Leveraging Diverse Propagation and Context for Multi-Modal Vehicular Applications

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***Abstract*—Vehicular wireless channels have a high degree of variability, presenting a challenge for vehicles and infrastructure to remain connected. The emergence of the white space bands for data usage enables increased flexibility for vehicular networks with distinct propagation characteristics across frequency bands from 450 MHz to 6 GHz. Since wireless propagation largely depends on the environment in operation, a historical understanding of the frequency bands' performance in a given context, could speed multi-band selection as vehicles transition across diverse scenarios. In this paper, we leverage knowledge of in-situ operation across frequency bands with real-time measurements of the activity level to select the optimal band for the particular application in use. To do so, we perform a number of experiments in typical vehicular topologies. With a model based on a Decision Tree and an in-situ training set, we can predict the throughput on a free channel. We can then consider the activity level per band to compute the resulting performance one could expect on context information to guide protocol. In the field, we exploit the propagation differences experienced per band to show that training on a repeatable route can yield vast performance improvements from prior schemes. We show that minimal amounts of training can provide such improvements and that a simple scheme that can allow multiband adaptation gains when there is insufficient levels of training.**

I. Introduction

Drivers can benefit from a wide array of vehicular applications ranging from real-time traffic monitoring and safety applications to *infotainment* applications spanning news, weather, audio, or video streams. However, the continuous use of such applications is limited due to the challenge of transmitting over highly-dynamic vehicular wireless channels. In such networks, the increasing availability of different frequency bands with correspondingly diverse propagation characteristics could allow flexibility and robustness of vehicular links. Even with such spectral flexibility, links are extremely tenuous, demanding nearly instantaneous decisions in order to remain connected and motivating an algorithm that can find the appropriate frequency band quickly and according to the current application.

Prior work has considered a number of challenges in leveraging the digital white space frequencies including spectrum sensing, frequency-agile operation, geolocation, solving stringent spectral mask requirements, and providing reliable service in unlicensed and dynamically changing spectrum along with corresponding protocols [1]. In particular, there has recently been an acceleration in spectrum sensing work [2]–[4]. Based on these works, protocols have been built for multi-channel and/or multi-band wireless operation [5]–[7]. Other works have presented a method for searching the most efficient transmission channel [8], discovering channel information from limited measurements [2], [7], and estimating channel quality through limit information [5].

While these works have considered spectral activity and developing protocols and algorithms to find spectral holes, less of a focus has been on coupling such information with the propagation changes that frequency differences of hundreds of MHz to GHz could have on the band decision. Moreover, it is well known that propagation greatly depends on the environment in operation [9]. Thus, knowledge of the environment in operation could allow the relationship between received power differences across multiple frequency bands to have much greater accuracy. In this paper, we present a multi-band adaptation protocol which leverage prior knowledge of given context as well as per band measurements and make a properly band selection. To do so, we use an off-the-shelf platform that allows direct experimentation across four different wireless frequency bands simultaneously from 450 MHz to 5.8 GHz while maintaining the same physical and media access layers.

The main contributions of our work are as follows:

- We first formulate the problem of selecting the optimal frequency band according to an application metrics to perform the following multiband algorithms.
- We consider four different algorithms for comparison. First, we consider a scheme in which the throughput is achieved on an emulated channel for the current received signal level. We then adjust the predicted best band choice according to the current activity level (real-time information). Second, we consider an approach based on machine learning which considers prior throughput for a given received signal and activity level combination. Third, we build a scheme which include the prior relationship of throughput, received signal level and context information in an look up table for repeatable travel in an area. Fourth, we split the area to different regions and apply machine learning in each region to get the property band selection. earning in addition to the received signal and activity level.
- We perform V-2-V experiments to evaluate each algorithm on a repeatable pattern that spans in-field environment with various activity levels and propagation characteristics within the regions.

The remainder of this paper is organized as follows. In Section II, we present the multiband adaptation problem and proposed algorithms. Section III discusses experimental evaluation of the multiband algorithms. We present related work in Section IV. A summary and discussion of future work is included in Section V.

II. Multiband Adaptation

In this section, we first focus on the problem formulation for multiband adaptation in vehicular wireless links and introduce the context information that we use. Based on the analysis of existing problems, we discuss two baseline methods for comparison and propose two machine-learning-based multiband adaptation algorithms for vehicular channels.

A. Problem Formulation

The problem we are going to resolve is to find a band has the best throughput in multiple available options as:

$$f:(v_{tx},v_{rx},P_R^1,...,P_R^n,B^1,...,B^n,P_N^1,...,P_N^n,)\rightarrow b_{best} \tag{1}$$

where v_{tx} and v_{rx} are the velocity of the transmitter and the receiver, P_R^i is the received power, P_N^i is the no-802.11 interference signal level and B^i is the *busy time*.

To represent the unusable level of the channel, we define *busy time*, B, as the percentage of time when the channel is occupied by all competing sources $x_j (j = 1, 2, 3, ...)$ other than the intended transmitter y. For 802.11-based transmissions, the busy time on band i could be defined as:

$$B^i = \frac{\sum_j \sum_k \frac{L_k^{x_j}}{R_k^{x_j}}}{\sum_k \frac{L_k^y}{R_k^y} + \sum_j \sum_k \frac{L_k^{x_j}}{R_k^{x_j}} + S\sigma} \tag{2}$$

where L and R represent the length of packet in bits and the data rate that packet is transmitted, respectively, for all external sources x_i as compared to the idle slots S times the slot duration σ and the packets from the intended transmitter y. When considering the level of activity of non-802.11 users (e.g., the bands currently licensed to TV and other non-802.11 devices), whether the signal level from these competing sources reaches a level to disrupt communication at the receiver would define a similar notion of busy time. However, since this depends on the environment, hardware, coding, and modulation level, we use the received signal level from non-802.11 interference sources P_N^i on band i as an input to our algorithms in various forms as shown in (1).

The existing patten embedded in the performance of different bands and collected context information e.g. v_{tx}, v_{rx}, B_i, P_N^i, P_R^i and location information, g, could be extracted and help make decisions for multiband adaptation in a similar context [10] .

B. Multiband Adaptation Algorithms

In order to evaluate the proposed multiband adaptation algorithms, we construct two simple multiband adaptation methods: (1) We search the most commonly selected band as the best band in the historical data and configure the most common band as the final decision. (2) For each band, we build a lookup table for throughput T_{ideal} in the ideal channel given $RSSI$ and obtain the best band according to following:

$$\max_i T_{ideal}^i \times (1 - B^i), \tag{3}$$

The throughput T_{ideal} is measured with Azimuth ACE-MX channel emulator [11]. The details of system setup and data collection are discussed in Section III.

Machine learning has been introduced as an important tool in wireless communication [12]. When the user enters an area, the machine learning algorithm can learn from the historical data and train a mapping function to select the potential optimal band given the input, e.g. RSSI, velocity and activity level. We propose two multiband adaptation algorithms based on two machine learning methods: the k-nearest neighbor (KNN) and the decision tree.

Location based Look-up Algorithm. KNN is a machine learning method based on searching closest training data points in the feature space and various modified versions has been applied successfully for classification [13]. In the Location based Look up Algorithm, we search the closest neighbors of a testing points by using the parameter one by one in the input set. The performance of the found training data points is averaged in each band. Then the band with the highest throughput performance is selected as the b_best. The Location based look-up algorithm involves the geographic information for the band selection comparing with *Machine Learning Algorithm*. The process of this algorithm is presented as 1:

For *Location Based Look up Algorithm*, B_i is the *busy time*; v_i is the *Velocity* of each band and r_i is the *RSSI* of each band. Context information c involves g, v, and B^i. In the process of each data point, we have 4 looking up process to narrow down the data points which is similar to the testing data point. First, we find an amount of historical data which is near the testing data in a distance range, if the amount of historical data which qualify the requirement, we increase the distance range; then we narrow the data in the previous looking up qualify the data has similar RSSI in a range, if the amount is less than a threshold Thr_{RSSI}, the RSSI range will be increased; the process is repeated for non 802.11 interference signal and velocity. At last, the average throughput of the most similar data will be adjust of the 802.11 *busy time* and tell the best band.

Region-based Decision Tree algorithm. Decision trees are one kind of the most widely used machine learning algorithms according to its low complexity and stable performance [14]. The decision tree can model the relationship in the training data between the context information and the optimal band as a set of tree-like deduction structure. Before implementing the training process, we prepare a training set including a group of training data points as $\{v_{tx},v_{rx},P_R^1,...,P_R^n,B^1,...,B^n,P_N^1,...,P_N^n,b_{best}\}$ based on the collected measurements. We obtain b_best by comparing the throughput performance of all available bands and selecting the band with the highest throughput. We choose C4.5 algorithm [15], an information entropy gain based and

Algorithm 1 Location based Look-up Algorithm

Input:

$P_R^i \in \{P_R^1, P_R^2 \ldots, P_R^n\}$;
$B^i \in \{B^1, B^2, \ldots, B^n\}$;
$P_N^i \in \{P_N^1, P_N^2 \ldots, P_N^n\}$;
$v_t x$
g: Location Information of Multi-band node
Thr_{Area}: Threshold of a Location
Thr_{RSSI}: Threshold of RSSI
$Thr_{Velocity}$: Threshold of Velocity
Thr_{AArea}: Threshold of Data Amount for Location
Thr_{ARSSI}: Threshold of Data Amount for RSSI
$Thr_{ANon802.11SI}$: Threshold of Data Amount for Non 802.11 Interference
$Thr_{AVelocity}$: Threshold of Data Amount for Velocity
$D^i \in \{D_1, D_2, \ldots, D_n\}$: Historical Look up data

Output:

b_{best}:Optimal transmission band

for $i <= n$ **do**
  Initialize $Data_{Location}, Data_{RSSI}, Data_{Velocity}$ to zero matrix;
  while $Amount(Data_{Location,i}) < Thr_{AArea}$ **do**
    $Data_{Location,i} \leftarrow f_{Lookup}(D^i, g, Thr_{Area})$: Find data in D^i whose distance less than Thr_{Area};
    $Thr_{Area} = Thr_{Area} \times 1.1$;
  end while
  while $Amount(Data_{RSSI,i}) < Thr_{ARSSI}$ **do**
    $Data_{RSSI,i} \leftarrow f_{Look-up}(D_{Location,i}, P_R^i, Thr_{RSSI})$: Find data in $D_{Location}$ the RSSI similar to P_R^i in range Thr_{RSSI};
    $Thr_{RSSI} = Thr_{RSSI} \times 1.1$;
  end while
  while $Amount(Data_{P_N,i}) < Thr_{ANon802.11SI}$ **do**
    $Data_{RSSI,i} \leftarrow f_{Look-up}(D_{Location,i}, P_N^i, Thr_{RSSI})$: Find data in $D_{Location}$ the RSSI similar to P_N^i in range Thr_{RSSI};
    $Thr_{ANon802.11SI} = Thr_{ANon802.11SI} \times 1.1$;
  end while
  while $Amount(Data_{Velocity,i}) < Thr_{AVelocity}$ **do**
    $Data_{Velocity,i} \leftarrow f_{Lookup}(D_{RSSI,i}, v_t x, Thr_{Velocity})$: Find data in D_{RSSI} the RSSI similar to $v_t x$ in range Thr_{RSSI};
    $Thr_{Velocity} = Thr_{Velocity} \times 1.1$;
  end while
  $Tpt_{L,i} = avr(Data_{Velocity,i})$;
  $Tpt_{e,i} = Tpt_{L,i} \times (1 - b_i)$;
end for
$b^* = Max\{Tpt_{e,1}, Tpt_{e,1}, \ldots, Tpt_{e,n}\}$;

widely used algorithm to build the decision tree used in our system. At each intermediate node, the learning algorithm calculate the information entropy gain of splitting the rest training data points based on each parameter in the input set, e.g. RSSI, velocity or activity level. Then it compare and select the parameter with the highest entropy gain to decide the test condition at each intermediate node until all training data points are classified. The leaf node indicates the optimal band for prediction in our application Then the trained decision structure is integrated into the transmission system. With the collected context information fed into, the decision structure can suggest the potential band with the best throughput performance for transmission.

The relationship between the context information and the best band could be changed at different locations because of different propagation environment. To reduce the interference of training data from different locations, we split the routing of the vehicles into several regions and implement the training process based on the historical data collected in each region. Then trained decision structure is integrated in our system for multiband adaptation in each region. The granularity of region division is one parameter that affect the training set as well as the performance of the resulting decision tree. We evaluate granularity of division in Section III.

III. Experimental Analysis for Prediction Algorithms

As discussed in Section 3, the algorithms are fit for different scenarios. To study the difference of the algorithms and find the parameter patterns of these schemes, we have developed indoor and in-field experiments on widely used off-the-shelf wireless platform. To ensure the results are broadly applicable across wireless device, we employ widely accepted 802.11 testbed. Gateworks 2358 with Ubiquiti XR serial radios,XR9 (900MHz), XR2 (2.4GHz),XR5 (5.8GHz), SmartBridges 450MHz Radio, open source Linux based software to make the experiment plan [16]–[18]. Another instrument involve in the experiments is channel emulator, Azimuth ACE-MX, which is used for channel emulation, allowing controllable propagation and fading characteristics with a broad range of industry-standard models in 450MHz-2700MHz, 3300MHz-3800MHz, 4900MHz-5900MHz [11].

A. Data of Hardware Performance Collection

To get data for *SNR based Throughput Look up Algorithm*, we use an experimental setup where two wireless nodes communicate across emulated channels generated by Azimuth ACE-MX channel emulator. The channel emulator can create repeatable channels for collecting RSSI and throughput data.

For this scenario, in a given band, we repeat the experiments under different configuration to get the throughput information across multiple bands in an ideal channel environment with different RSSI as shown in Figure 1.

There is performance difference of each radio. From the emulator experiment data, the throughput performance could be normalized for comparison across all the bands.

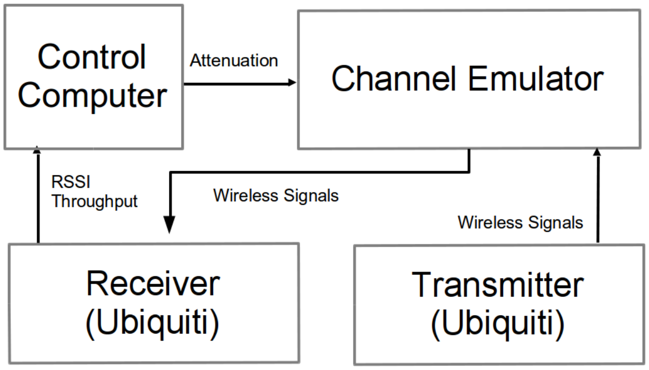

Fig. 1. Hardware Performance Experiment Setup

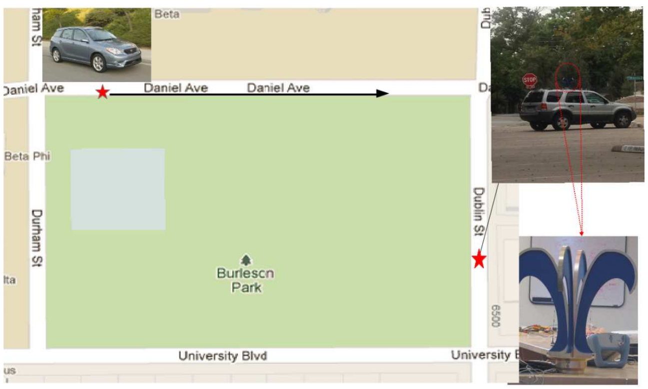

Fig. 2. In-field Experiment Setup

B. Experimental Design for In-field Data Collection

In the in-field experiments two Gateworks nodes with 4 radios are installed on two cars, one works as receiver, another works as transmitter moving around a public park as shown in Figure 2.

One of the car park in a fixed location work as a receiver, then another car work as a transmitter drive around the park for several loops to get the data with parameters. In receiver node, all the packets can be received are dumped for calculation of the parameters for algorithms.

As shown in in Figure 2, we use an multi-band antenna work with an spectrum analyzer to detect the signal in the air. All the activity can be seen on the data get from spectrum analyzer. Also, all the 802.11 packets are dumped by Tcpdump installed on Gateworks wireless nodes [19]. Then based on the time stamps, 802.11 packets can be recognized and only non 802.11 interference will be counted from the spectrum analyzer data.

Figure 3 shows the process to get the *Non 802.11 Interference Signal*. The spectrum analyzer (SA) samples match the dumped 802.11 packets are deleted, such as No. 3, No.4 and No.5. Then, the samples will not mix with the 802.11 packets and be counted twice in algorithms.

The in-field data is processed offline. As discussed in **??**, the throughput was normalized based on the emulator experiment to balance the diversity of hardware performance. Then, data

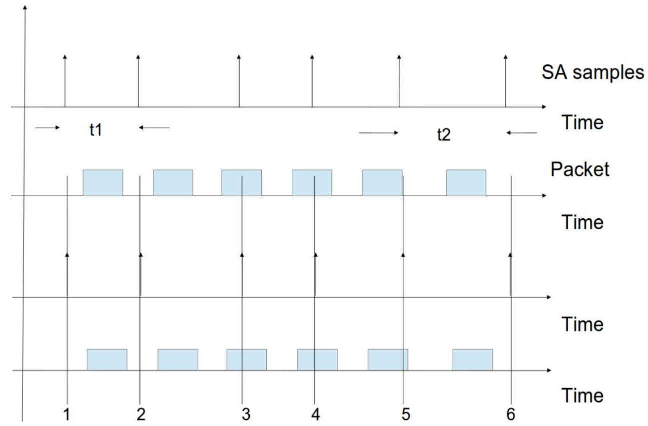

Fig. 3. Spectrum Analyzer Data Processing

from different devices and software is synchronized based on the GPS/System time stamps.

C. Performance Analysis of Algorithms

In the section II, we have introduced our algorithms for band adaptation. In this section, we investigate the performance for evaluation and compare the proposed schemes with the data collected in III-A and III-B.

To investigate the performance, *Accuracy* and *Throughput Gap* are used to represent the performance of band estimation. *Accuracy* is defined as the percentages of best band prediction matches the measured best band as Formula 4.

$$Accuracy = \frac{Correct\ Prediction\ Slots}{All\ Predict\ Time\ Slots} \tag{4}$$

Throughput Gap is the deference between the performance of estimation throughput and measured best throughput as defiend in Formula 5.

$$Throughput\ Gap = \frac{\sum Max\ Tpt - Estimate\ Band\ Tpt}{\sum Max\ Tpt} \tag{5}$$

For the *SNR based Throughput Look up Algorithm*, the *Accuracy* and *Throughput Gap* can be calculated through all the prediction and measured data. For *Machine Learning Algorithm* and *Location Based Algorithm*, the data set is divided in to training set and testing set for evaluation.

In figure 4 we show the performance of the 3 algorithms. The x-axis in figure 4 is the number of loops the mobile node traveled through the park. The flat curve with square represents the performance of *SNR based Look up Algorithm*, it keeps as 39.2% across all the data. The curve with "*" represents the performance of *Machine Learning Algorithm*. From the curve, we could see the accuracy of this algorithm is better than the *SNR based Look up Algorithm*, but the accuracy is not directly related to the amount of training set. There are multiple dips on the curve. Because the relationship between the context information and the best band changing from loop

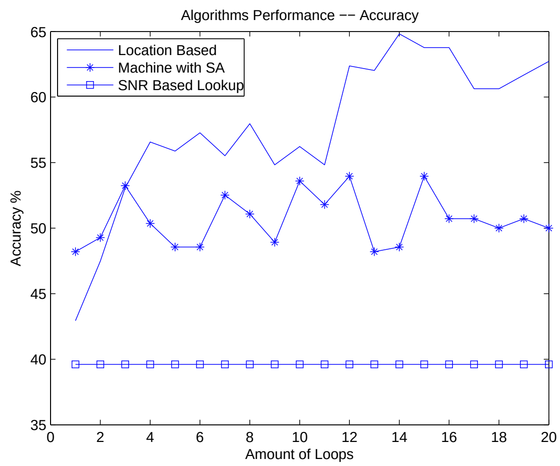

Fig. 4. Accuracy of 3 Algorithms

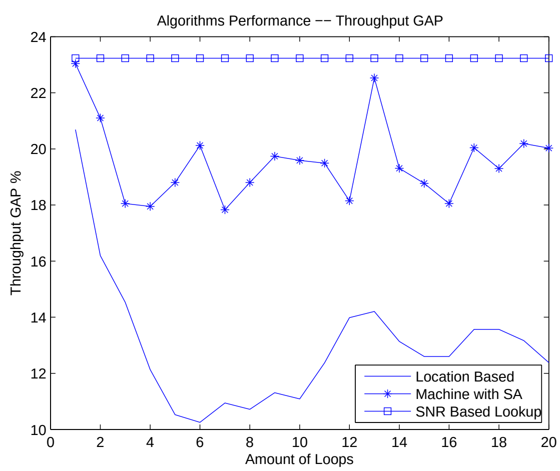

Fig. 5. Throughput Gap of 3 Algorithms

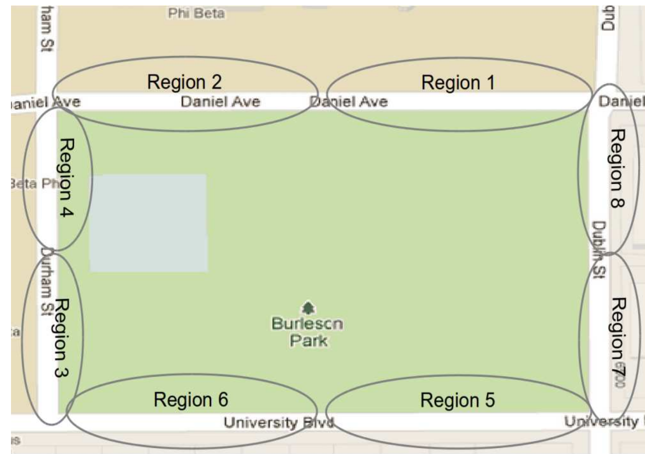

Fig. 6. Split Regions

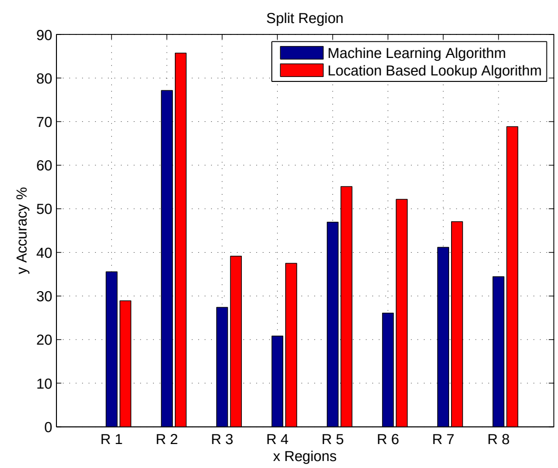

Fig. 7. Performance in Different Regions of Split Region Machine Learning Algorithm and Location Based Look up Algorithm

to loop, additional training data would be treated as noisy data in the expanded training set for *Machine Learning Algorithm*. It can increase the training set size, but it also introduce noise. When the pattern changed a lot, the accuracy can decrease. The *Location based Look up Algorithm* gets the highest accuracy as 65% in figure 4. We could see the *Accuracy* increase as the training data goes up through there is some dips on the curve. The in-situ data can not guarantee has the same performance distirbution even under the limitations. These reasons could bring the dips of the algorithms.

In figure 5, the *Throughput Gap* of the 3 algorithms are investigated. *SNR based Look up Algorithm* shows the gap upper bound in the figure. Both *Machine Learning Algorithm* and *Location based Look up Algorithm* have some gains as the training data increase in loops. Also, as explained in previous paragraph, the context information may change from loop to loop, time to time, this bring the dips on the two curves.

In figure 6, the loop around the park is divided into 8 regions.

The *Accuracy* performance of *Location based Look up Algorithm* and *Split Region Machine Learning Algorithm* in the same training set and testing set is shown in figure 7

Only in Region 1, the *Machine Learning Algorithm* has better accuracy than *Location based Look up Algorithm*. *Location based Look up Algorithm* has more limitation than *Machine Learning Algorithm* and considering the data points at the boundary of each region. This makes the *Location based Look up Algorithm* has a better accuracy.

We have investigated the performance of the algorithms in one experimental data set and shown the gains of them. Multi-band channels are complex system that knowing more information can make better decisions.

IV. Related Work

Federal Communications Commission (FCC) published a report discussed improving the way to manage the limited natural resource licensed in the United States [20]. The under utilization of the electromagnetic spectrum of licenced band leads to *Spectrum Opportunity* which provide space for performance improvement based on channel selection [21]. *Cognitive Radio* could be a powerful tool for the utility of the *Spectrum Opportunity* [12]. Analog TV bands will be released for wireless communication brings opportunity to combine current wireless bands and new available bands for performance improvement employing *Cognitive Radio* methods [5].

A bunch of work has been done on *Radio-scene analysis* and *Channel identification* for utility of channel adaptation dating back to Simon Haykin [12]. Some work of Multi-bands/Multi-channels in cognitive radios focus on optimize performance, such as avoiding frequency diversity [22]. In [23] an opportunistic algorithm is introduced to balance the cost of *spectrum sensing, Channel switching* and the gain of these activities.

Our work is motivated by prospective releasing band used for TV now and exploit the comparison across all the available bands in the future. It is an extension of multi-channel adaptation. Most of the published research focus on the stopping rules of spectrum sensing [7], [23]. In contrast, we use the data and framework to classify the performance across different bands based on the parameters we get from the context information.

V. Conclusion

In this paper, we investigated the multi-band adaption to leverage the propagation and context for vehicular utility. We did so by first testing and comparing the performance of different approaching multi-band selection algorithms. In our experimental analysis, we evaluated the performance of these algorithms on Gateworks hardware platform over in-field channels. Experimental results demonstrate that these algorithms can fit different utility environments. The accuracy of these algorithms can be up to 60.5%. Since for mobile utility, energy is limited, in the future work we plan to consider the energy efficient in multi-band adaptation.

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