CIPRA: Coherence-Aware Channel Indication and Prediction for Rate Adaptation

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***Abstract*—A number of rate adaptation protocols have proposed using instantaneous channel quality to select the physical layer data rate. However, due to fast channel variations, even aggressive probing of the channel before each data packet is often unable to offer an up-to-date notion of channel quality. In this paper, we propose a coherence-aware channel indication and prediction algorithm for rate adaptation (CIPRA) and evaluate it analytically and experimentally, considering both the measurement errors and the staleness of the channel quality indicator. CIPRA uses Minimum-Mean-Square-Error (MMSE), first-order prediction and jointly considers the time interval over which the prediction will occur and the coherence time of the channel to determine the optimal window size for previous channel quality indicator measurements. We also implement a Doppler shift estimation method in hardware to assist the proposed channel prediction algorithm. We show that CIPRA outperforms existing methods in terms of prediction fidelity and throughput via experimental results from an FPGA-based platform on emulated and in-field wireless channels. In our experiments in the field, CIPRA achieves up to 1.66 times the throughput achieved by the indication and prediction method currently used by off-the-shelf cards. CIPRA could be easily applied to other channel indicators, although we only evaluated RSSI-based rate adaptation in our experiments to isolate our gains.**

***Keywords*—Rate Adaptation, Prediction, RSSI, Channel Indication, Coherence Time, MMSE**

I. Introduction

Rate adaptation protocols can achieve high spectrum efficiency in fading channels by dynamically changing the data rate according to the channel quality. Rate adaptation protocols based on packet success/failure information have been implemented in commercial equipment and widely discussed [1]–[4]. However, these loss-based protocols usually require tens of frame slots to develop a reasonable estimation of the channel conditions [5]. Thus, for fast-fading channels (e.g. in vehicular networks), these protocols cannot track the changing channels well. To solve the fast-fading channel tracking problem, various channel-indicator-based rate adaptation protocols have been proposed [6]–[8]. SNR can be reported to the transmitter at the PHY-frame level to enable selection of the optimal rate in fast-fading channels. Some of the SNR-based rate adaptation protocols leverage the received signal strength indicator (RSSI) to calculate the SNR. However, in the presence of interference and noise, the signal power reported by RSSI can be highly noisy.

Typically, in SNR-based rate adaptation, the receiver decides the rate of the next transmitted packet according to the measured SNR of the current packet, whether the measurement originates from the RTS/CTS or DATA/ACK exchange [5], [9], [10]. There are still several potential problems with this mechanism. First, if the channel changes quickly, or there is a large time interval between two adjacent packets, the SNR reported by the last transmission may not accurately represent the instantaneous channel quality. Second, the SNR reported during the last transmission may not be accurate because of measurement errors from the indicator.

The rate selection problems caused by channel quality estimation errors have been studied in [11], [12]. Both works use filtering techniques to reduce the channel quality estimation errors in order to increase the rate selection accuracy. However, the delay incurred in filtering can make the rate prediction even more stale to predict the ongoing channel quality. To address the channel quality staleness problem, channel prediction has been extensively studied [13]–[20]. However, most of the authors assume a series of perfectly accurate channel measurements to predict the future channel state, which may not be possible in hardware. The estimation errors often make the prediction even more erroneous than simply using the reported value of the last transmission.

In this paper, we propose a coherence-aware MMSE first-order prediction algorithm, which takes both the measurement inaccuracy and measurement staleness into account. Prediction intervals and channel coherence time are jointly considered to select the optimal prediction window. We provide simulation results as well as experimental results from an FPGA-based platform on emulated and in-field wireless channels. The main contributions of our work are as follows:

1) We propose a coherence-aware MMSE first-order channel quality prediction algorithm, which takes into account both the measurement errors and staleness of the channel quality during the previous transmissions.
2) We analyze different channel predictions and compare them in terms of prediction errors as well as over- and under-selection probabilities for rate adaptation.
3) We present and implement a Doppler shift estimation method based on LCR (Level-Crossing Rate), with a homogeneous window to remove the effect of channel quality measurement errors, which achieves a good balance of complexity and accuracy.
4) We implement the existing channel prediction algorithms and the proposed algorithm on WARP [5] and experimentally compare them in terms of system throughput through both repeatable channel emulator tests and in-field experiments. In the field, CIPRA achieves up to 1.66 times the throughput achieved by

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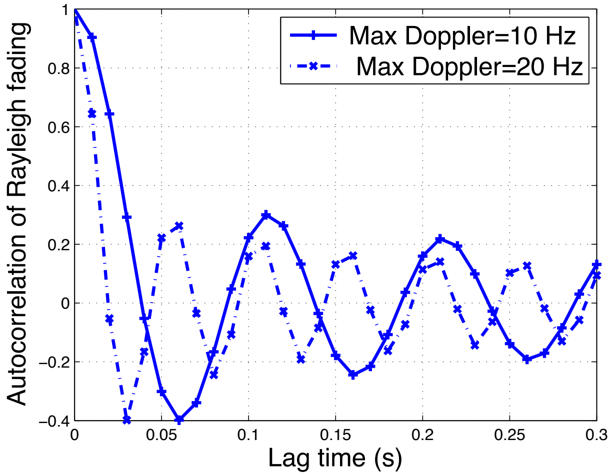

Fig. 1. Auto-correlation function of a Rayleigh fading channel with a maximum Doppler shift of 10 Hz.

the indication and prediction method currently used in off-the-shelf cards.

The rest of this paper is organized as follows. Section II presents an analysis of RSSI as a channel quality indicator and provides an on-line Doppler shift estimation method that is implemented on WARP. Next, we introduce our coherence-aware MMSE first-order prediction algorithm and analyze the performance of different prediction algorithms via simulation in Section III. An experimental evaluation system and numerical results are provided in Section IV, which shows vastly improved performance with our proposed algorithm. Related work is presented in Section V. Finally, Section VI contains concluding remarks and suggestions for future research.

II. Channel Quality Indication and On-line Doppler Shift Estimation

A. Channel Characteristics

Each of the multiple signal copies that result from multipath channel effect has differences in attenuation, delay, and phase shift. The constructive or destructive interference that results amplifies or attenuates the total signal power at the receiver, respectively. We use a Rayleigh fading channel model in the following analysis and simulation. The normalized autocorrelation function of a Rayleigh fading channel with motion at a constant velocity is a zeroth-order Bessel function of the first kind [21], [22]:

$$R(\tau) = J_0(2\pi f_d \tau) \tag{1}$$

where τ is the time delay, and f_d is the maximum Doppler shift.

The auto-correlation functions of a Rayleigh fading channel with a maximum Doppler shift of 10 Hz and 20 Hz are shown in Figure 1. This metric of auto-correlation can reflect the dependence between the channel qualities at different times.

B. Channel Quality Indication

Wireless channel quality is often affected by changing environments and interference. With the transmit signal power fixed, channel quality can be evaluated by the received signal quality. The most accessible channel quality indicator is the received signal strength indicator (RSSI). We use RSSI on WARP system as the channel indicator through this work.

RSS measurements are samples that may vary from sample to sample [5]. With a fixed transmit power and channel quality, the reported RSSI from WARP can vary on the order of 10 dB. Here is a summary of factors that may affect the channel quality estimation accuracy by RSSI.

1) **RSSI Signal Noise**. RSSI is measured in the transceiver and output as an analog signal, which often suffers from noise and interference on the board.
2) **RSSI ADC Performance**. An ADC is typically used to convert the RSSI signal from the analog to digital domain. The noise on the board, the resolution of the ADC, and the reference voltage stability of the ADC may all affect the digitized RSSI value.
3) **RSSI Sample Duration**. In the IEEE 802.11 standard, RSSI is calculated during the preamble of a physical layer frame. The limited duration of the preamble can not guarantee an accurate RSSI calculation.

Considering all the effects listed above, the RSSI accuracy may severely handicap an optimal rate selection decision. Despite these inaccuracies, we will show that our channel prediction can achieve large gains.

C. On-Line Doppler Shift Estimation

In this section, we introduce a Doppler shift estimation method for the purpose of implementation on our hardware platform. This method will later be applied in our channel prediction algorithm discussed in Section III. In general, Doppler shift estimation can leverage channel estimates, LCR (Level-Crossing Rate), a maximum likelihood function, or a correlation function [23]. LCR-based Doppler shift estimation achieves a good balance between complexity and accuracy. For Rayleigh fading channels, the LCR is expressed as [24]:

$$LCR = \sqrt{2\pi} f_d \rho e^{-\rho^2} \tag{2}$$

Here, f_d is the maximum Doppler shift, and ρ is the threshold normalized to the root mean square (RMS) signal level [24]. For a fixed Doppler shift, the LCR achieves its maximum value when $\rho = \sqrt{0.5}$, which is:

$$LCR = \sqrt{\pi} e^{-0.5} f_d \tag{3}$$

In hardware, the received signal usually suffers from additive noise. The level crossing resulted from the noise usually leads to over-estimation of the channel level-crossing rate. In [25], the author proposed an FFT-based Doppler-adaptive noise suppression method to remove the additive noise effect for LCR-based Doppler shift estimation. However, the FFT/IFFT processing is still costly in terms of system resources. In this paper, we create a homogeneous-window method to avoid over-estimation caused by the additive noise. The process of this method is described as follows:

1) Choose a threshold value from a pre-defined threshold set and compare the RSSI samples with this threshold. If the RSSI value of sample i is greater than the threshold, $c_i = 1$. Otherwise, $c_i = 0$.

TABLE I. DOPPLER SHIFT ESTIMATION ON WARP

f_{real}	10.0	20.0	30.0	40.0	50.0
f_{est}	11.4	21.8	31.1	41.2	51.6
f_{real}	60.0	70.0	80.0	90.0	100.0
f_{est}	60.6	70.2	79.6	87.5	96.1

2) Apply a sliding time window τ to the results in step 1. If $c_i == 1$ for all the samples in window τ, we denote the system state $S = 1$. If $c_i == 0$ for all the samples in window τ, we denote the system state $S = -1$. Otherwise, $S = 0$. For multiple adjacent samples that make the system stay in the same state, only one value is used.
3) Calculate the derivative of the state vector recorded in step 2 and count the number of transitions of the derivative from negative to positive in one second, denoted by n.
4) Repeat step 1 to step 3 for all the values in the predefined threshold set and finally find the maximum value of n.

To decide the time window τ, we should jointly consider the RSSI sample period and the Doppler shift range we want to estimate. In the IEEE 802.11 standard, the RSSI is reported every packet. For the maximum Doppler shift range of 1 Hz to 100 Hz, $\tau = 3\ ms$ works well in the experiment on the channel emulator. Table I shows the Doppler shift estimation by using the WARP board and the channel emulator, where f_{real} is the Doppler shift that we set on the emulator and f_{est} is the Doppler shift estimated by WARP. We observe that the proposed algorithm can obtain an accurate estimation of the Doppler shift.

III. CHANNEL PREDICTION

In order to select the optimal rate, the transmitter constantly needs the channel quality measurement from the receiver. Prior SNR-based protocols have frequently used the channel quality measured from the last packet transmission to the pertinent receiver [9], [10]. These channel indicator measurements are stale with sufficient levels of fading. In this section, we analyze a number of different channel quality prediction algorithms and propose an advanced algorithm to keep the transmitter in step with the fluctuating channel quality. In order to achieve an accurate prediction, we take both the measurement error of the channel indicator and the staleness of the reported channel quality from the receiver into account.

A. Existing Prediction Method

There are several mechanisms to predict future channel quality from the previous channel quality measurements for rate adaptation.

Follower. For this mechanism, the transmitter simply copies the channel measurements from the last packet transmission as the predicted value of the ongoing channel quality [16], which can simply be denoted as $\hat{\gamma}_n = \gamma_{n-1}$, where $\hat{\gamma}_n$ is the estimate of the ongoing channel quality, and γ_{n-1} is the channel quality measurement reported during the last packet transmission. This method suffers from both measurement errors and staleness of the past channel indicator values.

Moving Average. There are 3 main kinds of moving average methods: simple moving average, linear weighted moving average, and exponential weighted moving average [16]. Simple moving average is the unweighted mean of the previous points in a window size of w. The estimated channel quality is denoted as:

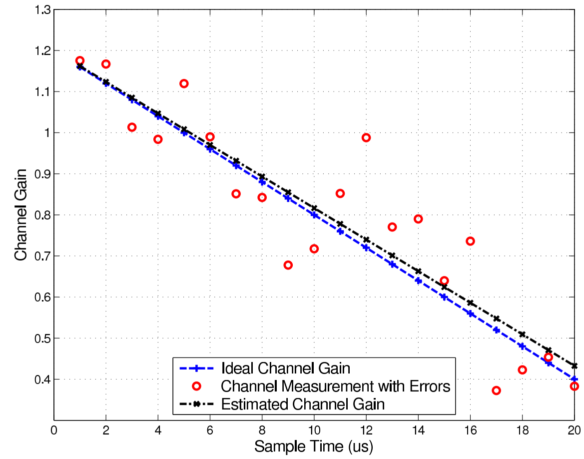

Fig. 2. channel quality reconstruction using MMSE first-order prediction.

$$\hat{\gamma}_n = \frac{\gamma_{n-1} + \gamma_{n-2} + \cdots + \gamma_{n-w}}{w} \quad (4)$$

For linear moving average (LWMA), weight factors are assigned to the past measurements in a linear progression with a window size of w. The estimated value can be expressed as:

$$\hat{\gamma}_n = \frac{w\gamma_{n-1} + (w-1)\gamma_{n-2} + \cdots + \gamma_{n-w}}{(w+1)w/2} \quad (5)$$

For exponential weighted moving average (EWMA), the weight of the measurements decreases with a factor of δ.

$$\hat{\gamma}_n = \delta\gamma_{n-1} + (1-\delta)\hat{\gamma}_{n-1} \quad (6)$$

All these moving average methods reduce the effect of the measurement errors, but make the staleness effect more severe than the follower method.

Linear prediction. By assuming that the channel quality indicator has a constant first-order derivative across three adjacent packets [16], we can predict the ongoing channel quality from the last two channel measurements.

$$\hat{\gamma}_n = \gamma_{n-1} + \Delta\gamma(t_n - t_{n-1}), \quad \Delta\gamma = \frac{\gamma_{n-1} - \gamma_{n-2}}{t_{n-1} - t_{n-2}} \quad (7)$$

where γ_{n-1} and γ_{n-2} are the channel measurements at time t_{n-1} and t_{n-2}, respectively. This method is more robust to the prediction staleness. However, the errors of the past measurements may make $\Delta\gamma$ twice as noisy, leading to a prediction with an intolerable noise level in some cases.

B. Coherence-aware MMSE First Order Perdition

From the discussion in Section III-A, some of the methods are more robust to measurement errors, while others are more robust to the prediction staleness. For a good prediction, both the measurement errors and staleness should be jointly considered. In this section, we propose a coherence-aware MMSE first-order prediction.

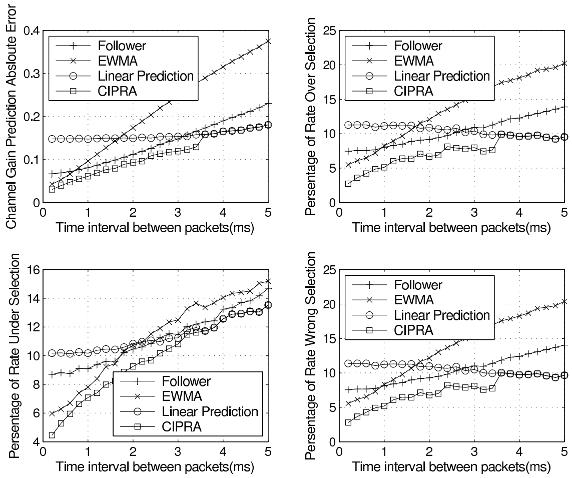

Fig. 3. channel quality prediction performances comparison

In Section II-A, we introduced the Rayleigh fading model and its auto-correlation. When doing the prediction, we need the previous measurements in a sliding time window T. From Figure 1, we see differing dependence between measurements with the same maximum Doppler shift and differing time delay, or with the same time delay and differing maximum Doppler shifts. Thus, when selecting the time window T, we should take the Doppler shift into account. We can denote T as $T = \frac{\beta}{f_d}$, where f_d is the Doppler shift that can be estimated by the method we proposed in Section II. β is a constant factor. In our simulation and experiments, we select $\beta = 0.064$, which empirically achieves the best accuracy.

Assuming that within the time window T, there are w channel measurements $\gamma_{n-1}, \gamma_{n-2}, \cdots, \gamma_{n-w}$ at time $t_{n-1}, t_{n-2}, \cdots, t_{n-w}$, respectively. From all the points within the window, we perform a first-order curve fit with the constraint of minimum square errors. To do so, we first assume the objective first order curve is $f(t) = at + b$, where a and b are parameters to be calculated. Then, we have:

$$\gamma\prime_{n-i} = f(t_{n-i}) = at_{n-i} + b \quad i = 1, 2, \cdots, w \tag{8}$$

The sum of the square errors between the samples on the curve $\gamma\prime_{n-i}$ and the actual measurements γ_{n-i} are:

$$E = \sum_{i=1}^{w} (\gamma\prime_{n-i} - \gamma_{n-i})^2 \tag{9}$$

Our objective is to find the value of a and b when E achieves its minimum value. We can expand (9) as:

$$\begin{aligned} E &= \sum_{i=1}^{w} (a^2 t_{n-i}^2 + 2a(b - \gamma_{n-i})t_{n-i} + (b - \gamma_{n-i})^2) \\ &= a^2 \sum_{i=1}^{w} t_{n-i}^2 + 2ab \sum_{i=1}^{w} t_{n-i} - 2a \sum_{i=1}^{w} \gamma_{n-i} t_{n-i} \\ &\quad - 2b \sum_{i=1}^{w} \gamma_{n-i} + \sum_{i=1}^{w} \gamma_{n-i}^2 + \sum_{i=1}^{w} b^2 \end{aligned} \tag{10}$$

Let us use the follow notation for simple expression: $\alpha_1 = \sum_{i=1}^{w} t_{n-i}^2, \alpha_2 = \sum_{i=1}^{w} t_{n-i}, \alpha_3 = \sum_{i=1}^{w} \gamma_{n-i} t_{n-i}, \alpha_4 = \sum_{i=1}^{w} \gamma_{n-i}, \alpha_5 = \gamma_{n-i}^2, \alpha_6 = w$. Then, we can simply express (10) as:

$$E = \alpha_1 a^2 + 2\alpha_2 ab - 2\alpha_3 a - 2\alpha_4 b + \alpha_5 + \alpha_6 b^2 \tag{11}$$

To find the minimum value of E, we take its derivative in terms of a and b, respectively. Then, we force both the derivatives to 0 to obtain the following pair of equations:

$$\begin{cases} \alpha_1 a + \alpha_2 b - \alpha_3 = 0 \\ \alpha_2 a + \alpha_6 b - \alpha_4 = 0 \end{cases} \tag{12}$$

From (10), we know that $E \geq 0$ for all a and b, which means that there exists a minimum value of E. The solution of a and b in the above equation pairs will enable E to achieve its minimum value. With a and b obtained, we can obtain our pre-estimate of $\hat{\gamma_n}\prime$ as:

$$\hat{\gamma_n}\prime = f(t_n) = at_n + b \tag{13}$$

We know that the fading channel does not strictly maintain a constant first-order derivative, especially for long intervals between packets. In a more extreme case, if the packet interval exceeds a certain time interval, the prediction may be uncorrelated with the real channel quality. Considering this, we use a weighting factor δ to weight the pre-prediction and the channel quality with the maximum probability. Consequently, the estimated channel quality $\hat{\gamma_n}$ is:

$$\hat{\gamma_n} = \delta(t_n - t_{n-1}) \cdot \hat{\gamma_n}\prime + (1 - \delta(t_n - t_{n-1})) \cdot \bar{\gamma} \tag{14}$$

where

$$\delta(t) = \begin{cases} 1 - t \cdot f_d & \text{if } t < \frac{1}{f_d} \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

Here, f_d in (15) is the maximum Doppler shift, and $\bar{\gamma}$ is the channel quality which has the greatest statistical probability of occurrence. For computational simplicity, we approximate it using the mean value of the channel quality measurements during the last 10 seconds.

Note that within the time window T, there is the probability of $w \leq 2$. When $w = 2$, our algorithm turns out to be the Linear Prediction. Similarly, if $w = 1$, our algorithm matches the Follower mechanism. For the case of $w = 0$, we choose the maximum probability channel quality $\bar{\gamma}$ as our prediction.

In Figure 2, we show the result of the MMSE first-order channel quality prediction. There is -15 dB measurement error compared to the channel quality. Clearly, the reconstructed channel response approaches the theoretical curve well. The square errors of the prediction is about -38 dB compared to the theoretical one, which means a 23-dB accuracy gain.

We simulated and evaluated Follower, EWMA, Linear Prediction, and our proposed algorithms using a Rayleigh fading model, as shown in Figure 3. We set the channel measurement error to -20 dB compared to the average channel quality. We can see that, for our proposed algorithm, both the prediction errors and the over-selection/under-selection probability are smaller than existing algorithms.

The computational complexity of the proposed algorithm is higher than the other algorithms discussed above. However, it takes less than 1 μs on the PowerPC embedded on WARP, which is much less than the DIFS/SIFS time of the transmission. As a result, it does not affect the system throughput.

TABLE II. THROUGHPUT WITH DIFFERENT COMBINATIONS OF CHANNEL INDICATOR AND PREDICTION METHODS

Doppler Shift	Throughput (Mbps)			
	Follower	EWMA	Linear	CIPRA
1 Hz	12.59	13.41	10.88	13.88
2 Hz	11.87	12.53	10.84	13.65
5 Hz	11.05	11.47	10.62	13.12
10 Hz	10.83	11.19	10.10	12.75

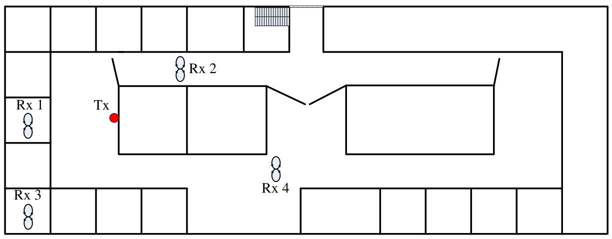

Fig. 4. The 8th floor layout of SMU Expressway Tower.

IV. Experimental Evaluation

In this section, we implement and evaluate the performance of our coherence-aware MMSE first-order prediction algorithm on the Wireless Open-Access Research Platform (WARP) using emulated and in-field wireless channels.

We conduct our experimental evaluation based on a full orthogonal frequency division multiplexing (OFDM) physical layer design per the IEEE 802.11a/g standard. The design operates in real-time, transmitting and receiving wide-band signals. We implement complete real-time signal processing, synchronization, and control systems in the fabric of the FPGA on WARP, which is a useful wireless communication system supporting a fully customized cross layer design [5].

A. Emulator Test

We use the Azimuth ACE-MX channel emulator to generate repeatable and controllable channel effects, which provides approximately the same effects as complex over-the-air channels.

In our channel emulator evaluation, we set the packet size to 1536 bytes. We use a two-tap Rayleigh fading channel with an average effective SNR of 15 dB. Both taps have a 0-dB relative attenuation, and the time delay between the taps is 0.5 μs. The result is shown in Table II, and indicates that CIPRA outperforms other methods significantly. The EWMA method performs better with less of a Doppler shift effect because there is less staleness when the Doppler shift is low. With an increasing Doppler shift, the linear method becomes comparatively better because of the increasing staleness effect of Follower and EWMA. The current configuration used in SNR-based rate adaptation mechanisms on off-the-shelf devices is RSSI and Follower. Thus, with a Doppler shift of 10 Hz, CIPRA achieves a throughput improvement of 28% over this configuration. Later, we show that results in the field exceed these gains as the channels become more complex.

B. Indoor Pedestrian Test

We conduct our indoor experiments on the 8th floor of the SMU Expressway Tower (floor plan shown in Figure 4). We set up two transmitter/receiver pairs, which are operating at the same time. One uses 2484 MHz (Ch. 14), and the other uses 2462 MHz (Ch. 11), which are orthogonal from

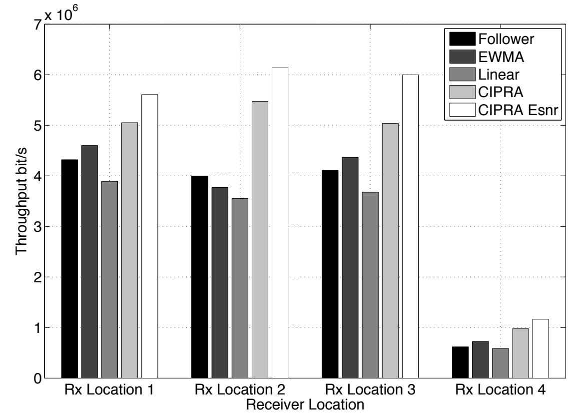

Fig. 5. The indoor experiment result.

Fig. 6. The experimental environment outside of SMU Expressway Tower.

one another. For each experiment, we run CIPRA on a tx/rx pair, and one of the other three methods on the other tx/rx pair. We co-locate the transmit antennas and co-locate the receive antennas to ensure the two links have very similar channels. For each comparison, we flip the links back and forth for each experimental trial to remove any unfair advantage between the two channels. The transmitters are located on the table in the lab, and we select four offices to locate mobile receivers, as shown in Figure 4. We randomly move the receiver nodes in each office to create time-varying channels. We show the average throughput of the four methods on the four different locations in Figure 5. CIPRA greatly outperforms other methods at all four locations with up to a 66% throughput improvement with an improved prediction algorithm from those currently used in practice.

C. Outdoor Vehicular Test

We now perform outdoor experiments in the parking lot of the SMU Expressway Tower (shown in Figure 6). The transmitter and receiver settings are the same as with the indoor experiment. We place the transmitters in the entrance of the tower and the receivers in a car with the antennas mounted on the roof. We drive the car along the path shown in Figure 6, with an average speed of 20 MPH. We also switch the channels of the two tx/rx pairs to remove the unfairness of different channels for each comparison. We show the average throughput of the four methods in Table III. Due to the higher Doppler shift in vehicular environment, the linear method has improved performance. CIPRA also outperforms the three other methods with up to 1.51 times the throughput.

TABLE III. THROUGHPUT RESULT FOR OUTDOOR EXPERIMENT

Follower	EWMA	Linear	CIPRA
3.07 Mbps	3.52 Mbps	3.95 Mbps	4.83 Mbps

V. RELATED WORK

Channel quality prediction has been explored for various purposes ranging from understanding wireless channel characteristics to improving rate adaptation, routing, and topology control. In [15], the authors implemented and compared packet-counting-based and SNR-based link quality estimation to further predict the packet success rate. In both [11] and [12], the authors leverage filtering to reduce the channel quality estimation errors in order to increase the rate selection accuracy for a rate adaptation protocols. Eyceoz [13] assumes that the fading channel is composed of several scattered components, and the factor of each component is constant. However, in real scenarios, the fading parameters are not constant nor are the measurements perfectly accurate. A Wiener LMS algorithm is presented by Lindbom [17] to improve the channel tracking performance. Dong [19] proposed an ESPRIT-type algorithm to predict the wide-band time-varying channel at different frequencies jointly and showed better performance than prediction over a single frequency. In [14], the authors proposed a pattern-matching method to predict the channel quality by finding the most similar channel varying pattern as the current channel changing trend. In contrast, we study the accuracy of a family of channel quality indicators as well as form prediction algorithms that are robust to the indicator measurement errors and staleness.

VI. CONCLUSION

In this paper, we proposed a coherence-aware MMSE first-order prediction algorithm (CIPRA), which considered both the measurement inaccuracy and staleness. Prediction intervals and channel coherence time were jointly considered to select the optimal prediction window. We also implemented a Doppler shift estimation method to assist our prediction algorithm. We compared CIPRA to the traditional channel quality prediction for rate adaptation protocols, performing experiments on an FPGA-based platform over emulated and in-field wireless channels. We show that our proposed algorithm can provide better prediction fidelity and results in 1.66 times the throughput versus the current configuration in off-the-shelf devices in the field. In the future, we plan to consider more complex, second-order prediction which may add performance gains to those already achieved by CIPRA. A wider family of channel indicators is also important to be investigated in our future work.

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