

MIMO Channel Prediction Results on Outdoor Collected Data

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Abstract— In this paper we analyze the performance of an autoregressive MIMO channel predictor on outdoor data collected with both vehicular and pedestrian transmitter motion. The metric of performance considered is aggregate beamforming gain obtained using dominant eigenmode MIMO communications when the transmit beamforming vector is chosen based on the channel prediction. We show that while the prediction range obtained on this real data is somewhat less than earlier published results based on simulated data, we are still able to obtain 2X to 3X greater feedback latency tolerance than without using these predictive techniques.

I. INTRODUCTION

Communications channel prediction is an essential technique for utilizing adaptive transmission schemes in scenarios where the channel varies rapidly due to motion and multipath. The adaptive transmission scheme of particular interest to the authors is informed transmitter MIMO across a distributed transmit array such as that shown in Fig. 1. Coherent transmission (beamforming) across a distributed network of radios causes the expected received power to grow quadratically with the number of transmitting radios. This feature can enable long distance communications using a network of small, low-power radios [1-7].

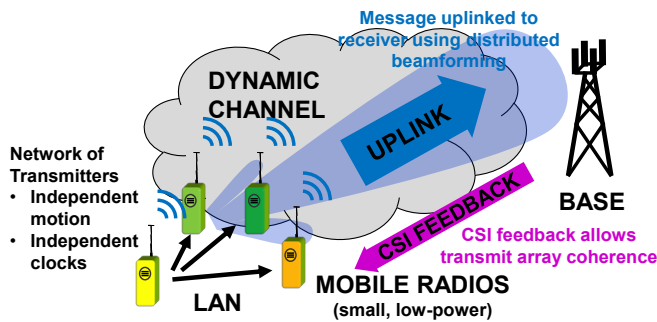


Fig. 1 Receiver-coordinated distributed transmit beamforming allows an ad-hoc network of transmitters to achieve longer communication ranges.

If it were possible to know the current channel state information at the transmit array, the size of the distributed array could be chosen to achieve arbitrarily long uplink ranges, but unfortunately estimation of the MIMO channel coefficients does not scale with the size of the array. As communications range increases, the per-channel SNR decreases and more integration time must be used during channel sounding to

achieve an accurate CSI estimate. This effect is shown in Fig. 2 for a feedback-based system that interleaves incoherent channel sounding slots and coherent uplink beamforming slots. This CSI estimation requirement ultimately limits the communications range that can be achieved using feedback-based informed transmit techniques in dynamic channel environments [8-10]. The minimum latency of the CSI feedback is half the channel sounding interval plus the time needed to calculate the CSI from the sounding samples and feed this back over the downlink channel.

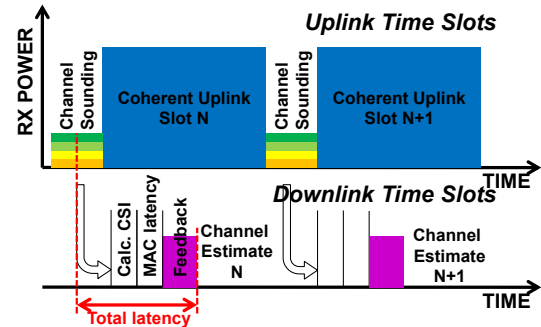
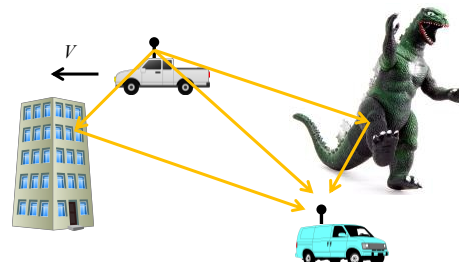


Fig. 2 Feedback latency is fundamentally limited by the duration of the channel sounding which must increase as per-channel SNR decreases at long ranges.

This minimum latency can easily be greater than the interval over which the channel can be modeled as stationary. In these situations, channel prediction techniques can increase the amount of latency that can be tolerated.

Dozens papers have addressed the problem of multipath channel prediction (see [11] for survey). The communications channel is generally modeled as a superposition of paths, each with its own complex amplitude and Doppler frequency which are either constant or change very slowly (Fig. 3).



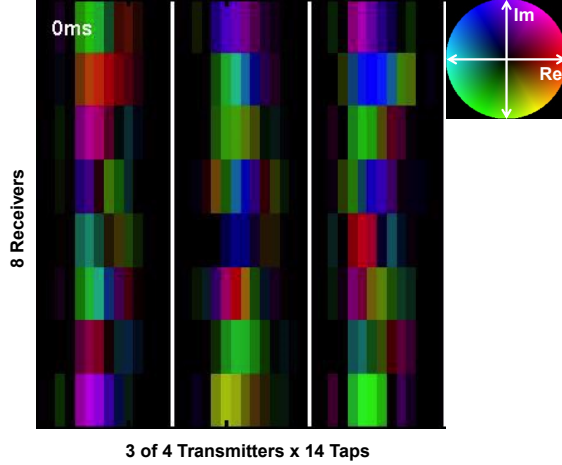


Fig. 7 Frequency selective MIMO channel at one snapshot in time.

C. Channel Prediction

For the purposes of this analysis, we treat each tap of each transmit-receive pair as an independent AR(2) process and fit the coefficients to the evolution of the estimated channel. Let $x[n]$ denote the channel coefficient corresponding to a particular (tap, TX channel, RX channel) triplet, then we model

$$x[n] = a_1 x[n-1] + a_2 x[n-2] + u[n] \quad (3)$$

where $u[n]$ is assumed to be a white noise process sequence. Each tap, transmitter, receiver triplet gets its own set of complex AR coefficients. We utilized the Burg method to estimate these coefficients. The Burg method guarantees a stable AR process model.

Once the AR process coefficients for a particular channel are estimated, they can be used to predict the value of the channel in the future. We can rewrite (3) as

$$\begin{bmatrix} x[n+1] \\ x[n] \end{bmatrix} = \underbrace{\begin{bmatrix} a_1 & a_2 \\ 1 & 0 \end{bmatrix}}_{\mathbf{A}} \underbrace{\begin{bmatrix} x[n] \\ x[n-1] \end{bmatrix}}_{\mathbf{x}[n-1]} + \begin{bmatrix} u[n] \\ 0 \end{bmatrix} \quad (4)$$

Given our assumption on the AR process noise, the MMSE p-step predictor is simply

$$\hat{\mathbf{x}}_{\text{ar}}[n+p] = \mathbf{A}^p \mathbf{x}[n], \quad (5)$$

where $x[n]$ corresponds to the known channel state at time n as generated by the LMS algorithm above. It is natural to compare the performance of this predictor against the “trivial” stationary predictor given by

$$\hat{\mathbf{x}}_{\text{triv}}[n+p] = \mathbf{x}[n], \quad (6)$$

Fig. 8 shows the performance of the AR predictor against the true channel when using 60ms of training and predicting ahead 40ms.

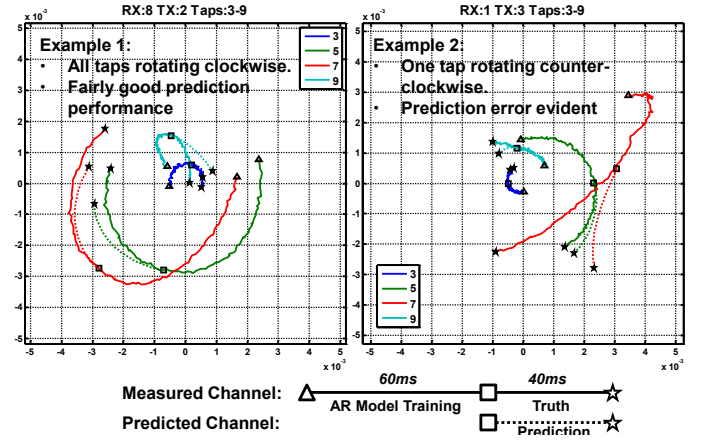


Fig. 8 Two examples of channel prediction performance against collected data for transmitters on a 10mph truck.

III. PERFORMANCE

A. Performance Metric

Most previous work on channel prediction has directly characterized the channel tracking accuracy; however this is only indirectly related to communications performance. The motivating application for this work is feedback-based dominant eigenmode MIMO communications, which uses beamforming on transmit and receive to maximize the aggregate SNR of the SISO channel formed. In this context, achieved beamforming is the appropriate performance metric for comparing the performance of a channel prediction scheme.

Fig. 9 illustrates dominant eigenmode MIMO communications where transmit and receive beamforming vectors are chosen to maximize the SNR of the resulting SISO channel.



Fig. 9 Dominant eigenmode MIMO communications

When the true channel matrix $\mathbf{H}_{\text{true}}[n]$ of a frequency-flat MIMO channel is known, the optimal beamforming vectors are obtained by first performing a singular value decomposition of the channel

$$\mathbf{H}_{\text{true}}[n] = \mathbf{U}[n]\mathbf{S}[n]\mathbf{V}[n]^H \quad (7)$$

and then selecting the receive and transmit beamforming vectors to be the left and right singular vectors corresponding to the largest (dominant) singular value

$$\mathbf{w}_{\text{opt}}^{\text{RX}}[n] = \mathbf{u}_1[n], \quad \mathbf{w}_{\text{opt}}^{\text{TX}}[n] = \mathbf{v}_1[n] \quad (8)$$

in which case the maximum beamforming gain of $S_{11}[n]$ is achieved.

The true channel matrix is not available at the transmitter primarily because of the feedback latencies discussed above and the transmitter must rely on an estimate $\hat{\mathbf{H}}[n]$ of the channel provided by the receiver. This estimate can be obtained using channel prediction techniques. The optimal

transmit beamforming vector given this channel estimate is the dominant right singular vector of the estimate

$$\hat{\mathbf{w}}^{\text{TX}}[n] = \hat{\mathbf{v}}_1[n] \text{ where } \hat{\mathbf{H}}[n] = \hat{\mathbf{U}}[n]\hat{\mathbf{S}}[n]\hat{\mathbf{V}}[n]^H \quad (9)$$

We note, however, that while feedback latency affects the fidelity of the channel estimate available to the transmitter, the receiver knows the current true channel state (up to channel estimation error which we ignore here) and can use this knowledge, along with the transmitters chosen beamforming vector, in selecting its receive beamforming vector. In a white-noise interference environment, the receive beamforming vector that maximizes beamforming gain is the matched filter

$$\hat{\mathbf{w}}^{\text{RX}}[n] = \frac{\mathbf{H}_{\text{true}}[n]\hat{\mathbf{v}}_1[n]}{\|\mathbf{H}_{\text{true}}[n]\hat{\mathbf{v}}_1[n]\|} \quad (10)$$

The beamforming loss, relative to omniscient knowledge of the channel can be calculated for a particular channel estimator as

$$\eta_{\text{dB}}[n] = 10 \log_{10} \left(\frac{\|\mathbf{H}_{\text{true}}[n]\hat{\mathbf{v}}_1[n]\|}{\|\mathbf{H}_{\text{true}}[n]\hat{\mathbf{v}}_1[n]\|_{S_{11}}[n]} \right) \quad (11)$$

These equations generalize to a frequency selective formulation.

B. Evaluation Methodology

Channel prediction performance was computed as follows:

- STEP 1: The AR model discussed above was used to independently predict each component (tap, transmitter, receiver) of the MIMO channel for prediction ranges of 10ms, 30ms, 50ms and 100ms.
- STEP 2: Beamforming gain was computed for (a) the true channel (optimal beamforming), (b) the AR-predicted channel and (c) the trivial channel predictor obtained by assuming a stationary channel.

Fig. 10 and Fig. 11 show, respectively, the beamforming performance of the AR(2) channel predictor and the trivial channel predictor at 3 different prediction intervals. The AR(2) predictor clearly out-performs the stationary predictor for vehicular motion.

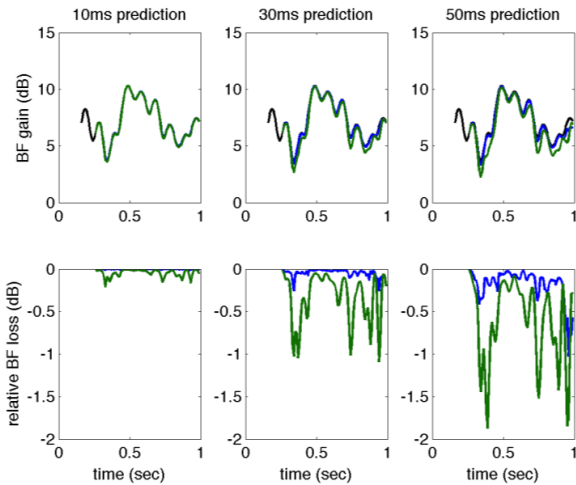


Fig. 10 Beamforming gain (top) and relative beamforming loss (bottom) for the 10mph truck collection. Three different prediction intervals show performance of omniscient channel knowledge (black), the AR(2) predictor (blue) and the trivial stationary estimate (green).

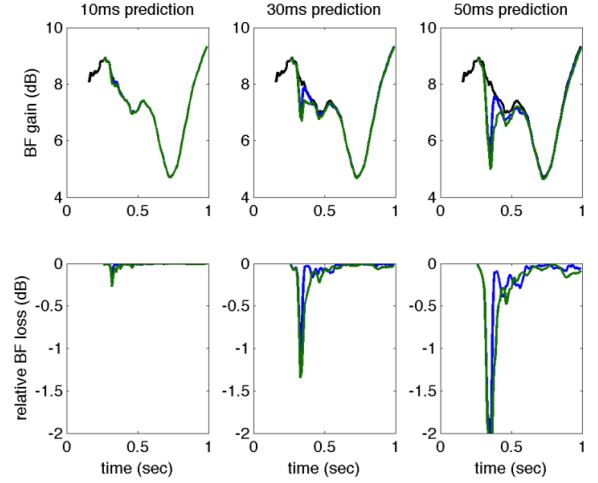


Fig. 11 Beamforming gain (top) and relative beamforming loss (bottom) for the "people bobbing" collection. Three different prediction intervals show performance of omniscient channel knowledge (black), the AR(2) predictor (blue) and the trivial stationary estimate (green).

C. Beamforming Loss Distributions

Fig. 12 shows the cumulative distribution (over time) of the channel predictors.

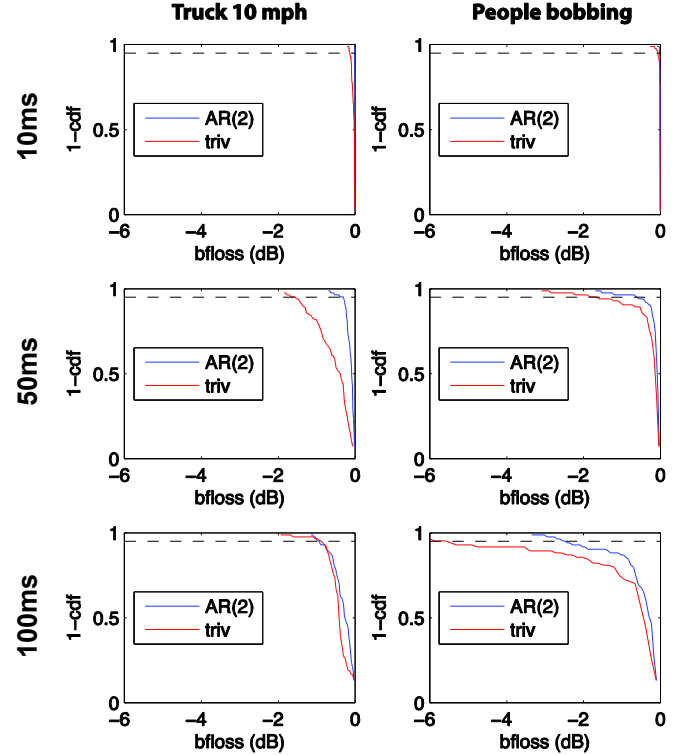


Fig. 12 Cumulative distributions of beamforming loss (relative to omniscient channel knowledge) for the AR(2) (blue) and trivial (red) predictors at three different prediction ranges.

We use the dashed 95% point to quantify the beamforming loss vs. prediction range for the channel predictors.

IV. CONCLUSIONS AND FUTURE WORK

TABLE II. summarizes the prediction performance of the AR and trivial channel predictors against the vehicular and pedestrian data collections as well as the expected performance of AR SISO channel predictors documented in the literature.

TABLE II. RESULTS SUMMARY

	Vehicular	Pedestrian
Wavelength	0.8 m	
Maximum velocity	4.5 m/s	~1 m/s
Prediction range (λ/V to $1.5\lambda/V$)	180ms to 280ms	800ms to 1200ms
AR predictor range	~100ms	~60ms
Trivial predictor range	~30ms	~30ms

As defined, the AR(2) predictor offers a channel prediction range of about $0.5 \lambda/V$ for a vehicular motion channel and only a $0.1 \lambda/V$ prediction range for a channel with pedestrian motion dynamics. In contrast, simulation results from the literature suggest that prediction ranges of $1.0 \lambda/V$ to $1.5 \lambda/V$ are possible using AR channel predictors. The performance mismatch is likely because the assumption of nearly-constant path amplitudes and Doppler frequency shifts is less applicable to these datasets. Nevertheless, the AR(2) predictor supports 2X (pedestrian) or 3X (vehicular) greater latencies than the trivial predictor.

Future work in this area may attempt to incorporate the spatial and delay structures of the MIMO channel into the AR model as suggested in [13]. This approach is challenging because it introduces non-linearities into the channel model.

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