7. INTERFERENCE CANCELLATION

- Interference cancellation (IC) is the most promising MUD technique known today. Several ways to view it:
  - removal of interferers without the need for whitening (Cholesky or Gauss elim, Sect 5.3)
  - attempt to approach ML performance with complexity linear in K (#users), not exponential
  - iterative solution of linear equations with nonlinear tentative decisions

Survey [Mosh 86] good (though a couple of errors).

- We'll look at several approaches, with a couple of implementation structures.

- No definitive test yet — in fact, no systematic comparison yet.

7.1 Background

- Interference cancellation results from convergence of several lines of thought.

- Similarity of decorrelation and ML:
  With M antennas, we receive

$$\underline{r} = \underline{\underline{S}}CA\underline{b} + \underline{n}$$

– Decorrelation (ZF) applies the pseudoinverse to recover $\underline{b}$

$$\hat{\underline{b}} = (\underline{\underline{S}}CA)^{\#}\underline{r}$$

$$= (A^{+}C^{+}\underbrace{\underline{\underline{S}}^{+}\underline{\underline{S}}}_{\underline{R}}CA)^{-1}A^{+}C^{+}\underbrace{\underline{\underline{S}}^{+}\underline{r}}_{\underline{y}}$$

$$= A^{-1}(C^{+}\underline{R}C)^{-1}C^{+}\underline{y} \qquad \text{(see p. 4.1.4)}$$

As we know, this is equivalent to the LS problem

$$\boxed{\hat{\underline{b}} = \underset{\underline{b}\in\mathbb{C}^{NK}}{\arg\min}\,\|\underline{r} - \underline{\underline{S}}CA\underline{b}\|^2}$$

Note domain of $\underline{b}$

– ML maximizes the likelihood $p_{r|b}(\underline{r}|\underline{b})$

$$p_{r|b}(\underline{r}|\underline{b}) = \alpha \exp\left(-\frac{1}{2\sigma_n^2}\|\underline{r} - \underline{\underline{S}}CA\underline{b}\|^2\right)$$

$$\boxed{\hat{\underline{b}} = \underset{\underline{b}\in Q^{NK}}{\arg\min}\,\|\underline{r} - \underline{\underline{S}}CA\underline{b}\|^2}$$

(see p. 6.3.2)

Q is constellation

– the only difference is the domains

- The whitening/DF receiver removes interference from previously decided bits (Section 5.3) by subtraction:

$$\begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_K \end{bmatrix} = \begin{bmatrix} F_{11} & & & 0 \\ F_{21} & F_{22} & & \\ F_{31} & F_{32} & F_{33} & \\ F_{K1} & \cdots & & F_{KK} \end{bmatrix} \begin{bmatrix} A_1 b_1 \\ A_2 b_2 \\ \vdots \\ A_K b_K \end{bmatrix} + \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_K \end{bmatrix}$$

- The decorrelator (ZF) and MMSE equations for $\hat{\underline{b}}$ can be solved iteratively.

$$\hat{\underline{b}} = A^{-1}(C^{+}\underline{R}C)^{-1}\underline{\xi} \qquad \text{ZF}$$

$$\hat{\underline{b}} = A\,(A^{2}C^{+}\underline{R}C + N_0 I_{NK})^{-1}\underline{\xi} \qquad \text{MMSE}$$

(Section 4.1)

[Junt98] demonstates the rapid convergence of steepest descent and conjugate gradient style algorithms, which successively revise $\hat{\underline{b}}$ as $\hat{\underline{b}}^{(0)}, \hat{\underline{b}}^{(1)}, \cdots \hat{\underline{b}}^{(j)}$ so that

$$\lim_{j\to\infty} \hat{\underline{b}}^{(j)} = \underset{\underline{b}}{\operatorname{argmin}} \| \underline{\xi} - \underbrace{C^{+}\underline{R}\,\underline{C}A}_{H}\,\underline{b} \|^{2} \qquad (\text{ZF}).$$

Jacobi iteration is another way to iterate to a solution

$$H = H_d + H_o \qquad (\text{p. } 4.3.5)$$

$$\hat{\underline{b}}^{(j)} = H_d^{-1}\left(\underline{\xi} - H_o\,\hat{\underline{b}}^{(j-1)}\right)$$

which can be interpreted as subtracting the effects of other users (as estimated in the previous iteration) and solving for each user data as if it were alone.

- Convergence:

  Why not work with $\hat{\underline{b}}^{(i)}$ drawn from the constellation in order to achieve good interference cancellation (i.e., subtraction), with iteration for continued improvement?

- A good idea, but there are some hooks.