Inaccurate Spectrum Databases? Public Transit to its Rescue!

Tan Zhang and Suman Banerjee
Department of Computer Sciences
University of Wisconsin-Madison, USA
{tzhang, suman}@cs.wisc.edu

ABSTRACT

Unlicensed, secondary users of TV whitespaces today rely on spectrum occupancy databases to determine what spectrum they can use for their communication needs. In this paper, we first show that such spectrum databases (that depend solely on propagation models as per guidelines of the FCC in the USA) can be quite inaccurate leading to under-utilization of spectrum. Next, we propose that these spectrum databases can be significantly augmented using opportunistic measurements when possible. Instead of incorporating primary detection functions in each secondary device, we propose to use vehicle-mounted spectrum sensors that collect and report measurements from the road, which can serve as useful "anchor points" to enhance existing propagation models.

We have currently deployed a version of our system on a single public transit bus traveling across Madison, WI, in the USA. Based on measurements collected at over 1 million locations across a 100 square-km area, we find commercial databases tend to over-predict the coverage of certain TV broadcasts, unnecessarily blocking the usage of whitespace spectrum over large area (up to 42% measured locations). We further propose a model-fitting approach that refines existing propagation models with measurements, reclaiming a substantial amount of wasted area (up to 33% measured locations).

Categories and Subject Descriptors

C.4 [**Performance of Systems**]: Design studies, Measurement techniques

General Terms

Algorithms, Design, Measurement, Performance

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Keywords

TV Whitespaces; Spectrum Database; Vehicular Sensing; Propagation Model Fitting

1. INTRODUCTION

Through recent rulings, various spectrum regulatory agencies across the world have opened up a wide swath of spectrum (512 MHz - 698 MHz), commonly referred to as TV whitespaces, for unlicensed use. As demand for mobile and wireless connectivity continues to grow, such spectrum is going to be particularly attractive to address continued spectrum crunch.

One of the fundamental issues in utilizing TV whitespace spectrum is to correctly determine vacant and good channels for unlicensed use. In the USA, a FCC-approved mechanism for determining whitespace spectrum is based on spectrum occupancy databases that rely on propagation models to predict the signal strength of nearby primary transmitters. Being based solely on a propagation model, such an approach is likely to have errors, e.g., available whitespaces are marked as occupied leading to wasted opportunities for communications. The focus of this paper is two-fold: (i) to study potential inaccuracies of existing spectrum databases that depend solely on the mandated propagation models; and (ii) to define an intuitive approach to improve the accuracy of these databases by utilizing local measurements to complement the propagation models. In particular, we describe the preliminary design and implementation of a whitespace measurement system, called *V-Scope,* which opportunistically collects local whitespace measurements using public transport vehicles and allows for improved accuracy of spectrum databases.

Whitespace determination approaches and limitations: In a whitespace network, the unlicensed, secondary devices (TVBDs) are required to only operate in channels in absence of primary incumbents. As per FCC's ruling [2], there exist three types of primary incumbents, i.e., digital TV, analog TV and wireless microphones. TVBDs are expected to use one of the following two approaches to detecting primary activity. The first and the preferred way is to query a spectrum occupancy database with the geo-location of a TVBD. The database leverages well-known propagation models (such as R6602 [2]) to predict the coverage contour of TV broadcasts. To take account the transmission range of TVBDs, the database adds some additional distance to the coverage contour to obtain the so-called protection contour. A channel is concluded as whitespaces if the TVBD's location is outside the protection contour and vice versa. To protect wireless microphones, the database reserves two dedicated channels for their exclusive usage, and reserves a fixed (2km) protection contour around each microphone operating in other channels. The second approach is to have TVBDs to conduct local spectrum sensing. The FCC imposes a very stringent sensing requirement, i.e., to detect primary signals at -114dBm. This is to avoid the hidden terminal scenario and fading-induced inaccuracy.

We note neither approach is sufficient for building an efficient whitespace network. The spectrum database has inevitable inaccuracy. This is because its underlying model is tuned to average propagation conditions, and unable to capture the environment-induced variation, e.g., shadowing and multipath fading of specific contours, objects, and topologies. Our measurement shows this variation can be as high as 25dBm for two locations separated by merely 10 meters. The local sensing approach, while pragmatic, requires delicate hardware for detecting weak primary signals, which can largely increase the cost of each TVBD. In this paper we explore a third alternative — an opportunistic whitespace measurement infrastructure that distributively provides local measurements to augment the existing spectrum occupancy databases generated from propagation models. This would still eliminate the need for expensive spectrum sensing hardware and their overheads in the end TVBD devices, while organically bringing some of the advantages of spectrum sensing. We show that such an approach can help better identify whitespace spectrum, while adhering to the spirit of the FCC rulings.

The V-Scope approach: Collecting spectrum measurements from arbitrary and disparate locations over a large area seems to be a fairly challenging and laborious task. In this paper, we explore the use of public transit buses operating in Madison, WI, USA to carry whitespace spectrum sensors and collect measurements opportunistically as they travel [1]. Clearly, such an approach has costs and overheads in deploying and managing whitespace sensors mounted on vehicles. However, the advantage of this approach is that it can be opportunistic — each "mobile" sensor can add a proportional volume of useful measurements. In addition, these measurements are likely to remain useful for some time in estimating the power of primary signals. Perhaps this measurement infrastructure is most useful in dense, urban areas where greater accuracy of determining whitespace

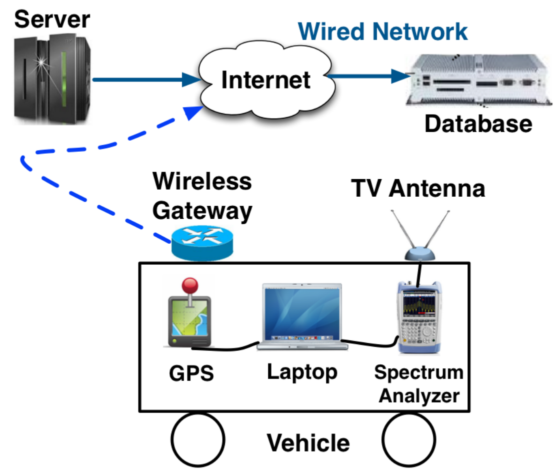


Figure 1: System architecture of *V-Scope*.

spectrum can make more spectrum "available" and can be particularly beneficial to users. In such scenarios, spectrum database providers can contract with public vehicle operators (or any 3rd party vehicle operator) to collect wide-area measurements with a few high-end spectrum analyzers, and in turn recoup these costs by adding them into existing fees to use such databases. In this paper, we do not explore the economic aspects of such opportunistic spectrum sensing, as it would really depend on the deemed value of the extra accuracy in determining whitespace spectrum. Instead, we focus on some of the technical issues in collecting whitespace measurements from (public transit) vehicles, and leveraging them to enhance existing spectrum occupancy information available from databases.

Key contributions: We have designed and deployed *V-Scope* on a single public transit bus in Madison, WI. Since our bus operator tends to rotate their buses through multiple routes in the course of each day, we have been able to collect spectrum measurements at more than one million locations over a 100 sq. km. area in and around our city over a two week period. In designing *V-Scope*, we have developed two specific techniques to address specific challenges: (i) a *zoom-in pilot tracking algorithm* for accurately measuring the power of TV signals up to -120dBm, and (ii) a *model refinement procedure* for augmenting existing propagation models (used by spectrum databases) with these local measurements, in which the spatial distribution of these measurements is non-uniform as the vehicle mobility is outside our control.

We show that current commercial spectrum databases that are based solely on propagation models waste whitespace spectrum over wide area (up to 42% measured locations). By combining *V-Scope* with even a simple propagation model (such as the free space model), we can significantly improve the accuracy of existing spectrum databases (that use the more sophisticated R6602 model), reclaiming a substantial amount of wasted area (up to 33% measured locations).

[1] Of course, public transit buses are just one of many possibilities for vehicles that can carry spectrum sensors; other potential examples are mail delivery trucks, taxicabs, and many other third party services that scour different city roads.

2. V-SCOPE DESIGN

In this section, we first give an overview of the *V-Scope* architecture, and then present the two key components in *V-Scope*.

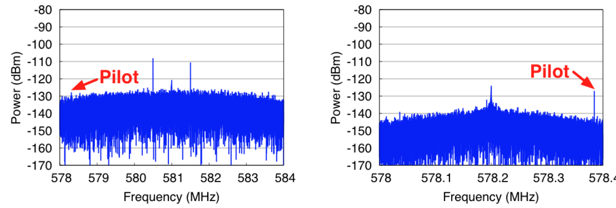
Overview: Figure 1 shows the overall architecture of *V-Scope*. It consists of a central server and multiple clients. Each client is running on a different vehicle and collects spectrum measurements during the drive. The measurement results are uploaded to the server using some wireless networks, e.g., cellular or WiFi networks. The server uses these measurements to construct region-specific propagation models that are tailored to local propagation environment. The refined model can be used by a database to predict primary signals in the vicinity of measured locations. The database may still use the global model (R6602) as fallback when no measurements are available.

V-Scope leverages two key techniques to refine a given propagation model. It first uses a pilot tracking algorithm to accurately detect and measure the power of a TV signal. Using these power estimates as "anchor points", *V-Scope* fits the parameters of a propagation model for each local region. We next explain these two steps in detail.

Zoom-in pilot tracking algorithm for accurately measuring the power of TV signals: Measuring the power of a TV signal can be very challenging because the noise generated by a spectrum analyzer is likely to overwhelm a weak TV signal. For example, our high-end spectrum analyzer (WSA4000 [10]) generates noise at -91dBm over a 6MHz TV channel, which is 23dB higher than the required sensing threshold (-114dBm). This harsh SNR condition prevents us from directly measuring the aggregate power of a TV channel. We note alternative approaches of using amplification hardware in front of a spectrum analyzer; however, this can cause strong primary signals to easily saturate the spectrum analyzer, thus reducing measurement accuracy in locations with strong TV reception.

V-Scope performs indirect power measurement by first detecting the pilot of a TV signal, then using this pilot to derive its total power. A pilot is a group of preambles appended at the beginning of each TV packet to assist decoding. They create a predominant peak in the frequency domain that is at a fixed location and more robust to noise than other spectral components. Unfortunately, even the pilot of a weak TV signal can be overwhelmed by noise. Figure 2(a) demonstrates this case with a digital TV signal at -114dBm. To reduce noise, *V-Scope* leverage a zoom-in technique by configuring the spectrum analyzer to capture at very narrow bands (488KHz) at the beginning of a TV channel. This can effectively reduce the noise floor, while producing a clear peak as shown in Figure 2(b). Since this peak is well distinguishable at the detection threshold, *V-Scope* uses it as an unique feature for detecting TV signals.

We benchmark the accuracy of the pilot-based detection algorithm in Table 1. The spectrum data was collected from 30 UHF channels at multiple locations. We use a high-end



(a) (b)

Figure 2: Different spectrum captures of a digital TV signal at -114dBm. (a) Full-channel capture; (b) Zoom-in capture at the first 488KHz band.

Detected Groundtruth	Digital	Analog	MIC
Digital	94.9	0.7	4.4
Analog	0.5	97.4	2.1
MIC	1.2	0.7	98.1

Table 1: Accuracy of primary detection algorithms.

TV receiver to establish the ground-truth. The identified TV signals (6 in total) were further attenuated for constructing spectrum traces at a wide range of power (-40dB to -114dB). We apply a standard cross-validation procedure by randomly choosing 90% data to detect the remaining 10%. We observe very low error rates (<5%) in detecting both analog and digital TV signals.

Merely knowing the presence of a TV signal is not sufficient for estimating its power. *V-Scope* leverages predetermined power relationships between a TV signal and its pilot to address this problem. According to TV standards [1], there is a fixed power offset between a TV signal and its pilot. For example, the pilot of a digital TV is required to be 11.3dB below the total power. We verify this power relationship using the data set mentioned above. Figure 3 shows that this relationship indeed holds for a DTV signal at a wide range of power, albeit with some variation (10 – 15dB). Thus, *V-Scope* can compute the total power of a TV signal by adding a constant offset η to its pilot power. Since the -114dBm detection threshold has taken account fading-induced inaccuracy [2], we choose η to be 20dB, adding an additional 5dB margin to provide extra safety in detecting primary users.

Putting it all together, our final algorithm starts by capturing spectrum fragments around the frequency of TV pilots. A potential pilot is extracted by first searching for the maximum FFT bin and then including all the continuous FFT bins around the max bin, if their power is higher than a threshold. From the obtained FFT bins, several features (e.g., power, center frequency and bandwidth) are extracted and fed to a decision tree based classifier for TV detection. Based on the type of the detected TV signal, a specific power offset η is added to the pilot power for calculating its total power.

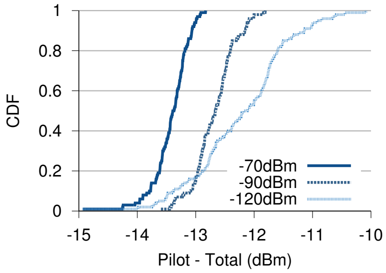


Figure 3: CDF of difference in power between a digital TV signal and its pilot.

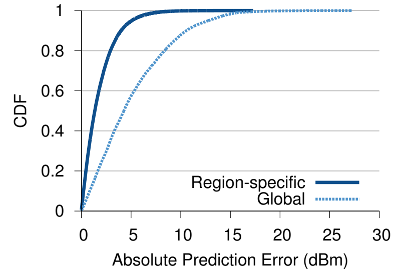


Figure 4: Optimum performance of fitted models in predicting the power of TV signals.

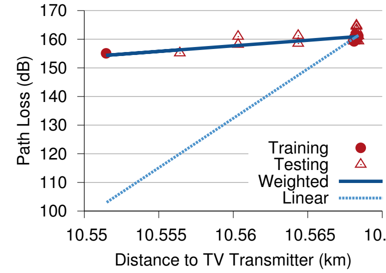


Figure 5: Example of a local path loss model fitted by linear regression and weighted regression.

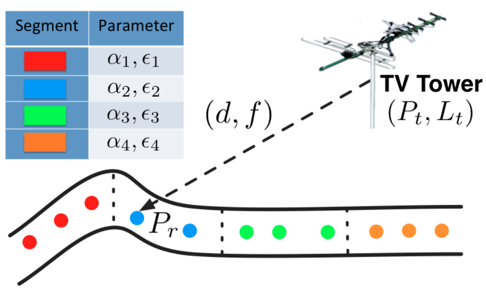


Figure 6: Illustration of region-specific models fitted by *V-Scope*.

Model refinement procedure for augmenting databases with local measurements: Using the estimated power of primary signals, *V-Scope* refines the parameters of a given propagation model to better predict the power of primary signals. It is based on a standard model-fitting procedure that takes the propagation model and measurements to construct a set of linear equations $Y_i = \alpha X_i + \epsilon$, where X_i is the distance of a measured location to the base station, Y_i is the measured power, and α, ϵ are tunable parameters of a model. It finds best parameter values by using the least-squares linear regression, with the objective of minimizing the squared sum of prediction errors ($\sum_i (Y_i - \alpha X_i - \epsilon)^2$). *V-Scope* have two improvement upon this approach – (i) fitting one set of parameters for each local area (i.e., region-specific) to better track local environment, and (ii) performing a weighted regression to remove the fitting bias caused by non-uniform distribution of measurements.

In *V-Scope*, we derive a region-specific model by fitting one set of parameters for each local region as shown in Figure 6. The motivation is that different regions are likely to have different propagation characteristics, especially in an urban environment. This can hardly be captured by a global propagation model, which uses a same set of parameters for predicting a wide area. To demonstrate this, we use linear regression to fit a different set of parameters (i.e., α, ϵ) of the free-space model using all the measurements in each 100m road segment. We then include the fitted parameters into the model to predict TV signals at all the measured locations in each segment. We compare this region-specific model with a global model using a single set of parameters fitted with all the measurements. Figure 4 shows that the region-specific model can achieve a median error of 1.4dBm and 75 quartile error of 2.6dBm, which are $3\times$ and $2.9\times$ lower than that of the global model. Thus, we fit one local model for each region to improve prediction accuracy.

In constructing local models, we note non-evenly spaced measurements collected on vehicles significantly degrade the performance of linear regression. Since a public vehicle drives at a varying speed and stops quite often, *V-Scope* collects measurements at non-uniform density. This causes linear regression to produce a biased model that favors densely measured area, while having large errors at sparsely measured area. The underlying reason is that linear regression tries to minimize the squared sum of fitting error; the locations with fewer measurements contribute less to the error sum, thus being under-fitted. Figure 5 shows the performance of a local model fitted with non-uniform measurements. We use 30 measurements (*Training*) to fit this model, and 29 of them are collocated at a bus stop. The model fitted by linear regression has up to 36dB error in predicting path loss compared to other groundtruth measurements (*Testing*).

The key intuition of our solution is to treat the measured locations, rather than measurements, fair in fitting a propagation model. *V-Scope* achieves this by using a weighted least-squares regression. It calculates a weight for each measurement based on its distance to other measurements. Formally, the regression algorithm aims to minimize the weighted sum of squares in fitting error: $WSS = \sum_i W_i (Y_i - \alpha X_i - \epsilon)$ with $W_i = \sum_j dist(i, j)$. This makes sparse measurements to carry larger weights, thus ensuring the sparsely measured area to be fitted equally well. Figure 5 shows the weighted regression has reduced the prediction error by 36dB compared to the linear regression.

To recapitulate, our model fitting procedure first bins measurements into road segments. For each segment, it computes a weight for each measurement based on its distance to other measurements in the same segment. It then applies these measurements and their weights to the weighted least-squares regression to construct the region-specific model.

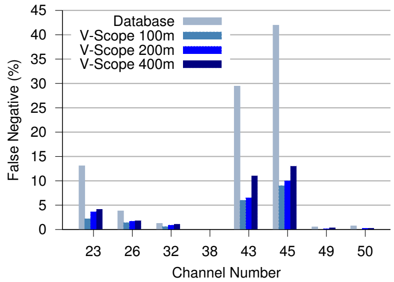


Figure 7: Accuracy of the database-only approach and measurement-assisted approach.

Figure 8: Error distribution of the database-only approach in channel 45.

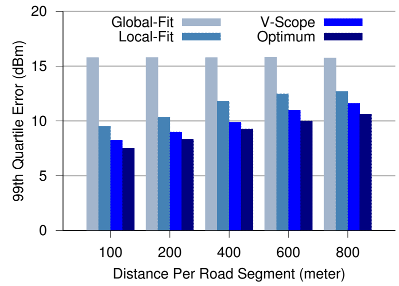


Figure 9: Accuracy of fitted models in predicting the power of TV signals.

3. IMPLEMENTATION

Hardware platform: We use a portable spectrum analyzer-WSA4000 [10] to collect spectrum measurements. It has a wide frequency range between 100KHz to 10GHz, and a capturing bandwidth from 488KHz to 100MHz. We configure the device to operate with the smallest bandwidth of 488KHz and the maximum FFT size of 32768, thus limiting the noise floor to be -147dBm per FFT bin. This allows us to reliably measure a TV pilot up to -140dBm, which is corresponding to a TV signal at -120dBm (Section 2).

Deployment: Our current deployment consists of one desktop server and one laptop-based client. The client is deployed on a metro bus traveling in and around Madison, WI. A laptop is used to control all the measurement procedures at the client. It instructs the spectrum analyzer to perform narrow-band captures in all 30 UHF channels. Using the collected spectrum samples (FFTs), the laptop detects primary signals and measure their power at very low latency (<500ms per channel). In the meanwhile, it obtains the measurement location from a GPS module, uploading the GPS readings and the detection results over a cellular gateway to the server. The server is situated in our university laboratory, with a well-provisioned Ethernet connection. It uses the GPS readings to query a commercial database (SpectrumBridge [9]), comparing the database's prediction with measurements. We have implemented the measurement procedure and the model fitting algorithm in 2000 lines of Python, along with a database query utility in 650 lines of C++.

4. EVALUATION

In this section, we evaluate the performance of a commercial database and *V-Scope* in identifying TV whitespaces. The dataset used in evaluation is collected during a two-week period, including measurements at more than 1 million distinct locations over a 100 square-km area in and around Madison, WI. We highlight our findings that the database has high inaccuracy in predicting certain TV broadcasts, unnecessarily preventing the whitespace usage at up to 42% measured locations. *V-Scope* can reclaim a substantial amount of spectrum wastage (up to 33% measured locations).

Accuracy of commercial spectrum databases: We start by evaluating the accuracy of a commercial database (SpectrumBridge [9]) in predicting TV broadcasts. There are totally 7 active TV channels in our measured area. We define two types of prediction errors, i.e., *false positive* and *false negative*. A false positive is a location where the database mis-predicts an occupied channel as whitespaces. The opposite is a false negative. We apply the -114dBm sensing threshold to our measurements to determine actual channel availability. We find very low (<0.4%) false positive rates in all the channels, which is similar to a prior report [4]. Thus, the current database can faithfully protect TV broadcasts.

However, Figure 7 shows non-negligible false negative rates in half of these channels. The worse channel (45) has 42% area unnecessarily blocked from unlicensed usage. We take a deeper look at the prediction errors in this worst channel based on measurements collected in a single day. Figure 8 shows the locations with channel 45 measured to be vacant, along with those mis-predicted as occupied by the database. We note most prediction errors are at the north-east side of the measured area, which is closer to the TV tower. Thus, we think these errors are likely caused by over-predicting the coverage of this TV broadcast.

Accuracy of region-specific model fitted by *V-Scope*: We compare our region-specific model with those fitted by three alternative approaches in predicting TV broadcasts. All the models are fitted from the free-space model. *Global-Fit* is a single model fitted for the entire measured area. *Local-Fit* is local models fitted by linear regression instead of weighted regression. *Optimum* is local models fitted by the same approach as *V-Scope*, but using all the measurements, thus indicating a performance upper-bound. Except for *Optimum*, all the models are fitted with a small fraction of measurements, and then used to predict other measured locations.

Figure 9 shows the 99th quartile error of different fitted models in predicting the power of TV signals. We first observe that *Global-Fit* has highest prediction error and achieves little improvement with more training data collected from smaller road segments. This is expected as the global can hardly be tailored to local propagation environments. We then note a 19%-40% improvement achieved by *Local-Fit* over *Global-Fit* because *Local-Fit* tunes a local model to each road segment. *V-Scope* outperforms *Local-Fit* by 8-13% owing to the use of the weighted regression. Furthermore, *V-Scope* achieves very close performance to that of *Optimum* (6-9% higher error). We believe the overall results are promising as 99% of errors in *V-Scope* are below 8dB.

Reclaimed area for whitespace usage by *V-Scope*: We use the *V-Scope* models fitted to 100m road segments to predict whitespaces. A channel is concluded as whitespaces if the predicted power is below the sensing threshold (-114dBm). Figure 7 shows the false negatives of *V-Scope* in all the active TV channels. We note that *V-Scope* can reclaim spectrum wastage at up to 33% measured locations (channel 45). We observe marginal improvement of using a segment size below 100m because most of the prediction errors are due to small-scale fading and temporal variation of signal strengths, which can hardly be captured by a propagation model. Finally, we report that *V-Scope* achieves a lower false positive rates (up to 0.27%) compared to the commercial database.

5. DISCUSSION AND FUTURE WORK

Predicting coverage of mobile transmitters: We intend to extend our model-fitting approach to predict the signal strength of wireless microphones and TVBDs. Our current algorithm requires precise information about the power and the location of a transmitter. But such information is not available for mobile transmitters in the current database due to scalability reasons. One possibility is to use measurements collected at different locations to derive this information, which we leave as future work.

Exploring sophisticated propagation models: *V-Scope* currently uses the free-space path loss model to construct local models. It is unclear whether more sophisticated models, e.g., Longley-Rice, are better for constructing local models and in what prediction range they are better. A major downside of these models is the computational overhead incurred by fitting more parameters. It is necessary to understand the trade-off between the accuracy and the computational complexity here.

Addressing temporal variations and measurement volume: One of the challenges in collecting opportunistic measurements is ensuring reliability of each individual measurement as the environmental conditions change with time. Care needs to be taken to ensure that only statistically significant measurements are used to augment existing databases, and stale measurements are appropriately invalidated. Finally, the volume of measurements to be collected and reported is a system overhead and needs to be traded against desired accuracy and robustness.

6. RELATED WORK

Spectrum occupancy database: Senseless [4] demonstrates the first effort in building a database-driven network over TV whitespaces. The proposed database uses a variant of the Longley-Rice (L-R) model augmented with terrain data, and is shown to incur low loss of whitespace spectrum. In the same year, the FCC mandates commercial databases to use an alternative, widely-used model (R6602 [2]). *V-Scope* finds non-negligible spectrum wastage in this database-only approach, possibly due to shadowing and fading in an urban environment. Recently, a database design (WISER [11]) that purely relies on measurements from sensors placed at strategic indoor locations is proposed for identifying indoor whitespaces. Combining the merits of Senseless and WISER, *V-Scope* uses opportunistic measurements collected on public vehicles to refine a propagation model, which is in turn used to better predict whitespaces in outdoor scenarios.

Propagation model enhancement: Some recent work [6–8] aims to improve propagation models with a few measurements. Caleb et.al [6] derive an adaptive path loss model for a 2.5GHz WiMax network by using least-square regression on measurements. A geostatistical approach has been proposed in [7], which interpolates measurements that are systematically sampled for constructing radio environment maps. Finally, authors in [8] predict the coverage of a WiFi mesh network by collecting measurements in different coverage sectors. Most of these approaches require measurement locations to be carefully chosen, which can hardly be guaranteed in vehicular sensing. *V-Scope* leverages weighted regression based on measurement sparsity to remove fitting bias caused by the non-uniform distribution of measurements.

Spectrum sensing: Energy detection is the most straightforward algorithm for primary detection. However, it fails to detect a primary signal below a certain SNR threshold [3]. Subsequent work [3,5] uses feature based detection by tracking the pilot of a TV signal. Built upon this idea, *V-Scope* uses a zoom-in technique to enhance the pilot detection, and derive the power of a TV signal from the extracted pilot.

7. CONCLUSION

In conclusion, we present the design of a vehicular sensing framework called *V-Scope*. *V-Scope* leverages public vehicles for collecting wide-area spectrum measurements in TV whitespaces. It uses these measurements for constructing region-specific propagation models, which are shown to be effective in augmenting the prediction of a commercial spectrum database. We believe this concept of opportunistic wardriving can have broader applications in dynamic spectrum access beyond TV whitespaces.

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