POWER MODULATION: APPLICATION TO INTER-CELL INTERFERENCE COORDINATION

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ABSTRACT

In this work, a novel technique which allows every transmitter in an interference network to have global channel state information (CSI) is proposed. The key feature of the proposed technique is that each transmitter acquires global CSI purely through the available feedback channel (i.e., a feedback of the received signal power). In the first step of the proposed technique, each transmitter uses several observations provided by the feedback channel to learn the channel gains perceived by its intended receiver. Secondly, this information is quantized, modulated, and transmitted to the other transmitters through the power levels used by the transmitters; the latter are indirectly observed through the received signal power. Hence, the interference is used as an implicit communication channel through which local CSI is exchanged. Once global CSI is acquired, it can be used to optimize any utility function which depends on it.

1. INTRODUCTION

Interference networks are wireless networks which are largely distributed in the sense of decision making and/or available information. The distributed nature of these systems typically induces some performance loss compared to a centralized solution. Implementing coordination is a way of partially bridging this gap. In most of the literature on coordination among autonomous decision-makers, like team decision problems (see e.g., [1]), the typical assumption is that decision-makers have access to dedicated channels to coordinate their actions. These dedicated channels allow the decision-makers to signal or communicate with each other without affecting the objective or utility function [2]. Typically, in an interference network, when there is no direct line of communication between the transmitters; the transmitters use a distributed or selfish strategy and work at a sub-optimal level of performance. For example, in the case of a distributed interference network with multiple carriers, the iterative water-filling algorithm (IWFA) is considered to be one of the state-of-the art distributed techniques [3] [4]. IWFA-like distributed algorithms have at least two attractive features: they only rely on local knowledge e.g., the individual signal-to-interference plus noise ratio (SINR), making them distributed information-wise; the involved computational complexity is typically admissible. IWFA operates over a period which is less than the channel coherence time and it does so in two steps: an exploration phase during which the transmitters update in a round robin manner their power allocation vector; an exploration phase during which the transmitters keep their power levels constant and at the values obtained at the end of the first phase. One drawback of IWFA is that convergence is not always ensured [4] and, when converging, it leads to a Nash point which is typically globally inefficient. One important message of the present paper is to show that IWFA-like distributed algorithms do not exploit the available feedback signal efficiently. In the exploration phase, instead of using several time-slots (and their associated SINR realizations) to allow the transmitters to converge to a Nash point, the feedback signal realizations can be used to acquire global CSI. The merit of the proposed technique has therefore the potential to cope with the global inefficiency issue. As for complexity, it has to be managed by a proper choice of global utility function which has to maximized during the exploitation phase. The key idea we propose is that feedback signals such as the SINR can be used both to estimate local CSI and to exchange it through an appropriate power modulation scheme. This idea is somewhat related to the new concept of coded power control which has been introduced in [5] for two-user interference channels when one master transmitter knows perfectly future realizations of the global channel state. Here, we address the case of causal, local, and imperfect CSI over block-fading multiuser interference channels and provide a practical technique to implement such a information-theoretic concept.

2. SYSTEM MODEL

Channel and communication model : The system under consideration is that of $K \geqslant 2$ pairs of interfering transmitters and receivers. Each transmitter-receiver pair can also be referred to as a user. Let the transmit power of user i be given by $p_i \in [0, P_{\max}]$ and the channel power gain of the link be-

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tween transmitter i and receiver j be $g_{ij} = |h_{ji}|^2$; h_{ji} may typically be the realization of a complex Gaussian random variable. The channel gain obeys a classical block-fading variation law and is assumed to be constant over each block of $T_1 + T_2 + T_3$ consecutive time-slots, T_m, $m \in \{1, 2, 3\}$, corresponding to Phase m of the proposed procedure; these phases are described further into this paper. In an interference channel for which receivers implement single-user decoding, the total received power at Receiver i on time-slot $t \geqslant 1$, ω_i is given by:

$$\omega_i(t) = g_{ii}p_i(t) + \sigma^2 + \sum_{j \neq i} g_{ji}p_j(t) \quad (1)$$

where σ^2 is the receive noise variance and $p_i(t)$ the power of transmitter i on time-slot t. All the channel coefficients can be expressed as elements of the $K \times K$ matrix $\mathbf{G} \equiv (g_{ij})_{i,j}$. We denote the $K-$dimensional (column) vector formed by the transmit power levels as $\underline{p} = (p_1, ..., p_K)^T$, T standing for the transpose operator. We assume that there is no direct communication channel between any two users. All the users transmit on the same bandwidth and in this work, we will focus on the single-carrier case and leave the multi-carrier case as a quite easy extension. Therefore all users interfere with each other at all times and the SINR at Receiver i is given by:

$$\gamma_i(t) = \frac{g_{ii}p_i(t)}{\sigma^2 + \sum_{j \neq i} g_{ji}p_j(t)}. \quad (2)$$

Feedback signal model : Receiver i computes the received signal (RS) power ω_i at each time slot, clips it if it reaches the maximum value $\omega_{\max}$, quantizes it in a uniform manner (in the log domain) with N bits (the quantizer is called $\mathcal{Q}$), puts these bits in serial and sends them to Transmitter i through a binary symmetric channel (BSC) with transition probability ϵ (see Fig. 1). The version of ω_i which is assumed to be available at Transmitter i is obtained from a dequantization operation $\mathcal{D}$ and is denoted by $\widetilde{\omega}_i$; it is therefore a noisy feedback (in contrast with the vast majority of papers related to the IWFA). The reason why we consider ω_i as the feedback signal instead of the SINR is fourfold; (i) It can be noticed that $\omega_i(t) = g_{ii}p_i(t) \times \left(1 + \frac{1}{\gamma_i(t)}\right)$. This shows that if Transmitter i knows $p_i(t)$, $g_{ii}(t)$, and has SINR feedback, then is also knows $\omega_i(t)$.; (ii) Assuming an RS feedback is very relevant in practice since existing wireless systems exploit this feedback signal e.g., under the name of RSSI (received signal strength indicator); (iii) The SINR is subject to higher fluctuations than the RS, which does not ease its transmission; (iv) As a crucial technical point, it can be checked that using the SINR as the transmitter observation leads to complex estimators [6] while the case of RS observations leads to a simple but very efficient estimation procedure, as shown further into this paper.

Network utility: For the exploitation phase, which is referred to as Phase 3 *any utility function* of the form $u(\underline{p}; \mathbf{G})$

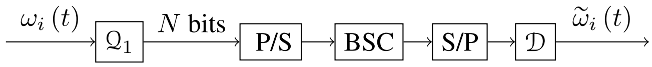

Fig. 1. Feedback signal model

might be considered. In the numerical part, we will make a specific choice namely, we consider the network sum-rate:

$$u^{\text{sum-rate}}(\underline{p}; \mathbf{G}) = \sum_{i=1}^{K} \log(1 + \gamma_i(\underline{p}; \mathbf{G})) \quad (3)$$

where a slight abuse of notation on is made on γ_i to emphasize the dependency of the SINR regarding the channel gain matrix. This specific choice of utility allows us to compare the proposed technique with the single-carrier version of the IWFA.

3. PROPOSED ESTIMATION TECHNIQUE

This work provides a procedure by which the transmitters can estimate partial information on $\mathbf{G}$ and exchange this information to obtain the complete $\mathbf{G}$. Once $\mathbf{G}$ is obtained a power vector $\underline{p}^\star$ can be found such that the network operates at an efficient point in terms of network utility. The process of achieving the desired power control vector is divided into three phases (see Fig. 2). The first phase is involved in estimating all the channel coefficients that are perceived by each receiver. Receiver i would estimate $\underline{g}_i = (g_{1i}, ..., g_{Ki})^T$. The second phase involves encoding this information into their transmit power levels as well as decoding the information received by observing -through the RS- the power levels of the other transmitters. The final phase would involve using all the collected information available to all the transmitters and setting the power control vector to the value obtained by optimizing u. Since the RS feedback is noisy and each transmitter has its own estimate for $\mathbf{G}$, the vectors computed by the transmitters differ in general, leading to a distributed CSI scenario [7]. A flowchart of the proposed scheme is shown in Fig. 3.

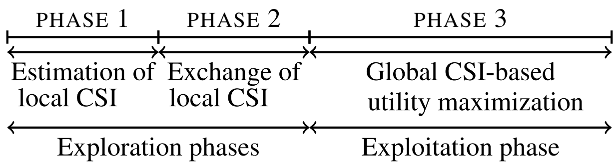

Fig. 2. The three main phases of the proposed scheme

3.1. Phase 1: Local CSI estimation in the power domain

The process of channel estimation is done by exploiting (1). The first phase lasts for a duration of T_1 time-slots. In each

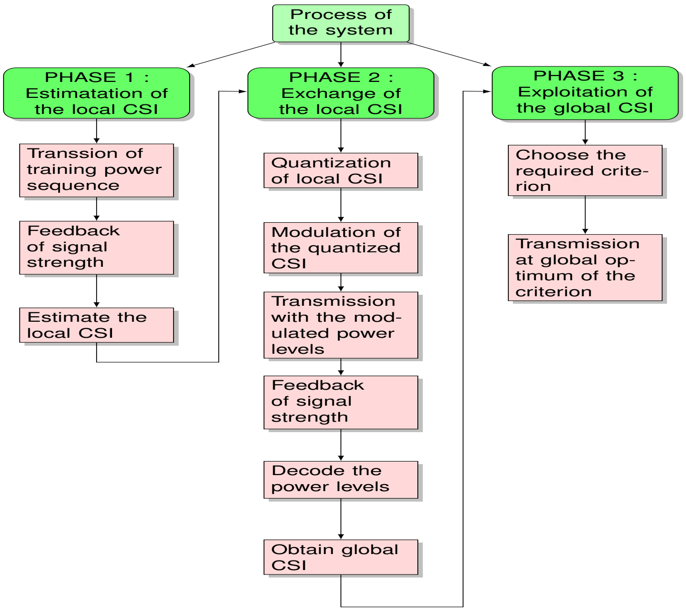

Fig. 3. The flowchart of the proposed scheme

time-slot, each of the transmitters transmits at a power level given by $p_i(t), t \in \{1, ..., T_1\}$. This sequence of power vectors used for Phase 1 is assumed to be known to all transmitters and therefore has the role of a training sequence. A difference between classical training-based estimation and Phase 1 is that estimation is performed in the *power domain* with the help of several time-slots and not in the amplitude or data symbol domain within one time-slot. Working in the symbol domain would allow one to have access to h_{ij} but the phase information on the channel coefficients is irrelevant regarding the utility function of the form $u(\underline{p}; \mathbf{G})$. By denoting $(\underline{p}(1)^T, ..., \underline{p}(T_1)^T)$ the sequence of training power vectors one can define the training matrix by:

$$\mathbf{S}(\mathbf{P}^1) = \begin{pmatrix} p_1(1) & \dots & p_K(1) \\ \vdots & \vdots & \vdots \\ p_1(T_1) & \dots & p_K(T_1) \end{pmatrix}. \tag{4}$$

With the above notations, the *noiseless* (assuming no noise in the feedback channel) RS vector $\underline{\omega}_i = (\omega_i(1), ..., \omega_i(T_1))^T$ can be merely expressed as:

$$\underline{\omega}_i = \mathbf{S}(\mathbf{P}^1) \times \underline{g}_i + \sigma^2 \underline{1} \tag{5}$$

where $\underline{1} = (1, 1, ..., 1)^T$. In this situation, we could estimate the channel gains using a Maximum Likelihood (ML) estimator or alternately the Moore-Penrose (MP) pseudo-inverse. Note that ω_i and $\widetilde{\omega}_i$ are not related to a simple observation equation of the type $\widetilde{\omega}_i = \omega_i + z$ where z is an independent and additive white Gaussian noise. In spite of the non-trivial structure for the noise on the RS it can be checked that the ML estimate(s) can be determined through a relatively simple equation which can be solved numerically provided computational complexity is not an issue. Motivated by a low-complexity solution we will only provide here an MP pseudo-inverse-based solution which is given by:

$$\widetilde{\underline{g}_i} = \left[\mathbf{S}(\mathbf{P}^1)^T \mathbf{S}(\mathbf{P}^1)\right]^{-1} \mathbf{S}(\mathbf{P}^1)^T \times \left(\widetilde{\underline{\omega}}_i - \sigma^2 \underline{1}\right) \tag{6}$$

where σ^2 is assumed to be known from the transmitters since it can always be estimated through conventional estimation procedures (see e.g., [8]). The choice of the training matrix will not be discussed here but it can optimized. A necessary condition on $\mathbf{S}(\mathbf{P}^1)$ is that $\det(\mathbf{S}(\mathbf{P}^1)^T \mathbf{S}(\mathbf{P}^1)) \neq 0$. For example, when $T_1 = K$ a simple choice is given by:

$$\mathbf{S}(\mathbf{P}^1) = P_{\max} \begin{pmatrix} 1 & 0.5 \\ 0.5 & 1 \end{pmatrix}, \tag{7}$$

which will be used in the simulation section.

3.2. Phase 2: Coding/decoding the local CSI to/from the power levels

In the second phase, each transmitter quantizes the information $\widehat{\underline{g}}_i$ (through a quantizer called $\mathcal{Q}_2$) and maps the obtained bits (through a modulator) into the sequence of power levels $\underline{p}'_i = (p_i(T_1 + 1), ..., p_i(T_1 + T_2))$ and estimate (through a demodulator) the power levels used by the other transmitters from the RS observations $\widetilde{\underline{\omega}}'_i = (\widetilde{\omega}_i(T_1 + 1), ..., \widetilde{\omega}_i(T_1 + T_2))$. To facilitate the corresponding operations, we assume that the used power levels on Phase 2 have to lie in $\mathcal{P} = \{P_1, ..., P_L\}$ with $\forall \ell \in \{1, ..., L\}$, $p_\ell \in [0, P_{\max}]$. At this point, it is of interest to summarize the overall processing chain for the CSI:

$$\begin{array}{ccccccc} \underline{g}_i & \xrightarrow{\text{Phase 1}} & \widetilde{\underline{g}}_i & \xrightarrow{\text{Quantizer}} & Q_2(\widetilde{\underline{g}}_i) & \xrightarrow{\text{Modulator}} & \underline{p}'_i \\ & & & & & & \downarrow \\ \widehat{\underline{g}}_i^j & \xleftarrow{\text{Dequantizer}} & \widetilde{\underline{p}}_i^j & & \xleftarrow{\text{Demodulator } \sharp j,\ j \neq i} & & \widetilde{\underline{\omega}}'_j \end{array} \tag{8}$$

where $\widehat{\underline{g}}_i^j$ is the estimate Transmitter j has about the channel vector $\underline{g}_i$.

Quantization operation $\mathcal{Q}_2$: Thus, the first step in the second phase is for each of the transmitters to quantize the real $K-$dimensional vector $\widetilde{\underline{g}}_i$ into a label of N_2 bits. With each of these labels, a sequence of T_2 power levels vector is associated, each level being in $\mathcal{P}$. For this purpose, the classical iterative Lloyd-Max (LM) algorithm could be used in order to minimize the distortion on $\widetilde{\underline{g}}_i$. However, this algorithm assumes that there is no noise on the information source but $\widehat{\underline{g}}_i$ contains both quantization noise (induced by $\mathcal{Q}$) and transmission noise (induced by the BSC). The more general scenario has been addressed in [10] where the authors exploit the statistical knowledge on the various noise sources to minimize the end-to-end distortion namely, the quantity $\mathbb{E}\|\widehat{\underline{g}}_i^j - \underline{g}_i\|^2$. To specify the corresponding quantizer, some notations are in order. Let ϕ be the p.d.f. of the noise due to channel estimation over Phase 1. Let $\pi_{n,\ell}$ be the transition probability of the discrete memoryless channel which corresponds to decoding as label ℓ the effectively transmitted label n. The generalized LM algorithm of [10] can be described for our problem as follows. First, select randomly $d = L^{T_2}$ sites $\underline{s}_\ell, \ell \in \{1, ..., d\}$ from a K-dimensional space. Then, the following steps are performed iteratively until the sites converge:

1. Compute the Voronoi region associated with each of these sites. For each site the corresponding Voronoi region $\mathcal{R}_\ell, \ell \in \{1, ..., d\}$ is defined by the set of all points closer to that site than to any other, i.e., $\mathcal{R}_\ell = \{\underline{x} \in \mathbb{R}^K : \|\underline{x} - \underline{s}_\ell\| \leqslant \|\underline{x} - \underline{s}_k\| \forall k \neq \ell\}$.
2. Compute the weighted centroids $\underline{v}_\ell, \ell \in \{1, ..., d\}$ as follows [10]:

$$\underline{v}_\ell = \frac{\int_{\mathcal{R}_\ell} \underline{g}_i f(\underline{g}_i) \sum_{n=1}^{d} \pi_{n,\ell} \int_{\mathcal{R}_n} \phi(\underline{y} - \underline{g}_i) \mathrm{d}\underline{y} \mathrm{d}\underline{g}_i}{\int_{\mathcal{R}_\ell} f(\underline{g}_i) \sum_{n=1}^{d} \pi_{n,\ell} \int_{\mathcal{R}_n} \phi(\underline{y} - \underline{g}_i) \mathrm{d}\underline{y} \mathrm{d}\underline{g}_i} \quad (9)$$

   where f is the p.d.f. of the variable to quantize that is, $\underline{g}_i$.
3. Set the d sites to be the d weighted centroids $\underline{v}_\ell$ as computed from Step 2.

Power modulation: For clarity, we assume $K = 2$ and explain at the end of the subsection how to deal with the case where $K > 2$. In this step, Transmitter $i \in \{1, 2\}$ sends the quantized channel $Q_2(\underline{\widetilde{g}}_i)$ to Transmitter $-i \neq i$ via the power level vector $(p_i(T_1 + 1), p_i(T_1 + 2), \ldots, p_i(T_1 + T_2))$ in the time slots $T_1 + 1 \leqslant t \leqslant T_1 + T_2$. As $Q_2(\underline{\widetilde{g}}_i)$ is quantized to $d = L^{T_2}$ symbols, there are exactly as many symbols as power level vectors in phase 2 (for each transmitter i). Therefore any one-to-one mapping between the two sets results in the power control for phase 2. For example; let $L = 2$ and $T_2 = 2$, user 1 will quantize estimate and quantize $(g_{11}, g_{2,1})$ to 4 symbols (2 bits). Let's represent the symbols after quantization by A and B for each channel. Here, $(g_{11}, g_{2,1})$ can be $(A, B), (A, A), (B, A)$ or (B, B) after quantization. Therefore a simple mapping scheme would be to chose $p_1(T_1 + 1) = P_{\text{max}}$ if $g_{11} = A$ and $p_1(T_1 + 1) = P_{\text{min}}$ otherwise; and $p_1(T_1 + 2) = P_{\text{max}}$ if $g_{21} = A$ and $p_1(T_1 + 1) = P_{\text{min}}$ otherwise. Once the quantized channel is mapped onto power levels, the next step is to identify the power levels used by the other transmitter. *Power demodulation*: The power levels are estimated as follows

$$\begin{cases} \widetilde{p}_1'(t) \in \arg\min\limits_{p_1' \in \mathcal{P}} |p_1' \widetilde{g}_{12} - (\widetilde{\omega}_2'(t) - p_2'(t) \widetilde{g}_{22} - \sigma^2)| \\ \widetilde{p}_2'(t) \in \arg\min\limits_{p_2' \in \mathcal{P}} |p_2' \widetilde{g}_{21} - (\widetilde{\omega}_1'(t) - p_1'(t) \widetilde{g}_{11} - \sigma^2)| \end{cases} \quad (10)$$

As g_{ji} for all j are known at Transmitter i, the above minimization operations can be performed. Note that since we deal with the 2−user case, only L tests have to be performed at each transmitter.

Handling multiple users: The above described method of Phase 2 can work well when $K = 2$. When the number of users is higher, the above demodulation scheme can be trivially extended. In this situation, Phase 2 can be be performed by scheduling the activity of all the users, such that only 2 users are active at any given time slot in Phase 2. Once all pairs of users have exchanged information on their channel states, Phase 2 is concluded. For example in the 3−user case, Phase 2 will have 3 sub-phases with each user in every other sub-phase and each pair can be active for $\frac{T_2}{3}$ time-slots.

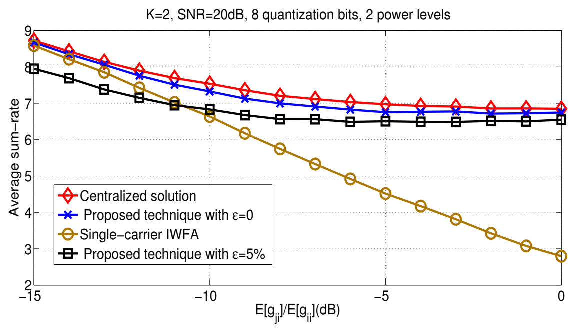

Fig. 4. Sum-rate against the interference level. The figure shows that by using the same feedback signal as the single-carrier IWFA during the exploration phase, it is possible to find a much better power vector for the exploitation phase.

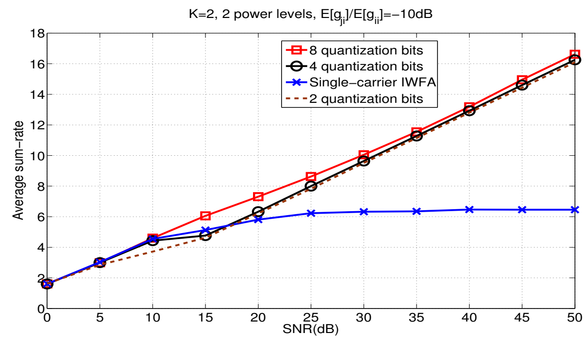

Fig. 5. The proposed technique outperforms the single-carrier IWFA in almost every case, with the exceptions being a small SNR or a high feedback quantization noise.

3.3. Phase 3: Exploitation phase

By the end of Phase 2, Transmitter i possesses the estimated channel matrix $\widehat{\mathbf{G}}_i$, leading to a distributed CSI scenario [7]. Therefore, at this point, transmitter i can find a power control vector as follows:

$$\underline{p}^i \in \arg\max_{\underline{p}} u(\underline{p}; \widehat{\mathbf{G}}_i) \quad (11)$$

and extract the power level it has to choose i.e., $p_i(t) = p_i^i$ for all $T_1 + T_2 + 1 \leqslant t \leqslant T_1 + T_2 + T_3$. The vectors computed by the transmitters may differ but in practice, the noise on the feedback signal has a typical level which allows the corresponding effect to be negligible if u is continuous in $\underline{p}$.

4. NUMERICAL ANALYSIS

For our numerical analysis, we make a specific choice of the utility by considering $u^{\text{sum-rate}}$. In [11], it is shown that for this kind of utility, the power control is binary, i.e., at the globally efficient point, $P_i^* \in \{0, P_{\max}\}$. Thus if $\mathbf{G}$ is known, an iterative search over all 2^K possibilities can be performed to obtain $\underline{P}^*$. The proposed scheme is also compared to the single carrier IWFA which is the Nash point of such a system where each transmitter blindly tries to optimize its individual rate $u_i = \log(1+\gamma_i)$, resulting in $p_i^{\text{NE}} = P_{\max}$. A distributed system that does not implement the proposed scheme would naturally operate at this point. In the simulations, we treat the two player case ($K = 2$), and assume that the error probability of BSC $\epsilon = 0$, unless otherwise stated.

With 2 power levels and 8 quantization bits, Fig. 4 plots the average sum-rate as function of $\mathbb{E}[g_{ji}]/\mathbb{E}[g_{ii}] (j \neq i)$. From this figure, we observe that our technique has a better performance than the single carrier IWFA for all interference values when $\epsilon = 0$. Even in the presence of feedback error (when $\epsilon = 0.05$, we see that the proposed technique outperforms the IWFA for large enough interference levels. Fig. 4 also shows the performance of our technique is close to the global optimum. Using more power levels is similar to using a larger constellation in conventional communication systems. Similarly, in our case, using a higher number of power levels could increase the quality of the CSI exchanged, but is more prone to errors. Fig. 5 plots the average sum-rate as function of SNR(dB). As expected, a higher SNR results in a higher sum rate and a lower quantization noise improves the performance of the technique.

5. CONCLUSION

From the analysis conducted in this work, it is seen that using power modulation to implicitly communicate with other transmitters could potentially improve the performance of the system. The performance gain when compared to a purely distributed solution is studied numerically for a specific utility and the results are seen to be promising. Our key observations are the following; (i) When the interference is large enough, the proposed method outperforms the Nash equilibrium (all users transmit at max power all the time) by a significant margin; (ii) If phase 2 is cost-less, any number of users can be supported by the proposed method and can achieve a utility close to the globally efficient point. (the time spent on phase 2 becomes more significant when the channel changes within a short time period). One of the the most straightforward and necessary extensions of this work would be the extension to a multi-carrier system, with Phase 1 and 2 remaining as it is, but with the information on each carrier channel fading matrix learned and broadcasted in parallel on each carrier. Additional extensions would include accounting for the cost in performing Phase 1 and 2, advanced estimators in Phase 1 and joint quantization and modulation for Phase 2 [10].

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