling and measurement-augmented modeling approaches.

**Low-cost white space detection:** Recently, there has been an increasing interest in cost-efficient white space access. Snoopy [53] is an example of a low-cost system that employs a frequency translator to use WiFi hardware to perform white space signal detection and white spaces usage. Earlier work based on the same idea has been presented to demonstrate the same idea where better sensitivity was achieved at the expense of hardware cost and complexity [12], [39]. Other systems presented low-cost custom-built hardware that can provide enough sensitivity for white space detection and usage [43], [48]. Such systems and prototypes are complimentary to Waldo as any of these systems can be used as part of the war-driving setup or as a client that can provide more accurate sensor readings. Waldo is more concerned with the utilization of such systems for efficient and safe white space detection. We count on such advancements in hardware design to make Waldo more robust and practical.

**Spectrum monitoring:** Spectrum monitoring applications include spectrum enforcement to avoid misuse of the spectrum by any party [41], [47] and transmitter identification and localization [40], [52]. Several other systems were presented to provide spectrum monitoring for analysis and detection of misuse (e.g., using USRPs [47], RTL-SDR [22], [40], [41], or even spectrum analyzers [33]). Such systems perform a job that’s complimentary to Waldo whose main task is safe and efficient white space detection. However, Waldo can be further extended to employ some of these techniques.

## 8. Conclusion

We introduced a new approach to white space detection that utilizes ground truth measurements of TV signal decodability. We showed that low-cost sensors can detect these opportunities efficiently while preserving spectrum incumbents safety through a large scale measurement study. We presented Waldo, a system that enables low-cost, local white space detection by taking advantages of the new detection approach and low-cost sensors. Waldo uses signal features in addition to location to model white space availability. We also deploy Waldo and compare it to the state-of-the-art in white space detection and show that it can outperform it by 10x in terms of detection error rate. Finally, we deploy Waldo on an Android phone and show that it can efficiently detect white spaces without exhausting the phones resources.

## Acknowledgments

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