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. Multi-band Adaptation—Motivation and Algorithms

In this section, we will investigate optimal band selection in wireless vehicular channels.

A. Problem Formulation of Multiband selection

Assume there are K bands, the throughput set across all bands as $T_{pt} = [r_1, r_2, ...r_k]$, which depends on the received signal power, noise, interference and other factors. The objective of this issue is to select the band which has the maximum throughput in K bands.

$$b^* = Max\{r_1, r_2, ...r_k\} \tag{1}$$

There are many factors need to be considered. Comparing with traditional frequency-selective channels, in multi-band scenario, path loss is an important factor for received signal power in different channels. Received signal in the same environment could vary according to the frequency. The received signal with path loss considering can be presented as: [9]

$$P_R = \frac{P_T G_T G_R \lambda}{d^\alpha (4\pi)^2} \tag{2}$$

here ,P_R is the received signal of receiver node, P_T is the transmitting power, G_T, G_R represent the antennas gain at transmitter and receiver respectively, λ is the wavelength,and α is the path loss exponent related to the environment.

Signal level is widely used to represent the channel state [10]. From Formula 2 we could see the signal is related to the wavelength, and the wavelength λ can be represented as $\lambda = \frac{C}{Frequency}$. So multi-band devices could have performance improvement because of the relationship between frequency and received signal.

Many hardware manufactures already perform the SNR/Received signal strength detection character as part of the hardware specification [11]. The RSSI (Received Signal Strength Indication) is consider as an important factor for throughput performance [12], [13].

Furthermore, except RSSI, other factors also represent the channel state. Channel Statistics information is used by lots of adaptation algorithms in previous research. FARA tracks the the number of active clients, then update the next-hop table for transmission [10]. The statistics of collisions and link errors also could be considered as channel qualification factors [14]. Our work also investigate the influence of activity in in-field channel.

The *Activity Level* represents the unusable level of the channel which is defined as a percentage of the occupy time ratio. The *Activity Level* is highly temporal correlated. The *Activity Level* of bands currently licensed to TV and other non-802.11 users is the time percentage occupied by these primary users. For 802.11 standard band, 2.4GHz and 5GHz, the activity level could be defined as:

$$Activity\,Level = \frac{\sum \frac{If\ Pkts}{Rate}}{\sum \frac{If\ Pkts}{Rate} + \sum Idle\ Time + \sum \frac{Ct\ Pkts}{Rate}} \tag{3}$$

here, the *Ct Pkts* are the packets received by receiver from a particular transmitter. *It Pkts* are the packets received from other nodes counted as interference packets. The summation of *It Pkts* period, *Idle Time* and *Ct Pkts* period is the duration of a time slot. The *Activity Level* is the *ratio* that occupied by the interference transmitter during a time slot.

As we discussed, path loss varies in different frequency, providing opportunity for maximizing throughput through band selection. However, for in-field application, due to environment, traffic and interference, it is difficult to quantitative analysis path loss. To implement multi-band selection, we employ the context idea to evaluate channel state instead of theoretic analysis of path loss and other parameters.

This work is to improve the performance of point to point multi-bands system in practical environments based on estimation of channel states according to prior performance.

Some multi-channel adaptation and rate adaptation research focuses on *RSSI and Activity* as represented by [5], [15]. which distinguish the performance is related to the channel state, but only involve the normal information and do not consider the variation across wide bands. Furthermore, the embedded temporal correlation of the wireless channel also represent the channel state [16]. A method to develop these work is to experimentally observe different band and consider path loss as prediction parameters [17].

$$f(SNR, Context\,Info) \rightarrow Performance\,Estimation \tag{4}$$

In this paper, our work involves historical information with *Context Info* for multi-band adaptation such as path loss of different bands. The *Context Info* has parameters related to the performance of wireless networks, such as velocity of nodes, the location, and previous activity of the channel. We use different sub-sets of the context information to design multiple algorithms for various vehicular environment.

B. Algorithms

Context Information provides a way for the optimum bands selection. However, it is usually difficult to directly get all the context Information at a time.Therefore, we develop methods to search the optimal band for maximizing throughput. In the following, we describe the ideal performance based algorithm, machine learning algorithm, location based look up algorithm, region slitted machine learning algorithm.

When a wireless node gets in to a strange area, there is only RSSI r_i, activity of channels can be collected by the device as *activity Level* a_i for each band among the available band $\{1, 2, \ldots, n\}$. Then, the node can only rely on hardware performance from manufacture or self test of the

Algorithm 1 SNR based Throughput Look-up Algorithm

Input:
$r_i \in \{r_1, r_2 \ldots, r_n\}$;
$a_i \in \{a_1, a_2, \ldots, a_n\}$;
$Ideal_i \in \{Ideal_1, Ideal_2, \ldots, Ideal_n\}$;
Output:
b^*:Optimal transmission band

for $i <= n$ **do**
  $Tpt_{ideal,i} \leftarrow f_{Look-up}(Ideal_i, r_i)$;
  $Tpt_{e,i} = Tpt_{ideal,i} \times (1 - Activity\ Level)$;
end for
$b^* = Max\{Tpt_{e,1}, Tpt_{e,1}, \ldots, Tpt_{e,n}\}$;

node *Hardware Performance Data*. For this case, we have the *SNR based Throughput Look-up Algorithm*

On the other side, people always drive cars, ride subway or bus entering some areas many times. In a familiar area, previous information collected in this area can be used for band selection. Machine learning algorithm, Location based algorithm, and Region split machine learning algorithm are tested in this case.

Machine learning is counted as an important tool in wireless communication [18]. When user re-entry an area, the previous data can be trained by machine learning algorithm and tell the device which band may have the best performance. *Decision Tree* is used as the machine learning tool in this paper. The *Machine Learning Algorithm* can lead to the optimum band selection through several steps:

Algorithm 2 Machine Learning Algorithm

Input:
$r_i \in \{r_1, r_2 \ldots, r_n\}$;
$a_i \in \{a_1, a_2, \ldots, a_n\}$;
$v_i \in \{v_1, v_2, \ldots, v_n\}$;
D: Collected data
Output:
b^*:Optimal transmission band

$M \leftarrow f_{DecisionTree}(D)$
$b^* \leftarrow f(M, r_i, a_i, v_i)$;

Machine Learning Algorithm can find the inner pattern of different parameters. However, the machine learning algorithm could not include context information which is not related to the performance directly, such as the location information. Also, due to the limited computation resource on mobile devices, it is difficult to train the data on the device itself. However, the location information is pretty important for vehicle utility. Even the areas have the same RSSI, interference activity, due to multi-path and different traffic nearby, the performance could be great different. Therefore, the *Location Based Look up Algorithm* is developed to consider the location based on the previous data collected. The algorithm is an iteration method to find the data near the location and look for the best performance across bands.

Algorithm 3 Location Based Look up Algorithm

Input:
$r_i \in \{r_1, r_2 \ldots, r_n\}$;
$a_i \in \{a_1, a_2, \ldots, a_n\}$;
$v_i \in \{v_1, v_2, \ldots, v_n\}$
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 Location
$Thr_{AVelocity}$;: Threshold of Data Amount for Location
$D_i \in \{D_1, D_2, \ldots, D_n\}$;: Collected Look up data
Output:
b^*: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**
    $Data_{RSSI,i} \leftarrow f_{Look-up}(D_{Location,i}, r_i, Thr_{RSSI})$: Find data in $D_{Location}$ the RSSI similar to r_i in range Thr_{RSSI};
    $Thr_{RSSI} = Thr_{RSSI} \times 1.1$;
  end while
  while $Amount(Data_{Velocity,i}) < Thr_{AVelocity}$ **do**
    $Data_{Velocity,i} \leftarrow f_{Lookup}(D_{RSSI,i}, v_i, Thr_{Velocity})$: Find data in D_{RSSI} the RSSI similar to v_i in range Thr_{RSSI};
    $Thr_{Velocity} = Thr_{Velocity} \times 1.1$;
  end while
  $Tpt_{L,i} = avr(Data_{Velocity,i})$;
  $Tpt_{e,i} = Tpt_{L,i} \times (1 - Activity\ Level)$;
end for
$b^* = Max\{Tpt_{e,1}, Tpt_{e,1}, \ldots, Tpt_{e,n}\}$;

The *Location Based Look up Algorithm* provide a simple way to include location information for prediction. To investigate the machine learning with location information, data is divided into different regions based on the location and develop as *Split Region Machine Learning Algorithm*

In *Split Region Machine Learning Algorithm* multiple Decision Tree are generated for different regions to involve location information. We have presented the 4 schemes and we will use in-field data to investigate the performances of the algorithms.

III. Experimental Analysis for Molting Prediction Algorithms

As discussed in Section 3, in multiple scenarios, the algorithms are fit for different environments. To study the difference of the algorithms and find the parameter patterns of these

Algorithm 4 Split Region Machine Learning Algorithm

Input:

$r_i \in \{r_1, r_2 \ldots, r_n\}$;
$a_i \in \{a_1, a_2, \ldots, a_n\}$;
$v_i \in \{v_1, v_2, \ldots, v_n\}$;
g:Location Information of Multi-band node;
$Region_j \in \{Region_1, Region_2, \ldots, Region_m\}$;
D: Collected Training data

Output:

b^*:Optimal transmission band

```
for j <= m do
    D_j ← f_RegionSplit(Region_j, D);
    M_j ← f_DecisionTree(D_j);
end for
for i <= n do
    for j <= m do
        if g in Region_j then
            M = M_j;
            Break;
        end if
    end for
    b* ← f(M, r_i, a_i, v_i);
end for
```

schemes, we have developed indoor and in-field experiments on widely used off-the-shelf wireless platform. To ensure our 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, as our testbed [19]–[21]. This multi-radio testbed have the capacity to measure the performance in the same traffic generating system, channel state of different bands simultaneously for the algorithms.

A. Data of Hardware Performance Collection

In order to collect 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 Azimuth ACE-MX 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 [22]. 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. For each band, on the receiver side we capture the RSSI and report the throughput values from Iperf [23] each second. Based on these data,the performance database can be created.

Also, there is performance difference of each radio. However, our work does not focus on these issues. From the

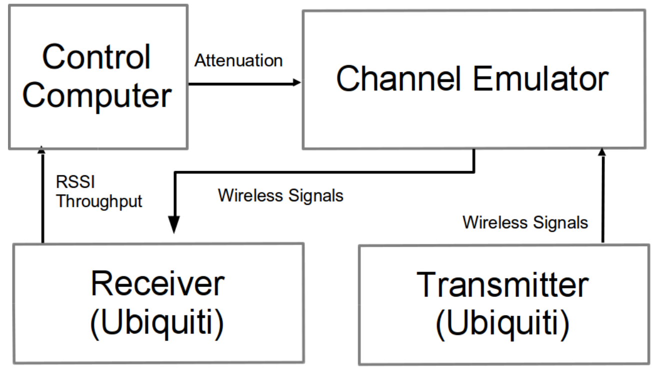

Fig. 1. Hardware Performance Experiment Setup

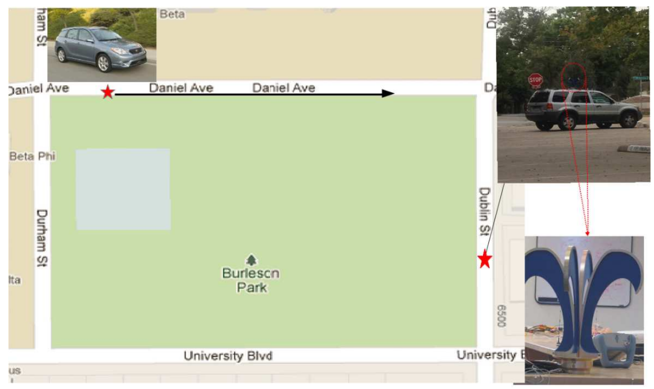

Fig. 2. In-field Experiment Setup

emulator experiment data, the throughput performance could be normalized for comparison.

B. Experimental Design for In-field Data Collection

To evaluate our algorithms, in-field experiments are taken for data collection. The in-field experiments have 2 Gateworks nodes, two nodes are installed on two cars, one works as receiver, another works as transmitter moving in a public park as shown in 2.

The same as in emulator experiments, we generate traffic and measure the throughput through Iperf. Then we dump all the transmitting packets and calculate the signal level from sniffer data in one receiver node. In receiver node, we dump all the packets it can received, then calculate the throughput and the signal level. We put the results in the algorithms to get the estimate optimize band, estimate throughput, measured throughput for evaluation. One of the car park in a fixed location, then another car drive around the park for several loops to get the data with parameters.

As shown in in 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 [24]. 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.

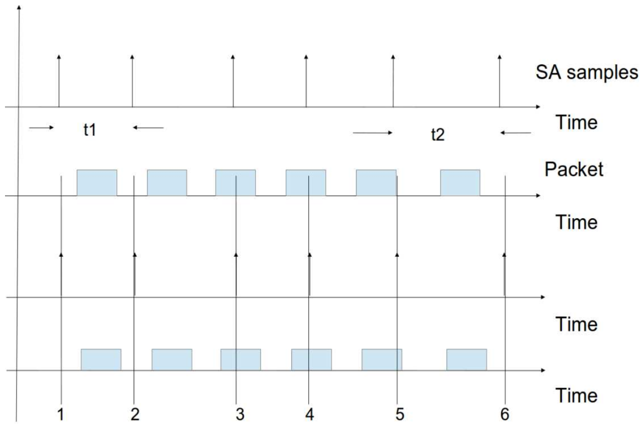

Fig. 3. Spectrum Analyzer Data Processing

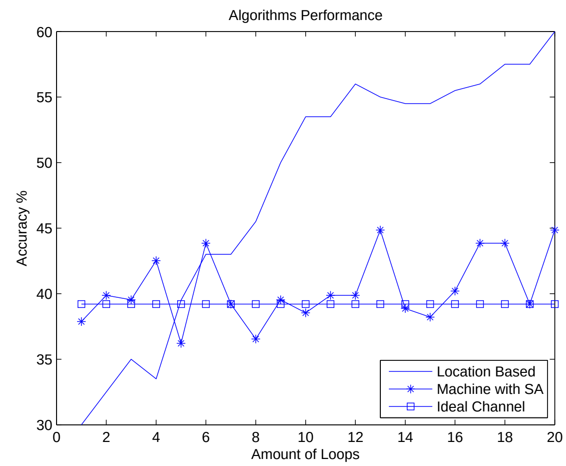

Fig. 4. Performance of 3 Algorithms

The in-field data is processed offline. As discussed in III-A, the throughput was normalized based on the emulator experiment to balance the diversity of hardware performance. Then, data from different devices and software is synchronized based on the GPS/System time stamps.

The in-field data will be divede into training data and testing data for *Location Based Algorithm*, *Machine Learning Algorithm* and *Split Region Machine Learning Algorithm*.

C. Performance Analysis of Algorithms

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

Throughput is the most important metric for any kind of networks and very sensitive to customers. In multi-band scenario, the object is to find the band has the best throughput. To investigate the performance, *Accuracy* is used to represent the band estimation. *Accuracy* is defined as the percentages of predict best band match the measured best band.

$$Accuracy = \frac{Correct\ Prediction\ Slots}{All\ Predict\ Time\ Slots} \tag{5}$$

Due to the hardware characteristics, the throughput will be normalized across the bands to remove the divergence of the radios. Then the data will be divided into different subsets fit for the algorithms introduced in II.

The *SNR based Throughput Look up Algorithm* does not rely on the collected throughput performance and the environment. It fits for each data point with dynamic parameters. This algorithm could be used in all data points and the *Accuracy* can be counted 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 has the same amount of data points. The *Accuracy* performance is counted as the correct prediction of the test set as defined in 5. The performance of these algorithms is dependent on the amount of training set. In figure 4 we show the variation of *accuracy* of different amount of training set for these three algorithms.

The x-axis in figure 4 is the number of loops the mobile node traveled through the park. The same testing set data is used for testing the *Accuracy* performance. *SNR based Throughput Look up Algorithm* is independent to the training data, in 4, the *Accuracy* performance is the same of all different loops. *Machine Learning Algorithm* curve in 4 represents this algorithm is sensitive to the training data. Only including the closest one or two loops can help to increase the accuracy. The class distribution of different loops would change and mix the training sets with different pattern of multiple loops without improving the accuracy performance. *Location based Look up Algorithm* has a performance improvement as the training data increase. The algorithm has the most strict conditions for each prediction, also has the best performance in these 3 algorithms when the training data is large enough. The best performance of *Location based Look up Algorithm* can go up to 60%.

Also, the data set is divided into multiple regions to test the *Split Region Machine Learning Algorithm*. There are 8 regions shown in 5.

The *Accuracy* performance of these 2 algorithms for the same training set and testing set is shown in figure 6

In each regions, the training set for machine learning algorithm is fewer than group all of the data as a training set. The inner process of the decision is different from one region to another region. In figure 6, most of the regions *Location Based Look up Algorithm* has better performance than *Split Region Machine Learning Algorithm*.

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

Electromagnetic radio spectrum is a limited natural resource licensed by governments. Federal Communications Commis-

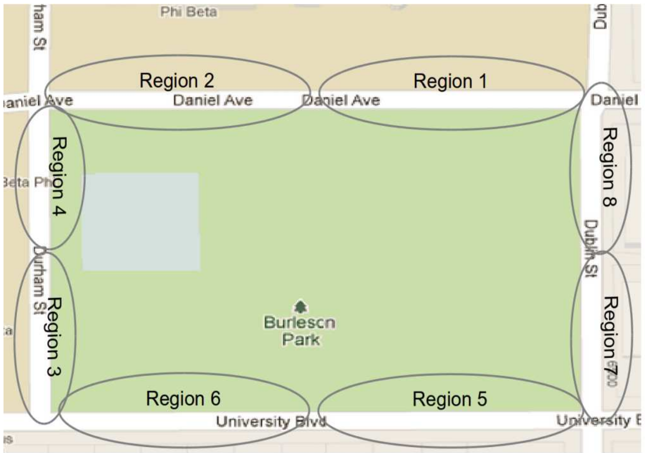

Fig. 5. Split Regions

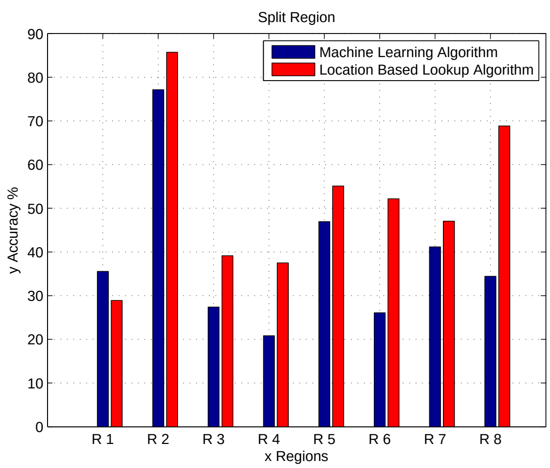

Fig. 6. Performance in Different Regions of Split Region Machine Learning Algorithm and Location Based Look up Algorithm

sion (FCC) published a report discussed improving the way to manage this resource in the United States [25].

The under utilization of the electromagnetic spectrum leads to a definition of *Spectrum Opportunity* as a band of frequencies assigned to a primary user, but at a particular time and specific geographic location, the band is not being utilized by that user [26].

The concept of *Cognitive Radio* is introduced as a novel approach for improving the utilization of the wireless spectrum and the tasks for cognitive radio is summarized in [18].

As analog TV bands will release, wireless communication has opportunity of these bands. Combine different bands to create Multi-bands/Multi-channels system is a new field of *Cognitive Radio* to improve the performance of wireless systems in different environments(e.g., as in [5]).

A bunch of work has been done on *Radio-scene analysis* and *Channel identification* dating back to Simon Haykin [18]. Some work of Multi-bands/Multi-channels in cognitive radios focus on optimize performance, such as avoiding frequency diversity [10]. In [27] 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 white band using for TV today and exploit the comparison across all the available bands in the future. It could be counted as an extension of multi-channel adaptation. Most of the research focus on the stopping rules of spectrum sensing [7], [27]. In contrast, we use the data and framework to classify the performance across different bands based on the parameters we get from the context-aware 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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