EliMO: Eliminating Channel Feedback from MIMO

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***Abstract*—MIMO beamforming provides high throughput for WiFi networks, but it also leads to high computation and communication overhead due to Channel State Information (CSI) feedback. Explicit CSI feedback provides high beamforming gains, but it introduces extremely high overhead. Implicit CSI feedback has low overhead, but it provides very low beamforming gains. We propose EliMO to completely Eliminate CSI feedback from MIMO without sacrificing beamforming gains. EliMO uses two-way channel estimation to allow WiFi Access Points (AP) to accurately estimate downlink CSI without explicit CSI feedback. To measure downlink CSI at the WiFi AP, the WiFi station (STA) puts the received signal of downlink training symbols into Feedback Training Field (FTF) and sends it back to the AP. The AP estimates the two-way channel using the received signal of FTF. Analysis and experiment results show that EliMO is able to provide as high beamforming gains as explicit CSI feedback and as low overhead as implicit CSI feedback. EliMO significantly reduces computation and communication costs of measuring and sending CSI feedback for smart devices, like smartphones, smartwatches, and wireless drones. We evaluate the throughput and energy consumption of EliMO by experiment measurements in both static and mobile scenarios. Evaluation results show that EliMO provides 5× and 4× throughput as implicit and explicit CSI feedback, respectively. Energy consumption of EliMO is only 85%/30% of that of implicit/explicit CSI feedback.**

I. Introduction

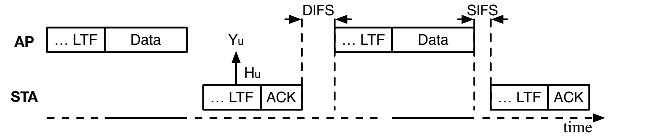
Multiple-Input Multiple-Output (MIMO) is the key technology for wireless networks to achieve high throughput. Along with Orthogonal Frequency-Division Multiplexing (OFDM), MIMO provides Channel State Information (CSI) per subcarrier, so that beamforming can be used to improve Signal-to-Noise Ratio (SNR) and throughput [1, 2]. MIMO beamforming provides high throughput by steering the radio energy to the direction of the target receiver, or sending multiple packets concurrently to different receivers. This is done by precoding the transmit signal to different spatial streams and antennas. Moreover, MIMO is able to select the best transmission strategies efficiently assisted by CSI, which helps combat multi-path and frequency-selective fading effects [3, 4].

However, CSI introduces extremely high overhead for MIMO receivers, especially for smart devices like smartphones, smartwatches, and wireless drones. To calculate the beamforming matrix and select the best transmission strategies, the transmitter needs CSI feedback that introduces a lot of computation and communication costs for MIMO receivers. First, MIMO receivers require computation resources to measure and estimate the CSI matrix. Second, the transmission time for data packets is dramatically sacrificed due to CSI feedback. For channel width of 80MHz, the size of CSI matrix is 1,700 bytes for 3×3 MIMO and 53,000 bytes for 8×8 MIMO [1, 5]. Moreover, multi-user MIMO has even higher overhead since it needs higher frequency of CSI measurements and feedback to deal with inter-user interference [1, 6]. Finally, MIMO receivers consume much energy for sending CSI feedback, which consumes up to 4 times energy as sending a data packet for a MIMO receiver. Thus it is crucial to reduce CSI feedback overhead, especially for smart devices like smartphones, smartwatches, and wireless drones.

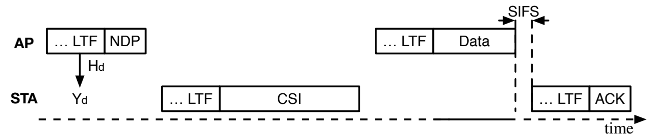
There are many methods on reducing CSI feedback overhead [7–10], but they are not optimized for smart devices and still introduce high computation and communication costs for MIMO receivers. First, MIMO receivers still need to continually measure and estimate the CSI matrix. Second, the STA needs to calculate when to send the CSI matrix and how much feedback is needed, which involves expensive matrix calculations. Finally, MIMO receivers still need to send CSI matrices to the transmitter, even though the feedback frequency and/or feedback size could be reduced. All these computation and communication costs of CSI feedback consume a lot of energy of the STA. The AP can use implicit CSI feedback, which uses the transpose of uplink CSI as the downlink CSI, to reduce feedback overhead [5]. But it has very low beamforming gains, since real-world MIMO channels are not reciprocal due to baseband-to-baseband channels and interferences [2, 5].

We propose EliMO to completely Eliminate CSI feedback from MIMO without sacrificing beamforming gains. EliMO completely eliminates the communication costs of sending the CSI matrix for MIMO receivers. In addition, the computation costs for MIMO receivers are significantly reduced. The challenge is how the WiFi AP could accurately estimate the downlink CSI without explicit CSI feedback. The EliMO protocol works as follows. The AP sends Long Training Field (LTF) in the packet header to the STA. The STA inserts the received signal of downlink LTF as Feedback Training Field (FTF) into the packet header and sends it back to the AP. The AP is able to estimate the downlink CSI based on the received signal of FTF, combined with the uplink CSI that is estimated by uplink LTF sent from the STA. In summary, we make the following contributions.

- We present two-way channel estimation allowing the AP to accurately estimate downlink CSI without explicit CSI feedback.
- We propose Feedback Training Field to completely eliminate CSI feedback without sacrificing beamforming gains.

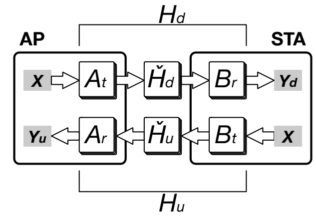


(a) Implicit CSI Feedback. The AP uses the transpose of H_u as H_d.

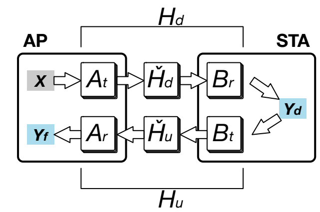


(b) Explicit CSI Feedback. The STA sends H_d in the CSI packet to the AP.

Fig. 1. MAC-layer operations for implicit and explicit CSI feedback. Dashed timeline is the transmission time of control frames. The STA spends much time and energy for transmitting control frames for explicit CSI feedback.



(a) Downlink/uplink CSI estimation for explicit/implicit CSI feedback



(b) Two-way CSI estimation for EliMO

Fig. 2. Downlink/uplink CSI estimation separately and two-way CSI estimation. H_d and H_u are baseband-to-baseband channels, and $\check{H}_d$ and $\check{H}_u$ are over-the-air channels. Implicit CSI feedback has low beamforming gains since H_d and H_u are not reciprocal in real-world MIMO systems.

We evaluate EliMO by experiment measurements in both static and mobile scenarios. Evaluation results show that EliMO is able to provide as low overhead as implicit CSI feedback and comparable SNR as explicit CSI feedback. The average throughput of EliMO is 5× and 4× of that of implicit and explicit CSI feedback, respectively, in static scenarios. In mobile scenarios, EliMO provides 3.6×/4.5× throughput as implicit/explicit CSI feedback. Energy consumption of EliMO is 85%/91% of that of implicit CSI feedback in static/mobile scenarios. The average energy consumption of EliMO is only 30% and 17% of that of explicit CSI feedback, in static and mobile scenarios, respectively.

The rest of the paper is organized as follows. Section II shows the key idea of EliMO and compares it with existing CSI feedback schemes in terms of SNR and overhead. Section III presents the EliMO protocol design, including frame format, two-way channel estimation, and MAC-layer operations. Experiment setup and evaluation results of EliMO for both static and mobile scenarios are given in Section IV. Section V summaries related works. Section VI concludes the paper and discusses future work.

II. Eliminating CSI Feedback from MIMO

This section presents the background and limitations of existing CSI feedback schemes. The key idea of EliMO is introduced to eliminate CSI feedback without scarifying beamforming gains. SNR and overhead analysis results are presented to show the effectiveness of EliMO.

A. MIMO Background

The received signal of beamforming at each sub-carrier is

$$Y = HQX + N, \tag{1}$$

where H is the CSI matrix, Q is the beamforming matrix, X is the transmit signal, and N is the noise signal. The beamforming matrix Q, which is usually a function of H, is used for mapping spatial streams to antennas. For Zero-Force BeamForming (ZFBF), which is a widely used beamforming algorithm, the beamforming matrix is $Q = H^*(HH^*)^{-1}$, where $(\cdot)^*$ is the conjugate transpose operation. Due to power constraint of each transmit antenna, the beamforming signal must satisfy $E[|[QX]_j|^2] \leq P_j$, where P_j is the power constraint for the jth transmit antenna [11]. Since the transmitter does not know H, it needs CSI feedback from the receiver.

IEEE 802.11n defines two CSI feedback methods, i.e., implicit and explicit [5], as shown in Fig. 1. The CSI matrix is estimated using Long Training Field (LTF), which is part of the packet header. The transmitter sends LTF, which contains predefined signal X, to the receiver. The receiver estimates downlink/uplink CSI H_d/H_u using received signal Y_d/Y_u. For implicit CSI feedback, the AP uses the transpose of H_u as H_d. This is based on the assumption that H_d and H_u are reciprocal. As shown in Fig. 1a, the AP measures H_u by the previous ACK packet, and H_u is used to calculate the beamforming matrix for the following data packet. Fig. 1b shows MAC-layer operations for explicit CSI feedback. The AP first sends Null Data Packet (NDP) to the STA to measure the downlink CSI. The STA estimates H_d and sends it in the CSI packet back to the AP. The AP calculates the beamforming matrix based on H_d for transmitting the data packet.

Both implicit and explicit CSI feedback have limitations that influence the performance and efficiency of WiFi STAs. The reason is that they estimate downlink and uplink CSI separately, leading to either low beamforming gains or high overhead. For implicit CSI feedback, the transpose of H_u is not an accurate estimation of H_d, since H_d and H_u are not reciprocal in real-world MIMO systems. As shown in Fig. 2a, baseband-to-baseband channels H_d and H_u are not reciprocal, even though over-the-air channels $\check{H}_d$ and $\check{H}_u$ are reciprocal [5]. Besides, downlink and uplink interferences are usually not reciprocal [2]. The channel reciprocity of multi-user beamforming is even worse due to inter-user interference. For explicit CSI feedback, the STA has very high communication and energy overhead. Since the STA needs to send the CSI matrix to the AP, the STA spends much time and energy for transmitting none-data frames, as shown in Fig. 1b. The communication costs of CSI feedback is very high, since the size of CSI is very large and it grows rapidly as the number of antennas and channel width increase [1, 8].

B. Key Idea of EliMO

We EliMO to completely Eliminate CSI feedback from MIMO without sacrificing beamforming gains. *The goal of EliMO is to provide as high beamforming gains as explicit CSI feedback and as low overhead as implicit CSI feedback*. EliMO significantly reduces computation, communication, and energy overhead for STAs without sacrificing beamforming gains. Fig. 2b shows the procedure of two-way channel estimation. The AP sends the training signal X to the STA, and the STA sends the received signal Y_d, in a amplify-and-forward way, back to the AP. The received signal of Y_d at the AP is Y_f, and the AP estimates the two-way channel based on X and Y_f. The STA does not need to demodulate Y_d. Besides, the STA does not need to calculate when and how to send CSI feedback. Thus the computation overhead of the STA is significantly reduced. Moreover, the STA does not need to send CSI back to the AP, so the communication overhead of sending CSI packets for the STA is completely eliminated. The only extra overhead of EliMO compared with implicit CSI feedback for the STA is sending Y_d, which is only 8μs. Finally, the energy consumption of sending CSI packets for the STA is also eliminated. In the following we show SNR and overhead analysis to show that two-way channel estimation is able provide high SNR with low overhead.

C. SNR Analysis

Since the transmit signal after using beamforming is QX, the effective MIMO channel is $H_{eff} = HQ$ [4]. In practical MIMO systems, there is always a time delay between when downlink CSI is measured and when the measured CSI is used to send the data packet. In this case, the effective CSI is

$$H_{eff} = H_{dd}Q = H_{dd}\hat{H}_d^*(\hat{H}_d\hat{H}_d^*)^{-1}, \tag{2}$$

where H_{dd} is the downlink CSI of the data packet, and $\hat{H}_d$ is the measured downlink CSI. Both H_{dd} and $\hat{H}_d$ are baseband-to-baseband channels, which consist of digital baseband and over-the-air channels. For over-the-air channels with multiple paths, the CSI value from the ith transmit antenna to the jth receive antenna at the kth sub-carrier is

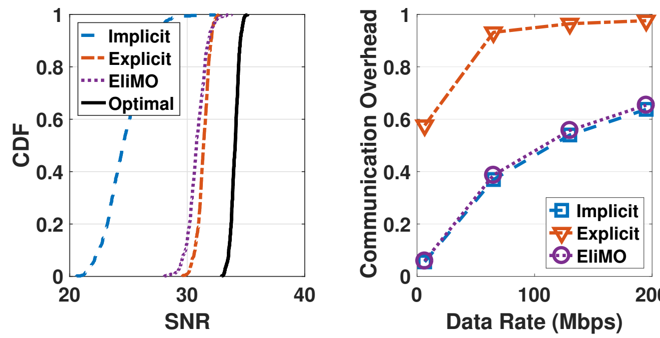
$$\check{h}_{ijk} = \sum_n^N a_n e^{-j2\pi d_{ijn}/\lambda_k}, \tag{3}$$

where a_n is the attenuation along the nth path, d_{ijn} is the distance between the ith transmit and the jth receive antenna along the nth path, λ_k is the wavelength of the kth sub-carrier, and N is the number of paths [12]. For baseband signal $x(t)$, the corresponding RF signal is $x_{rf}(t) = Re\{x(t)e^{-j2\pi f_c t}\}$, where f_c is the carrier frequency, and $Re\{\cdot\}$ returns the real part of the input [5].

The STA uses Minimum Mean Square Error (MMSE) [3, 4, 13] to decode the received signal. The SNR of the kth sub-carrier of the jth spatial stream is $snr_{k,j} = 1/Y_{jj} - 1$, where $Y = (H_{eff,k}{}^* H_{eff,k} + I_S)^{-1}$, $H_{eff,k}$ is the effective CSI of the kth sub-carrier, and I_S is an $S \times S$ identity matrix with $S = \min(N_t, N_r)$ as the maximum number of streams supported by the MIMO channel [3, 4]. The difference between H_{dd} and $\hat{H}_d$ introduces beamforming errors and influences the receiving SNR. The receiving SNR is

$$snr = \text{dB}(\sum snr_{k,j}/\sqrt{S}), \tag{4}$$

where $\sqrt{S}$ is the scaling factor [3, 4].



(a) CDF of SNR (b) Communication Overhead

Fig. 3. SNR and communication overhead analysis. EliMO provides as high SNR as explicit CSI feedback and as low overhead as implicit CSI feedback.

Fig. 3a shows the Cumulative Distribution Function (CDF) of SNR using implicit/explicit CSI feedback and two-way channel estimation. The initial distance between the AP and STA is 5 meters, and the STA moves away from the AP at the speed of 1.2 meters/second. The size of the CSI packet is $3 * 3 * 52 * 32/8 = 1,872$ bytes for a 20MHz WiFi channel with 3/3 transmitting/receiving antennas, 52 sub-carriers, and 32 bits of data for each CSI value. The size of the data packet is 1,500 bytes. EliMO has 7dB higher SNR than implicit CSI feedback, and only 0.8dB lower SNR than explicit CSI feedback. SNR analysis results in Fig. 3a demonstrate that *EliMO provides as high SNR as explicit CSI feedback*. This is validated by CSI traces from real-world experiments, which will be shown later in Section IV.

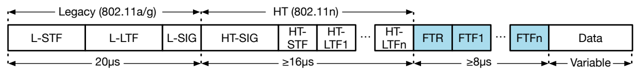
D. Overhead Analysis

For each data packet, control packets are needed for MAC-layer coordinations and beamforming matrix calculations, as shown in Fig. 1. Sending and receiving these control packets introduce computation and communication overhead for the STA. The communication overhead is defined as

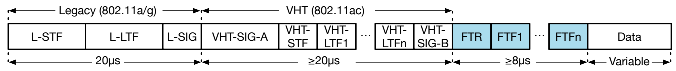
$$\tau = \frac{t_{control}}{t_{control} + t_{data}}, \tag{5}$$

where $t_{control}$ is the transmission time for control frames, and t_{data} is for data frames. Control frames are always transmitted using the lowest data rate, while data frames can use higher data rates. For a certain CSI feedback scheme, $t_{control}$ is relatively stable. When the data rate for data frames is much higher than that of control frames, which is the common case for 802.11n/ac, t_{data} is much smaller than $t_{control}$. In this case, the communication overhead is extremely high.

Fig. 3b shows the results of communication overhead of implicit/explicit CSI feedback and EliMO. The channel width



(a) 802.11n High Throughput (HT) mixed mode with FTR and FTF



(b) 802.11ac Very High Throughput (VHT) with FTR and FTF

Fig. 4. Frame Format of 802.11n/ac Packets with FTR and FTF

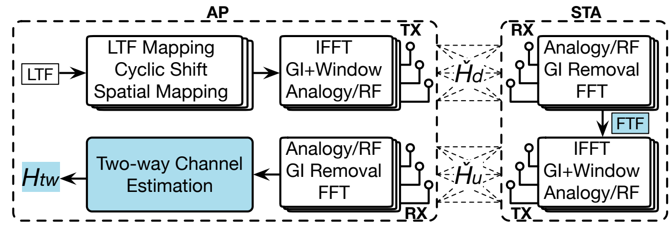


Fig. 5. Block diagram of two-way channel estimation using FTF. Two-way channel estimation includes the impact of digital baseband of both the AP and STA. Blocks in blue color are added by EliMO.

is 20MHz, and the data rate for data frames is in the range of 6.5-195Mbps for up to 3/3 transmitting/receiving antennas [5]. The communication overhead of EliMO is comparable as that of implicit CSI feedback, and is only 40% to 90% lower than that of explicit CSI feedback. Fig. 3b demonstrates that *EliMO introduces as low overhead as implicit CSI feedback*.

To sum up, FTF has comparable SNR as explicit CSI feedback and much higher SNR than implicit CSI feedback, as shown in Fig. 3a. The communication overhead of FTF is similar to that of implicit CSI feedback, and it is much lower than that of explicit CSI feedback, as shown in Fig. 3b.

III. ELIMO PROTOCOL DESIGN

This section presents the EliMO protocol design including frame format, two-way channel estimation, and MAC-layer operations. There are two challenges for EliMO to get high beamforming performance.

- The AP needs to accurately estimate the downlink CSI in the presence of two-way channel propagations and interferences.
- The AP needs to determine whether the measured downlink CSI is stale and when to request feedback training.

A. Frame Format

EliMO reuses the frame format of 802.11n/ac packet headers. Fig. 4 shows the frame format of EliMO for 802.11n mixed mode and 802.11ac packets. Two new fields, i.e., Feedback Training Request/Response (FTR) and Feedback Training Field (FTF), are inserted after 802.11n/ac packet headers. FTR indicates whether feedback training is requested or not and whether FTF is sent back or not. FTR is inserted right after the 802.11n/ac preamble. If the request field of FTR is 1, the AP sets the response field to 0, which means there is no FTF sent after FTR. When the STA receives the request of feedback training, it sets the response field of FTR to 1 and sends FTF following FTR. FTF is in corresponding with each HT/VHT-LTF. The length of FTR and FTF are both 4μs. If there is only one HT-LTF or VHT-LTF, the length of FTR plus FTF is 8μs. Comparing with implicit CSI feedback that typically has 150μs of control overhead, EliMO introduces only 8μs extra overhead.

B. Two-way Channel Estimation

The AP estimates the downlink CSI using the received signal of FTF, i.e., the received signal of downlink LTF that goes through both the downlink and uplink MIMO channel. The AP needs to accurately estimate the downlink CSI in the presence of two-way channel propagations and interferences. To address this issue, the STA amplifies the received signal of downlink LTF and sends duplicated FTFs back to the AP.

Fig. 5 shows the block diagram of two-way channel estimation. White blocks are components in existing 802.11n/ac systems, and blue blocks are added in EliMO. The AP sends LTF to the STA, which performs FFT on the received signal. The STA performs analogy/RF, Guard Interval (GI) removal, and FFT to include the impact of digital baseband of both the AP and STA. Since the STA does not need to demodulate the received signal, it has lower computation overhead. The STA amplifies the received signal and sends it back to the AP in FTF. The AP estimates the two-way channel, i.e., $H_{tw} := H_u H_d$, by the received signal and the original LTF signal. The AP also estimate the uplink CSI $\hat{H}_u$ by the received signal of uplink LTF from the STA. We use the pseudo-inverse of $\hat{H}_u$ and two-way channel H_{tw} to estimate the downlink CSI $\hat{H}_d$, i.e.,

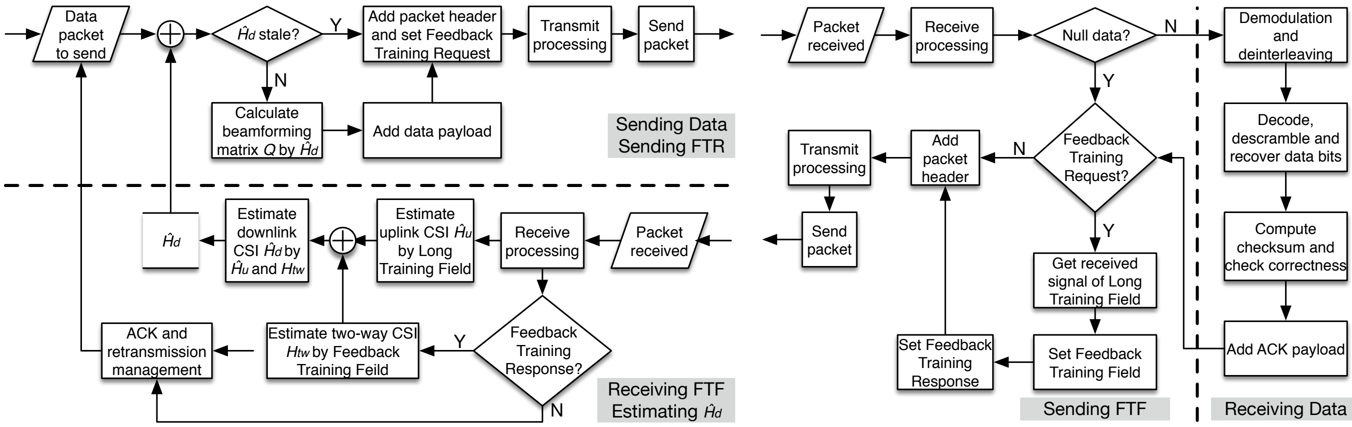
$$\hat{H}_d = \hat{H}_u^+ H_{tw} = (\hat{H}_u^* \hat{H}_u)^{-1} \hat{H}_u^* H_{tw} = (\hat{H}_u^* \hat{H}_u)^{-1} \hat{H}_u^* H_u H_d, \tag{6}$$

where $\hat{H}_u^+ = (\hat{H}_u^* \hat{H}_u)^{-1} \hat{H}_u^*$ is the pseudo-inverse of $\hat{H}_u$.

The estimation accuracy of $\hat{H}_d$ is impacted by two-way channel propagations and interferences. The received signal of FTF at the AP is

$$Y_f = H_u Y_d + N_u = H_u(H_d X + N_d) + N_u, \tag{7}$$

where N_d and N_u are downlink and uplink noise signals, respectively. The power of Y_f is impacted by two-way channel propagations, so the CSI estimation accuracy could be significantly influenced by the power of N_u. The STA sends the amplified signal αY_d, instead of Y_d, to the AP to improve estimation accuracy. The amplify factor α is constrainted by $E[|[\alpha Y_d]_i|^2] \leq P_i$, where P_i is the power constraint for the ith transmit antenna of the STA [11]. To reduce the impact of two-way channel interferences, the AP sends duplicated LTFs to the STA, and correspondingly the STA also sends duplicated FTFs to the AP. The received signals for the kth sub-carrier at the AP are $Y_f(k,1)$ and $Y_f(k,2)$. The AP first estimates uplink noise by $\hat{N}_u = \sum_{k=1}^{N_s} |(Y_f(k,1) - Y_f(k,2))(Y_f(k,1) - Y_f(k,2))^*|$ [8]. The AP estimates two-way channel H_{tw} and uplink channel $\hat{H}_u$ based on $\hat{N}_u$, and finally estimates downlink channel $\hat{H}_d$ using $\hat{H}_u$ and H_{tw}.



(a) MAC-layer operations of the AP side

(b) MAC-layer operations of the STA side

Fig. 6. Flow chart of MAC-layer operations of EliMO. (a) The AP side: blocks above the dashed line are for sending NDP and data packets; blocks below the dashed line are for receiving FTF and estimating downlink CSI. (b) The STA side: blocks on the left of the dashed line are for sending FTF, and the STA does not need to do demodulation if the received packet has no data payload; blocks on the right of the dashed line are for receiving data packets.

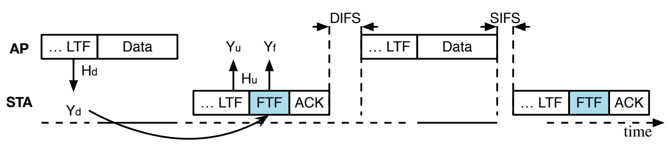


Fig. 7. MAC-layer operations of EliMO. The STA inserts Y_d in FTF and sends it to the AP along with LTF. Based on Y_u and Y_f, the AP estimates downlink CSI calculates the beamforming matrix for the following data packet.

C. MAC-layer Operations

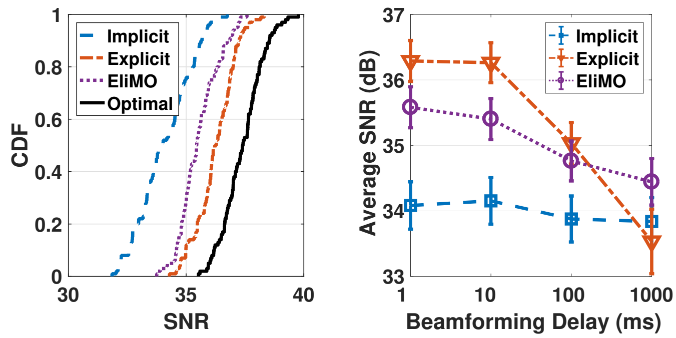
Timeline of MAC-layer operations of EliMO is shown in Fig. 7. The AP sends downlink LTF to the STA, and the STA puts the received downlink LTF signal Y_d in FTF. The STA sends FTF, along with uplink LTF, back to the AP. The received signal of uplink LTF is Y_u, and the received signal of FTF is Y_f. The AP estimates uplink CSI $\hat{H}_d$ using Y_u and two-way CSI using Y_f.

The beamforming performance of EliMO is influenced by the difference between $\hat{H}_d$ and H_{dd}. The AP needs to determine whether the measured downlink CSI is stale and when to request feedback training to reduce beamforming errors. EliMO addresses this issue by sending feedback request when the AP detects that the previous measured downlink CSI is stale. If $\hat{H}_d$ is stale, the AP needs to send Null Data Packet (NDP) with FTR to measure the current downlink CSI. The AP uses two metrics, CSI similarity and estimation delay, to determine whether $\hat{H}_d$ is stale or not. CSI similarity is calculated by

$$\rho = \frac{\sum_{k=1}^{N_s}(h(k,1)-\bar{h}_1)(h(k,2)-\bar{h}_2)}{\sqrt{\sum_{k=1}^{N_s}(h(k,1)-\bar{h}_1)^2}\sqrt{\sum_{k=1}^{N_s}(h(k,2)-\bar{h}_2)^2}}, \quad (8)$$

where $h(k,1)$ and $h(k,2)$ are the CSI magnitude of the kth sub-carrier, and $\bar{h}_1$ and $\bar{h}_2$ are the average CSI magnitude across N_s sub-carriers of two CSI measurements [4, 14]. When CSI similarity of either downlink or uplink CSI is larger than the threshold Thr_ρ, the AP sends NDP with FTR to the STA to measure the current downlink CSI. Based on experiment measurements, which will be shown in the next section, we find that $Thr_\rho = 0.98$ is able to distinguish whether the STA is moving or not. This is also in consistent with measurement results in [14]. Thus we use $Thr_\rho = 0.98$ as the CSI similarity threshold. Estimation delay δ is the time interval between when the previous downlink CSI is estimated and when the next data packet is transmitted. The AP also sends NDP when the estimation delay is larger than the threshold Thr_δ. Based on experiment results in both static and mobile scenarios, we choose $Thr_\delta = 100$ms as the threshold of estimation delay. Note that all calculations of detecting whether $\hat{H}_d$ is stale no not are done by the AP. No extra computation overhead is introduced for the STA.

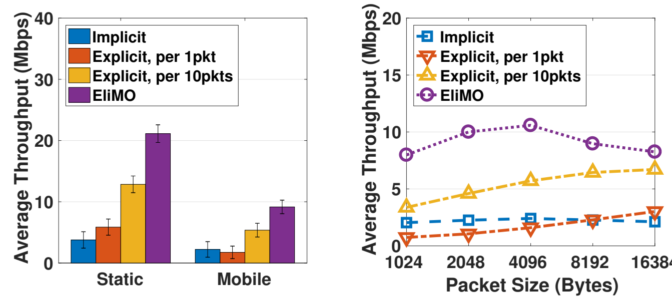
Fig. 6 shows the flow chart of EliMO for the AP and STA. For each data packet to be sent, the AP checks whether the previous downlink CSI $\hat{H}_d$ is stale or not based on CSI similarity ρ and estimation delay δ. If $\hat{H}_d$ is stale, the AP sends NDP with FTR to the STA to measure the current downlink CSI. If $\hat{H}_d$ is not stale, the AP calculates the beamforming matrix based on $\hat{H}_d$ and sends the data packet to the STA. In the packet header of the data packet, the AP sets the request field of FTR to 1. This is for estimating the downlink CSI for the next data packet. For each received packet, the AP estimates the uplink CSI $\hat{H}_u$ by uplink LTF and two-way CSI H_{tw} by FTF. The downlink CSI $\hat{H}_d$ is estimated by $\hat{H}_u$ and H_{tw}. At the STA side, each received packet is checked whether it contains data payload or not. If the received packet has no data payload, demodulation is not needed. If the packet has data payload, the STA demodulates and decodes the received signal to get the data bits. The STA checks correctness of the data packet and adds ACK payload to the packet to be sent to the AP. If feedback training is requested, the STA gets



(a) CDF of SNR

(b) SNR vs. Beamforming Delay

Fig. 8. Experiment Validation



(a) Average Throughput

(b) Throughput vs. Packet Size

Fig. 9. Evaluation Results of Average Throughput

the received signal of downlink LTF, puts it in FTF, and sets the response field of FTR to 1. Finally, the STA adds packet header with FTR and FTF, and sends the packet, either with or without ACK payload, to the AP.

IV. Evaluation

This section presents evaluation results, including throughput and energy consumption, of EliMO by experiment measurements in both static and mobile scenarios.

A. Experiment Setup

We conduct experiment measurements in indoor environments for both static and mobile scenarios. The AP is static, and the STA is either static or moving at the speed of about 1.2m/s. The AP and STA operate at 5GHz, and the channel width is 20MHz. The AP has 3 external antennas, and the STA has 3 internal antennas spaced 2.4 inches apart. The transmitting power of the AP/STA is fixed at 17/15dBm. The AP and STA are two laptops with Intel WiFi Link 5300 installed. Since we cannot program the power signal of the WiFi chipset, we are not able to implement EliMO in real-time. Thus we employ trace-driven evaluation by collecting CSI traces and evaluates EliMO off-line by Matlab implementations using the collected CSI traces.

Downlink and uplink CSI measurements are collected using openrf [15], which is based on 802.11n CSI tool [16]. Note that 802.11n CSI tool only provides CSI values of 30 subcarriers even though a 20MHz WiFi channel has 52 subcarriers [1, 2, 5, 6]. Two performance metrics, throughput and energy consumption, are evaluated in different scenarios comparing EliMO with implicit and explicit CSI feedback. The AP uses ZFBF as the transmit beamforming algorithm and the STA uses the MMSE receiving algorithm. The MCS index can be selected from 0 to 23 with the data rate ranging from 6.5 to 195Mbps [5]. We compare EliMO with implicit and explicit CSI feedback. There are two options for explicit CSI feedback: non-compressed, i.e., 1 CSI packet per data packet, and compressed, i.e., 1 CSI packet per 10 data packets.

B. Experiment Validation

We first validate the effectiveness of two-way channel estimation by experiments in real-world MIMO systems. Fig. 8 shows the CDF of SNR of experiment measurements in the mobile scenario. The SNR of EliMO is 1.5dB higher than that of implicit CSI feedback, and 1dB lower than that of explicit CSI feedback, as shown in Fig. 8a. EliMO is able to provide comparable SNR as explicit CSI feedback in real-world mobile environments. We also check the impact of beamforming delay, as shown in Fig. 8b. The average SNR of implicit CSI feedback does not change much as beamforming delay increases. The reason is that channel reciprocity has more impact on the accuracy of downlink CSI estimation than mobility. The average SNR of EliMO and explicit CSI feedback decreases when beamforming delay increases. This is because that the difference between the estimated CSI and data packet CSI increases as beamforming delay increases when the STA is moving. For beamforming delay of 1,000ms, the SNR decrease is 1dB for EliMO and 2.8dB for explicit CSI feedback. EliMO has lower SNR decrease since the time delay between uplink CSI and data packet CSI is very small and two-way channel estimation helps reduce the impact of mobility.

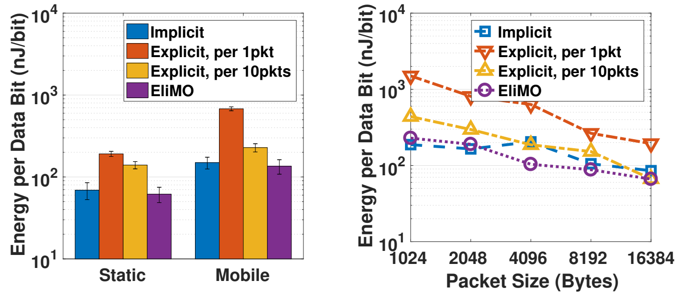
C. Throughput

The effective throughput is calculated by

$$tpt = \frac{\sum_{i=1}^{N'} size(pkt_i)}{t_{control} + t_{data}}, \tag{9}$$

where pkt_i is the ith data packet, and N' is the number of received packets. Implicit CSI feedback has low accuracy of downlink CSI estimation, so it provides low beamforming gains. This reduces the number of received packets N' and leads to low throughput for implicit CSI feedback. The transmission time of control frames $t_{control}$ is extremely high, which results in low throughput, for explicit CSI feedback. EliMO provides high throughput by reducing $t_{control}$ significantly while N' is not seriously influenced.

Fig. 9a shows the average throughput for data packets of different sizes and data rates. The average throughput of EliMO is 5×, 4×, and 1.7× of that of implicit, non-compressed explicit, and compressed explicit CSI feedback, respectively. The average throughput of the mobile scenario is lower than that of static scenarios for all feedback schemes. In the mobile scenario, EliMO still provides the highest throughput. The average throughput of EliMO is 3.6×/4.5×



(a) Average Energy per Data Bit (b) Energy per Data Bit vs. Packet Size

Fig. 10. Evaluation Results of Energy Consumption

of that of implicit/explicit CSI feedback. Fig. 9b shows the average throughput as the size of data packets changes. For data size of 1,024 bytes, the average throughput of EliMO is 6Mbps, 7Mbps, and 5Mbps higher than that of implicit, non-compressed explicit, and compressed explicit CSI feedback. For data size of 16,384 bytes, EliMO has 6Mbps, 5Mbps, and 1Mbps higher throughput than the other three feedback schemes.

D. Energy Efficiency

Energy efficiency of the STA is evaluated by energy consumption per data bit

$$eb = \frac{\sum_{i=1}^{N} (er(0) * size(ctr_i) + et(0) * size(csi_i))}{\sum_{i=1}^{N'} size(pkt_i)} + \frac{\sum_{i=1}^{N} er(m_i) * size(pkt_i)}{\sum_{i=1}^{N'} size(pkt_i)}, \quad (10)$$

where $et(m)$ and $er(m)$ stand for energy consumption per bit for transmitting and receiving, respectively, as using MCS index m [17, 18]. Energy consumption parameters, $et(m_i)$ and $er(m_i)$, for the Intel 5300 WiFi chipset are from [17]. For data packet of $size(pkt_i) = 1,500$ bytes and $m_i = 23$, explicit CSI feedback accounts 80% of the total energy consumption. Besides, $et(m_i)|_{m_i=0}$ for CSI packets is much larger than $er(m_i)|_{m_i \geq 0}$ for data packets [17, 18], so explicit CSI feedback consumes a lot of energy for the STA. For implicit CSI feedback, the number of received packets is smaller than EliMO due to low accuracy of downlink CSI estimation. This reduces the energy efficiency of the STA for implicit CSI feedback. EliMO remarkably improves the energy efficiency of the STA by eliminating explicit CSI feedback without sacrificing beamforming gains.

Energy consumption results are shown in Fig. 10. As shown in Fig. 10a, EliMO has slightly lower energy consumption as implicit CSI feedback in both static and mobile scenarios. For the static scenario, the average energy consumption of EliMO is only 30% and 50% of that of non-compressed and compressed explicit CSI feedback, respectively. For the mobile scenario, the average energy consumption of EliMO is 17%/57% of that of non-compressed/compressed explicit CSI feedback. Fig. 10b shows average energy consumption in terms of the size of data packets. For data packets of less than 2,048 bytes, EliMO consumes slightly higher energy than implicit CSI feedback. As packet size increases, energy consumption of EliMO is lower than that of implicit CSI feedback. For packet size of 16,384 bytes, EliMO has comparable energy consumption as compressed explicit CSI feedback. EliMO consumes much less energy than both non-compressed and compressed explicit CSI feedback when packet size is less than 16,384 bytes.

V. Related Work

There are many papers on reducing the overhead of CSI feedback. IEEE 802.11n/ac protocols allow feedback compression to share the same CSI for multiple data packets or multiple sub-carriers [5, 6]. CSI-SF [19] uses CSI values of one antenna to estimate CSI values of other antennas, which reduces overhead of CSI measurements and feedback. The STA can also use less bits of data for each CSI value [8, 9] to reduce the size of CSI matrix. AFC [8] adaptively selects feedback compression levels to reduce feedback overhead in different scenarios. Some papers use CSI similarity to detect whether the STA is moving or not, and adjust the frequency of CSI measurements accordingly [14, 20]. This helps to reduce feedback overhead if the STA is not moving. However, all these feedback compression schemes still need CSI feedback from the STA. It introduces high computation and communication overhead for the STA to calculate and send the CSI matrix. Besides, the STA needs to calculate when to send the CSI matrix and how much feedback is needed. This introduces computation overhead for the STA. The calculation and transmission of the CSI matrix consumes a lot of energy for the STA. EliMO completely eliminates CSI feedback and significantly improves the energy efficiency for the STA.

IEEE 802.11n allows implicit CSI feedback [5] to reduce the overhead of explicit CSI feedback. This is based on the assumption that downlink and uplink channels of the same carrier frequency are reciprocal. But this assumption does not hold in real-world MIMO systems wherein digital baseband channels [2, 5] and interferences are not reciprocal [2]. R2-F2 eliminates CSI feedback for cellular networks [21]. It estimates downlink CSI using uplink CSI at different carrier frequencies. But it does not consider the impact of digital baseband channels, which reduces CSI estimation accuracy seriously. Signpost [22] eliminates CSI feedback for uplink multi-user MIMO. It allows each user to predict its orthogonality to other users by its own CSI. But it only works in the uplink and eliminates CSI feedback from the AP for multi-user MIMO communications. EliMO eliminates CSI feedback in the downlink and reduces computation and communication overhead for the STA. Similar to EliMO, Echo-MIMO [23] also employs two-way channel estimation to eliminate downlink CSI feedback. But it is designed for narrow-band MIMO channels without frequency-selective effects, while WiFi has wide-band MIMO-OFDM channels with frequency-selective effects. It does not consider the impact of digital baseband channels. Besides, Echo-MIMO only focuses on theoretical analysis but does not test with real-world MIMO devices. EliMO is tested with real-world WiFi devices with the impact of wide-band channels, frequency-selective effectives, and baseband-to-baseband channels.

VI. Conclusions and Future Work

In this paper, we show that implicit CSI feedback has low beamforming gains and explicit CSI feedback has high computation and communication overhead. We propose EliMO to completely eliminate CSI feedback without sacrificing beamforming gains. We propose Feedback Training Field and two-way channel estimation to enable the AP to accurately estimate downlink CSI without explicit CSI feedback. Based on both theoretical analysis and experiment measurements, EliMO provides as low overhead as implicit CSI feedback and as high SNR as explicit CSI feedback. Experiment evaluation results show that EliMO provides much higher throughput and lower energy consumption for the STA than implicit and explicit CSI feedback.

Currently EliMO is evaluated by CSI measurement traces and off-line Matlab implementations. We plan to implement EliMO on real-world MIMO systems and evaluate it in real-time. We also want to make the EliMO protocol compatible with multi-user MIMO systems in the future. EliMO can also be used by other applications, such as motion tracking [24], activity recognition [25], and localization [26–28], using off-the-shelf WiFi chipsets. For example, existing CSI-based localization methods require extensive CSI measurements from multiple APs [26] or across multiple channels [27, 28], which introduce very high overhead for MIMO receivers. EliMO can help reduce both computation and communication costs for MIMO receivers, like smartwatches and drones, for these CSI-based localization approaches.

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