PARTIAL BEAMFORMING TO REDUCE ADC POWER CONSUMPTION IN ANTENNA ARRAY SYSTEMS

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ABSTRACT

In this paper, we consider a receiver setup with fewer analog to digital convertors (ADC's) than antennas. An analog preprocessing network (APN) is placed before the ADC's to reduce power consumption in the receiver. A set of low resolution beamformers is used to design the APN and cancel contributions of interfering users. Simulation results show that introduction of such APN design algorithms for a narrowband channel with 3 to 4 interfering users, 6 antennas and 3 ADCs results in a reduction of the total consumed receiver power by 15%.

Index Terms— analog beamforming, reduced rank processing, cross-spectral projections, passive weighing structures.

1. INTRODUCTION

Multiple antennas at the receiver exploit spatial diversity and achieve reliable communication close to theoretical limits. However each antenna requires a separate radio frequency (RF) and ADC block leading to an increase in power consumption. The ADC's already consume 40% of power in the receiver and multiple ADC's would result in further increase. The power consumption in digital components follows Moore's law and reduces by a factor of 32 every 10 years whereas the power in ADC's is expected to reduce by only a factor of 10. To make the theoretical gains promised by multiple input multiple output (MIMO) systems a reality, there is a need for novel methods to reduce the power dissipated at the ADCs.

In a multi-user communication setup signals from desired and interfering users are received by an antenna array, translated into intermediate frequency (IF), sampled and quantized using an ADC for each antenna, followed by combined baseband processing. The IF signals, containing contributions from the desired user, noise as well as that of interfering users are processed by the ADCs. The power consumed in ADC's depend on the sampling frequency (f_s) and resolution (res or number of bits) to store the antenna array signals: $P_{adc} \propto f_s 2^{res}$ [1]. In the presence of strong interferers, ADC's are forced to allot most of the bits in processing interfering signals. This scenario is prevalent in household environment where uncoordinated WLAN networks operate in same frequency band.

One approach to reduce the number of RF and ADC chains is to select the antenna outputs with largest energy [2]. In [3] an antenna selection scheme based on joint RF and baseband design, exploiting spatial multiplexing and diversity is proposed for single user MIMO. This technique uses a time varying RF-switch combination to select a subset of antennas from the array. However no information regarding channel estimation or coordination is specified and such techniques do not take multi-user interference or the frequency selective nature of the channel into account. These factors and that of implementing RF weights/switches hamper practical MIMO applications to achieve the required throughput and power consumption as specified in numerous wireless standards.

These factors motivate us to perform preprocessing before the ADC's and cancel the contribution of the interfering users in the analog domain. Even partial cancellation of interfering users allows the use of ADC's with reduced resolution. Consider a simple example of a common wireless channel with one interfering user transmitting signals of the same energy as that of the desired user. A coarse cancelation (say 50%) reduces the power consumed in the ADC by 25% and allows us to chop off 1 bit in the ADC of a 2 antenna receiver. If 40% of the receiver power can be attributed to the ADCs, then the total power consumed in the receiver can be reduced by 10%.

Setup and contributions: The signals received at the antenna array are translated into IF and fed to the APN. The APN output is sampled and quantized using a set of ADC's. The taps of the APN (modeled as phase and amplitude shifts), are designed using a set of low resolution beamformers (LRB's) as shown in Fig. 1. The prime reason for using LRB's is to enable computing certain statistics of the MIMO channel. The LRB's are squinted from each other [4, 5] and capture multipath and delay shifted versions of desired and interfering signals independent of

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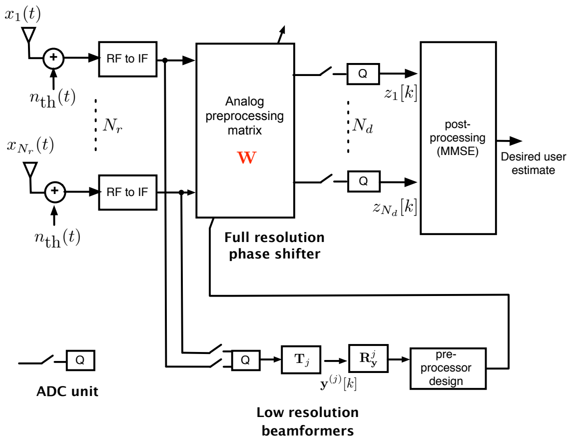

Fig. 1: Proposed receiver setup: reduced rank APN

APN. The power consumed in these LRB's is negligible, since their resolution is very small (usually 2-4 bits) when compared to that of the overall system. We compute the coefficients of the APN in two ways. In first scheme, the LRB outputs are used to estimate the covariance matrix of the antenna array signals. The dominant basis vectors of the covariance matrix give the taps of APN. In the second scheme, we select the basis vectors having least deviation from the cross spectral subspace of the desired user. This cancels the interfering users, which have large deviation from the desired user subspace.

The APN taps are designed as combination of phase shifters and automatic gain control (AGC) blocks and can be implemented using passive weighing circuits (PWS) [6]. These PWS (mostly comprising of RC circuits) occupy less area and consume negligible power. Such preprocessing schemes are coarse and cannot precisely cancel the contributions from an interfering user. Therefore, we extract multiple outputs from the APN, containing different combinations of desired and residual interfering users, followed by post-processing in digital baseband to estimate the desired user. Simulation results show that, for a multi-user narrowband channel with signal to interference ratio (SIR = -6 dB), nearly 75% of the interfering user contributions are canceled, leading to 60% reduction in ADC power for similar BER performance.

Notation: $*$, $(.)^T$, $(.)^H$, $\bar{(.)}$ and $(.)^\dagger$ represent convolution, transpose, Hermitian, conjugate and pseudo inverse. $\otimes$ and $\|.\|$ represent kronecker product and Frobenius norm. The vec($\mathbf{F}$) operation transforms a matrix to a vector while $\text{vec}^{-1}(\mathbf{f})$ does the opposite. The continuous time signals are indexed as (.) and sampled signals are indexed as [.].

2. SYSTEM MODEL

The common wireless channel with N_t users and N_r receive antennas can be modeled as $N_r \times N_t$ MIMO channel. For sake of simplicity, a 2-user narrowband system is considered, where user 1 is the desired user and user 2 is an interfering user. After downconversion to IF, the continuous time signals at antenna 1 and time t can be written as

$$x_1(t) = s^{(1)}(t)h_1^{(1)} + s^{(2)}(t)h_1^{(2)} + n_{1,\text{th}}(t) \quad (1)$$

where $s^{(j)}(t)$ denotes the continuous time signal from user j at time t, $h_i^{(j)}$ is the channel response from user j to antenna i and $n_{i,\text{th}}(t)$ is the thermal noise at antenna i. Extending (1) to N_r antennas and omitting the thermal noise term for the moment gives

$$\begin{aligned} \begin{bmatrix} x_1(t) \\ \vdots \\ x_{N_r}(t) \end{bmatrix} &= \begin{bmatrix} h_1^{(1)} & h_1^{(2)} \\ \vdots & \vdots \\ h_{N_r}^{(1)} & h_{N_r}^{(2)} \end{bmatrix} \begin{bmatrix} s^{(1)}(t) \\ s^{(2)}(t) \end{bmatrix} \\ \Leftrightarrow \quad \mathbf{x}(t) &= \begin{bmatrix} \mathbf{h}^{(1)}, & \mathbf{h}^{(2)} \end{bmatrix} \begin{bmatrix} s^{(1)}(t) \\ s^{(2)}(t) \end{bmatrix} \end{aligned} \quad (2)$$

Sample the antenna array signals with period T such that $\mathbf{x}[k] = \mathbf{x}(kT)$ and stack a block of N successive samples as $\mathbf{X} = [\mathbf{x}[0], \cdots, \mathbf{x}[N-1]]$. Each column of $\mathbf{X}$ contains N_r spatial signals. For N_t users $\mathbf{X}$ has factorization

$$\begin{aligned} \mathbf{X} &= \begin{bmatrix} \mathbf{h}^{(1)}, & \cdots, \mathbf{h}^{(N_t)} \end{bmatrix} \begin{bmatrix} \mathbf{s}^{(1)T} \\ \vdots \\ \mathbf{s}^{(N_t)T} \end{bmatrix} \\ \Leftrightarrow \mathbf{X} &= \mathbf{HS} \end{aligned} \quad (3)$$

where $\mathbf{s}^{(i)} = [s^{(i)}[0], \cdots, s^{(i)}[N-1]]^T, i = 1, \cdots, N_t$.

3. REDUCED RANK PROCESSING

3.1. Full rank least squares (LS)

If $\mathbf{H}$ is full column rank, we can construct an $N_r \times 1$ weight vector $\boldsymbol{\theta}$ acting on $\mathbf{x}[k]$ to obtain an estimate of $s^{(1)}[k]$ as $\hat{s}_f^{(1)}[k] = \boldsymbol{\theta}^H \mathbf{x}[k]$. The subscript f in $\hat{s}_f^{(1)}[k]$ denotes the fact that $\boldsymbol{\theta}$ acts on the full subspace spanned by the channel matrix $\mathbf{H}$. A reliable estimate of $\boldsymbol{\theta}$ is obtained by minimizing the mean squared error (MSE) between $s^{(1)}[k]$ and $\hat{s}_f^{(1)}[k]$, the solution is given by the well known Wiener-Hopf criterion [7]

$$\boldsymbol{\theta} = \mathbf{R}_{\mathbf{x}}^{-1} \mathbf{r}_{\mathbf{x}s} \quad (4)$$

where $\mathbf{R_x} = (1/N)\mathbf{X}\mathbf{X}^H$ and $\mathbf{r_{x}}_s = (1/N)\mathbf{X}\mathbf{s}^{(1)}$. Define the eigenvalue decomposition $\mathbf{R_x} = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^H$, where $\mathbf{U}$ is unitary and $\mathbf{\Lambda}$ is diagonal. We can then also write

$$\boldsymbol{\theta} = \mathbf{U}\mathbf{\Lambda}^{-1}\mathbf{U}^H\mathbf{r_x}_s = \mathbf{U}\mathbf{c_x}_s \tag{5}$$

The vector $\mathbf{c_{xs}}$ contains the cross spectral norm and provides connection with the cross spectral projetions described in Section 4.3 (see Fig. 2(a)).

3.2. Reduced rank LS

In our setup, we place an $N_r \times N_d$ matrix $\mathbf{W}$ (also referred to as APN) before the ADC's to transform the N_r antenna signals into N_d beamformed signals $\mathbf{z}(t) = \mathbf{W}^H\mathbf{x}(t)$ where $N_d < N_t \leq N_r$. The dimension of the APN output is less than the number of antennas, and allows us to use fewer ADC's. We cannot reduce to $N_d = 1$ because the APN is very coarsely quantized, hence will not cancel the interferer completely.

The outputs of the APN are sampled and digitized using N_d ADC's, which gives $\mathbf{z}[k] = \mathbf{z}(kT)$. Next, we use a beamformer $\boldsymbol{\vartheta}$ in the digital postprocessing stage to obtain an estimate of the desired user signal, $\hat{s}_r^{(1)}[k] = \boldsymbol{\vartheta}^H\mathbf{z}[k]$. $\boldsymbol{\vartheta}$ is designed similar to (4) as

$$\boldsymbol{\vartheta} = \mathbf{R_z}^{-1}\mathbf{r_z}_s$$

where $\mathbf{R_z} = \mathbf{W}^H\mathbf{R_x}\mathbf{W}$ and $\mathbf{r_z}_s = \mathbf{W}^H\mathbf{r_{xs}}$. The processing structure is as shown in Fig. 2(b). The model of $\mathbf{z}[k]$ is

$$\mathbf{z}[k] = \mathbf{W}^H\mathbf{H}\begin{bmatrix} s^{(1)}[k] \\ \vdots \\ s^{(N_t)}[k]\end{bmatrix} \tag{6}$$

We design $\mathbf{W}$ such that its columns span a subset of the column span of $\mathbf{X}$, given by the eigenvectors vectors $\mathbf{u}_k$ in $\mathbf{U}$. The APN design is reduced to a problem of selecting a set of N_d columns from $\mathbf{U}$; $\mathbf{U} = [\mathbf{u}_1, \cdots, \mathbf{u}_{N_r}]$, such that these columns contain maximum contributions from the desired user.

We refer to this as reduced rank LS since the digital beamformer $\boldsymbol{\vartheta}$ does not have access to the full subspace spanned by the channel matrix $\mathbf{H}$, but only a reduced subset of rank N_d. This is indicated by subscript r in user estimate $\hat{s}_r^{(1)}[k]$.

We include the following constraints in our model:

- A1: The number of ADC's (N_d) is less than the rank of $\mathbf{H}$.
- A2: Training symbols are embedded in the data packets to estimate the channel.
- A3: The signal vector $\mathbf{x}(t)$ is also sampled at a reduced rate f_s, after which a set of q independent, fixed LRB's $\mathbf{T}_1, \cdots, \mathbf{T}_q$ are applied to estimate the wireless channel. Each matrix $\mathbf{T}_j$ has size $N_r \times p$, where the number of output channels p is a design parameter.
- A4: The thermal noise $n_{i,\text{th}}(t)$ at antenna i is an uncorrelated zero mean complex gaussian wide sense stationary process with variance σ^2.

4. PREPROCESSOR DESIGN

The main problem at this point is the design of $\mathbf{W}$. For this we need to compute an estimate of $\mathbf{R_x}$ and possibly $\mathbf{r_{xs}}$. This can be done as follows.

4.1. Estimation of the data covariance matrix

The first step towards computing $\mathbf{W}$ is to estimate $\mathbf{R_x}$. In this section we estimate it using LRB's. Each LRB $\mathbf{T}_j$ transforms the antenna array signal; the output is $\mathbf{y}^{(j)}[k] = \mathbf{T}_j^H\mathbf{x}[t]$. The corresponding covariance matrix is

$$\hat{\mathbf{R}}_\mathbf{y}^j = \mathbf{T}_j^H\mathbf{R_x}\mathbf{T}_j\,, \quad j = 1, \cdots, q$$

We will use the identity

$$\text{vec}(\hat{\mathbf{R}}_\mathbf{y}^j) = (\bar{\mathbf{T}}_j^H \otimes \mathbf{T}_j)^H \text{vec}(\mathbf{R_x})$$

Similar as in [4, 5], we can compute the elements of $\mathbf{R_x}$ via

$$\begin{bmatrix} \text{vec}(\hat{\mathbf{R}}_\mathbf{y}^1) \\ \vdots \\ \text{vec}(\hat{\mathbf{R}}_\mathbf{y}^q)\end{bmatrix} = \begin{bmatrix} (\bar{\mathbf{T}}_1^H \otimes \mathbf{T}_1)^H \\ \vdots \\ (\bar{\mathbf{T}}_q^H \otimes \mathbf{T}_q)^H\end{bmatrix} \text{vec}(\mathbf{R_x})$$

$$\Leftrightarrow \quad \hat{\mathbf{r}}_\mathbf{y}^{\text{ef}} = \mathbf{T}_{\text{ef}}\mathbf{r_x} \tag{7}$$

The coefficients of $\mathbf{T}_j$ are obtained as in [5]. The matrices $\mathbf{T}_j$ and their number q are chosen such that $\mathbf{T}_{\text{ef}}$ is a full column rank, tall and skinny matrix. This requires at least that $qp^2 \geq N_r^2$. At this point, $\mathbf{R_x}$ is estimated as

$$\mathbf{R_x} = \text{vec}^{-1}(\mathbf{T}_{\text{ef}}^\dagger\hat{\mathbf{r}}_\mathbf{y}^{\text{ef}})$$

$\mathbf{r_x}\mathbf{s}$ can be computed in a similar way (assuming a training sequence is available).

4.2. Design 1: Select dominant paths

After estimating $\mathbf{R_x}$, the analog beamformer $\mathbf{W}$ can be chosen as the N_d dominant eigenvectors of $\mathbf{R_x}$. This beamformer retains signal components with sufficient energy at the antenna array and cancels less powerful signals. It does not distinguish between the desired user and

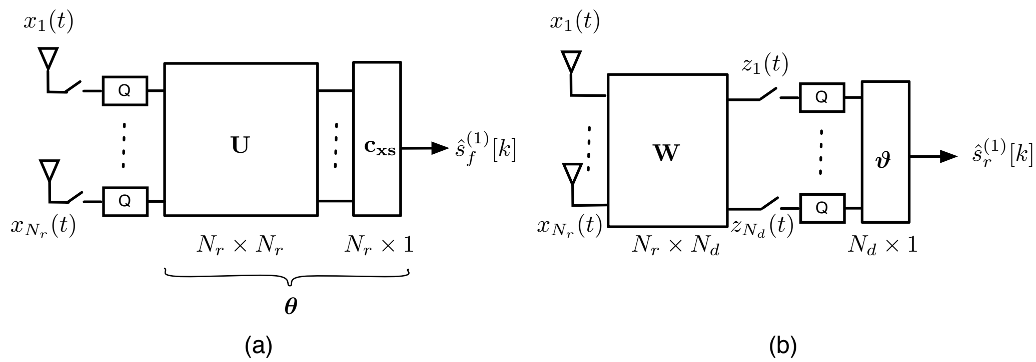

Fig. 2: (a) Full rank Wiener beamformer, (b) reduced rank beamformer

interfering users. The desired user estimate can be obtained through digital post-processing $\hat{s}_r^{(1)}[k] = \boldsymbol{\vartheta}^H \mathbf{z}[k]$, where $\boldsymbol{\vartheta}$ can be computed using a training sequence.

4.3. Design 2: Cross spectral projections

In a multi-user setup with strong interfering users (such as uncoordinated wireless networks), a weak desired signal may not be captured if $\mathbf{W}$ is selected from N_d dominant basis vectors of $\mathbf{R_x}$. In this section we show that instead of selecting the eigenvectors corresponding to the dominant eigenvalues, selecting eigenvectors corresponding to the N_d largest elements of the *cross spectral norm* $\mathbf{c_{xs}} = \boldsymbol{\Lambda}^{-1}\mathbf{U}^H\mathbf{r_{xs}}$ (cf. (4)) results in a reduced rank minimum MSE (MMSE) solution [7, 8]. The vector $\mathbf{r_{xs}}$ can be estimated using the LRB outputs and training signals similar to the technique in Section 4.1.

More specifically, the objective is to obtain $\mathbf{W}$, not from the dominant eigenvectors but from eigenvectors that result in largest energy when projected over the desired user cross spectral subspace. To illustrate this let us consider the full rank LS estimate $\hat{s}_f^{(1)}[k] = \boldsymbol{\theta}^H\mathbf{x}[k]$ with beamformer $\boldsymbol{\theta}$ as in (5), designed through the Wiener-Hopf criterion. The energy of the desired user estimate is

$$E\{|\hat{s}_f^{(1)}[k]|^2\} = (1/N)\boldsymbol{\theta}^H\mathbf{X}\mathbf{X}^H\boldsymbol{\theta} = \mathbf{c}_{\mathbf{xs}}^H\boldsymbol{\Lambda}\mathbf{c_{xs}}. \quad (8)$$

Eqn. (8) can be viewed as a sum of contributions $E\{|\hat{s}_f^{(1)}[k]|^2\} = \sum_{j=1}^{N_r}|c_j|^2\lambda_j$, where $\mathbf{c_{xs}} = [c_1, \cdots, c_{N_r}]^T$ and λ_j is the j-th eigenvalue in $\boldsymbol{\Lambda}$. We can view c_j as a cross spectral metric relating eigenvector $\mathbf{u}_j$ with $\mathbf{r_{xs}}$. This technique selects the N_d columns of $\mathbf{W}$ from the eigenvectors in $\mathbf{U}$ that correspond to the N_d largest terms $|c_j|^2\lambda_j$, where

$$|c_j|^2\lambda_j = \frac{|\mathbf{u}_j^H\mathbf{r_{xs}}|^2}{\lambda_j}, \quad j = 1, \cdots, N_r$$

This would maximize the contributions of the desired user at the output of APN. We denote this scheme as cross spectral projections (CSP).

5. SIMULATION RESULTS

The performance of APN is observed for a multi-user channel, where the desired user and 4 interfering users ocuppy the same IF band with signal to interference ratio (SIR = -6dB) and source angles angles of arrival $0°$, $-20°$, $-40°$, $20°$, $40°$. The data is transmitted in packets of 100 blocks, with each block containing $N = 64$ QPSK symbols. The receiver is neither synchronized nor does it have any coordination with the interferers. The signals are received using $N_r = 6$ array and transformed into $N_d = 3$ separate streams using the APN and input to the ADC. The N_d ADC's operate at full resolution (12 bits). The APN is designed to have 6-bit resolution. $\mathbf{R_x}$ and $\mathbf{r_{xs}}$ are designed using a set of $q = 4$ LRB's, each having $p = 3$ outputs.

Fig. 3 compares the effect of APN with respect to energies from desired and interfering users, as a function of direction of arrival (DOA). Curve 1 shows the array gain of a MIMO system using $N_r = N_d = 6$ ADC's. Curve 2 shows the signal energy of each source with APN designed from dominant eigen vectors of $\mathbf{R_x}$ and $N_d = 3$. Curve 3 shows the array gain when APN is designed using CSP scheme and $N_d = 3$. The CSP (curve 3) performs 8 dB and 20 dB isolation for 2 interfering signals, whereas the signal energy from desired user remains unaltered.

Fig. 4 shows the improvement in SINR due to the introduction of APN. The signals received at the antenna

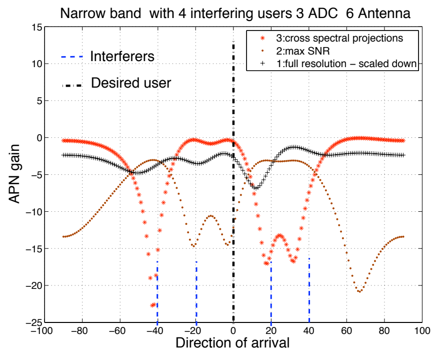

Fig. 3: Array gain for varying angle of arrival of sources

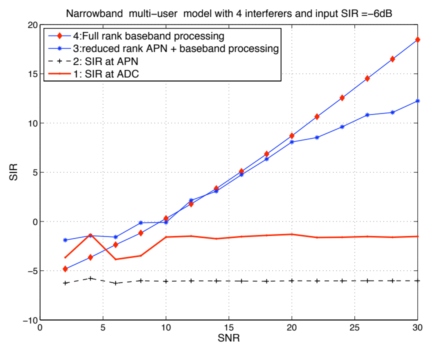

Fig. 4: SINR performance improvement due to the APN

array have SINR of -6 dB (curve 1) and APN (curve 2) improves the SINR to -1.7 dB (for input SNR:10 $\sim$ 20 dB). Curve 3 shows the APN followed by baseband processing in reduced rank, results in approximately the same MMSE as that of full rank processing (curve 4).

Fig. 5 compares the BER performance of a full rank scheme (curve 1) with 6 ADC's (12 bits each) with reduced rank scheme having $N_d = 3$ and $N_d = 4$ (12 bits each) corresponding to curves 3 and 4. The BER performance degradation from $N_r = 6$ to $N_d = 4$ is 0.5 dB and $N_d = 3$ is 3 dB. For comparative BER performance, introduction of APN results in reducing a 72 bit ADC arrangement to 48/36 bit arrangement and reduced power consumption. This performance degradation is negligible with respect to dramatic decrease in power consumption.

6. CONCLUSION

Simulation results show that in a narrowband environment the BER performance of APN with less ADC's is comparable to scheme using baseband processing with information from all antennas. Considering that ADC's are the

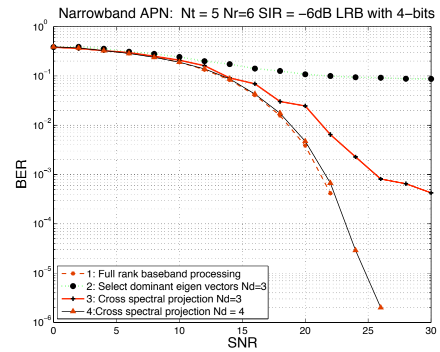

Fig. 5: BER performance comparison of the APN

major power spending unit in the receiver, these results provide significant insight into translating the theoretical performance of MIMO systems in practice.

7. ACKNOWLEDGEMENTS

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