

SP4COM

# Signal Processing for Communications

Multi-Antenna Interference Handling for Multi-User Multi-Cell

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## Course Arrangements

- course assistants: ?
- theoretical part: exam, open notes and handouts
- practical part:
  - (graded parts: copying forbidden, discussing solutions allowed)
  - 1 problem session (TD): not graded
  - 1 computer session (TP): graded  $\Rightarrow$  remotely this year
  - 3 (?) homeworks (graded)
- emphasis on problem solving, knowing how to apply the theory  
 $\Rightarrow$  TD/HW important
- copies of viewgraphs will be distributed throughout the term,  
also on the course web page :

<https://moodle.eurecom.fr/course/view.php?id=87>

or <http://my.eurecom.fr>

## Course Context

This course = complements to other courses to complete the coverage.

Transmission systems to be considered:

- wireless systems:
  - cellular systems, relays
  - wireless LANs, WiFi, mmWave, Femto/Small Cells, HetNets
  - Fixed Wireless Access (wireless DSL)
  - satellite
  - broadcasting systems: FM, DAB (digital audio/radio), analog TV, DVB (digital video/TV)
  - other wireless: point-to-point, private, ad hoc, sensor arrays, IoT
  - Cognitive Radio, localization, full duplex radio
  - multiple antennas: from beamforming to MIMO, Massive MIMO, Interference Alignment

## Course Context (2)

- voiceband modems (56K = V90) (voiceband of telephone line)
- Digital Subscriber Loop (xDSL, Asymmetric DSL, Symmetric DSL)  
(telephone line without bandwidth limitation)  
VDSL now uses MIMO techniques (G.Fast)
- ethernet, gigabit ethernet (coax cables)
- powerline communications (over 220V power net)
- optical communications
- Li-Fi (wireless over visible light)
- NFC (near field communications)
- underwater communications (marine biology,...)
- communications for control (drones, car, (VANETs), production,...)

## Overview

- *Multi-carrier Systems:*

OFDM (Orthogonal Frequency Division Multiplexing) systems, DMT (Discrete MultiTone) systems, cyclic prefixes, guard intervals, equalization techniques (TEQ and FEQ, per tone approaches), PAR issues, tone loading.

- *Synchronization:*

Basic techniques for single-carrier and multi-carrier systems timing recovery, phase locked loops (PLLs), analog and digital approaches (interpolation). Carrier recovery.

- *Equalizer Design Issues:*

FIR equalization, equalizer delay, equalization for continuous or packet transmission. Equalization options for time-varying systems.

## Overview (2)

- *Kalman Filtering:*  
Discrete-time state-space systems, prediction filtering, smoothing.
- *Channel Estimation:*  
Multi-carrier systems and 2D channel interpolation. Channel modeling and channel prediction in wireless systems, channel sparsification, long-term statistics.
- *Sinusoids in Noise:*  
Modal analysis techniques.
- *Blind and Semi-Blind Channel Estimation:*  
Multichannel systems, SIMO systems, FIR equalization, blind equalization, MIMO systems

### Overview (3)

- *Spatiotemporal Processing:*  
Multichannel systems, spatial processing, spatiotemporal processing, Single user systems, white and colored noise, multiuser systems. Options for utilizing spatial dimensions: interference cancellation, SDMA, spatial multiplexing.
- *CDMA systems:*  
Multiuser detection techniques, synchronous and asynchronous systems, frequency-flat and frequency selective systems, RAKE receivers.
- *xDSL Systems and Gigabit Ethernet:*  
An overview of single- and multi-carrier techniques. Equalization and synchronization approaches, echo cancellation for full duplex operation over twisted pairs, multirate filtering. Interference cancellation in cable bundles.

## Overview (4)

- *Powerline Communications:*  
Channel and noise characterization, communication approaches.
- *DAB/DVB Broadcasting Systems:*  
System scenarii and the choice of design parameters.
- *Fixed-Point Implementation and Round-Off Error Analysis:*  
Examples from fixed and adaptive filtering.
- *Further Advanced Techniques:*  
Equalization and lattice reduction techniques, linear precoding, Tomlinson-Harashima and dirty paper precoding.



## Overview (5)

- Interference single cell: Broadcast Channel (BC)
  - utility functions: SINR balancing, (weighted) sum rate (WSR)
  - BC with user selection: Dirty Paper Coding (DPC) vs beamforming (BF)
  - MIMO: role of receive (Rx) antennas
- Interference multi-cell/HetNets: Interference Channel (IC)
  - Degrees of Freedom (DoF) and Interference Alignment (IA), IA feasibility
  - IA forms: asymptotic symbol extension, decomposition, ergodic, signal scale, MIMO
  - multi-cell multi-user: Interfering Broadcast Channel (IBC)
  - max Weighted Sum Rate (WSR), min Weighted Sum MSE (WSMSE), UL/DL duality
  - Difference of Convex functions approach, relation to max Signal-to-Leakage-plus-Noise Ratio (SLNR)
  - Deterministic Annealing to find global maximum
  - FIR IA for Asynchronous FIR Frequency-Selective IBC

## Overview (6)

- Max WSR with Partial CSIT
  - CSIT: perfect, partial, Line-of-Sight (LoS), pathwise and non-Kronecker covariance
  - Expected WSR, Expected WSMSE, Massive MIMO limit, large MIMO asymptotics
- CSIT acquisition and distributed designs
  - distributed global CSIT acquisition, netDoF
  - topology, rank reduced, decoupled Tx/Rx design, local CSIT
  - Massive MIMO, mmWave and covariance CSIT
  - pathwise CSIT, BF as Dual UL pathwise LMMSE Rx
  - distributed designs

## Overview Part 1

- Lecture 1  
Spatial Receiver Structures (TDMA)
- Lecture 2  
Spatio-Temporal Receiver Structures (TDMA)
- Lecture 3  
Interference Cancellation (TDMA)
- Lecture 4  
CDMA Multi-User Detection/Interference Cancellation
- Lecture 5  
Downlink Processing, OFDM, SDMA, TX Diversity, Spatial Multiplexing
- Lecture 6  
Multi-cell multi-user systems (massive MIMO, interference alignment)

## References Part 1

- [1] S.R. Saunders, “Antennas and propagation for wireless communication systems”, Wiley, 1999.
- [2] L.C. Godara, “Handbook of antennas in wireless communications”, CRC Press, 2001.
- [3] J.C. Liberti, T.S. Rappaport, “Smart antennas for wireless communications: IS-95 and third generation CDMA applications”, Prentice-Hall, 1999.
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- [20] S. Catreux, V. Erceg, D. Gesbert, R.W. Heath Jr., “Adaptive modulation and MIMO coding for broadband wireless data networks, IEEE Communications Magazine, Vol. 40, No. 6, pp. 108-115, June 2002.
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## Lecture 1:

# Spatial Receiver Structures (TDMA)

## Overview

- cellular mobile systems context
- sources of multiple RX channels
- SIMO space-time channel models
- SIMO spatial processing
  - single-user, white noise
  - single-user, colored noise (interference cancellation)
  - multi-user detection, white and colored noise

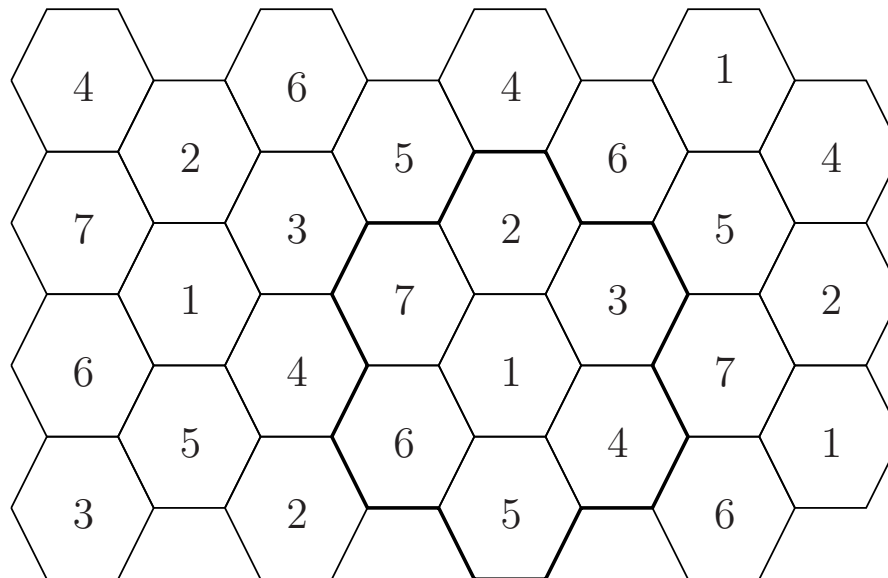
## Cellular Systems

- *Frequency reuse:*

Cells (served by one BS) are grouped into clusters.

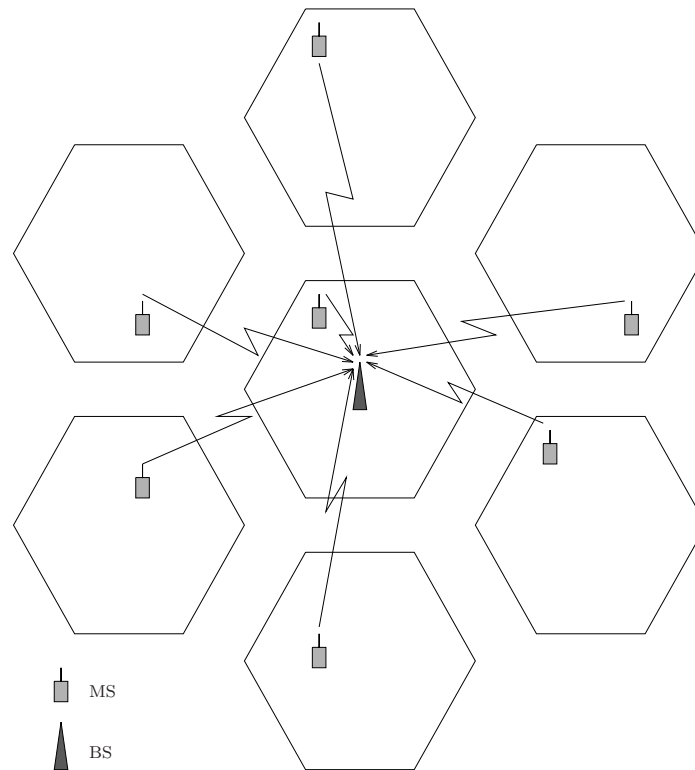
The surface is covered with a regular pattern of clusters.

The available frequency channels are partitioned over the cells of a cluster and reused in the various clusters. Example with reuse factor of 7:



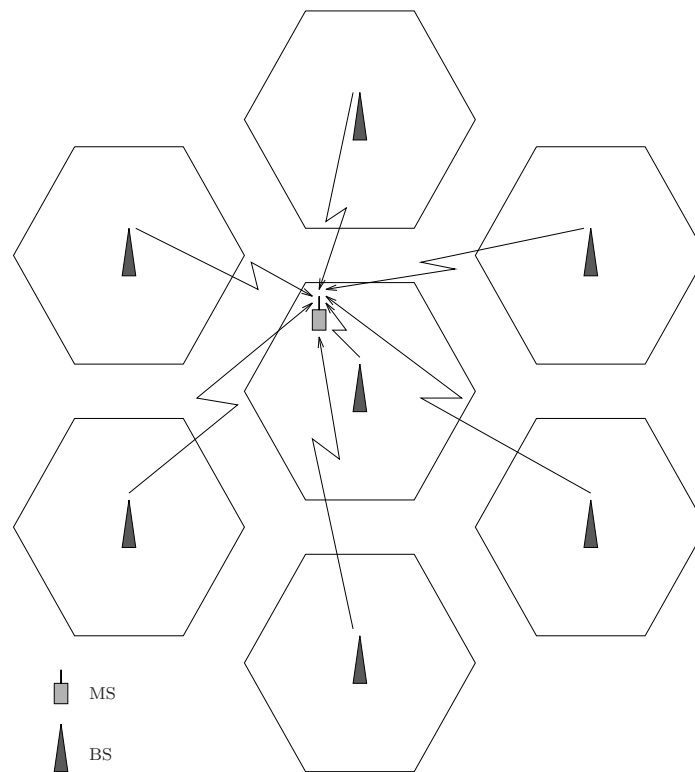
## Uplink Co-Channel Interference (CCI)

- Uplink: from Mobile Station (MS) to Base Station (BS).



## Downlink Co-Channel Interference (CCI)

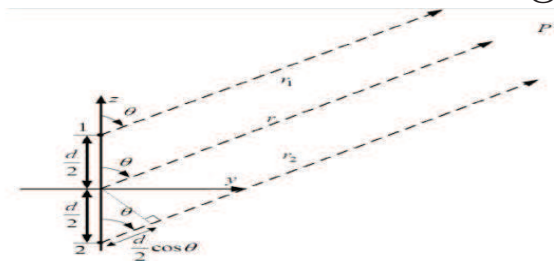
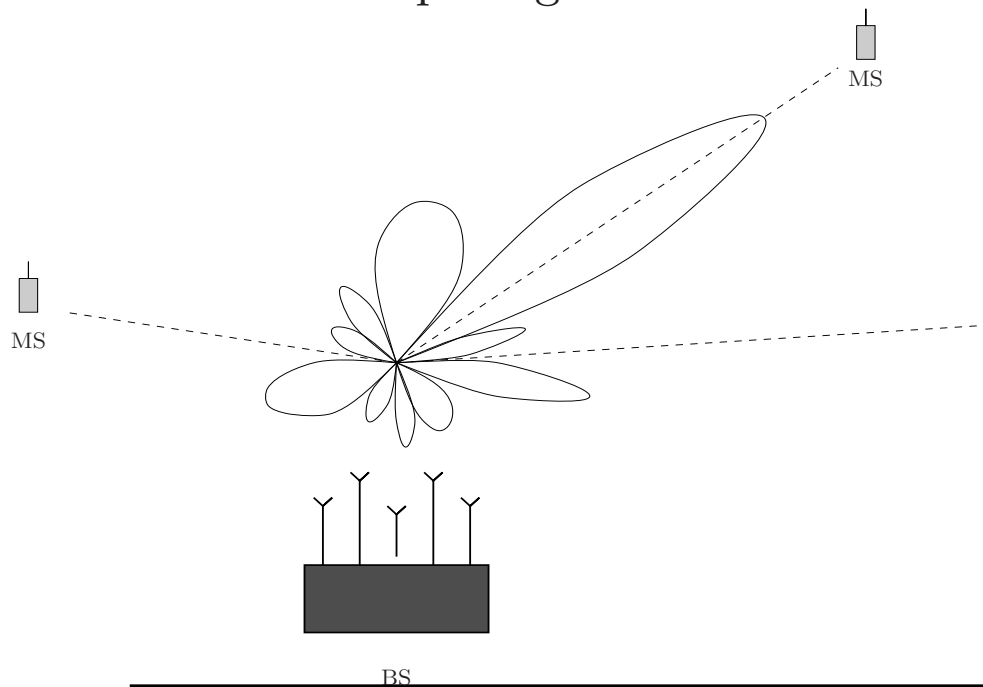
- Downlink: from Base Station (BS) to Mobile Station (MS).



## BS Antenna Array Beam Pattern

- A *beam* is steered in the direction of the user of interest. Sidelobes in the beampattern are unavoidable (// FIR filter) but nulls should be put in the directions of interferers.
- e.g.: uniform linear array (ULA) response of the form

$\mathbf{g}(\theta) = \left[ 1 \quad e^{j2\pi \frac{d}{\lambda} \sin(\theta)} \quad \dots \quad e^{j(m-1)2\pi \frac{d}{\lambda} \sin(\theta)} \right]^T$  where  $\theta =$  angle between the direction of arrival (DOA) and the normal to the ULA,  $d$  is the spacing between the  $m$  antennas and  $\lambda$  is the wavelength.



[H]

Figure 2.4: Beam Replication on Different Transmit-antenna

Figure 2.4 shows one beam (with an angle of departure  $\theta$ ) replications on different transmit-antenna. We can now easily obtain path difference between any couple of these replications. Difference between two consecutive replications is  $a = d/2 \cos(\theta)$ . A given path difference leads to a latency equal to the trajectory difference divided by light celerity:  $\tau_i = a/c$ .

As the signal has a carrier frequency  $f_c$ , the final coefficient between those consecutive replication of this beam is so  $e^{2\pi f_c d \frac{\cos(\theta)}{2c}}$ . By arranging different coefficient rowwise into one single vector we can define transmit-side response vector as:

$$\mathbf{h}_t(\theta_i) = \begin{bmatrix} 1 \\ e^{2j\pi f_c \tau} \\ e^{2j\pi f_c \tau 2} \\ \vdots \\ e^{2j\pi f_c \tau M} \end{bmatrix} \quad (2.4)$$

## Beamforming Primer

- **temporal** processing with a **FIR filter**:

$$H(z) = \sum_{k=0}^{N-1} h_k z^{-k} = \alpha \prod_{i=1}^{N-1} (1 - z_i z^{-1})$$

If zeros on 1-circle:  $z_i = e^{j2\pi f_i}$ ,  $H(e^{j2\pi f}) = \alpha \prod_{i=1}^{N-1} (1 - e^{j2\pi(f_i - f)})$  :

$N - 1$  zeros  $f = f_i$

- **Uniform Linear Array (ULA)**:

”**far field**” assumption  $\Rightarrow$  planar wavefront

”**narrowband**” (NB) assumption: time for wave to travel across

antenna array  $= \frac{(N-1)d}{c} \ll \frac{1}{\text{BW}}$

if inter-antenna spacing  $d = \frac{\lambda}{2} \Rightarrow$

NB:  $\frac{N-1}{2} \frac{\lambda}{c} = \frac{N-1}{2} \frac{1}{f_c} \ll \frac{1}{\text{BW}} \Leftrightarrow \frac{\text{BW}}{f_c} \ll \frac{2}{N-1}$

- time difference of arrival of wave impinging on array at angle  $\theta$   
between 2 consecutive antennas:  $\tau = \frac{d \sin \theta}{c}$

## Beamforming Primer (2)

- NB  $\Rightarrow$  modulated carrier  $\approx$  pure sinusoid :  
 $e^{j2\pi f_c(t-\tau)} = e^{-j2\pi f_c\tau} e^{j2\pi f_c t}$  : delay = phase shift
- **beamformer** = linear filter combining antenna outputs, BF output

$$y(t) = \sum_{i=0}^{N-1} w_i s(t - i\tau) \stackrel{\text{NB}}{=} \left( \sum_{i=0}^{N-1} w_i e^{-j i 2\pi \frac{d}{\lambda} \sin \theta} \right) s(t) = f(\theta) s(t)$$

$$f(\theta) = [w_0 \ w_1 \ \cdots \ w_{N-1}] \mathbf{g}(\theta),$$

$$\mathbf{g}(\theta) = \text{antenna array response/manifold}$$

$$|f(\theta)| = \text{antenna array diagram for given weights } w_i$$

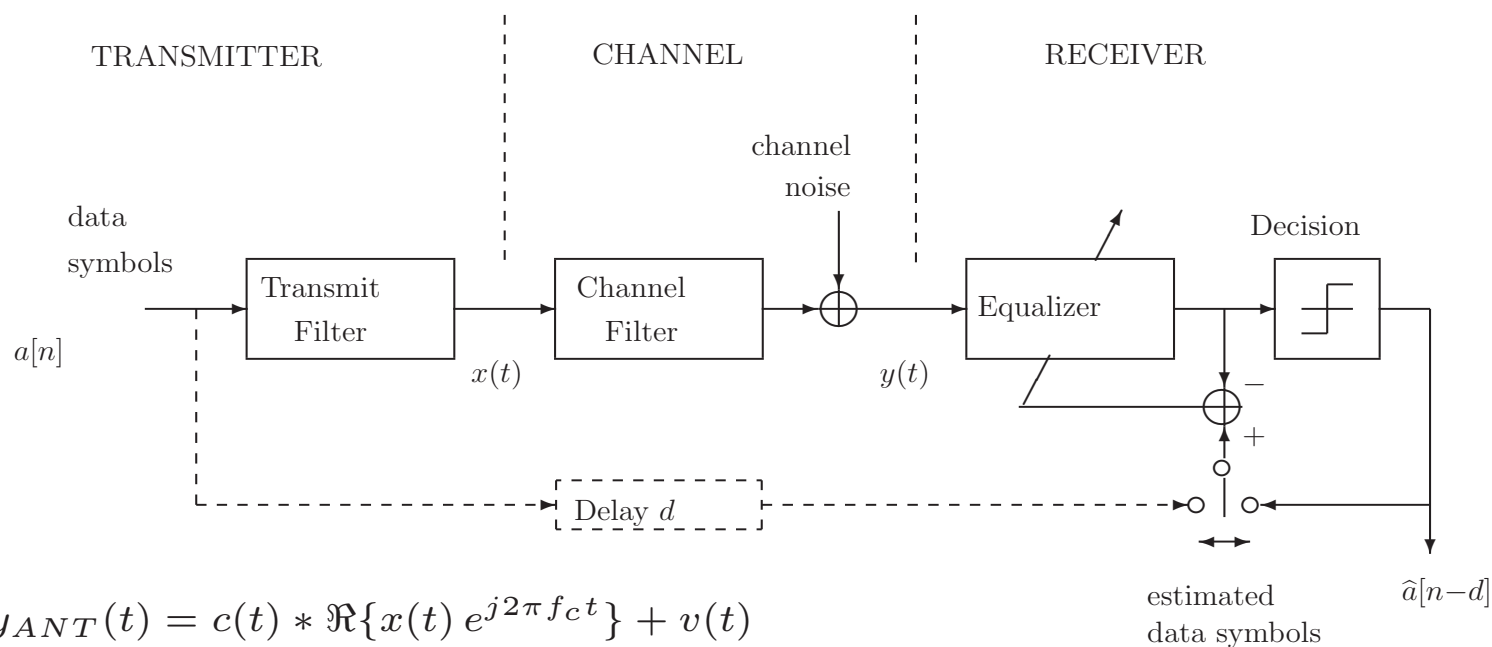
- If want to **cancel directions**:  $f(\theta_i) = 0, i = 1, \dots, N-1$   
 then with  $z_i = e^{j2\pi \frac{d}{\lambda} \sin \theta_i}$ ,  $z = e^{j2\pi \frac{d}{\lambda} \sin \theta}$ , and e.g.  $\alpha$  is adjusted for  
 $f(\theta_0) = 1$ ,

$$f(\theta) = \sum_{k=0}^{N-1} w_k z^{-k} = \alpha \prod_{i=1}^{N-1} (1 - z_i z^{-1}) \Rightarrow \{w_i\}$$

- **main lobe gain** =  $\max_{\theta} |f(\theta)| \sim N(\text{ - \# zeros})$

## Linear Modulation

- received signal before sampling:  $y(t) = \sum_n a[n] h(t - nT) + v(t)$
- $T$  = symbol period,  $\frac{1}{T}$  = symbol rate
- symbols  $a[n] \in \mathcal{A}$  symbol alphabet/constellation
- $h(t)$  = convolved impulse responses of TX filter, channel, RX filter



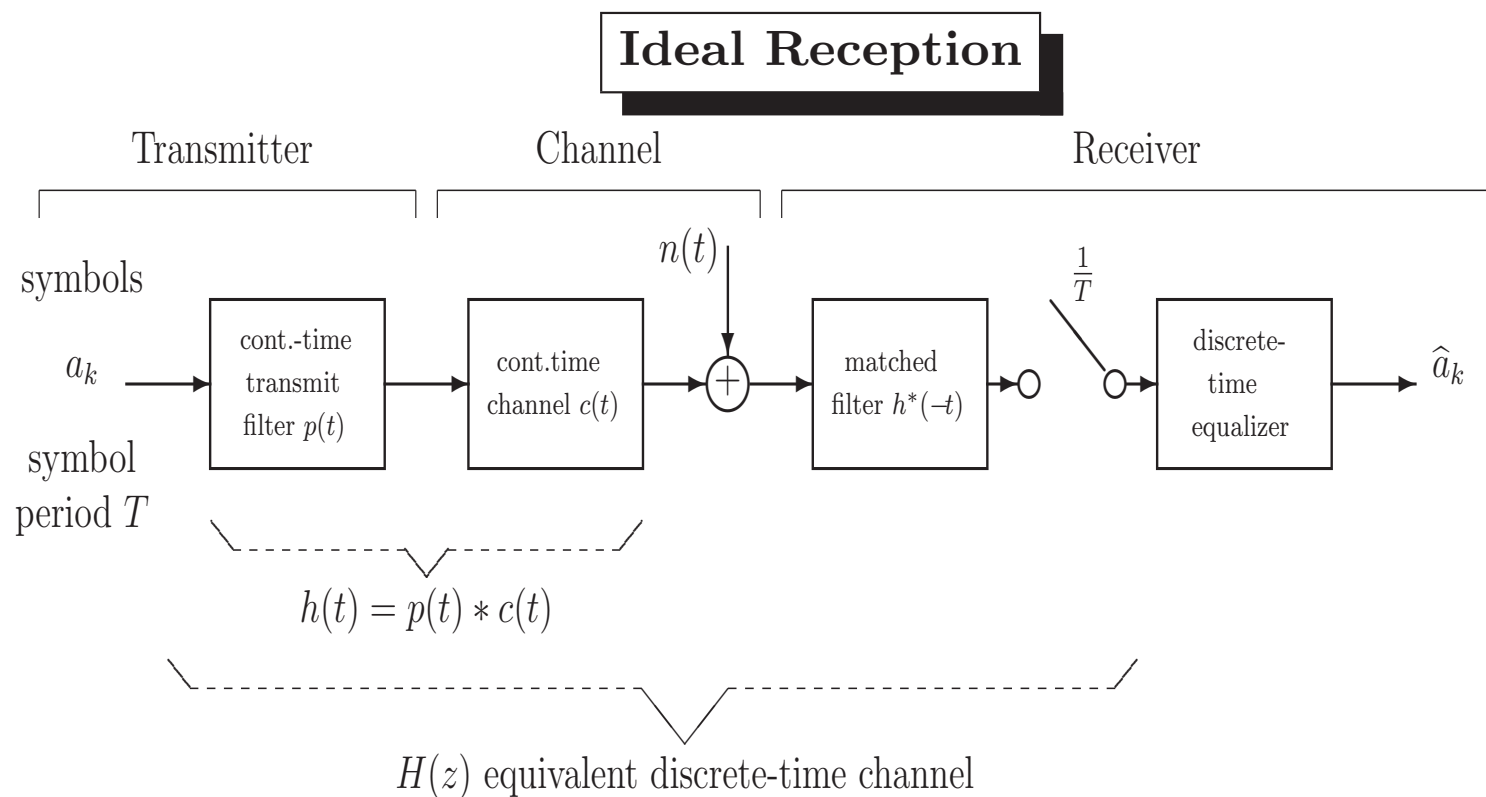
- $$y_{ANT}(t) = c(t) * \Re\{x(t) e^{j2\pi f_c t}\} + v(t)$$

$$y_{RX}(t) = LPF\{y_{ANT}(t) e^{-j2\pi f_c t}\}, \quad x(t) = a[n] * p(t) \text{ (discrete/cont. time I/O)}$$

$$= a[n] * \underbrace{LPF\{(c(t) * p(t)) e^{-j2\pi f_c t}\}}_{h(t)} + v(t) \text{ (+ S\&H DAC)}$$

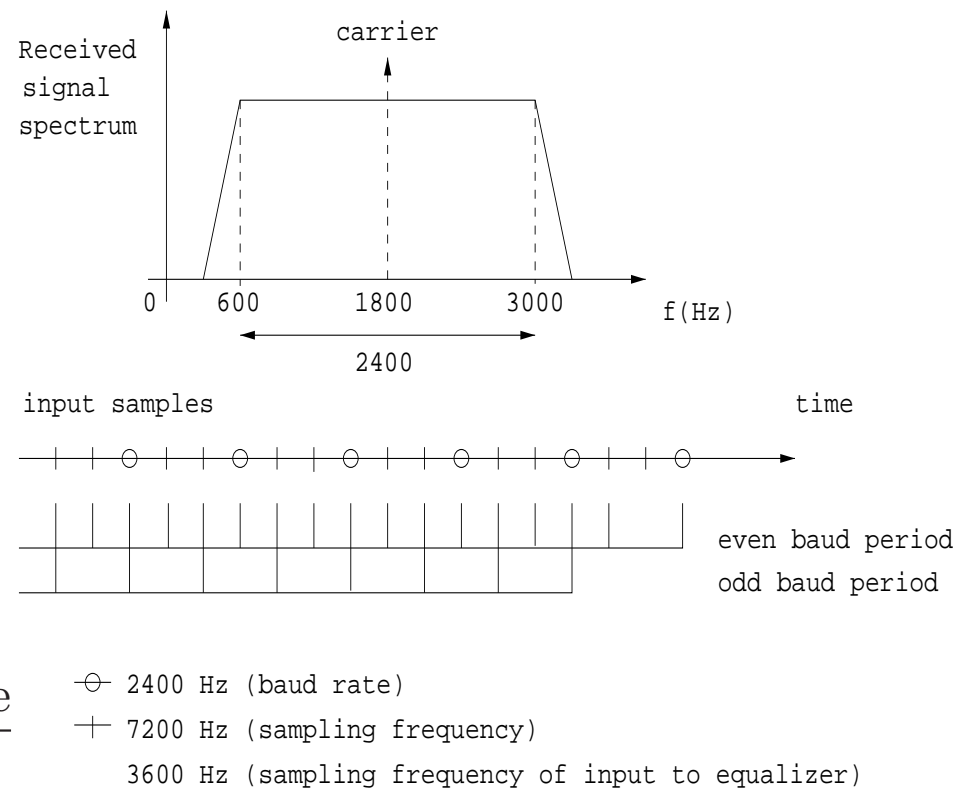
$$c(t) \Rightarrow h(t) \text{ complex due to up/down-modulation}$$





- assumes white noise
- output samples of matched filter at symbol rate  $\frac{1}{T}$  form *sufficient statistics* for the detection of the symbols  $a_k$
- matched filter and symbol rate sampling can be replaced by oversampling (satisfying Nyquist) and anti-aliasing filtering

## Excess Bandwidth and Oversampling



- Tx filter (Nyquist pulse) passes a bandwidth  $>$  symbol (baud) rate
- oversample to satisfy Nyquist

$$\text{oversampling factor} = \frac{\text{sampling rate}}{\text{symbol rate}}$$

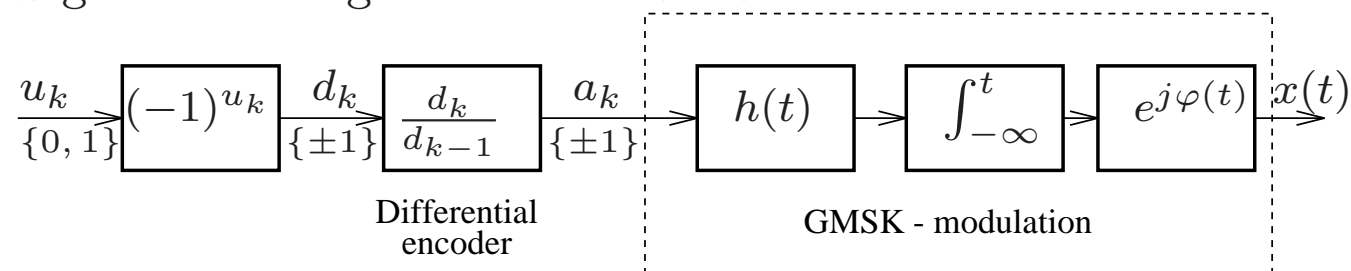
- example: CCITT V32  
9.6kbps voiceband modem
- example of oversampling factor  $= \frac{3}{2}$ , requires separate treatment of even and odd equalizer output samples (at symbol rate)

## Signal Imperfections in Wireless Communications

- *nonlinearities*: DAC, ADC, RF amplifier (saturation issue  $\Rightarrow$  peak "power" constraint on Tx signal, PAPR: OFDM vs. GMSK, SC-CP, CDMA)
- *interference*:
  - CCI: cochannel interference (same frequency band)
  - ACI: adjacent channel interference (next frequency band)
- *noise*:
  - manmade noise: impulsive noise from machines
  - thermal noise in electronics
  - interstellar noise
- residual *frequency offset* due to modulator-demodulator mismatch and Doppler effect
- (sampling) *clock drift* w.r.t. symbol rate clock
- channel *fading* (variation in time due to movement)

## Linearization of GMSK

- Gaussian Minimum Shift Keying: nonlinear modulation used in GSM
- Signal flow diagram for the GMSK modulation



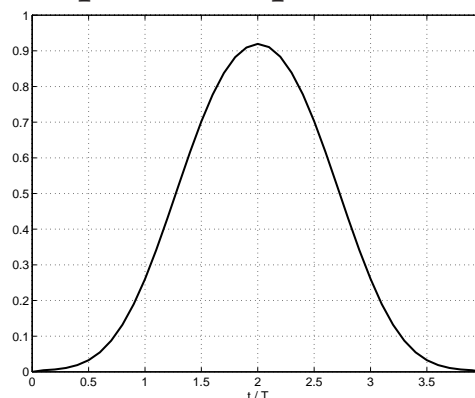
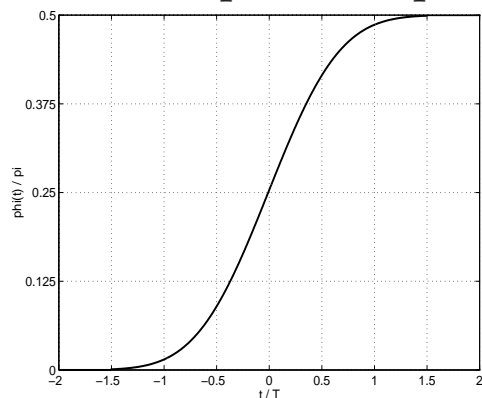
- GMSK signal:  $x(t) = e^{j\varphi(t)}$  where

$$\varphi(t) = \frac{\pi}{2} \sum_k a_k \int_{-\infty}^t \text{rect} \left( \frac{u - kT}{T} \right) * h(u) du = \sum_k a_k \phi(t - kT)$$

$$h(u) = \frac{1}{\sqrt{2\pi}\sigma T} e^{-\frac{u^2}{2\sigma^2 T^2}} \text{ where } \sigma = \frac{\sqrt{\ln(2)}}{2\pi BT}, \text{ } B \text{ is the 3dB bandwidth, } BT = 0.3.$$

## Linearization of GMSK (2)

- Phase impulse response and impulse response of GMSK

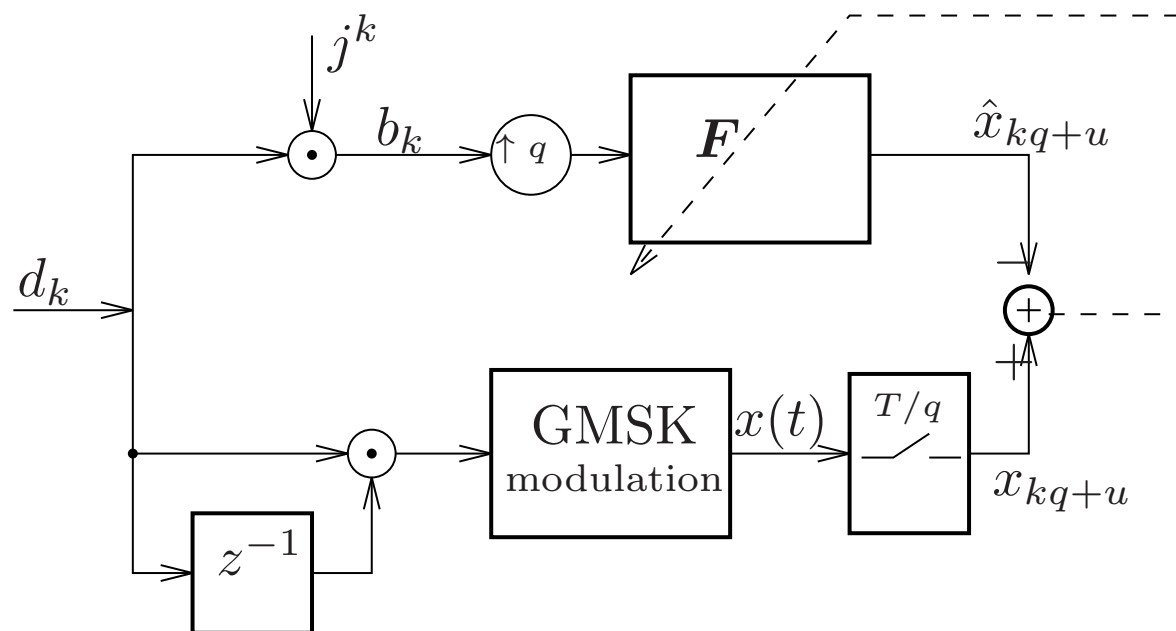


- From the phase impulse response  $\phi(t)$  we conclude that one symbol  $a_k$  will have an influence on three symbol periods  $(k-1, k, k+1)$ . Hence some ISI gets introduced by the modulation itself.

## Linearization of GMSK via LS

- A GMSK signal can be approximated by a linear filter with impulse response duration of about  $L_f T = 4T$ , fed by  $b_k = j^k d_k$ , a modulated version of the transmitted symbols ( $j^k = e^{j 2\pi \frac{1}{4} k}$ ).

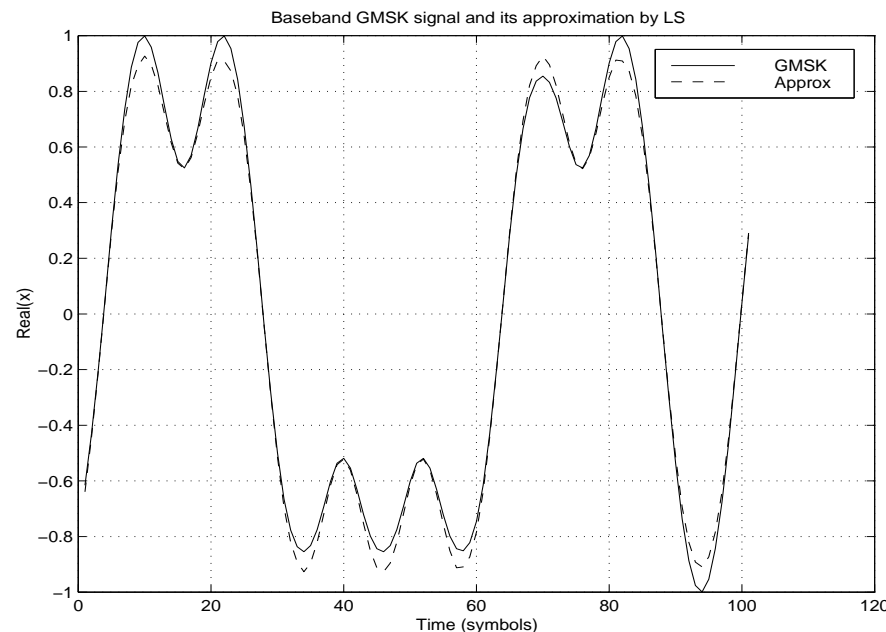
$b_k = \pm 1, k \text{ even}, b_k = \pm j, k \text{ odd}.$



- Least-squares estimation over a long stretch of signal.

## Linearization of GMSK via LS (2)

- To have an idea of the quality of this estimation, we plot simultaneously the real part of the baseband GMSK signal  $x(t)$  and the interpolated output of the discrete-time linear system  $\hat{x}(t)$  assuming the Nyquist theorem is satisfied (*i.e.*  $q = 6$ ).



- SNR = 25dB for the linearization approximation by LS (vs 20dB for the first term in Laurent's expansion).

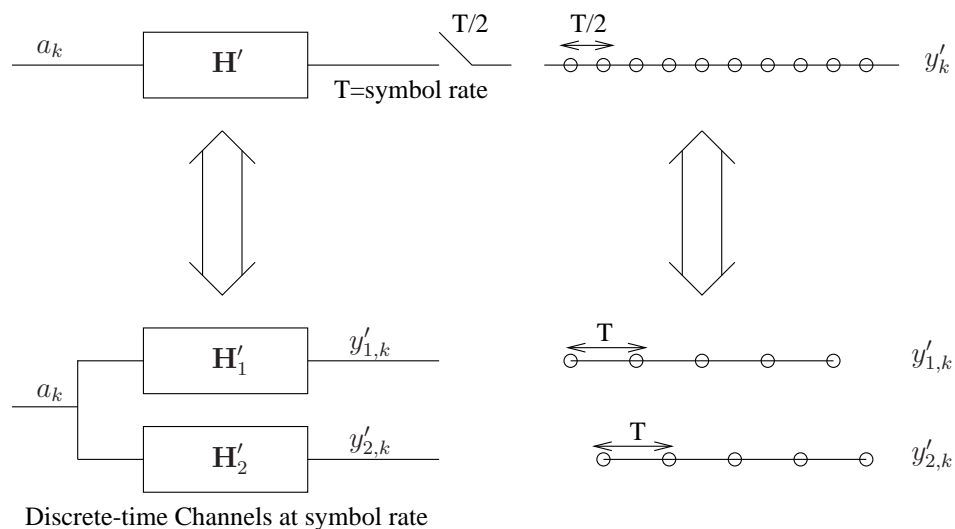
## Sources of Multiple Channels (1)

- oversampling (w.r.t. symbol rate  $\frac{1}{T}$ ) with factor  $r$ : case  $r = 2$

$$y_l = y(t_0 + lT/2) = \sum_n a_n h(t_0 + lT/2 - nT)$$

$$l = 2k \Rightarrow y_{1,k} = y_{2k} = \sum_n a_n h(t_0 + kT - nT) = \sum_n a_n h_{1,k-n}$$

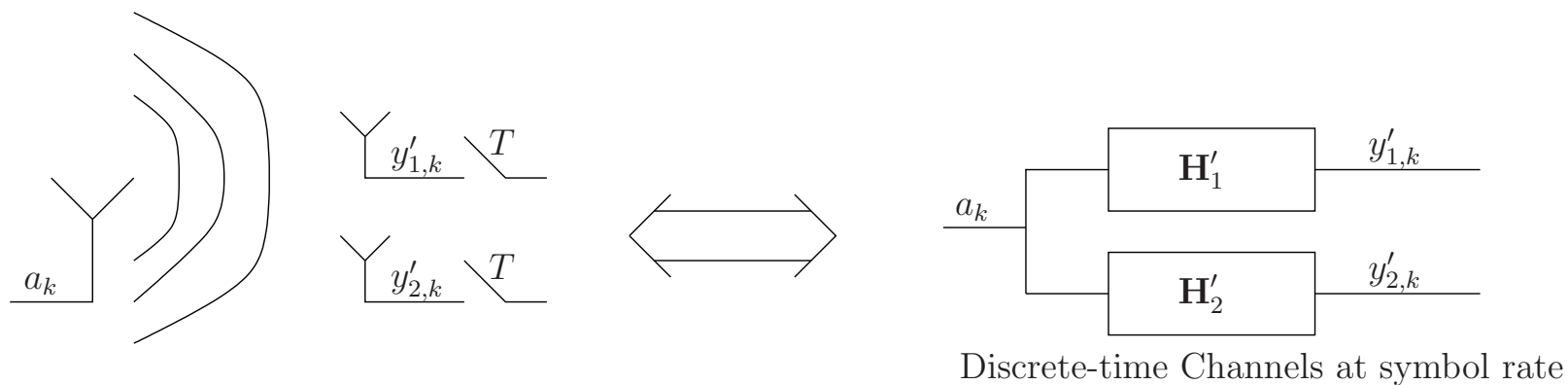
$$l = 2k+1 \Rightarrow y_{2,k} = y_{2k+1} = \sum_n a_n h(t_0 + \frac{T}{2} + kT - nT) = \sum_n a_n h_{2,k-n}$$





## Sources of Multiple Channels (2)

- reception through multiple sensors:
  - antennas
  - polarizations
  - 6 EM components  
(only 4 degrees of freedom though [Marzetta:isit02])
  - preformed beams



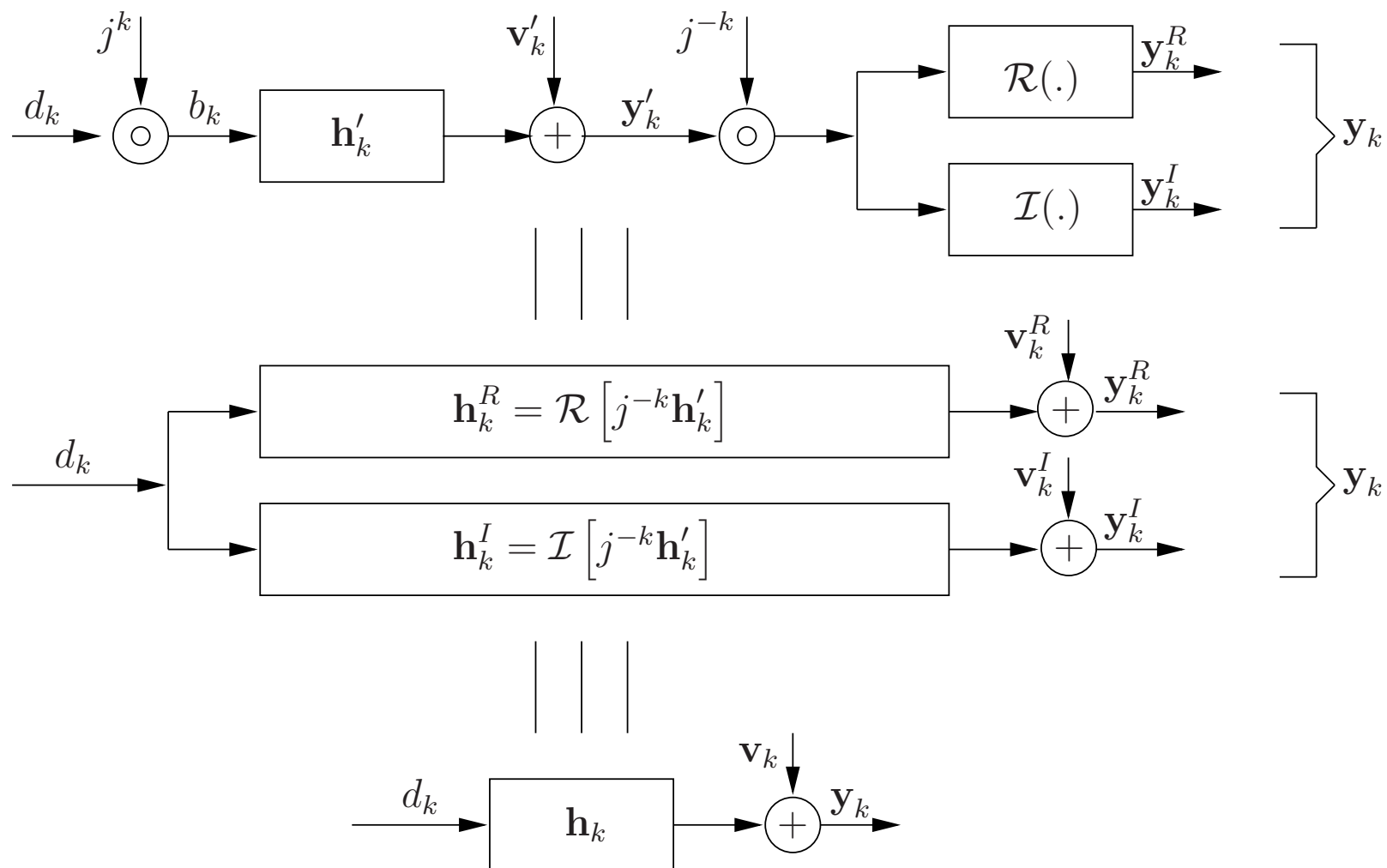
### Sources of Multiple Channels (3)

- if the symbol constellation is real (BPSK, PAM), and the signal is transmitted through modulation-demodulation, then we can work with in-phase and in-quadrature components and get a signal representation with double the number of channels and only real quantities:

$$y_k = \sum_n a_n h_{k-n} \Rightarrow \begin{cases} \mathcal{R}\{y_k\} &= \sum_n a_k \mathcal{R}\{h_{k-n}\} \\ \mathcal{I}\{y_k\} &= \sum_n a_k \mathcal{I}\{h_{k-n}\} \end{cases}$$

- ARQ protocols  $\Rightarrow$  reception of multiple versions of the same data packet

# Case of Linearized GMSK

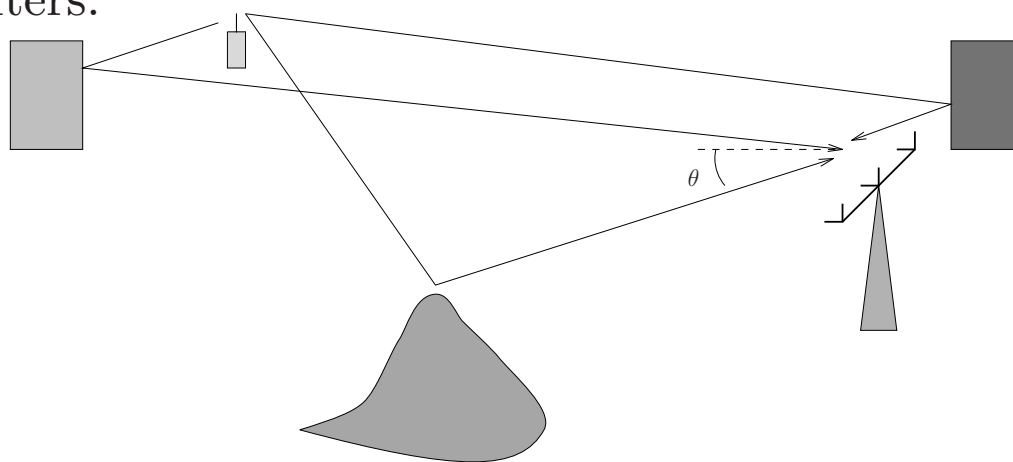


## Multipath Channel Model

- multipath scattering (local to mobile, local to base, remote)
- received impulse response from MS at  $i$ th element of  $m$ -element antenna array:

$$h_i(t, \tau) = \sum_{l=1}^M g_i(\theta_l) \alpha_l(t) p(\tau - \tau_l) = \left( \sum_{l=1}^M g_i(\theta_l) \alpha_l(t) \delta(\tau - \tau_l) \right) * p(\tau)$$

where  $M$  = number of multipaths,  $g_i(\theta_l)$  is the response of the  $i$ th antenna to the  $l$ th path from direction  $\theta_l$  with delay  $\tau_l$  and fading complex envelope  $\alpha_l(t)$ .  $p(t)$  is the convolution of transmission and receiver filters.



## Multipath Channel Model (2)

- Narrowband assumption: inverse of signal bandwidth large compared to time to travel across array. As a result, the  $g_i(\theta_l)$  reflect (mainly) the phase-shifts that the signal undergoes when impinging on the consecutive antenna elements from direction  $\theta_l$ . The  $g_i(\theta_i)$  also contain the variations in magnitude and phase of the individual amplifiers of the antenna receivers.

### Multipath Channel Model (3)

- stacking the impulse responses in a column vector:

$$\mathbf{h}(t, \tau) = \sum_{l=1}^M \mathbf{g}(\theta_l) \alpha_l(t) p(\tau - \tau_l)$$

$\mathbf{g}(\theta_l)$  is the array response vector in direction  $\theta_l$ . The *array manifold* is the set of array response vectors  $\mathbf{g}(\theta)$  for all possible angles  $\theta$ . It depends strongly on the channel frequency. The array manifold is a key quantity in direction-of-arrival (DOA) estimation. It allows to determine the direction  $\theta$  given an array response  $\mathbf{g}(\theta)$ .

- Due to the limited bandwidth of  $p(t)$ , delays  $\tau_l$  are not infinitely resolvable. So paths should be grouped in groups of resolvable delays. With one delay several angles can be associated.
- Whether to use the spatiotemporal impulse response or the multipath parameters depends on the number of paths vs. the delay spread. Multipath channel model: recently more important for mmWave communications.

### Multipath Channel Model (4)

- *slow* parameters: angles/DOAs  $\theta_l$ , delays  $\tau_l$
- *fast* parameters: complex amplitudes  $\alpha_l(t)$

Doppler spectrum

- *diversity degree*: number of (resolvable) fast fading sources  $\alpha_l(t)$   
= rank of channel impulse covariance matrix (averaged over fast parameters)  
= number of resolvable (in time or in space) paths

increasing oversampling beyond Nyquist or number of antennas  
beyond resolving path angles does not yield increased diversity

## Correlation and Covariance Matrices

- random vectors  $\mathbf{x}$  and  $\mathbf{y}$
- mean:  $m_{\mathbf{x}} = E \mathbf{x}$  ,  $m_{\mathbf{y}} = E \mathbf{y}$  (E = Expectation)
- correlation matrix:  $R_{\mathbf{xy}} = E \mathbf{x} \mathbf{y}^H$  ,  $R_{\mathbf{xx}} = E \mathbf{x} \mathbf{x}^H$
- covariance matrix:
 
$$C_{\mathbf{xy}} = R_{\mathbf{x}-m_{\mathbf{x}}, \mathbf{y}-m_{\mathbf{y}}} = E (\mathbf{x} - m_{\mathbf{x}})(\mathbf{y} - m_{\mathbf{y}})^H = R_{\mathbf{xy}} - m_{\mathbf{x}} m_{\mathbf{y}}^H$$
- Euclidean norms:  $\|\mathbf{x}\|^2 = \mathbf{x}^H \mathbf{x}$  ,  $\|\mathbf{x}\|_R^2 = \mathbf{x}^H R \mathbf{x}$
- vector power (mean square value):

$$\begin{aligned} E \|\mathbf{x}\|^2 &= \text{tr} \{ E \|\mathbf{x}\|^2 \} = E \text{tr} \{ \|\mathbf{x}\|^2 \} = E \text{tr} \{ \mathbf{x}^H \mathbf{x} \} \\ &= E \text{tr} \{ \mathbf{x} \mathbf{x}^H \} = \text{tr} \{ E \mathbf{x} \mathbf{x}^H \} = \text{tr} \{ R_{\mathbf{xx}} \} \end{aligned}$$

- LMMSE estimation:

estimate  $\hat{\mathbf{x}} = R_{\mathbf{xy}} R_{\mathbf{yy}}^{-1} \mathbf{y}$  , estimation error  $\tilde{\mathbf{x}} = \mathbf{x} - \hat{\mathbf{x}}$

$$\text{MSE} = E \|\tilde{\mathbf{x}}\|^2 = \text{tr} \{ R_{\tilde{\mathbf{x}}\tilde{\mathbf{x}}} \} = \text{tr} \{ R_{\mathbf{xx}} - R_{\mathbf{xy}} R_{\mathbf{yy}}^{-1} R_{\mathbf{yx}} \}$$



## Math/Stat Background: Covariance Matrices

- *positive semidefinite* matrix  $C$  : notation  $C \geq 0$  :

$$\forall \mathbf{u} \in \mathcal{C}^m : \mathbf{u}^H C \mathbf{u} \geq 0$$

*positive definite* matrix  $C$  : notation  $C > 0$  :

$$\forall \mathbf{u} \in \mathcal{C}^m \setminus \{0\} : \mathbf{u}^H C \mathbf{u} > 0$$

- covariance matrix

$$C_{\mathbf{X}\mathbf{X}} = E(\mathbf{x} - m_{\mathbf{X}})(\mathbf{x} - m_{\mathbf{X}})^H = \int dx_1 \cdots \int dx_m f_{\mathbf{X}}(\mathbf{x}) \underbrace{(\mathbf{x} - m_{\mathbf{X}})(\mathbf{x} - m_{\mathbf{X}})^H}_{\geq 0, \text{ rank } 1}$$

where  $C_{x_i x_j} = E(x_i - m_{x_i})(x_j - m_{x_j})^*$ .

- for *circular (proper) complex random vectors*,  $E \mathbf{x} \mathbf{x}^T = 0$  (without complex conjugate)
- Observe  $C_{\mathbf{X}\mathbf{X}} = C_{\mathbf{X}\mathbf{X}}^H \geq 0$  Hermitian and positive semidefinite, as weighted average of positive semidefinite matrices. Indeed,  
 $\mathbf{u}^H C_{\mathbf{X}\mathbf{X}} \mathbf{u} = \mathbf{u}^H (E(\mathbf{x} - m_{\mathbf{X}})(\mathbf{x} - m_{\mathbf{X}})^H) \mathbf{u} = E |\mathbf{u}^H (\mathbf{x} - m_{\mathbf{X}})|^2 \geq 0$ .

## Math/Stat Background: Eigen Decomposition (Covariance) Matrix

- *eigenvalues*  $\lambda_i$  and corresponding *eigenvectors*  $V_i$  of  $C$  :  $C V_i = \lambda_i V_i$

fix *norm*  $\|V_i\| = 1, \quad \|V_i\|^2 = V_i^H V_i$

- $(C - \lambda_i I_m) V_i = 0 \Rightarrow (C - \lambda_i I_m)$  *singular*

$\lambda_i$  solution of  $\det(C - \lambda I_m) = 0$  : *characteristic equation*

- $C = C^H \Rightarrow \lambda_i \in \mathcal{R}$ , orthonormal basis:  $V_i^H V_j = \delta_{ij}$ ,  $i, j = 1, \dots, n$

*Kronecker delta* :  $\delta_{ij} = \begin{cases} 1 & , i = j \\ 0 & , i \neq j \end{cases}$

- matrix  $V = [V_1 \cdots V_m]$  ( $m \times m$ ) :

$[V^H V]_{ij} = V_i^H V_j = \delta_{ij} \Rightarrow V^H V = I_m \quad V = \text{unitary matrix}$

- $I_m = V^H V \Rightarrow 1 = \det(I_m) = \det(V^H V) = \det(V^H) \det(V) = |\det V|^2 \Rightarrow |\det V| = 1$ . We can multiply the  $V_i$  with factors  $e^{j\theta_i}$  such that  $\det V = 1$ .

## Math/Stat Background: Eigen Decomposition (Covariance) Matrix (2)

- $C \geq 0$  positive semidefinite:  $\forall U \in \mathcal{C}^m : U^H C U \geq 0$
- take  $U = V_i : U^H C U = V_i^H C V_i = \lambda_i V_i^H V_i = \lambda_i \geq 0$
- order the  $\lambda_i : \lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_m \geq 0$
- If  $\lambda_m = 0$ ,  $C$  is singular  $\Rightarrow V_m^H C V_m = E |V_m^H (\mathbf{x} - m_{\mathbf{x}})|^2 = 0$  mean and variance of  $V_m^H (\mathbf{x} - m_{\mathbf{x}})$  are zero  $\Rightarrow V_m^H (\mathbf{x} - m_{\mathbf{x}}) = 0$  in mean square. This means that at least one variable  $x_i$  is a linear combination of the other variables and 1. We shall in general exclude this possibility  $\Rightarrow C > 0, \lambda_i > 0, i = 1, \dots, m$
- $C V_i - V_i \lambda_i = 0$  are the columns of the matrix  $C V - V \Lambda = 0$  where  $\Lambda = \text{diag} \{\lambda_1, \dots, \lambda_m\}$ . Using  $V^{-1} = V^H$ , we find

$$C = V \Lambda V^H = [V_1 \dots V_m] \text{diag} \{\lambda_1, \dots, \lambda_m\} [V_1 \dots V_m]^H = \sum_{i=1}^m \lambda_i V_i V_i^H$$

## Math/Stat Background: Optimization w.r.t. Complex Variables

- Consider cost functions  $f(\cdot)$  that satisfy some constraints (the *real*  $f(\mathbf{x}, \mathbf{x}^*)$  depends on both variables  $\mathbf{x}$  and  $\mathbf{x}^*$  in a symmetric fashion) that will always be satisfied in problems considered in this course.

- When optimizing w.r.t.  $\mathbf{x}$ , treat  $\mathbf{x}$  and  $\mathbf{x}^*$  as if they are independent (unrelated) variables. Intuition?  $\mathbf{x} = \mathbf{x}_R + j \mathbf{x}_I$  where  $\mathbf{x}_R, \mathbf{x}_I$  are independent variables.

- Example:  $\min_a \|\mathbf{y} - \mathbf{h} a\|^2$ .

$$\|\mathbf{y} - \mathbf{h} a\|^2 = (\mathbf{y} - \mathbf{h} a)^H (\mathbf{y} - \mathbf{h} a) = \mathbf{y}^H \mathbf{y} - \mathbf{y}^H \mathbf{h} a - a^* \mathbf{h}^H \mathbf{y} + a a^* \mathbf{h}^H \mathbf{h}$$

This is only linear in  $a$  or in  $a^*$  ! To end up with an equation in  $a$ , derive w.r.t.  $a^*$  instead of

$a$ :

$$\frac{\partial \|\mathbf{y} - \mathbf{h} a\|^2}{\partial a^*} = -\mathbf{h}^H \mathbf{y} + a \mathbf{h}^H \mathbf{h} = 0 \Rightarrow a = \frac{\mathbf{h}^H \mathbf{y}}{\mathbf{h}^H \mathbf{h}}$$

- Minimum? Yes: Hessian  $\frac{\partial}{\partial a} \frac{\partial}{\partial a^*} \|\mathbf{y} - \mathbf{h} a\|^2 = \frac{\partial}{\partial a^*} \left( \frac{\partial}{\partial a^*} \|\mathbf{y} - \mathbf{h} a\|^2 \right)^* = \mathbf{h}^H \mathbf{h} > 0$  where the first equality follows from the symmetry of  $f(\mathbf{x}, \mathbf{x}^*)$  in its arguments.

## Math/Stat Background: Optimization w.r.t. Complex Vectors

- $\mathbf{g}(\mathbf{x}, \mathbf{x}^*)$ :  $1 \times n$  row vector function, its gradient w.r.t.  $\mathbf{x}^*$  :

$$\frac{\partial \mathbf{g}(\mathbf{x}, \mathbf{x}^*)}{\partial \mathbf{x}^*} = \begin{bmatrix} \frac{\partial \mathbf{g}(\mathbf{x}, \mathbf{x}^*)}{\partial x_1^*} \\ \vdots \\ \frac{\partial \mathbf{g}(\mathbf{x}, \mathbf{x}^*)}{\partial x_m^*} \end{bmatrix} \quad m \times n$$

If  $g(\mathbf{x}, \mathbf{x}^*)$  is a scalar ( $n = 1$ ), then  $\frac{\partial g(\mathbf{x}, \mathbf{x}^*)}{\partial \mathbf{x}^*}$  is a column vector of the same dimensions as  $\mathbf{x}$ .

- in particular:  $\frac{\partial \mathbf{x}^H}{\partial \mathbf{x}^*} = \left[ \frac{\partial x_j^*}{\partial x_i^*} \right] = [\delta_{ij}] = I_m$
- The gradient (linear) operator commutes with (other) linear operations. Let  $\mathbf{y}$  be  $m \times 1$

$$\frac{\partial}{\partial \mathbf{x}^*} (\mathbf{x}^H \mathbf{y}) = \left( \frac{\partial \mathbf{x}^H}{\partial \mathbf{x}^*} \right) \mathbf{y} = I_m \mathbf{y} = \mathbf{y}.$$

## Math/Stat Background: Optimization w.r.t. Complex Vectors (2)

Example:

- training based channel estimation:  $\min_{\mathbf{h}} \sum_k \|\mathbf{y}[k] - \mathbf{h} a[k]\|^2.$

$$\begin{aligned} \sum_k \|\mathbf{y}[k] - \mathbf{h} a[k]\|^2 &= \sum_k (\mathbf{y}[k] - \mathbf{h} a[k])^H (\mathbf{y}[k] - \mathbf{h} a[k]) \\ &= \sum_k \{ \mathbf{y}^H[k] \mathbf{y}[k] - \mathbf{y}^H[k] \mathbf{h} a[k] - a^*[k] \mathbf{h}^H \mathbf{y}[k] + |a[k]|^2 \mathbf{h}^H \mathbf{h} \} \end{aligned}$$

This is only linear in  $\mathbf{h}$  or in  $\mathbf{h}^*$  ! To end up with an equation in  $\mathbf{h}$ , derive w.r.t.  $\mathbf{h}^*$  instead of  $\mathbf{h}$ :

$$\frac{\partial}{\partial \mathbf{h}^*} \sum_k \|\mathbf{y}[k] - \mathbf{h} a[k]\|^2 = - \sum_k a^*[k] \mathbf{y}[k] + \sum_k |a[k]|^2 \mathbf{h} = 0$$

$$\Rightarrow \mathbf{h} = \frac{1}{\sum_k |a[k]|^2} \sum_k \mathbf{y}[k] a^*[k]$$

- Minimum? Yes: Hessian (matrix of second-order derivatives)

$$\frac{\partial}{\partial \mathbf{h}^*} \left( \frac{\partial}{\partial \mathbf{h}^*} \sum_k \|\mathbf{y}[k] - \mathbf{h} a[k]\|^2 \right)^H = \left( \sum_k |a[k]|^2 \right) I_m > 0$$

## Spatial Case

- If channel *delay spread*  $<$  symbol period  $T \Rightarrow$  no Intersymbol Interference (ISI), sampled impulse response reduces to  $\mathbf{h}[0]$
- Single user case. Received signal sampled at the symbol rate ( $t = kT$ )

$$\mathbf{y}[k] = \mathbf{h} a[k] + \mathbf{v}[k]$$

$a[k]$  = transmitted symbol sequence (linear(izable) modulation),

$\mathbf{v}[k]$  = noise plus interference samples

$\mathbf{h} = \mathbf{h}[0]$  sometimes called the *spatial signature*  $= \sum_{l=1}^M \alpha_l \mathbf{g}(\theta_l)$

- *diversity*: Maximum Likelihood symbol detection, if  $\mathbf{v}(k)$  is spatially

and temporally white, leads to an SNR improvement by  $\sqrt{\sum_{i=1}^m |h_i|^2}$

which increases with  $m$ , becomes much less sensitive to the deep fades of the individual coefficients  $h_i$ .

### Spatial Case: Channel Estimation

- using a *training sequence*: a sequence of known symbols  $a[k]$

$$\hat{\mathbf{h}} = \frac{\sum_k \mathbf{y}[k] a^*[k]}{\sum_k |a[k]|^2}$$

- *blind* estimation: without training sequence (increases throughput)
  - second-order statistics based:

$$E \mathbf{y}[k] \mathbf{y}^H[k] = R_{\mathbf{y}\mathbf{y}} = \sigma_a^2 \mathbf{h} \mathbf{h}^H + \sigma_v^2 I_m$$

hence  $\mathbf{h} \sim$  largest eigenvector of  $R_{\mathbf{y}\mathbf{y}} = \sum_{i=1}^m \lambda_i V_i V_i^H$ .

$V_1 \sim \mathbf{h}$ ,  $\lambda_1 = \sigma_v^2 + \sigma_a^2 \|\mathbf{h}\|^2$ ,  $V_i \perp \mathbf{h}$ ,  $\lambda_i = \sigma_v^2$ ,  $i = 2, \dots, m$ .

- exploiting constellation property: *constant modulus*

consider linear combiner:  $z[k] = \mathbf{f} \mathbf{y}[k]$ .

$$\min_{\mathbf{f}} E (|z[k]|^p - 1)^2 \quad p = 1 \text{ or } 2 \text{ typically}$$

- exploiting *finite alphabet* nature of  $a[k]$ :  $a[k] \in \mathcal{A}$

$$\min_{\mathbf{h}, a[k] \in \mathcal{A}} \sum_k \|\mathbf{y}[k] - \mathbf{h} a[k]\|^2$$



### Spatial Single-User Receivers, White Noise

- Assume white noise first. Gaussian noise:  $\mathbf{v}[k] \sim \mathcal{CN}(0, \sigma_v^2 I_m)$  i.i.d.  
 $\mathcal{A}$  = symbol constellation (e.g. QAM)

- Maximum Likelihood Sequence Estimation (MLSE):

$$\min_{a[k] \in \mathcal{A}} \sum_k \|\mathbf{y}[k] - \mathbf{h} a[k]\|^2 \Rightarrow \min_{a[k] \in \mathcal{A}} \|\mathbf{y}[k] - \mathbf{h} a[k]\|^2, \forall k$$

$$\|\mathbf{y}[k] - \mathbf{h} a[k]\|^2 = \mathbf{y}[k]^H (I_m - \frac{\mathbf{h}\mathbf{h}^H}{\mathbf{h}^H \mathbf{h}}) \mathbf{y}[k] + \|\mathbf{h}\|^2 |a[k] - \hat{a}[k]|^2$$

$$\Rightarrow \hat{\hat{a}}[k] = \text{dec}(\hat{a}[k]), \hat{a}[k] = \frac{1}{\mathbf{h}^H \mathbf{h}} \mathbf{h}^H \mathbf{y}[k] = \arg \min_{a[k] \in \mathcal{C}} \|\mathbf{y}[k] - \mathbf{h} a[k]\|^2$$

$\hat{\hat{a}}$  : "hard" decision ( $\in \mathcal{A}$ ),  $\hat{a}$  : "soft" decision ( $\in \mathcal{C}$ )

- SNR:  $\hat{a}[k] = a[k] + \frac{1}{\mathbf{h}^H \mathbf{h}} \mathbf{h}^H \mathbf{v}[k] \Rightarrow \text{SNR} = \frac{\|\mathbf{h}\|^2 \sigma_a^2}{\sigma_v^2}$

MFB = Matched Filter Bound

- = SNR of MLSE when all other symbols known =  $\frac{\|\mathbf{h}\|^2 \sigma_a^2}{\sigma_v^2}$

**Math/Stat:  $p$ -norm**

- $\|\mathbf{h}\|_p = \left( \sum_{i=1}^m |h_i|^p \right)^{\frac{1}{p}}$

Important instances:

- $\|\mathbf{h}\| = \|\mathbf{h}\|_2 = \sqrt{\sum_{i=1}^m |h_i|^2}$

- $\|\mathbf{h}\|_1 = \sum_{i=1}^m |h_i|$

- $\|\mathbf{h}\|_\infty = \lim_{p \rightarrow \infty} \left( \sum_{i=1}^m |h_i|^p \right)^{\frac{1}{p}}$

- different:  $\|\mathbf{h}\|_0 = \lim_{p \rightarrow 0} \sum_{i=1}^m |h_i|^p = \# \text{ non-zero elements}$

- At high SNR:  $P_e = \frac{c}{\text{SNR}^d}$ ,  $d = \text{diversity order} = \# \text{ of (complex) constraints to impose on the channel response to lose the signal completely}$

## Spatial Single-User Receivers, White Noise (2)

- linear combining receivers:  $\hat{a}[k] = \mathbf{f} \mathbf{y}[k]$ ,  $\mathbf{f} : 1 \times m$

- SNR:  $\hat{a}[k] = \mathbf{f} \mathbf{h} a[k] + \mathbf{f} \mathbf{v}[k] \Rightarrow \text{SNR} = \frac{|\mathbf{f} \mathbf{h}|^2 \sigma_a^2}{\mathbf{f} \mathbf{f}^H \sigma_v^2}$

SNR is insensitive to a scale factor in  $\mathbf{f}$ .

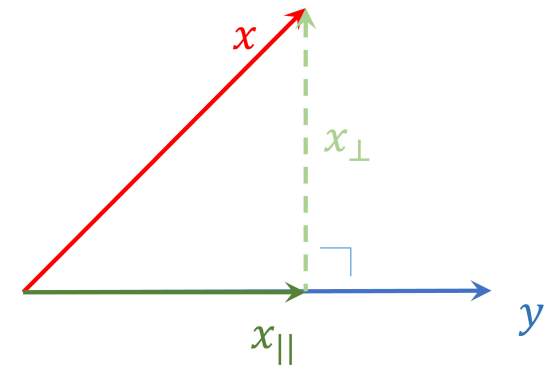
- selection combining:  $\mathbf{f} = \mathbf{e}_i^T$ ,  $|h_i| = \max_l |h_l| = \|\mathbf{h}\|_\infty$ ,  $\text{SNR} = \frac{\|\mathbf{h}\|_\infty^2 \sigma_a^2}{\sigma_v^2}$

$$\mathbf{e}_i^T = [\underbrace{0 \cdots 0}_{i-1} \quad 1 \quad \underbrace{0 \cdots 0}_{m-i}]$$

- equal gain combining:  $\mathbf{f} = [1 \cdots 1]$ ,  $\text{SNR} = \frac{m |\bar{h}|^2 \sigma_a^2}{\sigma_v^2}$ ,  $\bar{h} = \mathbf{f} \mathbf{h} / m$

more exactly, if  $h_i = |h_i| e^{j\phi_i}$ :  $\mathbf{f} = [e^{-j\phi_1} \cdots e^{-j\phi_m}]$ ,  $\text{SNR} = \frac{\|\mathbf{h}\|_1^2 \sigma_a^2}{m \sigma_v^2}$ ,

where  $\|\mathbf{h}\|_p = \left( \sum_{i=1}^m |h_i|^p \right)^{\frac{1}{p}}$ , hence phase alignment:  $\mathbf{f} \mathbf{h} = \|\mathbf{h}\|_1 = \sum_{i=1}^m |h_i|$



## Math/Stat: An Optimization Problem in Inner Product Spaces

- Result from inner product spaces:

vector space with inner product  $\langle x, y \rangle$ , norm  $\|x\|^2 = \langle x, x \rangle$

Result:  $\min_{x: \langle y, x \rangle = 1} \|x\|^2 \Rightarrow x = \frac{1}{\|y\|^2} y$

- Proof:  $x = x_{||} + x_{\perp}$ : component along  $y$  + component orthogonal to  $y$

$$\langle y, x \rangle = 1 = \langle y, x_{||} \rangle \text{ but } \|x\|^2 = \underbrace{\|x_{||}\|^2}_{\text{constrained}} + \underbrace{\|x_{\perp}\|^2}_{\text{unconstrained}}$$

$$\Rightarrow x_{\perp} = 0 \Rightarrow x = x_{||} = \alpha y$$

$$\langle y, x \rangle = 1 = \alpha \langle y, y \rangle = \alpha \|y\|^2 \Rightarrow \alpha = \frac{1}{\|y\|^2} \Rightarrow x = \frac{1}{\|y\|^2} y$$

### Spatial Single-User Receivers, White Noise (3)

- maximum ratio combining (spatial matched filter):

$$\begin{aligned}
 \arg \max_{\mathbf{f}} \text{SNR}(\mathbf{f}) &= \arg \max_{\mathbf{f}} \frac{|\mathbf{f}\mathbf{h}|^2 \sigma_a^2}{\mathbf{f}\mathbf{f}^H \sigma_v^2} = \arg \max_{\mathbf{f}} \frac{|\langle \mathbf{f}^H, \mathbf{h} \rangle|^2}{\|\mathbf{f}^H\|^2} \\
 &= \arg \min_{\mathbf{f}: \langle \mathbf{f}^H, \mathbf{h} \rangle = 1} \|\mathbf{f}^H\|^2 \Rightarrow \mathbf{f}^H = \frac{1}{\|\mathbf{h}\|^2} \mathbf{h} \\
 &\Rightarrow \mathbf{f} = \frac{1}{\|\mathbf{h}\|^2} \mathbf{h}^H \text{ or } \mathbf{f} = \mathbf{h}^H \text{ (scale unimportant)}
 \end{aligned}$$

$$\text{SNR}(\mathbf{f} = \mathbf{h}^H) = \frac{\|\mathbf{h}\|^2 \sigma_a^2}{\sigma_v^2} = \text{MFB}$$

$$\begin{aligned}
 \text{spatial matched filter: } \hat{a}[k] &= \sum_{i=1}^m h_i^* y_i[k] = \sum_{i=1}^m h_i^* (h_i a[k] + v_i[k]) \\
 &= \sum_{i=1}^m |h_i|^2 a[k] + \sum_{i=1}^m h_i^* v_i[k]
 \end{aligned}$$

$h_i = |h_i|e^{j\phi_i} \Rightarrow h_i^* = |h_i|e^{-j\phi_i}$  : compensate phase (align) and weigh  
 MF = F that maximizes SNR by phase compensation and weighting

## Spatial Single-User Receivers, Colored Noise

- (circular) Gaussian noise, spatially colored, temporally white:

$$f(\mathbf{v}) = \frac{e^{-\mathbf{v}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{v}}}{\pi^m \det(R_{\mathbf{v}\mathbf{v}})}$$

$$\mathbf{y}[k] = \mathbf{h} a[k] + \mathbf{v}[k], \quad \mathbf{v}[k] \sim \mathcal{CN}(0, R_{\mathbf{v}\mathbf{v}}), \text{ i.i.d. }, \quad \begin{cases} E \mathbf{v}[i] \mathbf{v}^H[k] = \delta_{ik} R_{\mathbf{v}\mathbf{v}} \\ E \mathbf{v}[i] \mathbf{v}^T[k] = 0 \end{cases}$$

- Maximum Likelihood Sequence Estimation (MLSE):  $(\|\mathbf{x}\|_R^2 = \mathbf{x}^H R \mathbf{x})$

$$\min_{a[k] \in \mathcal{A}} \sum_k \|\mathbf{y}[k] - \mathbf{h} a[k]\|_{R_{\mathbf{v}\mathbf{v}}^{-1}}^2 \Rightarrow \min_{a[k] \in \mathcal{A}} \|\mathbf{y}[k] - \mathbf{h} a[k]\|_{R_{\mathbf{v}\mathbf{v}}^{-1}}^2, \quad \forall k$$

$$\Rightarrow \hat{\hat{a}}[k] = \text{dec}(\hat{a}[k]), \quad \hat{a}[k] = \frac{1}{\mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h}} \mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{y}[k] = \arg \min_{a[k]} \|\mathbf{y}[k] - \mathbf{h} a[k]\|_{R_{\mathbf{v}\mathbf{v}}^{-1}}^2$$

- SNR:  $\hat{a}[k] = a[k] + \frac{1}{\mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h}} \mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{v}[k] \Rightarrow \text{SNR} = \sigma_a^2 \mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h}$

- MFB =  $\sigma_a^2 \|\mathbf{h}\|_{R_{\mathbf{v}\mathbf{v}}^{-1}}^2$

### Math/Stat: (Covariance) Matrix Square-Root

- "covariance" matrix  $R$  :  $R = R^H > 0$
- $R^{1/2}$  is a matrix square-root of  $R$  if  $R = R^{1/2} R^{H/2}$   
where  $R^{H/2}$  means  $(R^{1/2})^H$ ;  $R^{-1/2}$  means  $(R^{1/2})^{-1}$
- non-uniqueness: if  $R^{1/2}$  is a matrix square-root of  $R$  then so is  $R^{1/2} Q$   
for any unitary  $Q$  ( $Q Q^H = I$ ):  
 $R^{1/2} Q (R^{1/2} Q)^H = R^{1/2} Q Q^H R^{H/2} = R^{1/2} R^{H/2} = R$
- the "*symmetric*" square-root : eigen decomposition  $R = V \Lambda V^H$   
then  $R^{1/2} = V \Lambda^{1/2} V^H$  is symmetric (Hermitian in fact) (unique if  
require  $\Lambda^{1/2} > 0$ )
- the *Cholesky* factor: corresponds to the unique  $R^{1/2}$  that is (lower)  
triangular with positive real diagonal elements
- LDU (UDL) factorization (unique):  $R = L D L^H$  ( $U D U^H$ ),  $L$  ( $U$ ) =  
lower (upper) triangular with unit diagonal,  $D$  = diagonal (real and  
 $D > 0$ ), then  $R^{1/2} = L D^{1/2}$  (or  $U D^{1/2}$ ) is a Cholesky factor.

## Spatial Single-User Receivers, Colored Noise (2)

- linear combining receivers:  $\hat{a}[k] = \mathbf{f} \mathbf{y}[k]$ ,  $\mathbf{f} : 1 \times m$
- SNR:  $\hat{a}[k] = \mathbf{f} \mathbf{h} a[k] + \mathbf{f} \mathbf{v}[k] \Rightarrow \text{SNR} = \frac{|\mathbf{f} \mathbf{h}|^2 \sigma_a^2}{\mathbf{f} R_{\mathbf{v} \mathbf{v}} \mathbf{f}^H}$
- colored noise spatial matched filter:  $(R_{\mathbf{v} \mathbf{v}} = R_{\mathbf{v} \mathbf{v}}^{1/2} R_{\mathbf{v} \mathbf{v}}^{H/2}, R_{\mathbf{v} \mathbf{v}}^{1/2} = V \Lambda^{1/2} V^H)$

$$\max_{\mathbf{f}} \text{SNR}(\mathbf{f}) = \max_{\mathbf{f}} \frac{|\langle R_{\mathbf{v} \mathbf{v}}^{H/2} \mathbf{f}^H, R_{\mathbf{v} \mathbf{v}}^{-1/2} \mathbf{h} \rangle|^2}{\|R_{\mathbf{v} \mathbf{v}}^{H/2} \mathbf{f}^H\|^2} \quad \mathbf{h}' = R_{\mathbf{v} \mathbf{v}}^{-1/2} \mathbf{h}$$

$$\begin{aligned} \mathbf{f}' &= \mathbf{f} R_{\mathbf{v} \mathbf{v}}^{1/2} \\ \Rightarrow \min_{\mathbf{f}': \langle \mathbf{f}'^H, R_{\mathbf{v} \mathbf{v}}^{-1/2} \mathbf{h} \rangle = 1} \|\mathbf{f}'^H\|^2 &\Rightarrow \mathbf{f}'^H = \frac{1}{\|R_{\mathbf{v} \mathbf{v}}^{-1/2} \mathbf{h}\|^2} R_{\mathbf{v} \mathbf{v}}^{-1/2} \mathbf{h} \\ \Rightarrow \mathbf{f} &= \mathbf{f}' R_{\mathbf{v} \mathbf{v}}^{-1/2} = \frac{1}{\mathbf{h}^H R_{\mathbf{v} \mathbf{v}}^{-1} \mathbf{h}} \mathbf{h}^H R_{\mathbf{v} \mathbf{v}}^{-1} \text{ or } \mathbf{f} = \mathbf{h}^H R_{\mathbf{v} \mathbf{v}}^{-1} \text{ (scale unimportant)} \end{aligned}$$

$$\text{SNR}_{\max} = \text{SNR}(\mathbf{f} = \mathbf{h}^H R_{\mathbf{v} \mathbf{v}}^{-1}) = \sigma_a^2 \mathbf{h}^H R_{\mathbf{v} \mathbf{v}}^{-1} \mathbf{h} = \text{MFB}$$

- matched filter = max SNR receiver
- Noise whitening approach:  $\mathbf{y}'[k] = R_{\mathbf{v} \mathbf{v}}^{-1/2} \mathbf{y}[k] = R_{\mathbf{v} \mathbf{v}}^{-1/2} \mathbf{h} a[k] + \mathbf{v}'[k]$

$$R_{\mathbf{v}' \mathbf{v}'} = I, \sigma_{v'}^2 = 1, \mathbf{h}' = R_{\mathbf{v} \mathbf{v}}^{-1/2} \mathbf{h}$$



### Spatial Single-User Receivers, Colored Noise (3)

- colored noise MF

$$\mathbf{h}'^H \mathbf{y}'[k] = \underbrace{\mathbf{h}^H}_{\text{channel MF}} \underbrace{R_{\mathbf{v}\mathbf{v}}^{-H/2}}_{\text{whitening MF}} \underbrace{R_{\mathbf{v}\mathbf{v}}^{-1/2}}_{\text{noise whitening}} \mathbf{y}[k]$$

Receiver properties

- symbol estimation error:

$$\tilde{a}[k] = a[k] - \hat{a}[k] = a[k] - \mathbf{f} \mathbf{y}[k] = (1 - \mathbf{f} \mathbf{h}) a[k] - \mathbf{f} \mathbf{v}[k]$$

- receiver bias:  $E \tilde{a}[k] | a[k] = (1 - \mathbf{f} \mathbf{h}) a[k]$

- unbiased linear receiver:  $\mathbf{f} \mathbf{h} = 1$

$$\hat{a}[k] = \underbrace{\mathbf{f} \mathbf{h}}_{=1} a[k] + \mathbf{f} \mathbf{v}[k]$$

- Mean Squared Error (MSE):

$$\text{MSE} = E \|\tilde{a}[k]\|^2 = R_{aa} - \mathbf{f} R_{\mathbf{y}a} - R_{a\mathbf{y}} \mathbf{f}^H + \mathbf{f} R_{\mathbf{y}\mathbf{y}} \mathbf{f}^H = |1 - \mathbf{f} \mathbf{h}|^2 \sigma_a^2 + \mathbf{f} R_{\mathbf{v}\mathbf{v}} \mathbf{f}^H$$

- $\text{SNR} = \frac{|\mathbf{f} \mathbf{h}|^2 \sigma_a^2}{\mathbf{f} R_{\mathbf{v}\mathbf{v}} \mathbf{f}^H}$ , for unbiased receivers:  $\text{SNR} = \frac{\sigma_a^2}{\text{MSE}} = \frac{\sigma_a^2}{\sigma_{\tilde{a}}^2}$

### Math/Stat Background: Matrix Inversion Lemma (MIL)

- Let  $A + BCD$  be a (low rank) modification of  $A$  and let  $A^{-1}$  (and  $C^{-1}$ ) be available (and assume all inverses involved to exist). Then  $(A + BCD)^{-1}$  can be found with little work:

$$(A + BCD)^{-1} = A^{-1} - A^{-1}B(DA^{-1}B + C^{-1})^{-1}DA^{-1}$$

Proof:  $(A + BCD)(A^{-1} - A^{-1}B(DA^{-1}B + C^{-1})^{-1}DA^{-1}) = \dots = I$

- Typically  $B$  = column vector,  $D$  = row vector,  $C$  = scalar  $\Rightarrow$   $(A + BCD)^{-1}$  can be obtained from  $A^{-1}$  by just inverting a scalar, and multiplications.
- Often  $(A + BCD)^{-1}$  appears premultiplied with  $D$  or postmultiplied with  $B$ , which simplify, e.g.  
 $D(A + BCD)^{-1} = C^{-1}(DA^{-1}B + C^{-1})^{-1}DA^{-1}$  which, in the case of scalar  $C$ , is a scalar multiple of  $DA^{-1}$ , so  $D(A + BCD)^{-1}$  and  $DA^{-1}$  are proportional.

## Spatial Single-User Receivers, Colored Noise: (U)MMSE

- Minimum MSE receiver:

$$\begin{aligned}
 \mathbf{f}_{MMSE} &= R_{\mathbf{y}\mathbf{y}}^{-1} R_{\mathbf{a}\mathbf{y}} = \sigma_a^2 \mathbf{h}^H R_{\mathbf{y}\mathbf{y}}^{-1} \\
 &= \sigma_a^2 \mathbf{h}^H (R_{\mathbf{v}\mathbf{v}} + \mathbf{h} \sigma_a^2 \mathbf{h}^H)^{-1} \\
 &= (\mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h} + \sigma_a^{-2})^{-1} \mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1}
 \end{aligned}$$

using MIL:  $(A + BCD)^{-1} = A^{-1} - A^{-1}B(DA^{-1}B + C^{-1})^{-1}DA^{-1}$

and  $D(A + BCD)^{-1} = C^{-1}(DA^{-1}B + C^{-1})^{-1}DA^{-1}$

note:  $\mathbf{f}_{MMSE} \mathbf{h} = \frac{\mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h}}{\mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h} + \sigma_a^{-2}} < 1$  :  $\mathbf{f}_{MMSE}$  is a biased receiver

- since  $\text{SNR} = \frac{\sigma_a^2}{\text{MSE}}$  for unbiased receivers,

$$\arg \max_{\mathbf{f}: \mathbf{f}\mathbf{h}=1} \text{SNR}(\mathbf{f}) = \arg \min_{\mathbf{f}: \mathbf{f}\mathbf{h}=1} \text{MSE}(\mathbf{f}) = \mathbf{f}_{UMMSE} = (\mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h})^{-1} \mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1}$$

- since however  $\mathbf{f}_{MMSE} \sim \mathbf{f}_{UMMSE} \sim \mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1}$

$$\text{SNR}_{max} = \sigma_a^2 \mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h} = \text{SNR}(\mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1}) = \text{SNR}(\mathbf{f}_{MMSE}) = \text{SNR}(\mathbf{f}_{UMMSE})$$

but  $\text{SNR}_{max} = \frac{\sigma_a^2}{\text{MSE}(\mathbf{f})}$  only for  $\mathbf{f} = \mathbf{f}_{UMMSE}$

## Spatial Single-User Receivers, Colored Noise: LCMV/UMOE

- $\text{MSE} = \sigma_a^2 - \mathbf{f}\mathbf{h} \sigma_a^2 - \sigma_a^2 \mathbf{h}^H \mathbf{f}^H + \mathbf{f} R_{\mathbf{y}\mathbf{y}} \mathbf{f}^H = \sigma_a^2 (1 - \mathbf{f}\mathbf{h} - (\mathbf{f}\mathbf{h})^H) + \mathbf{f} R_{\mathbf{y}\mathbf{y}} \mathbf{f}^H$

- for unbiased receivers ( $\mathbf{f}\mathbf{h} = 1$ ):

$$\text{MSE} = \mathbf{f} R_{\mathbf{y}\mathbf{y}} \mathbf{f}^H - \sigma_a^2 = \text{OE} - \sigma_a^2 = V - \sigma_a^2$$

OE = Output Energy,  $V$  = output Variance

- Linearly Constrained Minimum Variance (LCMV) receiver:

$$\mathbf{f}_{LCMV} = \arg \min_{\mathbf{f}: \mathbf{f}\mathbf{h}=1} \mathbf{f} R_{\mathbf{y}\mathbf{y}} \mathbf{f}^H = (\mathbf{h}^H R_{\mathbf{y}\mathbf{y}}^{-1} \mathbf{h})^{-1} \mathbf{h}^H R_{\mathbf{y}\mathbf{y}}^{-1}$$

LCMV also called Unbiased Minimum OE (UMOE)

- can show:

$$\mathbf{f}_{LCMV} = (\mathbf{h}^H R_{\mathbf{y}\mathbf{y}}^{-1} \mathbf{h})^{-1} \mathbf{h}^H R_{\mathbf{y}\mathbf{y}}^{-1} = (\mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h})^{-1} \mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} = \mathbf{f}_{UMMSE}$$

- under unbiasedness constraint: minimizing MSE  $\equiv$  minimizing OE

## Spatial Single-User Receivers, Colored Noise: GSC

- Generalized Sidelobe Canceler (GSC) formulation of LCMV/UMOE

- introduce  $\mathbf{h}^\perp$  s.t.

$$[\mathbf{h} \ \mathbf{h}^\perp]^H \begin{bmatrix} \underbrace{\mathbf{h}}_{m \times 1} & \underbrace{\mathbf{h}^\perp}_{m \times (m-1)} \end{bmatrix} = \begin{bmatrix} \mathbf{h}^H \mathbf{h} & 0 \\ 0 & \mathbf{h}^{\perp H} \mathbf{h}^\perp \end{bmatrix} \text{ with } \mathbf{h}^{\perp H} \mathbf{h}^\perp \text{ nonsingular}$$

- reparameterize  $\mathbf{f}$  with  $\mathbf{f}_\parallel, \mathbf{f}_\perp$  :  $\mathbf{f} = \begin{bmatrix} \underbrace{\mathbf{f}_\parallel}_{1 \times 1} & \underbrace{-\mathbf{f}_\perp}_{1 \times (m-1)} \end{bmatrix} \underbrace{\begin{bmatrix} \mathbf{h}^H \\ \mathbf{h}^{\perp H} \end{bmatrix}}_{\text{invertible transformation}}$

- unbiasedness:  $\mathbf{f}\mathbf{h} = 1 = \begin{bmatrix} \mathbf{f}_\parallel & -\mathbf{f}_\perp \end{bmatrix} \begin{bmatrix} \mathbf{h}^H \mathbf{h} \\ 0 \end{bmatrix} = \mathbf{f}_\parallel \mathbf{h}^H \mathbf{h} \Rightarrow \mathbf{f}_\parallel = \frac{1}{\mathbf{h}^H \mathbf{h}}$

$\Rightarrow$  unbiased

$$\mathbf{f} = \underbrace{\frac{1}{\mathbf{h}^H \mathbf{h}} \mathbf{h}^H}_{\text{white noise } \mathbf{f}_{UMMSEw}} - \underbrace{\mathbf{f}_\perp}_{m-1 \text{ unconstrained parameters}} \mathbf{h}^{\perp H}$$

## Spatial Single-User Receivers, Colored Noise: GSC (2)

- colored noise UMMSE :  $\text{MSE} = \text{E} |\tilde{a}[k]|^2$   

$$-\tilde{a}[k] = -(1 - \underbrace{\mathbf{f}\mathbf{h}}_{=1}) a[k] + \mathbf{f}\mathbf{v}[k] = \underbrace{\frac{1}{\mathbf{h}^H \mathbf{h}} \mathbf{h}^H \mathbf{v}[k]}_{\mathbf{v}_1[k]} - \mathbf{f}_\perp \underbrace{\mathbf{h}^{\perp H} \mathbf{v}[k]}_{\mathbf{v}_2[k]} = \mathbf{v}_1[k] - \mathbf{f}_\perp \mathbf{v}_2[k]$$
  

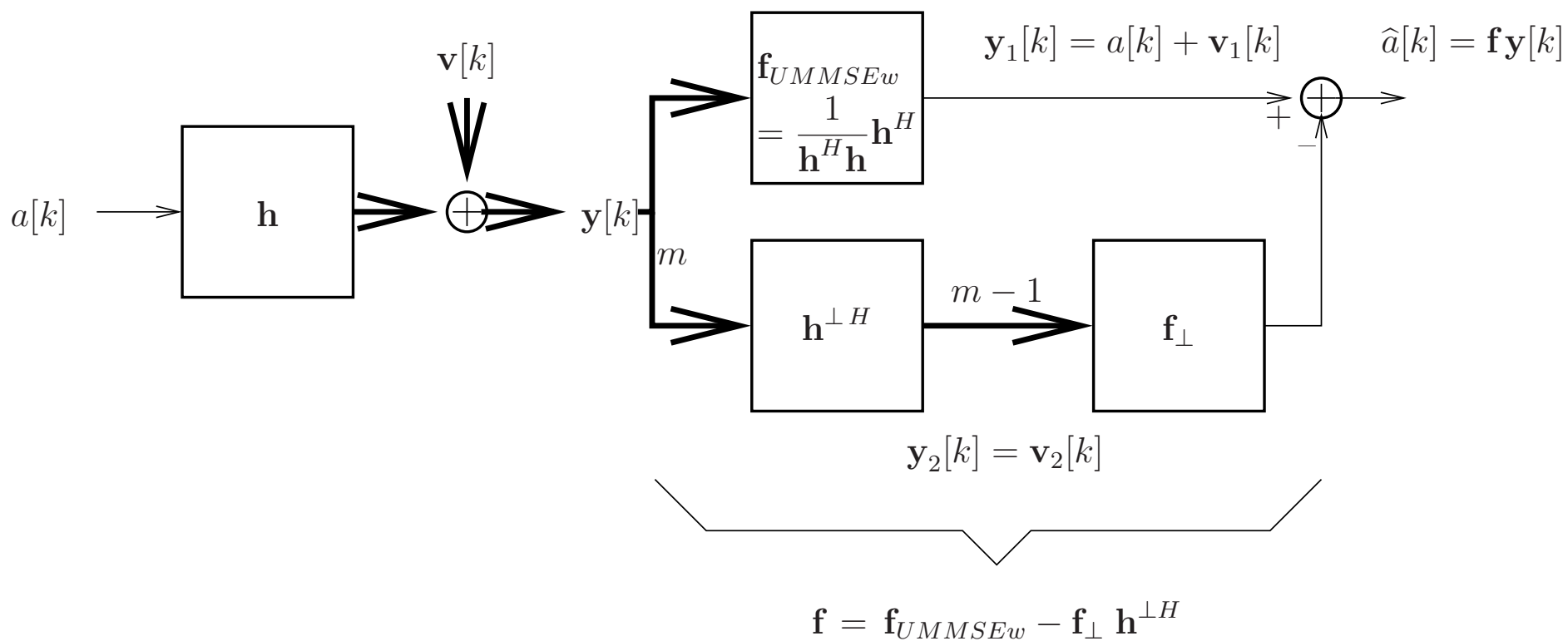
$$\Rightarrow \mathbf{f}_{\perp, UMMSE} = R_{\mathbf{v}_1 \mathbf{v}_2} R_{\mathbf{v}_2 \mathbf{v}_2}^{-1} \mathbf{v}_2$$
- colored noise UMOE  

$$\text{OE} = \mathbf{f} R_{\mathbf{y}\mathbf{y}} \mathbf{f}^H = \text{E} |\mathbf{f}\mathbf{y}[k]|^2 = \text{E} \left| \frac{1}{\mathbf{h}^H \mathbf{h}} \mathbf{h}^H \mathbf{y}[k] - \mathbf{f}_\perp \mathbf{h}^{\perp H} \mathbf{y}[k] \right|^2 = \text{E} |\mathbf{y}_1[k] - \mathbf{f}_\perp \mathbf{y}_2[k]|^2$$
  

$$\Rightarrow \mathbf{f}_{\perp, UMOE} = R_{\mathbf{y}_1 \mathbf{y}_2} R_{\mathbf{y}_2 \mathbf{y}_2}^{-1} \mathbf{y}_2$$
- however,  $\mathbf{y}_1[k] = a[k] + \mathbf{v}_1[k]$ ,  $\mathbf{y}_2[k] = \mathbf{v}_2[k]$   

$$\Rightarrow R_{\mathbf{y}_2 \mathbf{y}_2} = R_{\mathbf{v}_2 \mathbf{v}_2} \text{ and } R_{\mathbf{y}_1 \mathbf{y}_2} = R_{\mathbf{y}_1 \mathbf{v}_2} = R_{\mathbf{v}_1 \mathbf{v}_2}$$
  
and  $\mathbf{f}_{\perp, UMOE} = \mathbf{f}_{\perp, UMMSE}$  (= 0 for white noise)
- colored noise  $\mathbf{f}_{UMOE} = \mathbf{f}_{UMMSE} = \mathbf{f}_{UMMSE w} - \mathbf{f}_{\perp, UMMSE} \mathbf{h}^{\perp H} = \mathbf{f}_{UMOE w} - \mathbf{f}_{\perp, UMOE} \mathbf{h}^{\perp H}$

# Spatial Single-User Receivers, Colored Noise: GSC (3)



## Spatial Single-User Receivers, White Noise: Capon's Principle

- back to white noise case
- now suppose channel response  $\mathbf{h}$  not known
- Capon's principle
  - first apply LCMV (UMOE) for a hypothesized channel  $\hat{\mathbf{h}}$ , this leads to

$$\mathbf{f}_{LCMV} = (\hat{\mathbf{h}}^H R_{\mathbf{y}\mathbf{y}}^{-1} \hat{\mathbf{h}})^{-1} \hat{\mathbf{h}}^H R_{\mathbf{y}\mathbf{y}}^{-1} \quad \text{and} \quad \text{MOE} = (\hat{\mathbf{h}}^H R_{\mathbf{y}\mathbf{y}}^{-1} \hat{\mathbf{h}})^{-1}$$

- then maximize the resulting MOE w.r.t. the hypothesized channel

$$\begin{aligned} \arg \max_{\hat{\mathbf{h}}: \|\hat{\mathbf{h}}\|=1} \min_{\mathbf{f}: \mathbf{f}\hat{\mathbf{h}}=1} \text{OE} &= \arg \max_{\hat{\mathbf{h}}: \|\hat{\mathbf{h}}\|=1} (\hat{\mathbf{h}}^H R_{\mathbf{y}\mathbf{y}}^{-1} \hat{\mathbf{h}})^{-1} \\ &= \arg \min_{\hat{\mathbf{h}}: \|\hat{\mathbf{h}}\|=1} \hat{\mathbf{h}}^H R_{\mathbf{y}\mathbf{y}}^{-1} \hat{\mathbf{h}} \end{aligned}$$

$$\Rightarrow \hat{\mathbf{h}} = V_{\min}(R_{\mathbf{y}\mathbf{y}}^{-1}) = V_{\max}(R_{\mathbf{y}\mathbf{y}}) = \bar{\mathbf{h}} = \frac{1}{\|\mathbf{h}\|} \mathbf{h}$$



## Spatial Multi-User Receivers, MLSE White Noise

- $\mathbf{y}[k] = [\mathbf{h}_1 \cdots \mathbf{h}_p] \begin{bmatrix} a_1[k] \\ \vdots \\ a_p[k] \end{bmatrix} + \mathbf{v}[k] = \mathbf{h} \mathbf{a}[k] + \mathbf{v}[k] = [\mathbf{h}_1 \ \bar{\mathbf{h}}_1] \begin{bmatrix} a_1[k] \\ \bar{\mathbf{a}}_1[k] \end{bmatrix} + \mathbf{v}[k]$
- assume white Gaussian noise first:  $\mathbf{v}[k] \sim \mathcal{CN}(0, \sigma_v^2 I_m)$  i.i.d.
- Maximum Likelihood Sequence Estimation (MLSE):
 
$$\min_{\mathbf{a}[k] \in \mathcal{A}^p} \sum_k \|\mathbf{y}[k] - \mathbf{h} \mathbf{a}[k]\|^2 \Rightarrow \min_{\mathbf{a}[k] \in \mathcal{A}^p} \|\mathbf{y}[k] - \mathbf{h} \mathbf{a}[k]\|^2 \text{ exhaustive search}$$

$$\begin{aligned} \hat{a}_1[k] &= \frac{1}{\mathbf{h}_1^H \mathbf{h}_1} \mathbf{h}_1^H (\mathbf{y}[k] - \bar{\mathbf{h}}_1 \hat{\bar{\mathbf{a}}}_1[k]) \quad \text{DF} \\ \Rightarrow \hat{\bar{a}}_1[k] &= \text{dec}(\hat{a}_1[k]), \quad = \arg \min_{a_1[k]} \|\mathbf{y}[k] - \bar{\mathbf{h}}_1 \hat{\bar{\mathbf{a}}}_1[k] - \mathbf{h}_1 a_1[k]\|^2 \end{aligned}$$
- MFB = SNR of MLSE when all other symbols ( $\bar{\mathbf{a}}_1[k]$ ) known

$$\hat{a}_1[k] = a_1[k] + \frac{1}{\mathbf{h}_1^H \mathbf{h}_1} \mathbf{h}_1^H \mathbf{v}[k] \Rightarrow \text{MFB} = \text{SNR} = \frac{\|\mathbf{h}_1\|^2 \sigma_a^2}{\sigma_v^2}$$

“single-user MFB”

## Spatial Multi-User Receivers, MLSE Colored Noise

- (circular) Gaussian noise, spatially colored, temporally white:

$$\mathbf{y}[k] = \mathbf{h} \mathbf{a}[k] + \mathbf{v}[k], \quad \mathbf{v}[k] \sim \mathcal{CN}(0, R_{\mathbf{v}\mathbf{v}}), \text{ i.i.d. }, \quad \begin{cases} E\mathbf{v}[i]\mathbf{v}^H[k] = \delta_{ik} R_{\mathbf{v}\mathbf{v}} \\ E\mathbf{v}[i]\mathbf{v}^T[k] = 0 \end{cases}$$

- Maximum Likelihood Sequence Estimation (MLSE):

$$\begin{aligned} \min_{\mathbf{a}[k] \in \mathcal{A}^p} \sum_k \|\mathbf{y}[k] - \mathbf{h} \mathbf{a}[k]\|_{R_{\mathbf{v}\mathbf{v}}^{-1}}^2 &\Rightarrow \min_{\mathbf{a}[k] \in \mathcal{A}^p} \|\mathbf{y}[k] - \mathbf{h} \mathbf{a}[k]\|_{R_{\mathbf{v}\mathbf{v}}^{-1}}^2 \text{ exh. search} \\ \Rightarrow \hat{\hat{a}}_1[k] = \text{dec}(\hat{a}_1[k]), &\quad \begin{aligned} \hat{a}_1[k] &= \frac{1}{\mathbf{h}_1^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h}_1} \mathbf{h}_1^H R_{\mathbf{v}\mathbf{v}}^{-1} (\mathbf{y}[k] - \bar{\mathbf{h}}_1 \hat{\hat{\mathbf{a}}}_1[k]) \text{ DF} \\ &= \arg \min_{a_1[k]} \|\mathbf{y}[k] - \bar{\mathbf{h}}_1 \hat{\hat{\mathbf{a}}}_1[k] - \mathbf{h}_1 a_1[k]\|_{R_{\mathbf{v}\mathbf{v}}^{-1}}^2 \end{aligned} \end{aligned}$$

- MFB = SNR of MLSE when all other symbols ( $\bar{\mathbf{a}}_1[k]$ ) known

$$\hat{a}_1[k] = a_1[k] + \frac{1}{\mathbf{h}_1^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h}_1} \mathbf{h}_1^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{v}[k] \Rightarrow \text{MFB} = \text{SNR} = \|\mathbf{h}_1\|_{R_{\mathbf{v}\mathbf{v}}^{-1}}^2 \sigma_a^2$$

“single-user MFB”

## Spatial Multi-User Receivers, Colored Noise: S(I)NR

- linear combining receivers:  $\mathbf{f} : p \times m$ 

$$\begin{bmatrix} \hat{a}_1[k] \\ \vdots \\ \hat{a}_p[k] \end{bmatrix} = \hat{\mathbf{a}}[k] = \mathbf{f} \mathbf{y}[k] = \begin{bmatrix} \mathbf{f}_1 \\ \vdots \\ \mathbf{f}_p \end{bmatrix} \mathbf{y}[k] = \mathbf{f} \mathbf{h} \mathbf{a}[k] + \mathbf{f} \mathbf{v}[k]$$

$$\begin{cases} \mathbb{E} \mathbf{a}[i] \mathbf{a}^H[k] = \delta_{ik} \sigma_a^2 I_p \\ \mathbb{E} \mathbf{a}[i] \mathbf{a}^T[k] = 0 \text{ only if complex} \end{cases}$$

- S(I)NR:  $\hat{a}_i[k] = \mathbf{f}_i \mathbf{y}[k] = \underbrace{\mathbf{f}_i \mathbf{h}_i a_i[k]}_{\text{signal}} + \underbrace{\mathbf{f}_i \bar{\mathbf{h}}_i \bar{\mathbf{a}}_i[k]}_{\text{interference}} + \underbrace{\mathbf{f}_i \mathbf{v}[k]}_{\text{noise}}$

- $\text{SNR}_i = \frac{|\mathbf{f}_i \mathbf{h}_i|^2 \sigma_a^2}{\mathbf{f}_i R_{\mathbf{v}\mathbf{v}} \mathbf{f}_i^H}$

$$\text{SINR}_i = \frac{|\mathbf{f}_i \mathbf{h}_i|^2 \sigma_a^2}{\|\bar{\mathbf{h}}_i^H \mathbf{f}_i^H\|^2 \sigma_a^2 + \mathbf{f}_i R_{\mathbf{v}\mathbf{v}} \mathbf{f}_i^H} = \frac{|\mathbf{f}_i \mathbf{h}_i|^2 \sigma_a^2}{\mathbf{f}_i (\sigma_a^2 \bar{\mathbf{h}}_i \bar{\mathbf{h}}_i^H + R_{\mathbf{v}\mathbf{v}}) \mathbf{f}_i^H}$$

- 

$$= \frac{|\mathbf{f}_i \mathbf{h}_i|^2 \sigma_a^2}{\mathbf{f}_i R_{\mathbf{y}\mathbf{y}} \mathbf{f}_i^H - |\mathbf{f}_i \mathbf{h}_i|^2 \sigma_a^2} = \frac{|\mathbf{f}_i \mathbf{h}_i|^2 \sigma_a^2}{\text{OE} - |\mathbf{f}_i \mathbf{h}_i|^2 \sigma_a^2}$$

## Spatial Multi-User Receivers, Colored Noise: MF

- the Matched Filter maximizes SNR, hence MF Rx same as in the single-user case:

$$\mathbf{f}_i^{MF} = \mathbf{h}_i^H R_{\mathbf{V}\mathbf{V}}^{-1} \Rightarrow \mathbf{f}^{MF} = \mathbf{h}^H R_{\mathbf{V}\mathbf{V}}^{-1}$$

$\hat{\mathbf{a}}^{MF}[k] = \mathbf{h}^H R_{\mathbf{V}\mathbf{V}}^{-1} \mathbf{y}[k]$  is a sufficient statistic and will be the input for all multiuser detectors

$$\text{SINR}_i^{MF} = \frac{|\mathbf{h}_i^H R_{\mathbf{V}\mathbf{V}}^{-1} \mathbf{h}_i|^2 \sigma_a^2}{\|\bar{\mathbf{h}}_i^H R_{\mathbf{V}\mathbf{V}}^{-1} \mathbf{h}_i\|^2 \sigma_a^2 + \mathbf{h}_i^H R_{\mathbf{V}\mathbf{V}}^{-1} \mathbf{h}_i}$$

- $$= \frac{\text{MFB}_i}{1 + \frac{\|\bar{\mathbf{h}}_i^H R_{\mathbf{V}\mathbf{V}}^{-1} \mathbf{h}_i\|^2 \sigma_a^2}{\mathbf{h}_i^H R_{\mathbf{V}\mathbf{V}}^{-1} \mathbf{h}_i}} = \frac{\text{MFB}_i}{1 + \text{INR}_i^{MF}}$$

## Spatial Multi-User Receivers, Colored Noise

Receiver properties

- symbol estimation error:

$$\tilde{\mathbf{a}}[k] = \mathbf{a}[k] - \hat{\mathbf{a}}[k] = \mathbf{a}[k] - \mathbf{f}\mathbf{y}[k] = (I_p - \mathbf{f}\mathbf{h}) \mathbf{a}[k] - \mathbf{f}\mathbf{v}[k]$$

$$= (I_p - \text{diag}(\mathbf{f}\mathbf{h})) \mathbf{a}[k] - \overline{\text{diag}(\mathbf{f}\mathbf{h})} \mathbf{a}[k] - \mathbf{f}\mathbf{v}[k]$$

$$\tilde{a}_i[k] = (1 - \mathbf{f}_i \mathbf{h}_i) a_i[k] - \mathbf{f}_i \bar{\mathbf{h}}_i \bar{\mathbf{a}}_i[k] - \mathbf{f}_i \mathbf{v}[k]$$

- receiver bias:  $E \tilde{a}_i[k] |_{a_i[k]} = (1 - \mathbf{f}_i \mathbf{h}_i) a_i[k]$
- unbiased linear receiver:  $\mathbf{f}_i \mathbf{h}_i = 1$ ,  $i = 1, \dots, p$ ,  $\text{diag}(\mathbf{f}\mathbf{h}) = I_p$
- zero-forcing (ZF) Rx:  $\mathbf{f}\mathbf{h} = I_p \Rightarrow \mathbf{f}_i \mathbf{h}_i = 1$ ,  $i = 1, \dots, p$ : unbiased  
need  $m \geq p$  for ZF !

•

$$\begin{aligned} \text{MSE}_i &= E \|\tilde{a}_i[k]\|^2 = R_{a_i a_i} - \mathbf{f}_i R_{\mathbf{y} a_i} - R_{a_i \mathbf{y}} \mathbf{f}_i^H + \mathbf{f}_i R_{\mathbf{y} \mathbf{y}} \mathbf{f}_i^H \\ &= |1 - \mathbf{f}_i \mathbf{h}_i|^2 \sigma_a^2 + \|\bar{\mathbf{h}}_i^H \mathbf{f}_i^H\|^2 \sigma_a^2 + \mathbf{f}_i R_{\mathbf{v} \mathbf{v}} \mathbf{f}_i^H \\ &= (|1 - \mathbf{f}_i \mathbf{h}_i|^2 - |\mathbf{f}_i \mathbf{h}_i|^2) \sigma_a^2 + \mathbf{f}_i R_{\mathbf{y} \mathbf{y}} \mathbf{f}_i^H = (|1 - \mathbf{f}_i \mathbf{h}_i|^2 - |\mathbf{f}_i \mathbf{h}_i|^2) \sigma_a^2 + \text{OE}_i \end{aligned}$$

## Spatial Multi-User Receivers, Colored Noise (2)

- $$\text{SINR}_i = \frac{|\mathbf{f}_i \mathbf{h}_i|^2 \sigma_a^2}{\|\bar{\mathbf{h}}_i^H \mathbf{f}_i^H\|^2 \sigma_a^2 + \mathbf{f}_i R_{\mathbf{v}\mathbf{v}} \mathbf{f}_i^H}$$
  - for unbiased Rx: 
$$\text{SINR}_i = \frac{\sigma_a^2}{\|\bar{\mathbf{h}}_i^H \mathbf{f}_i^H\|^2 \sigma_a^2 + \mathbf{f}_i R_{\mathbf{v}\mathbf{v}} \mathbf{f}_i^H} = \frac{\sigma_a^2}{\text{MSE}_i}$$
  - $$\begin{aligned} \text{MSE} &= \sum_{i=1}^p \text{MSE}_i = \text{E} \|\tilde{\mathbf{a}}[k]\|^2 = \text{E} \tilde{\mathbf{a}}^H[k] \tilde{\mathbf{a}}[k] = \text{E} \text{tr} \tilde{\mathbf{a}}^H[k] \tilde{\mathbf{a}}[k] \\ &= \text{E} \text{tr} \tilde{\mathbf{a}}[k] \tilde{\mathbf{a}}^H[k] = \text{tr} \text{E} \tilde{\mathbf{a}}[k] \tilde{\mathbf{a}}^H[k] = \text{tr} R_{\tilde{\mathbf{a}}\tilde{\mathbf{a}}} \end{aligned}$$
- in general,  $\arg \min_{\mathbf{f}} \text{MSE} = \arg \min_{\mathbf{f}} R_{\tilde{\mathbf{a}}\tilde{\mathbf{a}}}$
- $$R_{\tilde{\mathbf{a}}\tilde{\mathbf{a}}} = \sigma_a^2 (I_p - \mathbf{f}\mathbf{h})(I_p - \mathbf{f}\mathbf{h})^H + \mathbf{f} R_{\mathbf{v}\mathbf{v}} \mathbf{f}^H$$
  - for ZF Rx: 
$$R_{\tilde{\mathbf{a}}\tilde{\mathbf{a}}} = \mathbf{f} R_{\mathbf{v}\mathbf{v}} \mathbf{f}^H, \quad \text{SINR}_i^{\text{ZF}} = \text{SNR}_i^{\text{ZF}}$$

## Spatial Multi-User Receivers: MMSE ZF

- Result from vector spaces with matrix valued inner product  
 $\langle X, Y \rangle = \langle Y, X \rangle^H$ , “norm”  $\|X\|^2 = \langle X, X \rangle$

Result:  $\min_{X: \langle Y, X \rangle = I} \|X\|^2 \Rightarrow X = Y \|Y\|^{-2} = Y \langle Y, Y \rangle^{-1}$

- MMSE ZF Rx, white noise: ZF:  $\mathbf{f}\mathbf{h} = I_p$ ,  $p \times (m-p)$  degrees of freedom remaining in  $\mathbf{f}$ : fix them to min. MSE:

$$\arg \min_{\mathbf{f}: \mathbf{f}\mathbf{h} = I_p} R_{\mathbf{a}\mathbf{a}} = \arg \min_{\mathbf{f}: \mathbf{h}^H \mathbf{f}^H = I_p} \mathbf{f}\mathbf{f}^H = \arg \min_{\mathbf{f}: \langle \mathbf{h}, \mathbf{f}^H \rangle = I_p} \|\mathbf{f}^H\|^2$$

with  $\langle \mathbf{g}, \mathbf{h} \rangle = \mathbf{g}^H \mathbf{h}$  for  $\mathbf{g}, \mathbf{h} \in \mathcal{C}^{m \times p}$

- result  $\Rightarrow \mathbf{f}^H = \mathbf{h} \|\mathbf{h}\|^{-2} = \mathbf{h} (\mathbf{h}^H \mathbf{h})^{-1} \Rightarrow \mathbf{f}^{MMSEZF} = (\mathbf{h}^H \mathbf{h})^{-1} \mathbf{h}^H$

## Spatial Multi-User Receivers: MMSE ZF (2)

- MMSE ZF Rx, colored noise: ZF:

$$\min_{\mathbf{f}: \mathbf{f}^H \mathbf{h} = I_p} \widetilde{R_{\mathbf{a}\mathbf{a}}} = \min_{\mathbf{f}: \mathbf{h}^H \mathbf{f}^H = I_p} \mathbf{f} R_{\mathbf{v}\mathbf{v}} \mathbf{f}^H \xRightarrow{\mathbf{f}' = \mathbf{f} R_{\mathbf{v}\mathbf{v}}^{1/2}} \min_{\mathbf{f}': \langle R_{\mathbf{v}\mathbf{v}}^{-1/2} \mathbf{h}, \mathbf{f}'^H \rangle = I_p} \underbrace{\|\mathbf{f}'^H\|^2}_{\|R_{\mathbf{v}\mathbf{v}}^{H/2} \mathbf{f}^H\|^2}$$

- result

$$\Rightarrow \mathbf{f}'^H = R_{\mathbf{v}\mathbf{v}}^{-1/2} \mathbf{h} \|\mathbf{h}\|^{-2} \Rightarrow \mathbf{f}^{MMSEZF} = (\mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h})^{-1} \mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1}$$

- note:  $\hat{\mathbf{a}}^{MMSEZF}[k] = \mathbf{f}^{MMSEZF} \mathbf{y}[k] = (\mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h})^{-1} \hat{\mathbf{a}}^{MF}[k]$

- $\widetilde{R_{\mathbf{a}\mathbf{a}}}^{MMSEZF} = (\mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h})^{-1}$

$$\Rightarrow \text{MSE}_i^{MMSEZF} = [(\mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h})^{-1}]_{ii}, \text{SINR}_i^{MMSEZF} = \frac{\sigma_a^2}{\text{MSE}_i^{MMSEZF}}$$

- can show:  $\mathbf{f}^{MMSEZF} = (\mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h})^{-1} \mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} = (\mathbf{h}^H R_{\mathbf{y}\mathbf{y}}^{-1} \mathbf{h})^{-1} \mathbf{h}^H R_{\mathbf{y}\mathbf{y}}^{-1}$



## ceivers: MMSE ZF

trix valued inner product

$$\|X\|^2 = \langle X, X \rangle$$

$$Y \|Y\|^{-2} = Y \langle Y, Y \rangle^{-1}$$

 $n = I_p$ ,  $p \times (m-p)$  degrees of

0 min. MSE:

$$\boxed{\mathbf{f}^H} = \arg \min \|\mathbf{f}^H\|^2$$

$$\mathbf{f}^{MMSEZF} = (\mathbf{h}^H \mathbf{h})^{-1} \mathbf{h}^H$$

$\Rightarrow L=0$

$$g^H = h (h^H h)^{-1}$$

$$\begin{bmatrix} \mathcal{L}_{//} \\ \mathcal{L}_{\perp} \end{bmatrix} \begin{matrix} p \\ m-p \end{matrix}$$



## Spatial Multi-User Receivers: (U)MMSE

- all users plus noise model:

$$\mathbf{y} = \mathbf{h} \mathbf{a} + \mathbf{v}$$

$$R_{\mathbf{y}\mathbf{y}} = \sigma_a^2 \mathbf{h} \mathbf{h}^H + R_{\mathbf{v}\mathbf{v}}$$

- one user plus interferers and noise model:

$$\mathbf{y} = \mathbf{h}_i a_i + \bar{\mathbf{h}}_i \bar{\mathbf{a}}_i + \mathbf{v}$$

$$R_{\mathbf{y}\mathbf{y}} = \sigma_a^2 \mathbf{h}_i \mathbf{h}_i^H + R_i$$

- same situation as single-user case but with  $R_{\mathbf{v}\mathbf{v}}$  replaced by  $R_i = \sigma_a^2 \bar{\mathbf{h}}_i \bar{\mathbf{h}}_i^H + R_{\mathbf{v}\mathbf{v}} = R_{\mathbf{y}\mathbf{y}} - \sigma_a^2 \mathbf{h}_i \mathbf{h}_i^H$  (“noise includes interference”)

- UMMSE: for unbiased  $\mathbf{f}_i$ :  $\text{SINR}_i = \frac{\sigma_a^2}{\text{MSE}_i} = \frac{\sigma_a^2}{\mathbf{f}_i R_i \mathbf{f}_i^H}$

## Spatial Multi-User Receivers: (U)MMSE (2)

- UMMSE:

$$\mathbf{f}_i^{UMMSE} = \mathbf{f}_i^{maxSINR} = (\mathbf{h}_i^H R_i^{-1} \mathbf{h}_i)^{-1} \mathbf{h}_i^H R_i^{-1} = (\mathbf{h}_i^H R_{\mathbf{y}\mathbf{y}}^{-1} \mathbf{h}_i)^{-1} \mathbf{h}_i^H R_{\mathbf{y}\mathbf{y}}^{-1}$$

- MMSE:

$$\mathbf{f}^{MMSE} = R_{\mathbf{a}\mathbf{y}} R_{\mathbf{y}\mathbf{y}}^{-1} = \sigma_a^2 \mathbf{h}^H R_{\mathbf{y}\mathbf{y}}^{-1} = (\mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h} + \sigma_a^{-2} I_p)^{-1} \mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1}$$

$$\hat{\mathbf{a}}^{MMSE}[k] = \mathbf{f}^{MMSE} \mathbf{y}[k] = (\mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h} + \sigma_a^{-2} I_p)^{-1} \hat{\mathbf{a}}^{MF}[k]$$

$$\mathbf{f}_i^{MMSE} = R_{a_i \mathbf{y}} R_{\mathbf{y}\mathbf{y}}^{-1} = \sigma_a^2 \mathbf{h}_i^H R_{\mathbf{y}\mathbf{y}}^{-1} = (\mathbf{h}_i^H R_i^{-1} \mathbf{h}_i + \sigma_a^{-2})^{-1} \mathbf{h}_i^H R_i^{-1}$$

$$\mathbf{f}_i^{UMMSE} = \frac{1}{\mathbf{f}_i^{MMSE} \mathbf{h}_i} \mathbf{f}_i^{MMSE} = \frac{1}{\sigma_a^2 \mathbf{h}_i^H R_{\mathbf{y}\mathbf{y}}^{-1} \mathbf{h}_i} \mathbf{f}_i^{MMSE} = (\mathbf{h}_i^H R_i^{-1} \mathbf{h}_i)^{-1} \mathbf{h}_i^H R_i^{-1}$$

$$\hat{a}_i^{UMMSE}[k] = \sigma_a^{-2} (\mathbf{h}_i^H R_{\mathbf{y}\mathbf{y}}^{-1} \mathbf{h}_i)^{-1} \hat{a}_i^{MMSE}[k]$$

### Spatial Multi-User Receivers: (U)MMSE (3)

- $\mathbf{f}_i$  unbiased  $\Rightarrow \text{MSE}_i = \mathbf{f}_i^H R_i \mathbf{f}_i$
- since  $\mathbf{f}_i^{MMSE} \sim \mathbf{f}_i^{UMMSE} \sim \mathbf{h}_i^H R_{\mathbf{y}\mathbf{y}}^{-1} \sim \mathbf{h}_i^H R_i^{-1} \not\sim \mathbf{h}_i^H R_{\mathbf{v}\mathbf{v}}^{-1}$

$$\begin{aligned} \text{SINR}_i^{max} &= \sigma_a^2 \mathbf{h}_i^H R_i^{-1} \mathbf{h}_i = \text{SINR}(\mathbf{h}_i^H R_{\mathbf{y}\mathbf{y}}^{-1}) = \text{SINR}(\mathbf{h}_i^H R_i^{-1}) \\ &= \text{SINR}(\mathbf{f}_i^{MMSE}) = \text{SINR}(\mathbf{f}_i^{UMMSE}) \end{aligned}$$

but  $\text{SINR}_i^{max} = \frac{\sigma_a^2}{\text{MSE}_i(\mathbf{f}_i)}$  only for  $\mathbf{f}_i = \mathbf{f}_i^{UMMSE}$

- in general

$$\max \left\{ \underbrace{\text{SINR}_i^{MF}}_{\max \text{ SNR}}, \underbrace{\text{SINR}_i^{MMSEZF}}_{\max \text{ SIR}} \right\} \leq \underbrace{\text{SINR}_i^{UMMSE}}_{\max \text{ SINR}} \leq \text{MFB}_i$$

### Spatial Multi-User Receivers: Nonlinear Rx

- for MMSE (ZF),  $\hat{\mathbf{a}}[k]$  found from

$$R \hat{\mathbf{a}}[k] = \hat{\mathbf{a}}^{MF}[k], \quad R = \mathbf{h}^H R_{\mathbf{v}\mathbf{v}}^{-1} \mathbf{h} + \epsilon \sigma_a^{-2} I_p, \quad \epsilon = \begin{cases} 0 & , \text{MMSE ZF} \\ 1 & , \text{MMSE} \end{cases}$$

- Serial/Parallel Interference Cancellation (SIC/PIC):

$$R = \text{diag}(R) + \overline{\text{diag}}(R)$$

$$\hat{\mathbf{a}}[k] = \text{dec}((\text{diag}(R))^{-1} (\hat{\mathbf{a}}^{MF}[k] - \overline{\text{diag}}(R) \text{dec}(\hat{\mathbf{a}}[k])))$$

iterative (multi-stage) versions possible/useful

without  $\text{dec}(\cdot)$ : iterative solutions for linear Rx

- Decision-Feedback (DF):  $R = L^H D L$ ,  $L = I + \overline{\text{diag}}(L)$

$$\hat{\mathbf{a}}[k] = \text{dec}(\underbrace{D^{-1} L^{-H}}_{\text{linear anticausal IC}} \hat{\mathbf{a}}^{MF}[k] - \underbrace{\overline{\text{diag}}(L) \text{dec}(\hat{\mathbf{a}}[k])}_{\text{nonlinear causal IC}})$$

one shot solution (no iterations)