A Novel Hybrid Approach to Improve Performance of Frequency Division Duplex Systems with Linear Precoding

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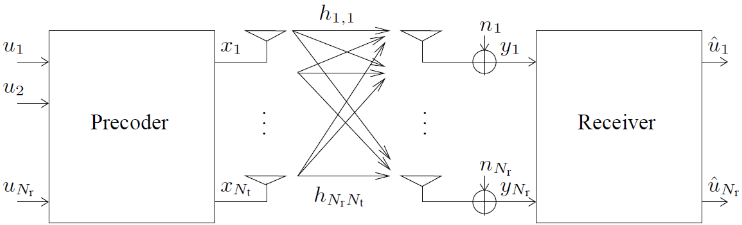
Introduction

- Demand of multimedia contents produces the development of new techniques to improve digital communications throughput.
- Precoding is an attractive way to remove interferences because it reduces cost and power consumption in the equipment.
- When using precoding the base station should know the *Channel State Information* (CSI) which is usually acquired at the receiver using supervised algorithms with pilot symbols.
- In *Frequency Division Duplex* (FDD) systems, used in fixed broadband wireless networks, CSI is sent by means of a feedback channel.
- In order to reduce the overhead due to the periodical transmission of pilot symbols, we propose to obtain the CSI combining supervised and unsupervised algorithms.

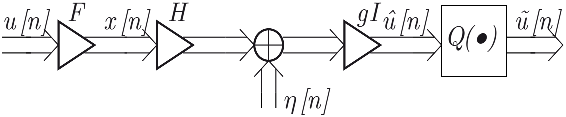
System Model



- Flat fading channels with Rayleigh distribution.
- The channel remains constant during several frames.
- Gaussian noise $\boldsymbol{\eta}[n] \sim \mathcal{N}_{\mathbb{C}}(0, \mathbf{C}_{\boldsymbol{\eta}}) \in \mathbb{C}^{N_r}$.
- Transmitted signal $\mathbf{x}[n] \in \mathbb{C}^{N_t}$.

Linear Precoding Design: Model

- System with Precoding over Flat MIMO Channel



- The data symbols $\mathbf{u}[n]$ are passed through the precoding filter $\mathbf{F}$ to form the transmit signal $\mathbf{x}[n] = \mathbf{F}\mathbf{u}[n] \in \mathbb{C}^N$.
- Therefore the received signal is $\mathbf{y}[n] = \mathbf{H}\mathbf{F}\mathbf{u}[n] + \boldsymbol{\eta}[n]$
- After multiplying by the received gain we get the estimated symbols $\hat{\mathbf{u}}[n] = g\mathbf{H}\mathbf{F}\mathbf{u}[n] + g\boldsymbol{\eta}[n]$

Linear Precoding Design: Wiener Filter

The Wiener filter for precoding is a very powerful transmit optimization that minimizes the MSE with a transmit energy constraint, i.e.

$$\{\mathbf{F}_{\mathrm{WF}}, g_{\mathrm{WF}}\} = argmin_{\{\mathbf{F},g\}} E\left[\|\mathbf{u}[n] - \hat{\mathbf{u}}[n]\|_2^2\right]$$
$$\text{s.t.: } trace(\mathbf{F}\mathbf{C}_{\mathbf{u}}\mathbf{F}^H) \leq E_{tx}. \quad (1)$$

where $\mathbf{C}_{\mathbf{u}} = E\left[\mathbf{u}^H[n]\mathbf{u}[n]\right]$ and E_{tx} is the transmit energy. Considering $g \in \mathbb{R}^+$, the solution for the Wiener filter is given by

$$\boxed{\begin{aligned} \mathbf{F}_{\mathrm{WF}} &= g_{\mathrm{WF}}^{-1}\left(\mathbf{H}^H\mathbf{H} + \xi I\right)^{-1}\mathbf{H}^H \\ g_{\mathrm{WF}} &= \sqrt{\frac{trace\left(\left(\mathbf{H}^H\mathbf{H} + \xi I\right)^{-2}\mathbf{H}^H\mathbf{C}_{\mathbf{u}}\mathbf{H}\right)}{E_{tx}}}. \end{aligned}} \quad (2)$$

Neural Network Approaches

- Our model assumes that the observations are linear and instantaneous mixtures of the user symbols

$$\mathbf{y}[n] = \mathbf{HFu}[n] + \boldsymbol{\eta}[n] = \mathbf{Au}[n] + \boldsymbol{\eta}[n]. \tag{3}$$

- In order to recover the user symbols, we will use a Neural Network whose output is a combination of the observations

$$\mathbf{z}[n] = \mathbf{W}^H[n]\mathbf{y}[n] = \mathbf{\Gamma}[n]\mathbf{u}[n]. \tag{4}$$

where $\mathbf{\Gamma}[n] = \mathbf{W}^H[n]\mathbf{A}$

- User symbols are optimally recovered when $\mathbf{W}[n]$ is selected such as every output extract a different single source
- This occurs when $\mathbf{\Gamma}[n] = \mathbf{D}[n]\mathbf{P}[n]$

Neural Network Approaches (cont.)

- Supervised Algorithms:
  - The channel matrix can be estimated minimizing the MSE between $\mathbf{y}[n]$ and $\mathbf{x}[n]$
  - Least Mean Squares (LMS) algorithm

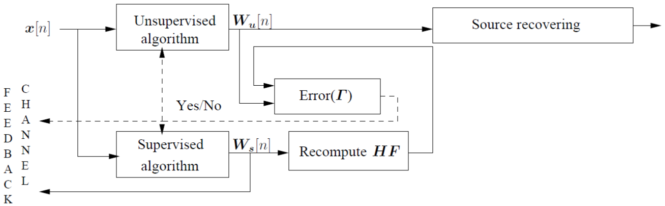
$$\mathbf{W}[n+1] = \mathbf{W}[n] - \mu \mathbf{y}[n](\mathbf{W}^H[n]\mathbf{y}[n] - \mathbf{x}[n])^H.$$

  - Wiener-Hopf solution: $\mathbf{W}[n] = \mathbf{C_y}^{-1}\mathbf{C_{yx}}$ where $\mathbf{C_y} = E[\mathbf{y}[n]\mathbf{y}^H[n]]$ and $\mathbf{C_{yx}} = E[\mathbf{y}[n]\mathbf{x}^H[n]]$.
- Unsupervised Algorithms:
  - Pilot symbols reduce system througput. Limitation avoided using Blind Source Separation (BSS) algorithms.
  - The source data can be recovered using unsupervised learning algorithms. For example: Infomax algorithm

$$\mathbf{W}[n+1] = \mathbf{W}[n] - \mu \mathbf{W}[n]\left(\mathbf{z}[n]\mathbf{g}^H(\mathbf{z}[n]) - \mathbf{I}\right). \quad (5)$$

Novel Combined Approach

- One of the advantages of unsupervised algorithms is their ability to track low channel variations.
- Supervised algorithms provide a fast channel estimation for low or high variations at the cost of using pilot symbols.
- We propose to combine these paradigms to obtain similar performance to supervised algorithms with less pilot symbols.
- *Idea:* determine dynamically the instants where pilot symbols must be transmitted.



Novel Combined Approach: Procedure

First frame:

- The receiver uses the supervised algorithm to estimate $\mathbf{H}$. This matrix is sent to the transmitter by the feedback channel.
- Both receiver and transmitter compute $\mathbf{F}$.
- The receiver initializates the unsupervised algorithm to $\mathbf{W}_u[n] = (\mathbf{HF})^{-H} = (\mathbf{A})^{-H}$.

Each time a new frame is received:

- If the channel has suffered a significant variation send an alarm to the transmitter asking for a "pilot frame". Then the receiver do the same as first frame.
- If the channel has not suffered a significant variation receiver computes $\mathbf{W}_u[n]$ and recover the data symbols $\mathbf{u}[n]$.

Novel Combined Approach: Decision Criterion

- How to determine significant channel variations?
- The permutation indeterminacy associated to unsupervised algorithms is avoided due to the initialization $\mathbf{W}_u[n] = (\mathbf{HF})^{-H} = (\mathbf{A})^{-H}$
- The optimum separation matrix produces a diagonal matrix for $\mathbf{\Gamma}[n] \Rightarrow$ the mismatch of $\mathbf{\Gamma}[n]$ with respect to a diagonal matrix allows us to measure the variations in the channel.
- Dispersion measure:

$$\mathrm{Error}[n] = \sum_{i=1}^{N_t} \sum_{j=1, j \neq i}^{N_t} \left(\frac{|\gamma_{ij}[n]|^2}{|\gamma_{ii}[n]|^2} + \frac{|\gamma_{ji}[n]|^2}{|\gamma_{ii}[n]|^2} \right) \quad (6)$$

- Decision criteria:

$$\begin{cases} \mathrm{Error}(\mathbf{\Gamma}[n]) > t \rightarrow \text{Use supervised approach} \\ \mathrm{Error}(\mathbf{\Gamma}[n]) \leq t \rightarrow \text{Use unsupervised approach} \end{cases} \quad (7)$$

Experimental Results: Data

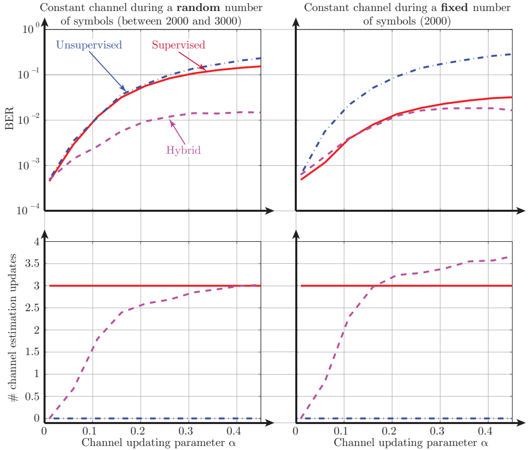
- We transmit the image *cameraman* (in tif format with 256 gray levels) using a QPSK (8 000 symbols) and a 4×4 MIMO system.
- The channel matrix is updated using the following model

$$\mathbf{H} = (1 - \alpha)\mathbf{H} + \alpha \mathbf{H}_{\text{new}} \tag{8}$$

where $\mathbf{H}_{\text{new}}$ is a 4×4 matrix randomly generated according to a Gaussian distribution.
- The SNR has been stated to 20 dB.
- Supervised Wiener-Hopf solution: 200 pilot symbols are transmitted each 2 000 symbols.
- Infomax algorithm ($\mu = 0{,}001$) has been initialized to the Wiener-Hopf solution.

Experimental Results: Performance

- Threshold $t = 0{,}7$, 200 independent realizations.



Conclusions

- In order to reduce the overhead due to the transmission of pilot symbols in FDD-LP systems, we have proposed to combine supervised and unsupervised algorithms.
- The algorithm selection is done by using a simple decision rule which allows to determine the case when the channel has suffered a considerable variation. This information is sent to the transmitter using the feedback channel.
- The experimental results show that the combined approach is an attractive solution because it provides an adequate BER with a reduced number of pilot symbols.