Multiband Networks Channel Assignment and Routing

TBA
Dinesh Rajan, and Joseph Camp

***Abstract*—**

I. Introduction

FCC is working on adopting rules to allow unlicensed radio transmitters to operate in the white space freed from TV band since 2010 [1]. White space is popularly referred to unused portions of the UHF and VHF spactrum includes, but not limited to FIXME. These bands provides superior propagation and building penetration compared to licensed wifi bands like the 2.4 and 5GHz bands, holding rich poetntial for expanding broadband capacity and improving access for wireless users. Point to point users may entend their connecting range in white space and avoiding excessive competing in their licened bands. Users in a networks can enjoy multiple benefits through multihop links combining white space and licensed bands. However, access to these advantages of white space bands also comes with both technical and commerical challenges. A direct request from the users would be the rules to assign the channels in different band according to their characteristics. More benefits could be obtained by multihop networks users. However, in a multihop networks, the problem becomes complex with tons of options come from multiple bands and multiple relay nodes combination as a NP-Hard problem.

To have a piece of partial optimization of this NP-Hard problem, some research has been working on different requirements. researchers works for on-demand optimization. and some multi-channel works also answer part of the channel assignment problem..

This paper is focusing on approaching multiband-multihop channel assignment and link selection optimization.

The main contributions of our work are as follows:

- We first develop a framework for multiband adaptation using both historical information and instantaneous measurements. This framework is broad enough to study adaptation across licensed, and unlicensed band including white space frequency bands.
- We propose two different machine-learning-based adaptive algorithms. The first machine learning algorithm, which we refer to as the *Location-based Look-up Algorithm*, is based on the idea of $k-$nearest-neighbor classification. The second machine-learing-based algorithm uses *decision trees* for classification. For comparison, we also create two baseline adaptation algorithms which attempt to make the optimal band selection based on only: *(i)* historical performance data, and *(ii)* instantaneous SNR measurements across various bands.
- We perform extensive outdoor V-2-V experiments to evaluate the proposed algorithms. Our results indicate that the proposed machine learning algorithms outperform these baseline methods in throughput by up to 49.3%.

II. Multiband Adaptation

In this section, we first formulate the multiband adaptation problem in vehicular wireless links and introduce the context information that we use. We then propose two machine-learning-based multiband adaptation algorithms for vehicular channels. For comparison, we also propose two baseline adaptation methods based on existing solutions.

A. Problem Formulation

Consider a system with n frequency bands, represented by an index set $\{1, 2, \dots, n\}$. The objective is to select the optimal band, b_{best}, to transmit at each time instant that maximizes a desired objective function such as throughput. The throughput r_i on band i depends on several factors such as received signal power P_R^i, noise power P_N^i, the activity/occupancy level B^i, the velocity of the transmitter, v_{tx}, the velocity of the receiver, v_{rx}, and other factors such as location and contextual information. This relationship is represented in general as $r_i = f(P_R^i, P_N^i, B^i, v_{tx}, v_{rx},\text{context-information})$. The objective can be stated as

$$b_{best} = \arg\max_i r_i \tag{1}$$

The framework allows us to separate the interference from other nodes using the same technology via the busy time and the interference from nodes using other technologies in the same and via the noise level P_N^i. For instance, an 802.11 node can observe the packets of other 802.11 nodes but only the increase noise levels from other Zigbee/Bluetooth nodes. The existing pattern embedded in the historical data connecting the performance of different bands and collected context information e.g., v_{tx}, v_{rx}, B^i, P_N^i, P_R^i could be extracted and help make decisions for multiband adaptation in a similar context [2].

To represent the utilization 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 is 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 $L_k^{x_j}$ and $R_k^{x_j}$ represent, respectively, the packet length in bits and the data rate at which that packet is transmitted, for external sources x_j; S and σ are the idle slots and the slot duration. When considering the activity level of non-802.11 users (e.g., the bands currently licensed to TV and other non-802.11 devices), we use the received signal level from non-802.11 interference sources P_N^i on band i as an input to our algorithms.

B. Multiband Adaptation Algorithms

In order to evaluate the proposed multiband adaptation algorithms, we construct two baseline 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 [3]. The details of system setup and data collection are discussed in Section **??**.

Machine learning has been introduced as an important tool in wireless communication [4]. 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., P_R^i, v and P_N^i. 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 have been applied successfully for classification [5]. In the Location based Look-up Algorithm, we search the closest neighbors of a testing point by using each parameter one by one in the input set. The performance of the selected training data points is averaged to generate an estimate of the performance at each band. Then the band with the highest throughput performance is selected as the b_{best}. The Location based Look-up Algorithm additionally involves geographic information for band selection.

For the Location-based Look-up Algorithm, context information involves location information g from GPS, v, P_R^i, P_N^i and B^i. To make a band prediction, we have four look-up blocks to narrow down the training data points which are similar to the testing data point. First, we search the historical data which is closest to the testing data based on GPS location, if the number of found historical data points is less than a predefined threshold, θ_{AArea}, we increase the distance range (the actual threshold is discussed in Section **??**). Then based on the filtered historical data, we search the close data points based P_R^i with a threshold for number of data points, θ_{ARSSI}. A similar process is repeated based on P_N^i and v, respectively. After deciding the final data set, we average the throughput of data points at each band. The key steps of this algorithm are presented as Algorithm 1.

Algorithm 1 Location-based Look-up Algorithm

Input:
g: Location information of multiband node
θ_{Area}: Threshold of a location
θ_{RSSI}: Threshold of RSSI
$\theta_{Velocity}$: Threshold of velocity
θ_{AArea}: Threshold of data amount for a location
θ_{ARSSI}: Threshold of data amount for RSSI
$\theta_{ANon802.11SI}$: Threshold of data amount for non-802.11 interference
$\theta_{AVelocity}$: 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 $Amount(Data_{Location,i}) < \theta_{AArea}$ **do**
    $Data_{Location,i} \leftarrow f_{Lookup}(D^i, g, \theta_{Area})$: Find data in D^i whose distance less than θ_{Area};
    $\theta_{Area} = \theta_{Area} \times 1.1$;
  end while
  while $Amount(Data_{RSSI,i}) < \theta_{ARSSI}$ **do**
    $Data_{RSSI,i} \leftarrow f_{Look-up}(D_{Location,i}, P_R^i, \theta_{RSSI})$: Find data in $D_{Location}$ the RSSI similar to P_R^i in range θ_{RSSI};
    $\theta_{RSSI} = \theta_{RSSI} \times 1.1$;
  end while
  while $Amount(Data_{P_N,i}) < \theta_{ANon802.11SI}$ **do**
    $Data_{RSSI,i} \leftarrow f_{Look-up}(D_{Location,i}, P_N^i, \theta_{RSSI})$: Find data in $D_{Location}$ the RSSI similar to P_N^i in range θ_{RSSI};
    $\theta_{ANon802.11SI} = \theta_{ANon802.11SI} \times 1.1$;
  end while
  while $Amount(Data_{Velocity,i}) < \theta_{AVelocity}$ **do**
    $Data_{Velocity,i} \leftarrow f_{Lookup}(D_{RSSI,i}, v, \theta_{Velocity})$: Find data in D_{RSSI} the RSSI similar to v in range θ_{RSSI};
    $\theta_{Velocity} = \theta_{Velocity} \times 1.1$;
  end while
  $T_{a,i} = avr(Data_{Velocity,i})$;
  $T_{e,i} = T_a^i \times (1 - B^i)$;
end for
$b_{best} = \max_i\{T_e^1, \ldots, T_e^i, \ldots, T_e^n\}$;

Region-based Decision Tree Algorithm. Decision trees are a widely-used machine learning algorithm due to its low complexity and stable performance [6]. A 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 structures. Before implementing the training process, we prepare a training set including a group of training data points of $\{v_{tx}, v_{rx}, P_R^1, ..., P_R^n, B^1, ..., B^n, P_N^1, ..., P_N^n, b_{best}\}$ 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 [7], a widely-used algorithm based on the information entropy gain to build the decision tree used in our system. At each intermediate node in the decision tree, the learning algorithm calculates the information entropy gain of splitting the remaining training data points based on each parameter in the input set, e.g., P_R^i, v or P_N^i. Then, it compares and selects 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 nodes indicate the optimal band for prediction in our application. Then, the trained decision structure is integrated into the transmitter protocol stack. With the collected context information, the decision structure can suggest the band with the best throughput performance.

The relationship between the context information and the best band could differ at different locations because of diverse propagation environment characteristics. To reduce the heterogeneity of training data from different locations, we split the vehicular route into several regions and implement the training process based on the historical data collected in each region. Then, the trained decision structure is integrated in our system for multiband adaptation in each region. The granularity of region division is one parameter that affects the training set as well as the performance of the resulting decision tree. We evaluate granularity of these divisions in Section **??**.

III. Conclusion

In this paper, we investigated the multiband adaptation to leverage the propagation and context for vehicular applications. We did so by proposing two machine-learning-based schemes and compared there performance against two baseline schemes. In our experimental analysis, we evaluated the performance of these algorithms in the field on an off-the-shelf platform. Experimental results demonstrate that the proposed algorithms can achieve up to 49.3% greater throughput than the baseline algorithms with an accuracy up to 65%. Since for mobile networks have limited energy, in future work we plan to examine the energy efficiency of the simultaneous use of multiple, diverse radios.

References

[1] FCC, "White space," http://www.fcc.gov/topic/white-space, 2012.

[2] R. Meikle and J. Camp, "A global measurement study of context-based propagation and user mobility," in *Proceedings of the 4th ACM international workshop on Hot topics in planet-scale measurement*. ACM, 2012, pp. 21–26.

[3] "Aximuth ACE-MIMO Channel Emulator," http://www.azimuthsystems.com, Mar. 2011.

[4] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *Selected Areas in Communications, IEEE Journal on*, vol. 23, no. 2, pp. 201–220, 2005.

[5] H. Zhang, A. Berg, M. Maire, and J. Malik, "Svm-knn: Discriminative nearest neighbor classification for visual category recognition," in *Computer Vision and Pattern Recognition, 2006 IEEE Computer Society Conference on*, vol. 2, 2006, pp. 2126–2136.

[6] R. Banfield, L. Hall, K. Bowyer, W. Kegelmeyer, *et al.*, "A comparison of decision tree ensemble creation techniques," *IEEE Trans on Pattern Analysis and Machine Intelligence*, vol. 29, no. 1, p. 173, 2007.

[7] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. Witten, "The weka data mining software: an update," *ACM SIGKDD Explorations Newsletter*, vol. 11, no. 1, pp. 10–18, 2009.