Perspective: Eliminating Channel Feedback in Next Generation Cellular Networks

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The ever-increasing demand for data has forced cellular networks towards advanced multi-antenna (MIMO) techniques. However, advanced MIMO solutions such as massive MIMO, coordinated multi-point, distributed MIMO, and multi-user MIMO, all require the base station to know the downlink channels to the client. In the absence of this information, the base station cannot beamform its signal to its users. Therefore, base stations require user devices to perform the measurements and send the channels back to the basestation as feedback. This feedback generates significant overhead that scales linearly with the number of antennas, and is a bottleneck for next generation of cellular networks with large antenna deployments.

Our work, R2-F2 (originally described in [10]), takes a different approach. R2-F2 enables cellular base stations to estimate the downlink channels *without* any user feedback at all. R2-F2 uses channel measurements on the uplink, i.e. on signals transmitted from the client and received at the base station, to infer downlink channels. The key challenge in building R2-F2 is that a majority of cellular networks (all major networks in United States) use different frequencies for uplink transmissions from the client and downlink transmissions from the basestation, i.e. they use Frequency-division Duplexing (FDD). Therefore, to infer downlink channels from uplink channels, R2-F2 must answer a fundamental question: *How do we infer the wireless channels on one frequency band by observing those channels on a different band?*

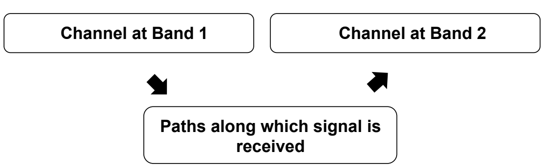

Figure 1: R2-F2's Approach: R2-F2 extracts the paths of the signal from channels on frequency band-1 to reconstruct the corresponding channels on frequency band-2.

To answer this fundamental question, R2-F2 builds a new bridge between two different streams of wireless networking research: communication and localization. R2-F2 infers wireless channels across frequencies by leveraging a simple observation: while the channels change with frequencies, the underlying physical paths traversed by the signal stay the same. R2-F2 builds on past research in RF-based localization [9, 12] to develop a transform that can infer parameters (like distance, angle, etc.) of the physical paths traversed by the signal from uplink channels measured at the base station. Once it has characterized the physical paths, it can invert the transform to convert these physical paths to wireless channels on a different frequency on the downlink (see Fig. 1). Since R2-F2 can convert channels from one frequency band to another frequency band, it enables cellular networks to benefit from MIMO techniques without incurring the channel feedback overhead.

1 IMPACT AND FOLLOW-UP

R2-F2 advances the state-of-the-art along two axes. First, it proposes the use of computational techniques at the physical(PHY) layer, i.e., relying on channel estimates that are not physically measured but computationally estimated. Second, it shows how wireless channels measured at one frequency band can be translated into wireless channels at a different frequency band. Both these contributions have been built upon by researchers in the area, and have led to new research directions. We discuss these directions below:

Pushing PHY Techniques to the Edge: The proliferation of low power resource-constrained IoT devices has precipitated the trend of minimizing resource usage on the end user devices and pushing computations to the edge devices (like IoT base stations, Wi-Fi access points, etc.). A subset of this trend has been to offload the physical layer compute from the client to the edge. R2-F2 was an early work in this direction as it eliminates the channel estimation and channel feedback overhead of the client.

Ever since, multiple researchers have focused on building on R2-F2 to develop more accurate computational methods for similar problems in cellular networking research. One line of work has focused on using super-resolution to better estimate the underlying physical parameters from wireless channels [11, 13]. Inspired by the same intuition as R2-F2 some recent work [2, 7] has adopted deep learning methods for accomplishing the task of converting uplink channels to downlink channels without requiring any additional information.

Beyond cellular networks, multiple researchers [3, 4] have built on R2-F2 to demonstrate the benefits of channel prediction in unlicensed spectrum like Wi-Fi or LPWANs. For instance, [4] builds a channel prediction algorithm for low power sensor networks that can increase battery life of sensors by 230%. It does so by predicting wireless channels across frequency bands, and using this prediction to pick a frequency that optimizes the communication between the sensor and the base station. The channel computation and optimization is done on the base station to offload any overheads on the client device.

mmWave Beam Alignment: Recent years have seen proliferation of research in the mmWave networking space. mmWave frequency bands offers orders of magnitude higher bandwidth than Wi-Fi or cellular networks, and hence are crucial for high throughput applications like wireless virtual reality, or video streaming. Since mmWave devices operate at much higher frequencies (28 GHz or 60 GHz, as opposed to sub-6 GHz for Wi-Fi), they experience significantly higher attenuation. To overcome this attenuation, they must use narrow beams to communicate between the transmitter and receiver. As a consequence, the transmitter and receiver must align their beams before communication can begin. This beam alignment process leads to latencies of tens of milliseconds, thereby negating the advantage of mmWave networks for latency sensitive applications, and mobile devices where the alignment needs to be periodically performed.

An active area of research [1, 8] aims to perform this beam alignment using wireless channel information on other frequency bands (like Wi-Fi). The core idea is that the correct beam alignment depends on the physical configuration of the underlying paths that the signal can travel from the transmitter to the receiver. Similar to R2-F2, the physical configuration of paths can be inferred using wireless channels at much lower frequencies like Wi-Fi and cellular without requiring directional beams and beam alignment. Once these physical parameters of the underlying space are identified, these parameters can be used to infer the possible beam alignments at the higher frequencies used for mmWave transmissions.

Physical Layer Security: Wireless channels sit at the core of physical layer security methods. Past work has tried to use wireless channels as secure keys for information exchange under the assumption that wireless channels cannot be inferred without explicitly measuring them between two locations. The ability to infer these channels without explicitly measuring them has opened up new possibilities for security attacks and defences.

Since R2-F2 demonstrates the ability to measure wireless channels across frequencies, new security methods [6] use the inferred channels as alternatives to key exchange in cellular networks. The base station and client can now have a shared key (i.e. the downlink channel) without requiring either of them to send this key to each other. On the other hand, new attacks [14] have emerged that exploit this ability to infer wireless channels to estimate wireless channels between two devices by snooping on communication between them. When viewed in conjunction with newer and more accurate computational techniques for inferring channels, this line of research can lead to more potent attacks over time.

1.1 Impact Beyond Research

R2-F2 bridged wireless communication and localization to show how wireless channels can be inferred across frequency bands by going through underlying physical representations. To illustrate such cross-connections between different areas of wireless networking research, the paper has become a core part of wireless networking education: CMU, Princeton, Purdue, Northwestern, Shanghai Jiao Tong, and other universities teach R2-F2 in their wireless networking classes.

The challenge of reducing uplink feedback in multi-antenna system has been acknowledged to be a key issue for next generation cellular systems in the LTE standardization process [5]. Given the increased focus on using computational techniques at the physical layer, we envision that in the following decade, many of the techniques and systems discussed here will be parts of standards for cellular systems.

2 CONCLUSION

R2-F2 demonstrated how the performance of next-generation cellular networks can be enhanced by the use of computational techniques that leverage the interactions between wireless signals and their physical environments. In the last three years, this intuition has led to follow-up work in multiple research domains: cellular networks, mmWave systems, and wireless security. Beyond research, the work has percolated into education curriculum for wireless networking, and has contributed to discussions in the LTE standards body. We hope that in the next few years, one of R2-F2's iterations will form a core component of multi-antenna cellular networks deployed worldwide.

REFERENCES

[1] Ali, A., Gonzalez-Prelcic, N., and Heath, R. W. Millimeter wave beam-selection using out-of-band spatial information. *IEEE Transactions on Wireless Communications* (2018).

[2] Arnold, M., Dörner, S., Cammerer, S., Yan, S., Hoydis, J., and Brink, S. T. Enabling FDD massive MIMO through deep learning-based channel prediction. *arXic e-prints* (2019).

[3] Chowdhery, A., and Jamieson, K. Aerial channel prediction and user scheduling in mobile drone hotspots. *IEEE/ACM Transactions on Networking* (2018).

[4] Gadre, A., Narayanan, R., Luong, A., Kumar, S., Rowe, A., and Iannucci, B. Frequency Configuration for Low-Power Wide-Area Networks in a Heartbeat. USENIX NSDI.

[5] Ji, H., Kim, Y., Lee, J., Onggosanusi, E., Nam, Y., Zhang, J., Lee, B., and Shim, B. Overview of full-dimension mimo in lte-advanced pro. *IEEE Communications Magazine* (2017).

[6] Li, G., Hu, A., Sun, C., and Zhang, J. Constructing reciprocal channel coefficients for secret key generation in fdd systems. *IEEE Communications Letters* (2018).

[7] Sadegh Safari, M., and Pourahmadi, V. Deep UL2DL: Channel Knowledge Transfer from Uplink to Downlink. *arXiv e-prints* (2018).

[8] Sur, S., Pefkianakis, I., Zhang, X., and Kim, K.-H. Wifi-assisted 60 ghz wireless networks. ACM MobiCom.

[9] Vasisht, D., Kumar, S., and Katabi, D. Decimeter-level localization with a single wifi access point. In *USENIX NSDI* (2016).

[10] Vasisht, D., Kumar, S., Rahul, H., and Katabi, D. Eliminating channel feedback in next-generation cellular networks. ACM SIGCOMM.

[11] Wang, M., Gao, F., Jin, S., and Lin, H. An Overview of Enhanced Massive MIMO with Array Signal Processing Techniques. *arXiv e-prints* (2019).

[12] Xiong, J., and Jamieson, K. Arraytrack: A fine-grained indoor location system. In *USENIX NSDI* (2013).

[13] Yang, W., Chen, L., and Liu, Y. E. Super-resolution for achieving frequency division duplex (fdd) channel reciprocity. In *IEEE 19th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)* (2018).

[14] Zhang, X., and Knightly, E. W. CSISnoop : Inferring Channel State Information in Multi-User MIMO WLANs. *IEEE/ACM Transactions on Networking* (2019).