Abstract—In this paper, we investigate spatial intercell interference cancellation – an efficient technique to mitigate intercell interference in multicell networks. We consider a practical model for channel state information (CSI), where the transmit CSI is acquired through downlink training and uplink feedback. Due to the requirement of channel information from multiple base stations, the training and feedback design is quite different from conventional single-cell processing systems. We optimize training and feedback, where both analog and digital feedback is considered. For analog feedback, it is shown that the downlink training optimization provides a more significant performance gain than feedback optimization; while conversely for digital feedback over a finite-rate feedback channel, the feedback bit allocation is more important than the training optimization.

I. INTRODUCTION

Multicell processing is an efficient technique to mitigate intercell interference in multicell networks. By coordinating the transmission and reception of multiple base stations (BSs), this technique can in principle eliminate intercell interference and transform cellular networks from the familiar interference-limited state to a noise-limited one [1].

The demand for a large amount of channel state information (CSI) is a major obstacle for multicell processing. In [2], [3], it was shown that when the CSI overhead is taken into account, conventional single-cell processing can be quite attractive relative to multicell processing. In [4], the optimal channel training in uplink multicell MIMO networks was investigated. In [5], [6], limited feedback techniques were developed to provide partial CSI to the coordinating BSs. These results demonstrate the importance of CSI overhead/accuracy in multicell processing. However, an accurate characterization of the multicell processing system with both CSI training and feedback, and the corresponding performance optimization, are not yet available.

In this paper, we focus on the downlink coordination with a specific multicell processing technique – intercell interference cancellation (ICIC). ICIC places low demands on the backhaul capacity, as it does not need to share data information between BSs, and only local CSI is required at each BS [7]. We investigate the performance of ICIC with a practical CSI model, where the transmit CSI is obtained through downlink training and uplink feedback. The pilot symbols from the home and neighboring BSs are received with different path loss at each user. Likewise, the feedback for home and neighboring BSs have different effects on the system performance, related to the signal power and interference power, respectively. Therefore, training and feedback should be carefully designed in the ICIC system, which is the focus of the paper.

The training and feedback optimization for the beamforming and multiuser MIMO systems were investigated in [8] and [9], respectively. These studies focused on the overhead optimization, which cannot be easily implemented in practical systems. In this paper, we take a more feasible approach. For training optimization, we consider optimal pilot/data power allocation with a fixed training interval. For analog feedback, we optimize the power allocated to feedback for different BS channels. For digital feedback, we optimize the numbers of feedback bits allocated for different BS channels. The training optimization is common for all the BSs, while the feedback optimization is performed individually by each user.

Contributions: In this paper, we investigate the ICIC system with CSI training and feedback. High-SNR approximations are derived for the average achievable throughput, based on which the training and feedback phases are optimized. For analog feedback with a fixed feedback interval, it is shown that downlink training optimization provides a more significant performance gain than uplink feedback optimization. On the other hand, for digital feedback over a finite-rate feedback channel, the uplink feedback bit allocation is more important than the training optimization. The performance gain of training and feedback optimization is demonstrated through simulation, which shows that ICIC provides significant average and edge throughput gains over single-cell beamforming.

II. SYSTEM MODEL

A. Signal Model

We consider a 2-cell network as shown in Fig. 1, where each BS has $N_t$ transmit antennas and there is one active
single-antenna user in each cell. Universal frequency reuse is assumed, and each user suffers from intercell interference from the co-channel transmission in the other cell. The BS and user in the i-th cell are indexed by i, while the BS and user in the other cell are indexed by \( i = \text{mod}(i, 2) + 1 \) for \( i = 1, 2 \).

We focus on the downlink transmission. For the data symbol transmission, the discrete baseband signal received at the i-th user \((i = 1, 2)\) is given as

\[
y_i = \sqrt{P_d} L_{i,i} h_{i,i}^* f_i x_i + \sqrt{\frac{P_d}{L_{i,i}}} h_{i,i}^* f_i x_i + z_i, \tag{1}
\]

where \( a^* \) is the conjugate transpose of a vector \( a \) and \( x_i \) is the transmit signal from the i-th BS for the i-th user, with the power constraint \( \mathbb{E}[|x_i|^2] = 1 \), \( z_i \) is the complex white Gaussian noise with zero mean and unit variance. \( P_d \) is the transmit power for data symbols and \( L_{i,j} \) is the pathloss from BS j to user i, given by \( L_{i,j} = \eta (D_0/d_{i,j})^\alpha \), where \( D_0 \) is the reference distance, \( \eta \) is a unitless constant that depends on the antenna characteristics, and \( d_{i,j} \) is the distance between user i and BS j. \( h_{i,j} \) is the \( N_t \times 1 \) channel vector from BS j to user i, where each component is i.i.d. \( \mathcal{CN}(0,1) \). We consider a block fading model, where the channel is constant over each block of length \( T \) and is independent for different blocks.

The precoding vector \( f_i \) at BS i is normalized, i.e., \( \|f_i\|^2 = 1 \), and is designed based on the available CSI at the BS. With ICIC, the precoder is designed to cancel intercell interference for the neighboring cell. Taking cell 1 as an example, to cancel its interference for users in cell 2, 3, \ldots, \( N_B \) (\( N_B \leq N_t \)), \( f_1 \) is chosen in the direction of the projection of \( h_{1,1} \) on the nullspace of vectors \( \mathbf{H} = [h_{2,1}, h_{3,1}, \ldots, h_{N_B,1}] \) [10], i.e., the precoding vector is the normalized version of the vector \( \mathbf{w}_i^{(1)} = \left( I - \mathbf{H} \left( \mathbf{H}^H \mathbf{H} \right)^{-1} \mathbf{H}^H \right) h_{1,1} \). From [10], with perfect CSI we have \( \|f_1^H h_{1,i}\|^2 \sim \chi^2_{(N_t-(K-1))} \).

The receive signal-to-interference-plus-noise ratio (SINR) for user i is

\[
\text{SINR}_i = \frac{P_d L_{i,i} |h_{i,i}^* f_i|^2}{1 + \frac{P_d}{L_{i,i}} |h_{i,i}^* f_i|^2}. \tag{2}
\]

Treating intercell interference as additive white Gaussian noise, we are interested in the following average achievable throughput

\[
R_i = \mathbb{E} \left[ \log_2 (1 + \text{SINR}_i) \right], \quad i = 1, 2. \tag{3}
\]

As the capacity of this kind of interference channel is unknown even with perfect CSI, our focus is on the achievable throughput with specific training and feedback methods. Note that at low SNR, it is necessary to switch between single-cell beamforming and ICIC to maximize the system throughput [7]. In this paper, we mainly focus on the high-SNR regime, where the performance gain of ICIC is more prominent.

### B. The CSI Model

We focus on the FDD (Frequency Division Duplex) system, where downlink training and uplink feedback are applied to provide transmit CSI. Each fading block of length \( T \) is divided into three phases: a downlink training phase of \( T_t \) channel uses, an uplink feedback phase of \( T_{fb} \) channel uses, and the data transmission phase of \( T_d \) channel uses.

Denote \( N_B \) as the number of BSs. We consider orthogonal training, where the training phase spans \( T_t \) (\( T_t \geq N_B N_t \)) channel uses, using orthogonal training sequences \( \Phi_0, \Phi_1, \ldots, \Phi_{N_B N_t-1} \), with \( \Phi_i \in \mathbb{C}^{T_t \times 1} \). The set of training sequences is partitioned into \( N_B \) disjoint groups each with \( N_t \) sequences, denoted as \( \Phi_i \) for the \( i \)-th BS. The power scaling factor is \( \sqrt{T_t / N_t} P_t \) so the transmit power for the pilot symbols from each BS is \( T_t P_t \), which sets the power constraint for each pilot symbol to be \( P_t \). For simplicity, we normalize \( T \) and \( T_t \) as \( T = \frac{T_t}{N_t} \), and \( T_t = \frac{T_t}{N_t} \).

Different from conventional single-cell processing systems, we assume that each user estimates CSI from both its home BS and the neighboring BS. The user i estimates the channel from BS j based on the observation

\[
s_{i,j} = \sqrt{T_t P_t L_{i,j}} h_{i,j} + z_{i,j}, \quad i,j = 1,2. \tag{4}
\]

where the channel \( h_{i,j} \) is with covariance \( \kappa_{i,j}^2 1_{N_t} \), and the estimation noise \( z_{i,j} \) is with covariance \( \sigma_{i,j}^2 1_{N_t} \). With the MMSE estimator, \( \hat{s}_{i,j} \) is independent of the estimate \( h_{i,j} \) and the estimation noise \( n_{i,j} \) as \( \hat{s}_{i,j} = h_{i,j} + n_{i,j} \).

### III. Training with Analog Feedback

We first consider analog feedback where the estimated CSI at each user is fed back to the BS using unquantized and uncoded QAM [11]. The uplink feedback channel is assumed to be an unfaded AWGN channel as in [9].

As each user needs to feed back CSI for \( N_B \) BSs (\( N_B = 2 \) in the paper), we divide the feedback block \( T_{fb} \) into \( N_B \) equal-length sub-blocks. During the \( j \)-th sub-block, at user i, the estimated CSI is modulated by a \( \frac{T_{fb}}{N_B} \times N_t \) unitary spreading matrix with the power constraint \( \frac{T_{fb}}{N_B} P_{fb,ij} \) [11]. We assume orthogonal feedback, so \( \frac{T_{fb}}{N_B} P_{fb,ij} \geq N_B N_t \). Although the feedback can be received by both BSs, the home BS i is responsible for the final channel estimation as it is closer to user i, i.e., BS i will estimate both \( h_{i,1} \) and \( h_{i,2} \) and will pass the estimation to the neighboring BS over the
backhaul link. In the following discussion, we focus on the power allocation \( P_{fb,i,1}, P_{fb,i,2} \), with the constraint

\[
T_{fb} \frac{P_{fb,i,1}}{N_B} + T_{fb} \frac{P_{fb,i,2}}{N_B} = T_{fb} P_{fb}^u, \tag{6}
\]

where \( P_{fb}^u \) is the uplink transmit power constraint. We assume that \( T_{fb} \) is fixed, as the modification of \( T_{fb} \) will affect the uplink traffic channel while our discussion focuses on the downlink transmission.

As the uplink channel is modeled as an unfaded AWGN channel with pathloss, the received feedback vector at the \( i \)-th BS after de-spreading is

\[
g_{i,j} = \frac{\sqrt{\frac{T_{fb}}{N_B}} P_{fb,i,j} L_{i,i}}{\sqrt{1 + T_{fb} P_{fb,i,j}}} \bar{h}_{i,j} + \bar{w}_{i,j}, \tag{7}
\]

where \( \bar{w}_{i,j} \) is the equivalent noise, and \( \bar{w}_{i,j} \sim CN(0, \sigma^2_{ij}) \)

with \( \sigma^2_{i,j} = \frac{\frac{T_{fb}}{N_B} P_{fb,i,j} L_{i,i}}{1 + T_{fb} P_{fb,i,j}} + 1 \). If \( i = j \), the feedback is for the home BS channel, which determines the signal power; if \( i \neq j \), the feedback is for the neighboring BS channel, which is related to the interference level. This motivates the feedback power allocation with the constraint (6).

The MMSE estimate of the channel vector is

\[
\hat{h}_{i,j} = \frac{\sqrt{\frac{T_{fb}}{N_B}} P_{fb,i,j} L_{i,i} \bar{t}_i P L_{i,j}}{\sqrt{1 + T_{fb} P_{fb,i,j}}} g_{i,j}, \tag{8}
\]

with variances \( \kappa^2_{i,j} = \frac{T_{fb} P_{fb,i,j} L_{i,i}^2}{(1 + T_{fb} P_{fb,i,j})(1 + T_{fb} P_{fb,i,j})} \). The preceeding vectors are designed assuming that \( \hat{h}_{i,j} \) (\( i, j = 1, 2 \)) are the actual CSI.

\section*{A. Training Optimization}

We first consider training optimization. With perfect CSI, intercell interference is completely cancelled, and the average achievable throughput for the \( i \)-th user \((i = 1, 2) \) at high SNR can be approximated as \( R_i \approx \mathbb{E} \left[ \log_2 \left( L_{i,i} P_{t,i} \lambda^2(N_t - 1) \right) \right] \), where \( \lambda^2 \) denotes a chi-square random variable with \( 2n \) degrees of freedom. As \( \mathbb{E} \left[ \log \lambda^2 \right] = \psi(n) \), with \( \psi(\cdot) \) as Euler’s digamma function, we get

\[
R_i \approx \log_2 \left( P_{t,i} L_{i,i} e^{\psi(N_t - 1)} \right). \tag{9}
\]

Following the distribution of signal and interference terms, at high SNR the rate loss \( R_i - R_i,_{aFB} \) due to training and analog feedback can be approximated as

\[
R_i - R_i,_{aFB} \approx \log_2 \left( 1 + L_{i,i} P_{t,i} \left( \frac{1}{N_B} P_{fb,i,i} L_{i,i} + \frac{1}{T_{fb} P_{fb,i,i}} \right) \right), \tag{10}
\]

which is a constant rate loss if \( \frac{P_{fb}}{P_{t,i}} \) and \( \frac{P_{t,i}}{P_{fb,i,i}} \) are constants.

Substituting (9), we get the following high-SNR approximation for \( R_i,_{aFB} \)

\[
R_i,_{aFB} \approx \log_2 \left( \frac{L_{i,i} e^{\psi(N_t - 1)}}{P_{d,i}^{-1} + (\bar{T}_i P_{t,i})^{-1}} + \frac{P_{fb,i,i}}{N_B L_{i,i}} P_{t,i} \right). \tag{11}
\]

For given \( T_{fb} \) and \( P_{fb,i,i} \), the throughput maximization problem is equivalent to the following minimization problem

\[
\min_{T_{fb}, T_{ul}} \frac{1}{P_{d,i}} + \frac{1}{T_{fb} P_{t,i}}. \tag{12}
\]

This is a convex optimization problem, and following the KKT (Karush-Kuhn-Tucker) condition we can get the solution

\[
P_{d,i}^* = \frac{(T - T_{fb}) P_{d,i}}{T_{fb} P_{d,i}}, \quad P_{t,i}^* = \frac{(T - T_{fb}) P_{d,i}}{T_{fb} P_{d,i}}. \tag{13}
\]

The solution depends only on the intervals of different transmission phases, i.e., \( T_{f}, T_{d}, \) and \( T_{fb} \). When \( T \) is large with \( T_{f} \) and \( T_{fb} \) fixed, we have \( P_{t,i}^* \sim \sqrt{T P_{d,i}} \), i.e., pilot power increases with the block length \( T \).

\section*{B. Feedback Optimization}

Next, we consider feedback optimization, i.e., optimizing \( (P_{fb,i,1}, P_{fb,i,2}) \) for \( i = 1, 2 \). Note that the uplink feedback optimization is done individually for each user, while the downlink training optimization is the same for all users. The feedback optimization is over the following approximation for the average SINR

\[
\text{SINR}_i \approx \frac{P_{t,i} L_{i,i} \lambda^2_i (N_t - 1)}{1 + P_{d,i} \lambda^2_i}, \quad i = 1, 2. \tag{14}
\]

This is reasonable as \( \log_2(1 + \text{SINR}_i) \) gives an upper bound on the average achievable rate for user \( i \). From (14), the feedback power allocation problem at user \( i \) can be stated as

\[
(P_{fb,i,1}^*, P_{fb,i,2}^*) = \arg \max_{P_{fb,i,1}, P_{fb,i,2}} \frac{\lambda^2_i}{1 + P_{d,i} \lambda^2_i}. \tag{15}
\]

Denote \( x \triangleq \frac{T_{fb}}{N_B} P_{fb,i,i} L_{i,i}, \quad a \triangleq T_{fb} P_{t,i,i}, \quad b \triangleq P_{d,i}, \quad \) and \( \rho \triangleq T_{fb} P_{d,i} L_{i,i}, \) then problem (15) is equivalent to

\[
\max_{0 \leq x \leq \rho} \frac{x}{1 + \frac{x}{1 + a + \frac{x}{1 + b}}}, \tag{16}
\]

Denote \( \lambda_1 \triangleq 1 + \rho, \lambda_2 \triangleq \frac{ab}{1 + a + \frac{x}{1 + b}} \), the objective function can be rewritten as

\[
1 + a + b \left\{ 1 + \frac{1}{1 + \lambda_1 + \lambda_2} \left[ \frac{1 + \frac{ab}{1 + a + \frac{x}{1 + b}}}{x - (\lambda_1 + \lambda_2)} - 1 + \lambda_1 \right] \right\}. \tag{17}
\]

So the maximization problem is equivalent to max\(0 \leq x \leq \rho f(x)\) with \( f(x) \triangleq \frac{(\lambda_1 + \lambda_2)x}{x(\lambda_1 + \lambda_2) - 1 + \frac{ab}{x(\lambda_1 + \lambda_2)}} \). As \( \lambda_1 > 0, \lambda_2 > 0, \) and \( \lambda_1 = \rho + 1 > x, \) the first and second terms are both concave, so the objective function is concave. Setting \( \frac{df(x)}{dx} = 0, \) we
have

\[
(1 + \lambda_1) - (\lambda_1 + \lambda_2) \lambda_2] x^2 - 2(\lambda_1 + \lambda_2)(1 + \lambda_1 + \lambda_2)x + \lambda_1(\lambda_1 + \lambda_2)(1 + \lambda_1 + \lambda_2) = 0. 
\]

Denote \((x_1^*, x_2^*)\) as the solution pair of (17), if \(x_i^* \in [0, \rho], i = 1, 2\), then it is the solution for the original problem; otherwise, the maximal value is obtained at the edge and \(x^* = \rho\) is the solution, as \(x = 0\) makes the objective function to be 0 which is obviously not the maximum.

IV. TRAINING WITH DIGITAL FEEDBACK

In this part, we consider digital feedback, also called limited feedback [12], which feeds back quantized CSI. We assume user \(i\) \((i = 1, 2)\) feeds back in a total of \(B_i\) bits, among which \(B_{i1}\) bits is for the channel estimate \(\hat{h}_{i1}\) of BS 1 and \(B_{i2}\) bits for the channel estimate \(\hat{h}_{i2}\) of BS 2. The feedback channel is assumed to be error-free and without delay. The feedback interval is \(T_{fb} = \mu B_i\), where \(\mu\) is a conversion factor that relates bits to symbols.

The channel estimate \(\hat{h}_{i,j}, i, j = 1, 2\), is fed back using a quantization codebook known at both the transmitter and receiver, which consists of unit norm vectors of size \(2^B_i\). We assume each user has multiple codebooks, with the codebook of size \(2^B_i\) denoted as \(C_{i,j} = \{c_1, c_2, \ldots, c_{2^{B_i}}\}\). The quantized channel vector is \(\hat{h}_{i,j} = \arg \max_{e \in C_{i,j}} \|\hat{h}_{i,j} - e\|\). The random vector quantization (RVQ) codebook [13] is used to facilitate the analysis, where each quantization vector is independently chosen from the isotropic distribution on the \(N_t\)-dimensional unit sphere.

Denote \(\xi_{i,j} \triangleq \mathbb{E}_{\theta_{i,j}}[\cos \theta_{i,j}] = \mathbb{E}_{\theta_{i,j}}[\hat{h}_{i,j}^* \hat{h}_{i,j}] / \|\hat{h}_{i,j}\|\), and then with RVQ [13]

\[
\xi_{i,j} = 1 - 2^{B_{i,j}} \cdot \beta \left(2^{B_{i,j}} \cdot \frac{N_t}{N_t - 1}\right) \geq 1 - 2^{-\frac{B_{i,j}}{N_t - 1}}, 
\]

where \(\beta(x, y)\) is the Beta function.

A. Training Optimization

Similar to (10), we first get the following approximation for the rate loss due to training and digital feedback

\[
R_i - R_i,\text{AFB} \approx \log_2 \left(1 + \frac{1}{T_{i} P_L L_i, i} \left(1 + \frac{1}{T_{i} P_L L_i, i} + 2^{-\frac{B_{i,j}}{N_t - 1}}\right)\right). 
\]

With \(P_d, P_l \rightarrow \infty\) and \(\frac{B_{i,j}}{N_t} = \nu\), the rate loss is approximately

\[
\log_2 \left(1 + \frac{1}{T_{i} P_L} L_i, i P_d 2^{-\frac{B_{i,j}}{N_t - 1}}\right),
\]

which grows with \(P_d\) for fixed \(B_{i,j}\). This shows that the system throughput is limited by the residual interference due to the quantization error.

Then we can get the following approximation for the average achievable rate for user \(i\) \((i = 1, 2)\)

\[
R_i,\text{AFB} \approx \log_2 \frac{L_i, \xi_i e^{\psi(N_t)}}{P_d^{-1} + (T_{i} P_l)^{-1} + L_i, i 2^{-\frac{B_{i,j}}{N_t - 1}}}.
\]

This is similar to (11) for analog feedback. Therefore, the optimal \((P_d, P_l)\) are also given in (13).

B. Feedback Optimization

We assume each user can adaptively select the number of feedback bits and apply the corresponding quantization codebook for channel feedback for different BSs. The feedback optimization is based on the following approximation for the average SINR

\[
\text{SINR}_i \approx \frac{P_d L_i, i \xi_i (N_t - 1)}{1 + P_d L_i, i \xi_i^2 + P_d L_i, i \xi_i 2^{-\frac{B_{i,j}}{N_t - 1}}},
\]

which follows the distributions of signal and interference terms. Applying the bound in (18), the feedback bit allocation problem is formulated as

\[
\arg \max_{B_{i1} + B_{i2} = B_i} \frac{1 - 2^{-\frac{B_{i,j}}{N_t - 1}}}{1 + P_d L_i, i \xi_i^2 + P_d L_i, i \xi_i 2^{-\frac{B_{i,j}}{N_t - 1}}},
\]

which is done individually at each user. This is an integer programming problem. To get an analytical solution, we will first relax the \(B_{i1}\) and \(B_{i2}\) to be integers.

Denote \(a_0 \triangleq \frac{1}{P_d L_i, i \xi_i^2}, B_0 \triangleq 2^{-\frac{B_{i,j}}{N_t - 1}}\), and \(x \triangleq 2^{-\frac{B_{i,j}}{N_t - 1}}\). Then problem (20) is reformulated as \(x^* = \arg \max_{x < x_1} 1 - \frac{1 - x^2}{2x + a_0}\). The objective function \(f(x) = \frac{1 - x}{2x + a_0}\) is concave, and set \(\frac{\partial f(x)}{\partial x} = 0\), we have the solution \(x^* = \sqrt{\frac{a_0}{a_0 + a_0}} - \frac{a_0}{a_0}\). Then the following solution will be used for feedback bits allocation

\[
B_{i1}^* = \left[-(N_t - 1) \log_2 x^*\right],
\]

\[
B_{i2}^* = B_i - \left[-(N_t - 1) \log_2 x^*\right].
\]

V. NUMERICAL RESULTS

Consider the 2-cell model in Fig. 1. We assume that the downlink and uplink transmissions have the same power constraint, i.e., \(P_d = P_u\). The cell radius is \(R = 1\ km\), the pathloss exponent is \(\alpha = 3\), and \(N_t = 4\). As do not consider training and feedback overhead optimization, the training and feedback intervals are fixed to be \(T_i = N_B N_t\) and \(T_{fb} = N_B^2 N_t\), respectively, with \(N_B = 2\).

Fig. 2 shows the performance gain of training and feedback optimization by comparing the following different systems: Training + aFB I (analog feedback, no optimization); Training + aFB II (digital feedback, applying training power allocation (13)); Training + aFB III (analog feedback, applying training power allocation (13) and feedback power allocation (15)); Training + dFB I (digital feedback, no optimization); Training + dFB II (digital feedback, applying training power allocation (13)); Training + dFB III (digital feedback, applying training power allocation (13) and feedback bits allocation (21)).

We see that training and feedback optimization provides a significant performance gain. For training with analog feedback, training optimization is more important, and additional uplink feedback power allocation provides limited performance gain. For training with digital feedback, training optimization alone provides little performance gain, and the
feedback bit allocation is more important. This is because we assume a fixed number of feedback bits and the uplink is the limiting factor for the channel estimation accuracy, so the feedback optimization is more important.

In Fig. 3, the average sum throughput and edge throughput, which is represented by the 5th percentile throughput, are compared for different systems with each user randomly and uniformly located on the line connecting 2 BSs in each cell. The adaptive ICIC system and the conventional single-cell beamforming system with perfect CSI are also shown for comparison. We can see that the analog feedback system provides performance close to the perfect CSI case, and the digital feedback system with $B = T_f$ is not as good but still provides significant gain over single-cell beamforming with perfect CSI. In addition, training and feedback optimization improves the performance of both analog and digital feedback systems.

Fig. 2. Effective sum rates considering training/feedback overhead for different systems, with edge SNR 15 dB, and $B = T_f$. User 1 is at $(−0.1R, 0)$ and user 2 is at $(0.1R, 0)$.

Fig. 3. Performance comparison of different systems, with $T = 500$, and $B = T_f$, for the digital feedback system. “aFB” denotes the system with training and analog feedback, while “dFB” denotes the system with training and digital feedback.

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