Geometry-Based Channel Recognition for Context-Aware Applications

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***Abstract*—Environmental factors that lead to the movement and type of obstacles in and around wireless links are well-known to directly affect channel characteristics. However, while mobile users typically have repeatable daily or weekly patterns with common locations being frequently visited, many protocols along the network stack do not attempt to identify when physical locations are revisited. If wireless channels could be recognized as previously visited, the observance of good and bad decisions in that particular context could dramatically improve some network protocols. In this paper, we present a channel recognition framework which uses the geometrical shape of the link-level performance in a particular context across transmission modes and channel qualities. When attempting to recognize a channel condition, the performance of data transmissions is observed and compared against known channel types to detect similar behavior. The matching channel type can be used as an input to the link adaptation training and resulting decision structure. We perform extensive experimentation on controlled repeatable channels as well as in-field channels to show the validity of the classification algorithm.**

I. INTRODUCTION

Channel properties have long been shown to be highly dependent upon the environment of operation, whether from the mobility of the sender, receiver, or reflecting obstacles, topological and land use features, or weather conditions [1], [2]. In spite of this well-known dependency, protocols which adapt the modulation rate, coding scheme, multi-input, multi-output (MIMO) configuration, or frequency band (i.e., link adaptation mechanisms) have yet to fully leverage such a relationship between the surrounding environmental conditions and the channel type. Instead, link adaptation protocols detect environmental changes with probes to measure the current channel quality [3], [4], packet failure statistics on the channel [5], [6], [7], or measuring and feeding back MIMO channel state matrices [8], consuming precious bandwidth. With the diverse conditions that users encounter, relying on direct channel measurements to adapt links can cause a number of sub-optimalities such as: goodput losses due to control overhead [9], channel staleness [10], inappropriate training data per context [11], and inability to converge to the most appropriate transmission parameters [12].

Due to the observed inefficiencies of link adaptation in mobile settings [13], recent work has begun to exploit knowledge of the surrounding context to improve wireless performance. For example, instantaneous channel quality combined with relative velocity are used in [14], [15], pedestrian directionality and speed as well as knowledge of indoor/outdoor settings is used in [16], and binary classification based on machine learning is used for rate adaptation in [17], [18]. However, in these works, a mapping between contextual attributes and the channel behavior has not been established nor exploited. Nonetheless, to establish and leverage such a mapping, channel properties must be recognizable to the link adaptation algorithm to discern which prior decisions and the result thereof have applicability in the current environment.

Mobile devices such as smart phones and laptops have integrated sensors like GPS modules and accelerometers. The rich information collected by these sensors allows mobile devices to be aware of the context in which the wireless transmissions happen. The context information includes geographical and mobility characteristics for the device along with the instantaneous wireless channel quality. With data mining and machine learning, the collected data can provide guidelines for large amounts of mobile devices to improve their wireless transmission efficiency according to observed decisions and resulting performance in a particular context.

In this paper, we propose a channel recognition scheme based on the geometrical shape of link-level performance according to instantaneous channel quality, velocity of the device, and the channel type. We extract channel features by collecting performance data under different transmission modes and context tuples. Then, we introduce the mechanism by which unknown wireless environments are considered according to the geometric shape of the link-level performance. Confidence values are calculated to measure the similarity of the unknown channel to previously observed channel types, which is used to direct the channel recognition. If the unknown channel is recognized, additional network performance observations may add to the training. If the unknown channel is unrecognized, then a new channel type may form from the observed network performance. Experiments on controlled, repeatable and in-field channels show that the device is able to distinguish between diverse channel types based on context information using the extracted features.

Section II briefs the related works in the literature regarding channel recognition and other context-based channel classification approaches. Section III gives the details about how to describe the feature of channels and Section IV explains the proposed channel classification method. We conclude our paper in Section VI.

II. RELATED WORKS

Wireless channels have been classified into a large number of distinct types based upon the statistical attributes of the transmitted signal [19]. Such qualitative classifications include: *(i)* slow versus fast fading, quantifying the degree to which channel fluctuations occur [20], *(ii)* frequency selectivity versus flat fading, quantifying the diversity of channel quality across sub-carriers of a given frequency band [21], *(iii)* the number of multipath components that characterize the channel, quantifying the strength and delay spread of the reflections of the same transmitted signal [22], [23], *(iv)* Doppler spread [24], quantifying the coherence time of the channel based on the relative velocity of the sender and receiver, and *(v)* large-scale path loss, quantifying the attenuation encountered in a given environment with or without transmission through obstacles [25], [26]. Given the number of factors that compose a channel model and the wide variance that can exist in each metric, the number of channel types that exist approaches infinity. Moreover, these existing methods for channel classification do not help provide any direct indicator of the link-level performance. For example, the information of a channel falling into a fast-fading channel type will not currently assist the link adaptation for a transmitter which plans to send data in that channel.

According to the aforementioned metrics for defining wireless channels, channel modeling improves the ability to predict performance [27]. The focus of prior work is on improving the precision of the channel models by considering an increasing number of parameters (e.g., antenna height and transmission power). Most existing channel modeling methods require a precise description of the dominant physical characteristics of the wireless signal as it propagates through the channel [28], [29]. However, such an assumption of precise channel knowledge is unrealistic as it is rarely possible to measure those characteristics directly or precisely [30], [31]. Such measurements are usually taken offline and with the help of a channel sounder, which is often not available in the field. Moreover, because of the channel complexity and the existence of device-dependent factors, no well-established mapping exists between the channel description and the throughput of certain devices in this channel. From the perspective of link adaptation, the information that the device can benefit most from channel classification or channel modeling is the target rate that can give the highest throughput in the current channel. In contrast to prior approaches, we propose that two channels can be essentially treated as the same type if their transmission mode performance at all possible and reasonable combinations of contextual attributes are similar, leading to the proposed context-based link-level adaptation.

Context-aware Collection, Decision and Distribution (C2D2) engine [32] is designed and there are rate selection schemes based on context-awareness [14], [11] that can fit into the decision module in C2D2. The proposed algorithm in the paper can also be part of the decision module to assist the transmission rate selection.

More specifically, geometrical patterns have been used to characterize propagation models of wireless channels. A geometrical-based channel model is proposed in [33] and uses three parameters of the signal to characterize a channel: the power of the multipath component, the time-of-arrival of the component, and the angle-of-arrival of the components. An interference classification approach has used the angular difference between the current measurement and the stored reference power values of the interference to identify the interfering source [34]. Also, the authors choose the transmission channel based on the identified interference. In contrast to prior work, we use the geometrical-based model to recognize the channel type based on transmission mode performance to lead to better link adaptation decisions.

III. Channel Features

This section explains how to extract channel features from the wireless performance data measured between two wireless devices in a certain channel and how these features provide help to rate adaptation decisions. Using experimental data, we illustrate how the feature extraction works.

Consider a wireless transmitter and receiver pair which has a total of N_{mode} different *transmission modes*. For example, with M distinct modulation orders, C distinct coding rates, and H distinct MIMO configurations, there are $N_{mode} = MCH$ available transmission modes. We consider *data throughput* as the metric of wireless performance. For each transmission mode, the achievable throughput value depends on several different factors. These factors include not only the traditional indicators of signal quality such as the signal strength and the noise level. There are also some *contextual attributes* that relate to performance. For example, the velocity between the transmitter and receiver can be one of these factors since it relates to the maximum Doppler bandwidth. Other environmental parameters that potentially affect the throughput can also be considered, depending on the algorithmic complexity allowed in the hardware.

Assume the number of factors that we consider in the system is N_{factor}. We can construct a *context space* $\mathcal{P}$ with N_{factor} dimensions in which each point P_i ($f_1^i, f_2^i, ..., f_{N_{factor}}^i$) represents a certain set of factor values. Each real scenario that is measured/modeled in these N_{factor} factors can be mapped to one point in the space. Then, we represent the throughput of a certain transmission mode using t_i for each point P_i in the context space. This can yield a mapping $\mathcal{T} : P \rightarrow t$. Now $\mathcal{T}$ contains the performance information of one transmission mode. For a certain channel, we can find N_{mode} such tables along with the context space as a whole set of performance data $\mathcal{D} = \{\mathcal{P}, \mathcal{T}_1, \mathcal{T}_2, ..., \mathcal{T}_{N_{mode}}\}$. $\mathcal{D}$ contains the *features* of a wireless channel.

Like fingerprint to humans, the channel feature can be used to identify a channel. Each channel instance has a unique $\mathcal{D}$. However, we can selectively leverage part of the features to categorize channel instances and the methodology of feature selection is based on the purpose of categorization. Fig. 1 depicts an example of transmission mode behavior for three wireless channels when we only look at the transmission mode that achieves the highest throughput at a given context point P_i. In this example, there are $N_{mode} = 8$ transmission modes and and $N_{factor} = 2$ context factors: velocity between transmitter and receiver and received signal strength. $\mathcal{P}$ becomes a *context plane*. The granularity of the signal strength in $\mathcal{P}$ is 5 dbm, while the granularity for the velocity is 15 kmph. For the representation of throughput variance, the transmission mode with the highest throughput for each P_i, is shown by differently colored dots. The three plots depict the performance data set from three different channels. Fig. 1 shows the exacted features of different channel types. From the visual perspective, Channel 1 and Channel 2 are similar in performance, while Channel 3 is dramatically different.

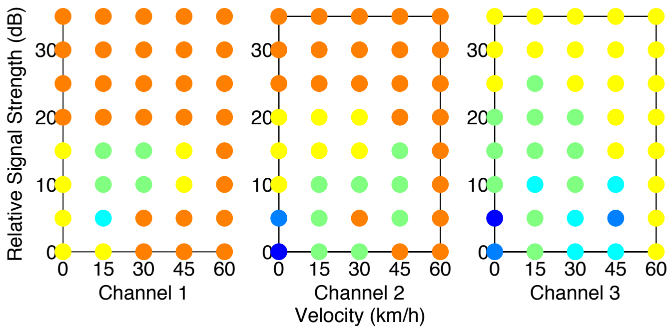


Fig. 1. Using highest throughput mode to depict channel feature.

As far as the concern of link-level adaptation, it is the performance variance of different transmission modes that are important in making rate decisions. The key idea behind our proposed channel classification process is: *channels that have the same or similar variance can be categorized as a single channel type*. The variance can be evaluated in many forms. The example in Fig. 1 leverages the top-performing transmission mode but it is difficult to develop an algorithm to determine visual similarity. Another example is to use the ranking of throughput values of different modes to capture the variance: for each $P_i \in \mathcal{P}$, we save the order of the $\mathcal{T}_j(P_i)$, where $j = 1...N_{mode}$, where having the same order for all P_i can be classified as one channel type. The performance order of different transmission modes in a channel is hard to measure as it needs a rotation of all the available transmission modes to collect performance probe data to compose a feature point P_i. In Section IV, we introduce a scalable classification algorithm which does not require large amount of probe points in undetermined channel.

IV. Geometry-based Channel Recognition

In this section, we introduce the proposed channel recognition based on the geometric shape of the performance data measured in the unknown channel and the previously observed channel types. As the algorithm does not limit the number of context information sources, for the simplicity of explanation, we measure two context factors: *(i)* relative velocities of the transmitter and the receiver and *(ii)* the transmitted signal strength (or the channel attenuation) as in Section III.

The sets of pre-defined channel types, velocities, and signal strength values in the training set can be represented by $\mathcal{C} = \{c_1, c_2, ..., c_C\}$, $\mathcal{V} = \{v_1, v_2, ..., v_V\}$, and $\mathcal{S} = \{s_1, s_2, ..., s_S\}$, respectively. Similarly, the transmission modes in a system can be represented by $\mathcal{M} = \{m_1, m_2, ..., m_{N_{mode}}\}$. As an initial starting point for a training set, we measure the achievable throughput $G_{c,v,s,m}$ using mode m in the channel model c with the velocity v and signal strength s for each of the ITU channel models (Table I) using a channel emulator. This training set serves as a group of previously-observed wireless channels by a given transmitter-receiver pair. For each model c, the $V \cdot S \cdot N_{mode}$ throughput values constitute the performance data d_c. A complete training set $\mathcal{R} = \{d_1, d_2, ..., d_C\}$ contains $C \cdot V \cdot S \cdot N_{mode}$ throughput values, which describes the system performance in these C channels.

With the aforementioned training set $\mathcal{R}$, we now use $N(N \geq 2)$ throughput values measured on an undetermined channel type (e.g., a channel observed in the field). The undetermined channel type's contextual attributes are used to classify the channel into one of the C channels. For each record $i(i = 1, ..., N)$, $\hat{G}_i$ denotes the measured throughput, using mode $\hat{m}_i$, and $\hat{v}_i$, $\hat{s}_i$ represent the corresponding velocity and signal strength, respectively. Then, we search the training set and find the throughput of all the channel models with the same contextual attributes and transmission mode. In other words, we look for $G_{c,\hat{v}_i,\hat{s}_i,\hat{m}_i}$ of all the C channel models. It is possible that $\hat{V}_i$ is not in $\mathcal{V}$ (same for $\hat{s}_i$). In this case, a linearly interpolated throughput $\tilde{G}_{c,\hat{v}_i,\hat{s}_i,\hat{m}_i}$ is calculated based on the throughput of the nearest velocity and signal strength values. The problem we seek to address is understanding how close or far the behavior of an undetermined channel type is compared to previously-observed channel types to be considered a known or unknown channel.

If plotted in a 3-D space where the x-, y-, and z-axis are signal strength, velocity, and throughput, respectively, the training set for a particular channel (d_c) is a family of meshes, where each mesh represents the throughput of a certain transmission mode with respect to signal strength and velocity. With interpolation, the meshes can be filled and turned into surfaces. By labeling all the $\tilde{G}_{c,\hat{v}_i,\hat{s}_i,\hat{m}_i}$, we can draw C curves as shown in Fig. 2, indicating the throughput variation trend is on the order of i from 1 to N. Similarly, we can also draw the curve of the throughput for the undetermined test channel. Let $\gamma_{c,i}$ denote the angle between the training set vector, $\overline{TSV}_c$, as:

$$((\hat{s}_{i+1}, \hat{v}_{i+1}, \tilde{G}_{c,\hat{v}_{i+1},\hat{s}_{i+1},\hat{m}_{i+1}}), (\hat{s}_i, \hat{v}_i, \tilde{G}_{c,\hat{v}_i,\hat{s}_i,\hat{m}_i})) \tag{1}$$

and the measured vector, $\overline{MV}$, which can be represented by:

$$((\hat{s}_{i+1}, \hat{v}_{i+1}, \hat{G}_{i+1}), (\hat{s}_i, \hat{v}_i, \hat{G}_i)) \tag{2}$$

for channel type c. The similarity index γ_c is defined as:

$$\gamma_c = \sum_{i=1}^{N-1} \gamma_{c,i}. \tag{3}$$

The channel recognition algorithm computes the channel model $c_{fit} = c_{j_0}$ that most likely has the same performance as the undetermined channel. We can formally represent this as $j_0 = \arg_j \min \gamma_{c_j,i}$. In this way, we find one existing channel type that has the most similar performance as the undetermined channel.

Fig. 2 is a representative 3-D plot for $C = 4$ and $N = 5$. In the figure, the surfaces in $\mathcal{R}$ are not plotted as their presence blocks the inner points. We can see that the throughput of the channel model A follows the trend of that of the undetermined channel, which results in the minimum γ_c compared with other channel models. The geometry-based channel recognition exploits the channel characteristic information lying in throughput measurement. When N grows, more features are provided by $\{\hat{G}_i\}$ and the resulting recognition is more accurate. Thus, there is a natural trade-off between calculation complexity and the estimation accuracy, which is quantified in Fig. 4(a).

V. Channel Recognition Evaluation

Channel emulators can reproduce the same channel conditions across multiple tests, providing a useful method to verify

Model	Pedestrian A		Pedestrian B		Vehicular A		Vehicular B		Custom Channel	
Tap	Delay (μs)	Power (dB)	Delay (μs)	Power (dB)	Delay (μs)	Power (dB)	Delay (μs)	Power (dB)	Delay (μs)	Power (dB)
1	0	0	0	0	0	0	0	-2.5	0	0
2	.11	-9.7	.2	-.9	.31	-1.0	.30	0	.15	-4.0
3	.19	-19.2	.8	-4.9	.71	-9.0	8.9	-12.8	.38	-8.7
4	.41	-22.8	1.2	-8.0	1.09	-10.0	12.9	-0.0	.85	-12.9
5	-	-	2.3	-7.8	1.73	-15.0	17.1	-25.2	1.40	-15.3
6	-	-	3.7	-23.9	2.51	-20.0	20	-16.0	-	-

TABLE I. POWER-DELAY PROFILES OF THE ITU CHANNEL MODELS USED ON THE CHANNEL EMULATOR.

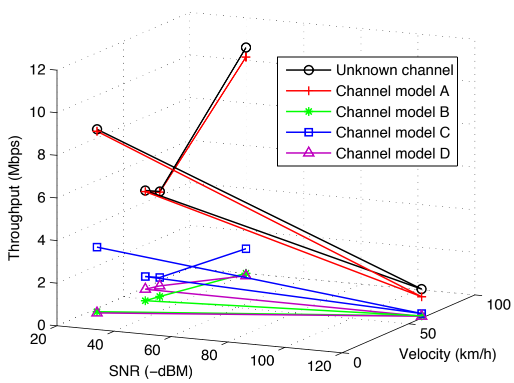


Fig. 2. Throughput versus SNR and velocity for different channel types in 3-D space.

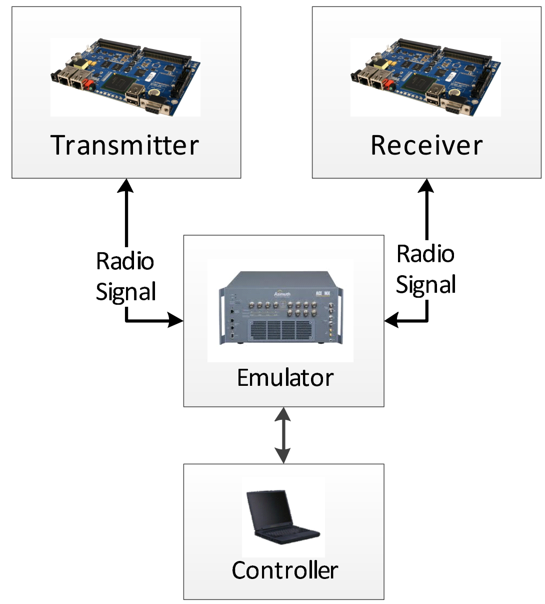


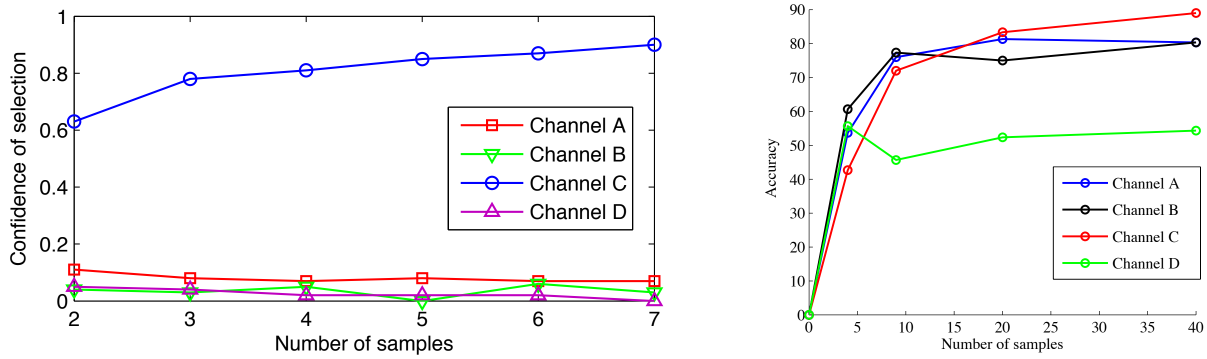
Fig. 3. Experiment setup

the channel recognition algorithm. We use an Azimuth ACE-MX [35] channel emulator for evaluation. Azimuth ACE-MX has the set of pedestrian and vehicular channel models as described in Table I. We create a custom channel model $c_{new} \notin \mathcal{C}$ from random choices of power and delay for five taps (see Table I for specific values), which we use to evaluate our geometry-based channel recognition. We use two GW2358-4 wireless router equipped with Ubiquiti XR5 radios. They are both connected via an Azimuth ACE-MX. Fig. 3 shows the experimental setup.

We select N sets of (c_{new}, s_i, v_i, m_i), measure the resulting throughput $\{\hat{G}_i\}$, and check if the algorithm can choose the model $c_{fit} \in \mathcal{C}$ which is most similar to c_{new}. As stated in Section III, we seek to select the transmission mode that maximizes throughput. Therefore, the definition of c_{fit} is the channel model that, once fed into a link adaptation decision structure along with the contextual attributes, outputs the transmission mode $m_{best} \in \mathcal{M}$ that achieves the maximum throughput in c_{new}. To determine c_{fit}, we first find m_{best} by measuring the throughput of all the $m_k \in \mathcal{M}$ in the undetermined channel with the same contextual attributes. We can more formally state this as: $M_{best} = \arg\max_{M_k} G_{c_{new},v_i,s_i,m_k}, k = 1, ..., R$. Then, we consider C scenarios such that $c_{fit} = c_j, j = 1, ..., M$. For each scenario, we input (c_j, v_i, s_i) to the decision tree [11], [36] and check if the output transmission mode m_j matches with m_{best}. We can repeat the procedure by choosing different v and s and find the c_j which has the most matching instances, which we call the *exhaustive search* algorithm and compare it with the performance of the geometry-based channel recognition algorithm.

We have done the iterative evaluation as shown in Fig. 4(a). The confidence of selecting channel model C is the highest out of all channels with just two records and has a monotonically increasing confidence level with additional records. On the other hand, for the other channel models the confidence is low with seven records. Fig. 4(b) shows that more training data will lead to more accurate channel recognition. A large training set will provide more detail about the throughput relationships across different SNR and velocity combinations. Thus, channel recognition can reduce the effect of errors in angular calculation introduced by interpolation, but requires additional samples.

It should also be noted that an incorrect channel recognition result does not necessarily mean a lower system throughput. Classifying an undetermined channel into other channel models besides c_{fit} may not result in the highest throughput m_{best}, but the output transmission mode of the decision structure may still achieve a throughput improvement compared to other link adaptation protocols.



(a) Channel Recognition Confidence.

(b) Channel Recognition Accuracy.

Fig. 4. Recognizing a custom channel type in terms of link-level throughput (left) and accuracy of channel recognition according to measurement samples (right).

VI. Conclusion

We have proposed a performance-based channel feature extraction. The channel characteristic is described by the achieved data throughput under different transmission modes and different environmental contexts. Then, leveraging the collected channel features, a geometry-based channel classification is introduced. In controlled, repeatable and in-field channels, we demonstrate the validity of the channel recognition algorithm. In the algorithm, if the confidence of all the channel types encountered are smaller than a certain threshold δ, then the algorithm would flag this channel as a new environment. We expect that the choice of the threshold will determine the total number of different channel types observed. In the future, we will quantify the trade-off between the number of different channel types and the throughput improvement possible in each of those scenarios. For instance, if there is a particular channel condition for which the confidence of recognition falls below the specified threshold, it would be classified as a new channel type. However, if the additional gains in throughput over a system when it is classified as an existing channel type is small, then it may not be efficient to include this as a new channel type. Increasing δ will lead to a larger number of channel types, while decreasing δ could lead to diverse channel conditions being grouped in the same type, resulting in reduced throughput achieved by the link adaptation.

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