# 1 SIMO Systems

Remarks

- In SIMO Systems only <u>coding</u> and <u>diversity</u> <u>gains</u> can be exploited (no multiplexing gains)

- To realize these gains diversity combining has to be performed

- Diversity combining schemes vary in complexity and performance

- There are <u>many</u> diversity combining schemes. Here we consider:
  - Maximal ratio combining (MRC)
  - Equal gain combining (EGC)
  - Selection combining (SC)

- Diversity combining problem
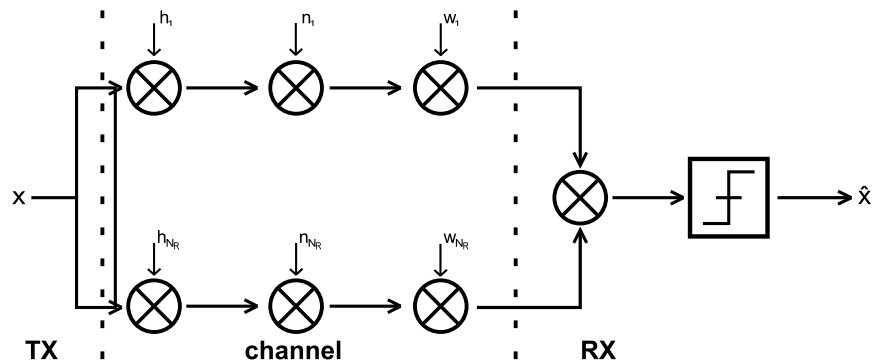
  - how to choose combining weights w_n?
  - what performance (e.g. error rate, outage probability) is achieved?
  - what <u>diversity</u> and coding/combining gain is achieved?
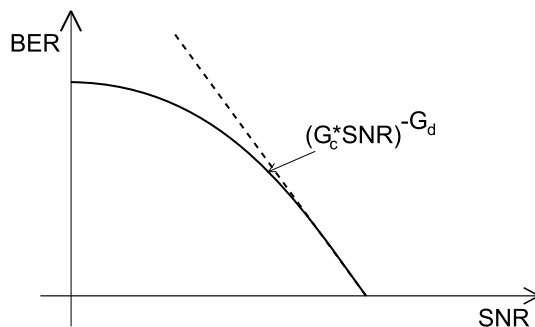
- G_c : Coding gain
- G_d : Diversity gain

1.1 Preliminaries

Consider an equivalent system:

$$y = hx + n;$$

$$\mathcal{E}\{|x^2|\} = E_s; \qquad\qquad \mathcal{E}\{|n^2|\} = \sigma_n^2; \qquad\qquad \mathcal{E}\{|h|^2\} = 1$$

- Instantaneous SNR: $\gamma_t = \frac{E_s}{\sigma_n^2} \cdot |h|^2$
- Average SNR: $\bar{\gamma}_t = \mathcal{E}\{\gamma_t\} = \frac{E_s}{\sigma_n^2}$

Bit and Symbol Error Rate

- The Bit and Symbol Error Rate of many modulation schemes can be expressed for given γ_t as:

$$P_e(\gamma_t) = aQ\{\sqrt{b\gamma_t}\}$$

where:

- $Q(x) = \frac{1}{\sqrt{2\pi}} \cdot \int_x^\infty e^{-\frac{t^2}{2}} \, dt$
- $P_e(\gamma_t)$ may be exact result or approximation
- BPSK: exact with $a = 1, b = 2$
- M-ary QAM: tight approximation with $a = 4\left(1 - \frac{1}{\sqrt{M}}\right), b = \frac{3}{M-1}$

$\left(Einschub : Gray - Code : BER = \frac{1}{\log_2 M} \cdot SER\right)$

- Alternative representation of Q - function:

$$Q(x) = \frac{1}{\pi} \int_0^{\frac{\pi}{2}} e^{-\frac{x^2}{2sin^2\theta}} \, d\theta$$

$\rightarrow$ Integral limits are fixed and do not depend on integration variables!

- Average error probability

$$P_e = \mathcal{E}\{P_e(\gamma_t)\} = \int_0^\infty aQ(\sqrt{bx})p_{\gamma_t}(x) \, dx$$

  - Integral may be difficult to solve analytically
  - Integral has infinite support $\rightarrow$ numerical evaluation difficult

- Using alternative representation of Q-function we get:

$$P_e = \int_0^\infty \frac{a}{\pi} \int_0^{\frac{\pi}{2}} e^{-\frac{bx}{2sin^2\theta}} p_{\gamma_t}(x) \, d\theta \, dx$$

$$= \frac{a}{\pi} \int_0^{\frac{\pi}{2}} \int_0^\infty p_{\gamma_t}(x) e^{-\frac{b}{2sin^2\theta}} \, dx \, d\theta \qquad\qquad = \frac{a}{\pi} \int_0^{\frac{\pi}{2}} M_{\gamma_t}\left(\frac{b}{2sin^2\theta}\right) \, d\theta$$

where:

- $M_{\gamma_t}(s) = \int_0^\infty p_{\gamma_t}(x)e^{-sx}\ dx$ is the Laplace transform of p_{γ_t}

- $M_{\gamma_t}(-s)$ is the so called Moment Generation Function (MGF) of p_{γ_t}

- Here, we will also refer to $M_{\gamma_t}(s)$ as MGF

- $M_{\gamma_t}(s)$ is sometimes easier to obtain than p_{γ_t}

- The above integral can be easily evaluated numerically because of the finite integral limits

Outage probability

- The outage probability is the probability that the channel cannot support a certain rate, R, i.e. (where γ_T is the threshold SNR):

$$C = \log_2(1 + \gamma_t) < R \quad \leftrightarrow \quad \gamma_t < 2^R - 1 \triangleq \gamma_T$$
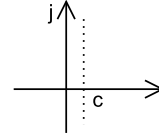
Thus, the outage probability is given by:

$$P_{out} = P_0\gamma_t < \gamma - T\ = \int_0^{\gamma_T} p_{\gamma_t}(x)\ dx$$

- Using the inverse Laplace Transform

$$p_{\gamma_t}(x) = \frac{1}{2\pi j}\int_{c-j\omega}^{c+j\omega} M_{\gamma_t}(s)e^{sx}\ dx$$

where $c > 0$ is a small constant that lies in the region of convergence of the integral, we obtain:

- 1.

$$P_{out} = \frac{1}{2\pi j}\int_{c-j\omega}^{c+j\omega} M_{\gamma_t}(s)\int_0^{\gamma_T} e^{sx}\ dx\ ds = \frac{1}{2\pi j}\int_{c-j\omega}^{c+j\omega} M_{\gamma_t}(s)e^{\gamma_T s}\ \frac{ds}{s}$$

$\left(\text{lower integral limit is 0 since } p_{\gamma_t}(0) = 0\right)$

- and 2.:

$$p_{\gamma_t}(x) = \int_0^x p_{\gamma_t}(t)\ dt = 0$$

$$\text{for } x = 0 \text{ note: } p_{\gamma_t}(x) \xleftarrow[transform]{Laplace} \frac{1}{s}M_{\gamma_t}(s)$$

General combining scheme

$$y = \left(\sum_{n=1}^{N_R} h_n w_n\right)x + \sum_{n=1}^{N_R} w_n n_n$$

$$\gamma_t = \frac{\epsilon_s \left|\sum_{n=1}^{N_R} h_n w_n\right|^2}{\sigma_n^2 \sum_{N=1}^{N_R} |w_n|^2}$$

where w_n depends on the particular combining scheme.

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1.2 MRC (Maximum Ratio Combining)

- what weight w_n maximize γ_t?

  - Cauchy-Schwarz inequality

  $$\left| \sum_{n=1}^{N_R} h_n w_n \right|^2 \leq \sum_{n=1}^{N_R} |h_n|^2 \cdot \sum_{n=1}^{N_R} |w_n|^2$$

  where equality holds if and only if $w_n = c \cdot h_n^*$ for some non-zero constant c.

  - for $w_n = h_n^*$, we obtain

  $$\gamma_t = \frac{\epsilon_s}{\sigma_n^2} \cdot \frac{\left(\sum_{n=1}^{N_R} |h_n|^2 \right)^2}{\sum_{n=1}^{N_R} |h_n|^2} = \frac{\epsilon_s}{\sigma_n^2} \sum_{n=1}^{N_R} |h_n|^2$$

  - $w_n = h_n^* \forall n$ are the MRC combining weights.

- For performance analysis we assume <u>independent identically distributed (IID)</u> Rayleigh fading

  $$\rightarrow \mathcal{E}\{|h_n|^2\} = 1; \quad \bar{\gamma} = \frac{\epsilon_s}{\sigma_n^2}; \quad \gamma_n = \frac{\epsilon_s}{\sigma_n^2} |h_n|^2$$

  $$p_\gamma(x) = \frac{1}{\bar{\gamma}} e^{-\frac{x}{\bar{\gamma}}}; \quad x \geq 0$$

  $$M_\gamma(s) = \frac{1}{1 + s\bar{\gamma}}$$

- Error rate

  $$\gamma_t = \sum_{n=1}^{N_R} \gamma_n$$

  $\rightarrow$ sum of IID random variables (r.v.s.)

  $$M_{\gamma_t}(s) = \left(M_\gamma(s) \right)^{N_R} = \frac{1}{(1 + s\bar{\gamma})^{N_R}} = \frac{1}{\bar{\gamma}^{N_R}} \cdot \frac{1}{(s + \frac{1}{\bar{\gamma}})^{N_R}}$$
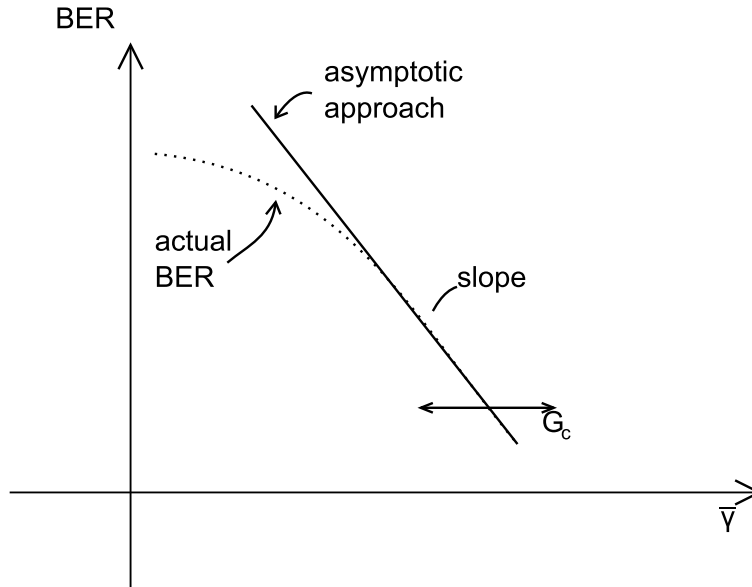
  inverse Laplace-transform (from tables)

  $$p_{\gamma_t}(x) = \frac{1}{\bar{\gamma}^{N_R}} \cdot \frac{x^{N_R - 1}}{(N_R - 1)!} e^{-\frac{x}{\bar{\gamma}}}; \quad x \geq 0$$

- Direct approach

  $$p_e = \int_0^\infty a \cdot Q\left(\sqrt{ax} \right) p_{\gamma_t}(x) \, dx = a \left(\frac{1 - \mu}{2} \right)^{N_R} \cdot \sum_{n=0}^{N_R - 1} \binom{N_R - 1 + n}{n} \left(\frac{1 + \mu}{2} \right)^n$$

  where $\mu = \sqrt{\dfrac{b\bar{\gamma}}{2 + b\bar{\gamma}}}$

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- MGF approach

$$p_e = \frac{a}{\pi} \int_0^{\frac{\pi}{2}} M_{\gamma_t}\left(\frac{b}{2\sin^2\theta}\right) d\theta$$

$$= \frac{a}{\pi} \int_0^{\frac{\pi}{2}} \frac{1}{\bar{\gamma}^{N_R}\left(\frac{b}{\sin^2\theta} + \frac{1}{\bar{\gamma}}\right)^{N_R}} \, d\theta \quad \text{(numerisch berechnen!)}$$

- high SNR: $\quad \bar{\gamma} \to \infty \Longleftrightarrow \frac{1}{\bar{\gamma}} \to 0$

$$p_e = \frac{a}{\pi} \cdot \frac{1}{\bar{\gamma}^{N_R}} \cdot \left(\frac{2}{b}\right)^{N_R} \int_0^{\frac{\pi}{2}} \sin^{2N_R}\theta \, d\theta$$

$$\text{(from MGF approach: } \int_0^{\frac{\pi}{2}} \sin^{2N_R}\theta \, d\theta = \frac{\pi}{2^{N_R+1}} \cdot \binom{2N_R}{N_R}\text{)}$$

$$= \frac{a}{2^{N_R+1} \cdot b^{N_R}} \begin{pmatrix} 2N_R & N_R \end{pmatrix} \frac{1}{\bar{\gamma}^{N_R}} \quad \text{as } \bar{\gamma} \to \infty$$

$$\overset{!}{=} \left(\frac{1}{G_c \bar{\gamma}}\right)$$

where: Diversity gain: $G_d = N_R$

Combining/Coding gain: $G_c = 2b\left(\frac{a}{2}\binom{2N_R}{N_R}\right)^{-\frac{1}{N_R}}$

- MRC exploits the maximal possible diversity

- Diversity gain is not affected by correlation as the branches are not <u>fully</u> correlated

- Diversity gain depends on fading distribution

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Outage probability

$$P_{out} = \int_0^{\gamma_T} p_{\gamma_t}(x) \, dx = \frac{1}{\bar{\gamma}^{N_R}} \int_0^{\gamma_T} \frac{x^{N_R-1}}{(N_R-1)!} e^{-\frac{x}{\bar{\gamma}}} \, dx$$

$$= 1 - e^{-\frac{\gamma_T}{\bar{\gamma}}} \cdot \sum_{n=1}^{N_R} \frac{\left(\frac{\gamma_T}{\bar{\gamma}}\right)^n}{(n-1)!}$$

- Approximation (Taylor series): $\bar{\gamma} \to \infty : -e^{-\frac{x}{\bar{\gamma}}} = 1 - \frac{x}{\bar{\gamma}} + O(\frac{1}{\bar{\gamma}})$ where a function $f(x)$ is $O(x)$ if $\lim_{x \to \infty} \frac{f(x)}{x} = 0$.

$$\Rightarrow P_{out} = \frac{1}{\gamma^{N_R}} \int_0^{\gamma_T} \frac{x^{N_R-1}}{(N_R-1)!} \left(1 - \frac{x}{\bar{\gamma}} + O\left(\frac{1}{\bar{\gamma}}\right)\right)$$

- Diversity and coding gain can also be defined for P_{out}

1.3 EGC (Equal Gain Combining)

Combining Weights

- For MRC, both, the amplitudes and phases of the channel gains $h_n = |h_n|e^{j\varphi_n}$ have to be known (or estimated in practice)
- In EGC it is assumed that only the phases are known and weights $w_n = e^{-j\varphi_n}$ are used.

$$\Rightarrow \gamma_t = \frac{E_s}{\sigma_n^2} \frac{\left|\sum_{n=1}^{N_R} |h_n|e^{j\varphi_n}e^{-j\varphi_n}\right|^2}{\sum_{n=1}^{N_R} |e^{-j\varphi_n}|^2} = \frac{E_s}{\sigma_n^2} \frac{1}{N_R} \left(\sum_{n=1}^{N_R} |h_n|\right)^2$$

$$= \frac{1}{N_R} \left(\sum_{n=1}^{N_R} \sqrt{\gamma_n}\right)^2 ; \text{ with } \gamma_n = \frac{E_s}{\sigma_n^2} |h_n|^2$$

Performance Analysis

- IID case
  $\Rightarrow \sqrt{\gamma_n}$ is Rayleigh distributed
  $\Rightarrow$ Exact analysis is much more difficult than for MRC $\Rightarrow$ see book by Simon & Alouini p.341

- Approximate result

$$P_e = \frac{a}{2} \left[1 - \sqrt{\frac{2b\bar{\gamma}}{5 + 2b\bar{\gamma}}} \sum_{n=0}^{N_R-1} \frac{\binom{2n}{n}}{4^n(1 + \frac{2}{5}b\bar{\gamma})^n}\right]$$

- high SNR

$\Rightarrow$ use high SNR analysis of Wang & Giannakis, 2003

$\Rightarrow$ at high SNR, only pdf of γ_n around 0 is relevant for performance

$$\Rightarrow \overset{\text{Rayleigh}}{p_\gamma(x)} = \frac{1}{\bar{\gamma}} e^{-\frac{x}{\bar{\gamma}}} \overset{\text{Taylor Serie}}{=} \frac{1}{\bar{\gamma}} + O\left(\frac{1}{\bar{\gamma}}\right) \text{ as } x \to 0$$

- need pdf γ_t: (γ_n bekannt, $\to$ ges.: Wurzel, etc.)

(cumulative distribution function of $\sqrt{\gamma}$ ($\overset{\text{i.i.d}}{=} \sqrt{\gamma_n}$) (cdf))

$$P_{\sqrt{\gamma}}(x) = \Pr\{\sqrt{\gamma} \le x\} = \Pr\{\gamma \le x^2\} = P_\gamma(x^2) = \text{cdf of } \gamma$$

$$\to p_{\sqrt{\gamma}}(x) = \frac{d}{dx} P_{\sqrt{\gamma}}(x) = 2x \cdot p_\gamma(x^2) = \frac{2x}{\bar{\gamma}} + O\left(\frac{1}{\bar{\gamma}}\right)$$

- Laplace Transformation to MGF

$$\to M_{\sqrt{\gamma}}(s) = \mathcal{L}\{p_{\sqrt{\gamma}}(x)\} = \frac{2}{\bar{\gamma}} \cdot \frac{1}{s^2} + O\left(\frac{1}{\bar{\gamma}}\right)$$

$$\sqrt{\gamma_t} = \sum_{n=1}^{N_R} \frac{\sqrt{\gamma_n}}{N_R}$$

$$M_{\sqrt{\gamma_t}}(s) = \mathcal{E}\left\{\exp(-s\sqrt{\gamma_t})\right\} = \mathcal{E}\left\{\exp\left(-\frac{s}{\sqrt{N_R}} \cdot \sum_{n=1}^{N_R} \sqrt{\gamma_n}\right)\right\} = \left(\mathcal{E}\left\{\exp\left(-\frac{s}{\sqrt{N_R}} \cdot \sqrt{\gamma_n}\right)\right\}\right)^{N_R}$$

$$= \left(M_{\sqrt{\gamma}}\left(\frac{s}{\sqrt{N_R}}\right)\right)^{N_R} = \left(\frac{2}{\bar{\gamma}} \cdot \frac{N_R}{s^2}\right)^{N_R} + O\left(\frac{1}{\bar{\gamma}^{N_R}}\right)$$

- inverse Laplace Transform

$$p_{\sqrt{\gamma_t}}(x) = \mathcal{L}^{-1}\left\{M_{\sqrt{\gamma_t}}(s)\right\} = \left(\frac{2N_R}{\bar{\gamma}}\right)^{N_R} \cdot \frac{x^{2N_R-1}}{(2N_R-1)!} + O\left(\frac{1}{\bar{\gamma}^{N_R}}\right)$$

$$P_{\gamma_t}(x) = \Pr\{\gamma_t \le x\} = \Pr\{\sqrt{\gamma_t} \le \sqrt{x}\} = P_{\sqrt{\gamma_t}}(\sqrt{x}) \to \text{cdf of } \sqrt{\gamma_t}$$

$$p_{\gamma_t}(x) = \frac{d}{dx} P_{\gamma_t}(x) = \frac{1}{2\sqrt{x}} \cdot p_{\gamma_t}(\sqrt{x}) = \frac{1}{2}\left(\frac{2N_R}{\bar{\gamma}}\right)^{N_R} \cdot \frac{x^{N_R-1}}{(2N_R-1)!} + O(\bar{\gamma}^{-N_R})$$

$$\to M_{\gamma_t}(s) = \mathcal{L}\{p_{\gamma_t}(x)\} = \frac{1}{2}\left(\frac{2N_R}{\bar{\gamma}}\right)^{N_R} \cdot \frac{(N_R-1)!}{(2N_R-1)! \, b^{N_R}} + O(\bar{\gamma}^{-N_R})$$

- Error Probability:

$$P_e = \frac{a}{\pi} \int\limits_0^{\frac{\pi}{2}} M_{\gamma_t} \left(\frac{b}{2\sin^2(\theta)} \right) \mathrm{d}\theta$$

$$= \frac{a}{\pi} \frac{1}{2} \left(\frac{2N_R}{\bar{\gamma}} \right)^{N_R} \frac{(N_R-1)!}{(2N_R-1)!} \frac{2^{N_R}}{b^{N_R}} \underbrace{\int\limits_0^{\frac{\pi}{2}} \sin^{2N_R}(\theta) \mathrm{d}\theta}_{\frac{\pi}{2^{2N_R+1}} \binom{2N_R}{N_R} = \frac{\pi (2N_R)!}{2^{2N_R+1}(N_R!)^2}} \quad + O\left(\frac{1}{\bar{\gamma}^{N_R}} \right)$$

$$= \frac{a N_R^{N_R}}{2 b^{N_R} N_R!} \frac{1}{\bar{\gamma}^{N_R}} + O\left(\frac{1}{\bar{\gamma}^{N_R}} \right) \stackrel{!}{=} \left(\frac{1}{G_c} \right)^{G_d}$$

$\implies$ Diversity gain: $G_d = N_R$

$\implies$ Combining gain: $G_c = \frac{b}{N_R} \left(\frac{2N_R!}{a} \right)^{\frac{1}{N_R}}$

vergleiche auch Blatt mit Kurven III und IV

A similar asymptotic analysis can be conducted for the outage probability.

1.4   SC (Selection Combining)

Combining weights

- only the strongest branch is chosen
- strongest branch: $\hat{n} = \underset{n}{\mathrm{argmax}}\, \gamma_n \longrightarrow \gamma_t = \gamma_{\hat{n}}$
- only on RF receiver chain required $\to$ saves hardware complexity

Performance analysis

- cdf of: γ_t

$$P_{\gamma_t}(x) = \mathrm{Pr}\{\gamma_{\hat{n}} \leq x\} = \mathrm{Pr}\{\gamma_1 \leq x \cap \gamma_2 \leq x \cap \ldots \gamma_{N_R} \leq x\}$$
$$\stackrel{(IID)}{=} \left(\mathrm{Pr}\{\gamma_n \leq x\} \right)^{N_R} = \left(P_\gamma(x) \right)^{N_R}$$

- pdf:

$$p_{\gamma_t}(x) = \frac{d}{dx} P_{\gamma_t}(x) = N_R \left(P_\gamma(x) \right)^{N_R-1} \cdot p_\gamma(x)$$

where:
$$p_{\gamma_t}(x) = \frac{1}{\bar{\gamma}} e^{-\frac{x}{\bar{\gamma}}}; \quad x \geq 0$$

$$P_\gamma(x) = \int_0^x p_\gamma(x)\, dx = 1 - e^{-\frac{x}{\bar{\gamma}}}; \quad x \geq 0$$

$$\to p_{\gamma_t}(x) = \frac{N_R}{\bar{\gamma}} \left(1 - e^{-\frac{x}{\bar{\gamma}}} \right)^{N_R-1} e^{-\frac{x}{\bar{\gamma}}}; \quad x \geq 0$$

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Error probability

- direct approach → closed-form solution possible
- MGF approach
  - Binomial expansion

  $$p_{\gamma_t}(x) = \frac{N_R}{\bar{\gamma}} e^{-\frac{x}{\bar{\gamma}}} \sum_{n=0}^{N_R-1} \binom{N_R-1}{n} 1^{N_R-1-n} \left(-e^{-\frac{x}{\bar{\gamma}}}\right)^n$$

  $$= \frac{N_R}{\bar{\gamma}} \sum_{n=0}^{N_R-1} \binom{N_R-1}{n} \cdot (-1)^n e^{-\frac{x(n+1)}{\bar{\gamma}}}; \quad x \geq 0$$

  - MGF

  $$M_{\gamma_t}(s) = \frac{N_R}{\bar{\gamma}} \sum_{n=0}^{N_R-1} \binom{N_R-1}{n} (-1)^n \frac{1}{s + \frac{n+1}{\bar{\gamma}}}$$

  –

  $$P_e = \frac{a}{\pi} \int_0^{\frac{\pi}{2}} M_{\gamma_t}\left(\frac{b}{2\sin^2\theta}\right) d\theta = \frac{aN_R}{\pi\bar{\gamma}} \sum_{n=0}^{N_R-1} \binom{N_R-1}{n} (-1)^n \int_0^{\frac{\pi}{2}} \frac{d\theta}{\frac{b}{2\sin^2\theta} + \frac{n+1}{\bar{\gamma}}}$$

  $$\rightarrow \text{ can be evaluated numerically}$$

  - high SNR approach ⇒ $\bar{\gamma} \to \infty$

  $$p_{\gamma_t} = \frac{N_R}{\bar{\gamma}} \left[1 - \exp\left(-\frac{x}{\bar{\gamma}}\right)\right]^{N_R-1} \exp\left(-\frac{x}{\bar{\gamma}}\right)$$

  $$\overset{\bar{\gamma}\to\infty}{=} \frac{N_R}{\bar{\gamma}} \left[1 - \left(1 - \frac{x}{\bar{\gamma}} + O\left(\bar{\gamma}^{-1}\right)\right)\right]^{N_R-1} \left(1 - \frac{x}{\bar{\gamma}} + O\left(\bar{\gamma}^{-1}\right)\right) i$$

  $$= \frac{N_R}{\bar{\gamma}^{N_R}} x^{N_R-1} + o\left(\bar{\gamma}^{-N_R}\right)$$

  - MGF:

  $$M_{\gamma_t}(s) = \frac{N_R}{\bar{\gamma}^{N_R}} \frac{(N_R-1)!}{s^{N_R}} + O\left(\bar{\gamma}^{-N_R}\right)$$

  $$\left[\rightarrow P_e = \frac{a}{\pi} \int_0^{\frac{\pi}{2}} M_{\gamma_t}\left(\frac{b}{2\sin^2(\theta)}\right) d\theta\right]$$

  $$= \frac{a(2N_R)!}{b^{N_R} 2^{N_R+1} N_R!} \frac{1}{\bar{\gamma}^{N_R}} + O(\bar{\gamma}^{-N_R})$$

  ⟹ Diversity gain: $G_d = N_R$

  ⟹ Combining gain: $G_c = 2b \left(\frac{2N_R!}{a(2N_R)!}\right)^{\frac{1}{N_R}}$

– Outage Probability

$$P_{out} = \Pr\{\gamma_{\hat{n}} \leq \gamma_T\} = P_{\gamma_{\hat{n}}}(\gamma_T) = \left[1 - \exp\left(-\frac{\gamma_T}{\bar{\gamma}}\right)\right]^{N_R}$$

$$\text{high SNR: } P_{out} = \left(\frac{\gamma_T}{\bar{\gamma}}\right)^{N_R} + O\left(\bar{\gamma}^{-N_R}\right)$$

1.5 Comparison

- Diversity Gain:
  MRC, EGC and SC all achieve the maximum possible diversity gain of $G_d = N_R$

- Combining Gain:
  The combining gains of MRC, EGC and SC are different

  – MRC/EGC:

$$\frac{G_C^{EGC}}{G_C^{MRC}} = \frac{\frac{1}{2b}\left(\frac{a}{2}\binom{2N_R}{N_R}\right)^{\frac{1}{N_R}}}{\frac{N_R}{b}\left(\frac{a}{2}\frac{1}{N_R!}\right)^{\frac{1}{N_R}}} = \frac{[(2N_R)!]^{\frac{1}{N_R}}}{2N_R(N_R)^{\frac{1}{N_R}}} \leq 1$$

  (independent of a or b which are modulation parameters, only depends on number of antennas)

$$N_R \gg 1: \qquad N_R! \approx \sqrt{2\pi}e^{-N_R}N_R^{N_R+\frac{1}{2}} \qquad (Stirling)$$

$$\left.\frac{G_C^{EGC}}{G_C^{MRC}}\right|_{N_R \gg 1} = \frac{\left(\sqrt{2\pi}e^{-2N_R}(2N_R)^{2N_R+\frac{1}{2}}\right)^{\frac{1}{N_R}}}{2N_R\left(\sqrt{2\pi}e^{-N_R}N_R^{N_R+\frac{1}{2}}\right)^{\frac{1}{N_R}}} = \frac{2 \cdot 2^{\frac{1}{2N_R}}}{2} \overset{N_R \to \infty}{\longrightarrow} \frac{2}{e} \equiv -1.3\text{dB}$$

  – MRC/SC:

$$\frac{G_C^{SC}}{G_C^{MRC}} = \frac{2b\left(\frac{a}{2}\binom{2N_R}{N_R}\right)^{\frac{1}{N_R}}}{2b\left(\frac{a}{2}\frac{(2N_R)!}{N_R!}\right)^{\frac{1}{N_R}}} = \frac{1}{(N_R!)^{\frac{1}{N_R}}} \leq 1$$

$$\left.\frac{G_C^{SC}}{G_C^{MRC}}\right|_{N_R \gg 1} = \frac{1}{\sqrt{2\pi}^{\frac{1}{N_R}}e^{-1}N_R^{1+\frac{1}{2N_R}}} \overset{N_R \to \infty}{\longrightarrow} \frac{e}{N_R}$$

  $\to$ loss increases with N_R

2 MISO Systems

Remarks

- Similar to SIMO systems, in MISO systems only coding and diversity gains can be obtained.

- To realize these gains, a careful transmitter design is necessary

- System design depends on whether or not channel state information (**CSI**) is available at transmitter

2.1 Naive Approach

- Assume we simply send the same signal over all N_T transmit antennas
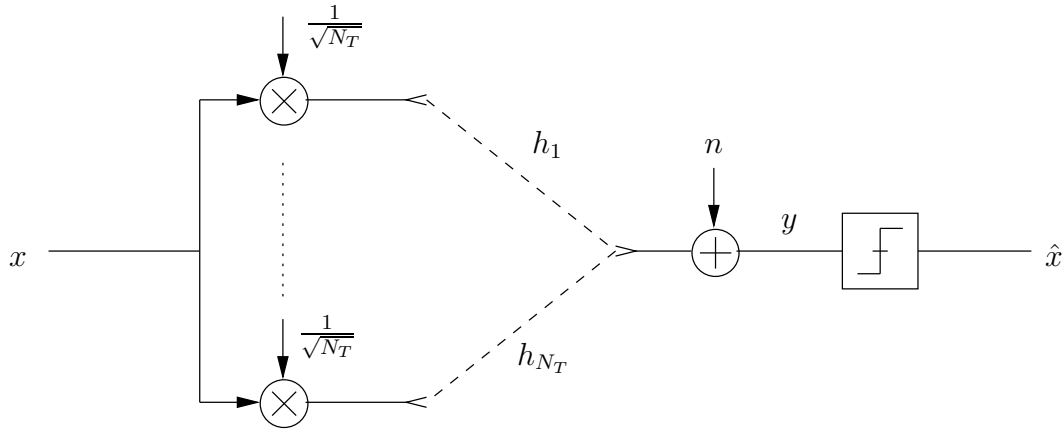
- Transmit power: $\mathcal{E}\left\{\left|\frac{1}{\sqrt{N_T}}x\right|^2 + \ldots, \left|\frac{1}{\sqrt{N_T}}x\right|^2\right\} = \mathcal{E}\left\{N_T\frac{1}{N_T}|x|^2\right\} = E_s$

- Received signal: $y = \frac{1}{\sqrt{N_T}}\sum\limits_{n=1}^{N_T} h_n \cdot x + n$

- Rayleigh fading: h_n are zero mean complex gaussian random variables
  $\rightarrow h$ is also zero mean complex gaussian

- i.i.d.:

  - $\mathcal{E}\{|h_n|^2\} = 1 \; \forall n$

  - $\mathcal{E}\{|h|^2\} = \frac{1}{N_T}\mathcal{E}\left\{\left|\sum\limits_{n=1}^{N_T} h_n\right|^2\right\} = \frac{1}{N_T}\mathcal{E}\left\{\sum\limits_{n=1}^{N_T} |h_n|^2\right\} = 1$

  - statistical properties of h are independent of N_T

  - the multiple transmit antennas have no benefit at all

  - more sophisticated transmitter designs necessary

2.2 Full CSI Available at the Transmitter

- $h_n, n \in \{1, \ldots, N_T\}$ is known at the transmitter
- Perform "precoding" (beamforming) with coefficients w_n
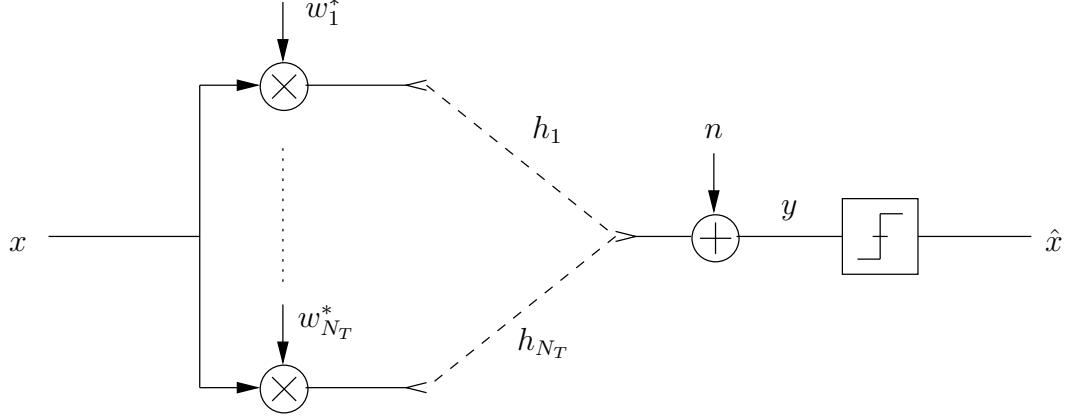
- Transmit Power: Two constraints maybe considered
    - Average transmit power constraint

$$P_{av} = \mathcal{E}\left\{\sum_{n=1}^{N_T} |w_n^* x|^2\right\} = \sum_{n=1}^{N_T} |w_n|^2 \underbrace{\mathcal{E}\{|x|^2\}}_{E_s} = \mathcal{E}_s \Rightarrow \sum_{n=1}^{N_T} |w_n|^2 = 1$$

    - Power constraint for each transmit antenna

$$\rightarrow |w_n| = \frac{1}{\sqrt{N_T}} \qquad \rightarrow P_{av} = E_s$$

- Recveived signal: $y = \underbrace{\sum_{n=1}^{N_T} w_n^* h_n}_{h} x + n$ (equivalent SISO channel)

Maximum Ratio Transmission (MRT)

- we have only the average power constraint: $\sum_{n=1}^{N_T} |w_n|^2 = 1$

- SNR: $\gamma_t = \frac{E_s |h|^2}{\sigma_n^2} = \frac{\mathcal{E}_s \left| \sum_{n=1}^{N_T} w_n^* \cdot h_n \right|^2}{\sigma_n^2}$

- Maximize SNR under constraint $\sum_{n=1}^{N_T} |w_n|^2 = 1$

- constraint optimization problem $\rightarrow$ Lagrange method

$$L = \frac{E_s}{\sigma_n^2}\left|\sum_{n=1}^{N_T} w_n^* \cdot h_n\right|^2 + \lambda\left(\sum_{n=1}^{N_T} |w_n|^2 - 1\right); \quad \text{where: } \lambda = \text{Lagrange Multiplier}$$

$\Rightarrow$ Wirtinger Kalkül: treat z and z^* as independent variables for differentiation:

$$\frac{\partial z^*}{\partial z} = 0; \quad \frac{\partial |z|^2}{\partial z} = \frac{\partial z \cdot z^*}{\partial z} = z^*$$

$$\frac{\partial x^2}{\partial x} = 2x; \quad \frac{\partial (z^*)^2}{\partial z^*} = 2 \cdot z^*; \frac{\partial |z|^2}{\partial z} = z^*$$

$$\frac{\partial L}{\partial w_m^*} = \frac{\epsilon_s}{\sigma_n^2}\left(\sum_{n=1}^{N_T} w_n^* \cdot h_n\right)^* h_m + \lambda w_m$$

$$\rightarrow w_m = \underbrace{\frac{\epsilon_s}{\sigma_n^2 \cdot \lambda}\left(\sum_{n=1}^{N_T} w_n^* h_n\right)^*}_{\text{const., independent of } m := c} h_m$$

$$\rightarrow w_m = c \cdot h_m$$

$$\rightarrow \sum_{n=1}^{N_T} |w_n|^2 = 1 \rightarrow c^2 = \frac{1}{\sum\limits_{n=1}^{N_T} |h_n|^2}$$

$$\rightarrow w_n = \frac{h_n}{\sqrt{\sum\limits_{n=1}^{N_T} |h_n|^2}} \equiv \text{MRT gains}$$

$$\rightarrow \text{SNR} = \frac{E_s}{\sigma_n^2}\left|\sum_{n=1}^{N_T} \frac{|h_n|^2}{\sqrt{\sum_{n=1}^{N_T} |h_m|^2}}\right|^2 = \frac{\epsilon_s}{\sigma_n^2}\sum_{n=1}^{N_T} |h_n|^2$$

$\Rightarrow$ same SNR as for maximum ration combining (MRC)

$\Rightarrow$ MRT with N_T transmit antennas achieves the same performance as MRC with N_T receive antennas

$\Rightarrow$ MRT/MRC can be extended to $N_T \times N_R$ MIMO systems

  $\rightarrow$ has the same performance as MRC with $N_T \cdot N_R$ receive antennas and one transmit antenna

Equal Gain Transmission (EGT)

- we employ gains: $w_n = \frac{1}{\sqrt{N_T}} \cdot \frac{h_n}{|h_m|} \rightarrow |w_n| = \frac{1}{\sqrt{N_T}}$

- SNR:

$$\gamma_t = \frac{E_s}{\sigma_n^2} \left| \sum_{n=1}^{N_T} w_n^* h_n \right|^2$$

$$= \frac{E_s}{\sigma_n^2} \left| \sum_{n=1}^{N_T} \frac{1}{\sqrt{N_T} \cdot \frac{|h_n|^2}{|h_n|}} \right|^2 = \frac{1}{N_T} \cdot \frac{\mathcal{E}_s}{\sigma_n^2} \left| \sum_{n=1}^{N_T} |h_n| \right|^2$$

$$\gamma_n = \frac{E_s}{\sigma_n^2} |h_n|^2$$

$$\text{same SNR as for EGC} \rightarrow \gamma_t = \frac{1}{N_T} \left| \sum_{n=1} N_T \sqrt{\gamma_n} \right|^2$$

$\rightarrow$ EGC with N_T transmit antennas achieves the same performance as EGC with N_T receive antennas

Transmit Antennas Selection

- select antenna with maximum channel gain for transmission:

$$w_n = \begin{cases} \frac{h_n}{|h_n|}, & \text{if } n = \hat{n} \\ 0, & \text{otherwise} \end{cases} \quad \text{where } \hat{n} = \operatorname*{argmax}_n |h_n|$$

- antenna selection with N_T transmit antennas achieves the same performance as *Selection Combining* with N_T receive antennas

2.3 No CSI at Transmitter - Space-Time-Coding

- $h_n, n \in \{1, \ldots, N_T\}$, is only known at the receiver
- "Space-time-coding" has to be employed to realize diversity gain
- $T \times N_T$ matrics $\mathbf{X}$ are transmitted in T symbol intervals over N_T antennas
- $\mathbf{X}$ is drawn from a matrix alphabet $\mathcal{X}$
- Example:

$$\mathbf{X} = \begin{pmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,N_T} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,N_T} \\ \vdots & \vdots & \ddots & \vdots \\ x_{T,1} & x_{T,2} & \cdots & x_{T,N_T} \end{pmatrix}$$

- We distinguish:
  - Space-time-block-codes (STBCs)
    $\rightarrow$ $\mathbf{X}$ is obtained by mapping K scalar symbols $s_k, \ k = 1, \ldots, K$ from a scalar alphabet $\mathcal{A}$ to matrix $\mathbf{X}$

- Space-time-trellis-codes (STTCs)
  $\rightarrow$ **X** is obtained from scalar symbols s_k through a trellis encoding process.
  [see: Tarokh, Seshadri, Calderbank: Space-time-codes for high datarate wireless communication: Performance criterions and coder construction; IEEE Trans. Inf. Theory 1998]

- here: We concentrate on space-time-block-codes (STBCs), but many results can be easily extended to space-time-trellis-codes

- STBCs:
  - K M-ary scalar symbols (e.g. M-PSK symbols) are mapped to STBC matrices **X**
    $\mathbf{S} = [s_1, \ldots, s_K] \rightarrow \mathbf{X}$
    $s_k \in \mathcal{A} \rightarrow x \in \mathcal{X}$ with $|\mathcal{X}| = M^K$

  - Example: "Alamouti"-Code

  $$\mathbf{X} = \frac{1}{\sqrt{2}} \begin{pmatrix} s_1 & s_2 \\ -s_2^* & s_1^* \end{pmatrix}$$

  [Alamouti: A simple transmit diversity technique for wireless communication, IEEE JSAC 1998]

2.3.1 Optimal Detection

- Signal model:

$$\begin{pmatrix} y_1 \\ \vdots \\ y_T \end{pmatrix} = \mathbf{X} \begin{pmatrix} h_1 \\ \vdots \\ h_{N_T} \end{pmatrix} + \begin{pmatrix} n_1 \\ \vdots \\ n_T \end{pmatrix}$$

$$\mathbf{y} = \mathbf{X} \cdot \mathbf{h} + \mathbf{n}$$

- Optimal detection - ML-detection
  - **h** is known at receiver
  - **n** is AWGN with $\mathcal{E}\{\mathbf{n} \cdot \mathbf{n^H}\} = \sigma_\mathbf{n}^2 \cdots \mathbf{I}_{T \times T}$
  - $p(\mathbf{y}|\mathbf{x})$

  $$= \frac{1}{\pi^T |\sigma_n^2 \mathbf{I}_{T \times T}|} \exp\left(-(\mathbf{y} - \mathbf{xh})^H (\sigma_n^2 \mathbf{I}_{T \times T})^{-1}(\mathbf{y} - \mathbf{xh})\right)$$

  $$= \frac{1}{\pi^T \sigma_n^{2T}} \exp\left(-\frac{1}{\sigma_n^2}(\mathbf{y} - \mathbf{xh})^H(\mathbf{y} - \mathbf{xh})\right) = \frac{1}{\pi^T \sigma_n^{2T}} \exp\left(||\mathbf{y} - \mathbf{xh}||^2\right)$$

  $\rightarrow$ the optimal estimate $\hat{\mathbf{X}}$ or equivalently the optimal estimate $\hat{\mathbf{s}}$ can be obtained as

  $$\hat{\mathbf{s}} = \underset{\mathbf{s} \in \mathcal{A}^K}{\mathrm{argmax}}\, p(\mathbf{y}|\mathbf{x}) = \underset{\mathbf{s} \in \mathcal{A}^K}{\mathrm{argmin}}||\mathbf{y} - \mathbf{hx}||^2$$

  - Disadvantage: In general, metric $||\mathbf{y} - \mathbf{hx}||^2$ has to be calculated M^K times
    $\rightarrow$ complexity increases exponentially with K

2.3.2 Types of STBCs

- Orthogonal STBCs (OSTBCs)

  - OSTBCs are a special class of STBCs which allow independent detection of each $s_k \rightarrow$ only $K \cdot M$ metrics have to be evaluated

  - Rate STBCs: $R_{STBC} = \frac{K}{T}$

  - Examples:

    * Alamouti Code $(K = 2, T = 2) \rightarrow R_{STBC} = 1$

    $$\mathbf{X} = \frac{1}{\sqrt{2}} \begin{pmatrix} s_1 & s_2 \\ -s_2^* & s_1^* \end{pmatrix} \updownarrow T$$
    $$\underset{\longleftrightarrow N_T}{}$$

    $\rightarrow$ only "full rate" OSTBC for complex s_k

    * $N_T = 3, K = 3, T = 4$

    $$\mathbf{X} = \frac{1}{\sqrt{3}} \begin{pmatrix} s_1 & s_2 & s_3 \\ -s_2^* & s_1^* & 0 \\ s_3^* & 0 & -s_3^* \\ 0 & -s_3^* & s_2^* \end{pmatrix} \rightarrow R_{STBC} = \frac{K}{T} = \frac{3}{4}$$

  - Orthogonality: $\mathbf{X}^H \mathbf{X} = const \cdot \mathbf{I}_{N_T \times N_T}$

  - Independent detection of s_1 & s_2 for Alamouti Code

    $$\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \frac{1}{\sqrt{2}} \begin{pmatrix} s_1 & s_2 \\ -s_2^* & s_1^* \end{pmatrix} \begin{pmatrix} h_1 \\ h_2 \end{pmatrix} + \begin{pmatrix} n_1 \\ n_2 \end{pmatrix}$$

    $$\rightarrow \underbrace{\begin{pmatrix} y_1 \\ y_2 \end{pmatrix}}_{\tilde{y}} = \frac{1}{\sqrt{2}} \underbrace{\begin{pmatrix} h_1 & h_2 \\ h_2^* & -h_1^* \end{pmatrix}}_{\tilde{F}} \underbrace{\begin{pmatrix} s_1 \\ s_2 \end{pmatrix}}_{s} + \underbrace{\begin{pmatrix} n_1 \\ n_2^* \end{pmatrix}}_{\tilde{n}}$$

  $\left(\text{Anmerkung: } \underline{\text{nur}} \begin{pmatrix} s_1 \\ s_2 \end{pmatrix} \text{ gewünscht, nicht: } s_1^*, s_2^* \right)$

  $$\mathbf{F}^H \mathbf{F} = \frac{1}{2} \begin{pmatrix} h_1^* & h_2 \\ h_2^* & -h_1 \end{pmatrix} \begin{pmatrix} h_1 & h_2 \\ h_2^* & -h_1^* \end{pmatrix} = \frac{1}{2} \begin{pmatrix} |h_1|^2 + |h_2|^2 & 0 \\ 0 & |h_1|^2 + |h_2|^2 \end{pmatrix}$$

  $\rightarrow \frac{\sqrt{2}}{\sqrt{|h_1|^2 + |h_2|^2}} \cdot \mathbf{F}$ is unitary matrix

  $\rightarrow \frac{2}{|h_1|^2 + |h_2|^2} \cdot \mathbf{F}^H \cdot \tilde{\mathbf{y}} = \mathbf{s} + \frac{2}{|h_1|^2 + |h_2|^2} \cdot \mathbf{F}^H \cdot \tilde{\mathbf{n}}$
  $\left(\frac{2}{|h_1|^2 + |h_2|^2} \cdot \mathbf{F}^H \cdot \tilde{\mathbf{n}} \text{ is AWGN vector with covariance matrix } \frac{2\sigma_n^2}{|h_1|^2 + |h_2|^2} \cdot \mathbf{I}_{T \times T} \right)$

  $\rightarrow$ ML decision: $\hat{\mathbf{s}} = \underset{\mathbf{s}}{\text{argmin}} \left|\left| \frac{2}{|h_1|^2 + |h_2|^2} \cdot \mathbf{F}^H \cdot \tilde{\mathbf{y}} - \mathbf{s} \right|\right|^2$

  $\rightarrow$ independent ML decoding

  $$\hat{s}_1 = \underset{s_1}{\text{argmin}} \left| s_1 - \frac{h_1^* y_1 + h_2 y_2^*}{\frac{1}{\sqrt{2}}(|h_1|^2 + |h_2|^2)} \right|$$

  $$\hat{s}_2 = \underset{s_2}{\text{argmin}} \left| s_2 - \frac{h_1^* y_1 - h_2 y_2^*}{\frac{1}{\sqrt{2}}(|h_1|^2 + |h_2|^2)} \right|$$

- independent decoding property can be proved for all OSTBCs

- low complexity is at the expense of a rate-loss compared to other STBCs for $N_T > 2$

  $\rightarrow$ Frequenzhopping

  $\rightarrow$ keine Kanalinformation aus vorher empfangenen Symbolen möglich $\Rightarrow$ Kanal ändert sich ständig: nur Entscheidung, ob Rauschen oder Signal + Rauschen

- Performance Analysis of Alamouti Code
  - Decision-variables after combining

$$r_1 = \sqrt{2}\frac{h_1^* y_1 + h_2 y_2^*}{|h_1|^2 + |h_2|^2}$$

$$r_2 = \sqrt{2}\frac{h_1^* y_1 - h_2 y_2^*}{|h_1|^2 + |h_2|^2}$$

because of symmetry it suffices to consider r_1

$$r_1 = \sqrt{2}\frac{h_1^*\left(\frac{1}{\sqrt{2}}s_1 h_1 + \frac{1}{\sqrt{2}}h_2 s_2 + n_1\right) + h_2\left(-\frac{1}{\sqrt{2}}h_2 s_1^* + \frac{1}{\sqrt{2}}h_1 s_2^* + n_2\right)^*}{|h_1|^2 + |h_2|^2}$$

$$= \sqrt{2}\frac{\frac{1}{\sqrt{2}}\left(|h_1|^2 + |h_2|^2\right)s_1 + h_1^* n_1 + h_2 n_2^*}{|h_1|^2 + |h_2|^2}$$

$$= 1 \cdot s_1 + n_{eq}$$

where

$$n_{eq} = \sqrt{2}\,\frac{h_1^* n_1 + h_2 n_2^*}{|h_1|^2 + |h_2|^2}$$

$$\text{SNR} \rightarrow \gamma_t = \frac{E_s \cdot 1^2}{\sigma_{eq}^2} \quad \text{with} \quad \mathcal{E}\{|s_1|^2\} = \mathcal{E}_s$$

$$\sigma_{eq}^2 = 2\frac{|h_1|^2 \sigma_n^2 + |h_2|^2 \sigma_{eq}}{\left(|h_1|^2 + |h_2|^2\right)^2} = \frac{2\sigma_n^2}{|h_1|^2 + |h_2|^2}$$

$\rightarrow$ $\gamma_t = \frac{1}{2}\frac{E_s}{\sigma_n}\left(|h_1|^2 + |h_2|^2\right)$

$\rightarrow$ $\text{SNR}_{\text{Alamouti}} = \frac{1}{2}\text{SNR}_{\text{MRC}} = \frac{1}{2}\text{SNR}_{\text{MRT}}$

$\rightarrow$ Alamouti code has diversity gain $G_d = 2$

$\rightarrow$ Transmission with Alamouti STBC requires 3dB higher SNR to achieve same performance as MRT $\rightarrow$ 3dB loss in coding gain G_c

$\rightarrow$ Lack of CSI knowledge at transmitter "costs" 3dB in power efficiency

$\rightarrow$ General:

  $\cdot$ OSTBCs achieve a diversity gain of $G_d = N_T$ if only one receive antenna is available

  $\cdot$ if N_R receive antennas are available, MRC can be used at the receiver to yield a diversity gain of $\underline{G_d = N_T N_R}$

- Other STBCs:

- Quasi orthogonal STBCs

    * higher rate than OSTBCs

    * only subset of symbols have to be decoded jointly

    * Example: $K = N_T = T = 4$

$$\mathbf{X} = \frac{1}{2} \begin{pmatrix} s_1 & s_2 & s_3 & s_4 \\ -s_2^* & s_1^* & -s_4^* & s_3^* \\ -s_3^* & -s_4^* & s_1^* & s_2^* \\ s_4 & -s_3 & -s_2 & s_1 \end{pmatrix}$$

    * Anmerkung 1: $\mathbf{X}$ ist ähnlich zu Alamouti Code

    * Anmerkung 2: $\mathbf{X}^H \mathbf{X}$: viele Nicht-diagonal Elemente sind Null; die, die ungleich Null sind, zeigen, welche Symbole gemeinsam entschlüsselt werden müssen

- Golden Code for $N_T = N_R = 2$: achieves a rate of $R_{STBC} = 2$ and full diversity of $G_d = N_T, N_R = 4$

- Differential STBCs: $\mathbf{X}_k = \mathbf{X}_{k-1} \cdot \mathbf{D}_k$. $\mathbf{X}_k$ is transmitted, $\mathbf{D}_k$ is transmitted

- Linear dispersion codes: designed to achieve high mutual information

- noncoherent STBCs (On-Off-Keying)

2.3.3 Space Time Code Design

Given:

- Code $\mathscr{X} = \{\mathbf{X}_1, \ldots, \mathbf{X}_{|\mathscr{X}|}\}$
- Channel: IID Rayleigh-fading:

    - $h_n \sim \mathrm{C}\mathcal{N}(0, 1); \quad n \in \{1, 2, \ldots, N_T\}$
    - AWGN $n \sim \mathrm{C}\mathcal{N}(0, \sigma_n^2)$

Problem: How should we design codebook $\mathscr{X}$?

- Need to derive error rate for general codebooks $\mathscr{X}$!

    - Codeword error rate

$$P_e = \frac{1}{|\mathscr{X}|} \sum_{i=1}^{|\mathscr{X}|} \Pr\{\mathbf{x}_i \neq \hat{\mathbf{x}}_i\}$$

    where $\hat{\mathbf{x}}_i$ is the detected codeword and we assume that all codewords are equally likely

<u>Problem:</u> $\Pr\{\mathbf{x}_i \neq \hat{\mathbf{x}}_i\}$ is not tractable in general

- Use union bound to upper bound $\Pr\{\mathbf{x}_i \neq \hat{\mathbf{x}}_i\}$ as upper sum over <u>pairwise error probabilities</u>(PEP) $\Pr\{\mathbf{x}_i \to \mathbf{x}_j\}$ where it is assumed that $\mathbf{x}_i$ was transmitted and $\mathbf{x}_i$ and $\mathbf{x}_j$ are the only codewords in the codebook

$$\boxed{P_e \leq \frac{1}{|\mathscr{X}|} \sum_{i=1}^{|\mathscr{X}|} \sum_{j=1}^{|\mathscr{X}|} \Pr\{\mathbf{x}_i \to \mathbf{x}_j\} \text{ where } j \neq i}$$

<u>Calculation of PEPs</u>
Recall: $\hat{\mathbf{x}} = \underset{\mathbf{x}\in\mathscr{X}}{\operatorname{argmin}}||\mathbf{y} - \mathbf{xh}||^2$
Now, $\mathbf{x}_i$ and $\mathbf{x}_j$ are the only alternatives and an error is made if $||\mathbf{y} - \mathbf{x}_i\mathbf{h}||^2 > ||\mathbf{y} - \mathbf{x}_j\mathbf{h}||^2$
since $\mathbf{x}_i$ was sent but $\mathbf{x}_j$ was detected

$$\to ||\mathbf{x}_i\mathbf{h} + \mathbf{n} - \mathbf{x}_i\mathbf{h}||^2 > ||\mathbf{x}_i\mathbf{h} + \mathbf{n} - \mathbf{x}_j\mathbf{h}||^2$$
$$||\mathbf{n}|| > ||(\mathbf{x}_i - \mathbf{x}_j)\mathbf{h} + \mathbf{n}||^2$$
$$\to ||\mathbf{n}|| > \underbrace{\mathbf{h}^H(\mathbf{x}_i - \mathbf{x}_j)^H(\mathbf{x}_i - \mathbf{x}_j)\mathbf{h}}_{\Delta} + \mathbf{h}^H(\mathbf{x}_i - \mathbf{x}_j)\mathbf{n} + \mathbf{n}^H(\mathbf{x}_i - \mathbf{x}_j)\mathbf{h} + ||\mathbf{n}||^2$$

$$\to \underbrace{-\mathbf{h}^H(\mathbf{x}_i - \mathbf{x}_j)^H\mathbf{n} - \mathbf{n}^H(\mathbf{x}_i - \mathbf{x}_j)\mathbf{h}}_{z} > \Delta$$

for given $\mathbf{h}$, z is a gaussian random variable

$$\sigma_z^2 = \mathcal{E}\{|z|^2\} = \mathcal{E}\{2\mathbf{h}^H(\mathbf{x}_i - \mathbf{x}_j)\overbrace{\mathbf{nn}^H}^{\sigma_n^2\mathbf{I}}(\mathbf{x}_i - \mathbf{x}_j)\mathbf{h} + 2\mathbf{h}^H(\mathbf{x}_i - \mathbf{x}_j)^H\overbrace{\mathbf{nn}^T}^{=0}(\mathbf{x}_i - \mathbf{x}_j)^*\mathbf{h}^*\}$$
$$= 2\sigma_n^2\Delta + 0$$

$$\Pr\{\mathbf{x}_i \to \mathbf{x}_j\} = \int_{\Delta}^{\infty} \frac{1}{\sqrt{2\pi}\sigma_z}\exp\left(-\frac{z^2}{2\sigma_z^2}\right)\mathrm{d}z, \; t = \frac{z}{\sigma_z}$$

$$= \frac{1}{\sqrt{2\pi}}\int_{\frac{\Delta}{\sigma_z}}^{\infty} e^{-\frac{t^2}{2}}\mathrm{d}t = Q\left(\frac{\Delta}{\sigma_z}\right) = Q\left(\frac{\Delta}{\sqrt{2\sigma_n^2\Delta}}\right)$$

$$= Q\left(\sqrt{\frac{\Delta}{2\sigma_n^2}}\right)$$

- $\Pr\{\mathbf{x}_i \to \mathbf{x}_j\} = \mathcal{E}\left\{Q\left(\sqrt{\frac{\Delta}{2\sigma_n^2}}\right)\right\}$
  - to avoid cumbersome Q-function we use Chernoff bound:

$$\boxed{Q(x) \leq \frac{1}{2}e^{-\frac{x^2}{2}}}$$

$$\Pr\{\mathbf{x}_i \to \mathbf{x}_j\} \leq \frac{1}{2}\mathcal{E}_h\left\{\exp\left(-\frac{\mathbf{h}^H\mathbf{Q}\mathbf{h}}{4\sigma_n^2}\right)\right\}$$
$$\text{where } \mathbf{Q} = (\mathbf{x}_i - \mathbf{x}_j)^H(\mathbf{x}_i - \mathbf{x}_j)$$

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- Eigendecomposition: $\mathbf{Q} = \mathbf{U}^H \mathbf{\Lambda} \mathbf{U}$ with $\mathbf{\Lambda} = \mathrm{diag}\{\lambda_1, \ldots, \lambda_r, 0, \ldots, 0\}$ $\qquad r = \mathrm{rank}\{\mathbf{Q}\}$

- Elements $\mathbf{h}$ are i.i.d. Gaussian
    - $\underline{\beta} = \mathbf{U}\mathbf{h}$ has also i.i.d. Gaussian random variables as elements since $\mathbf{U}$ is unitary matrix
    - $\mathbf{h}^H \mathbf{Q} \mathbf{h} = \underbrace{\mathbf{h}^H \mathbf{U}^H}_{\underline{\beta}^*} \mathbf{\Lambda} \underbrace{\mathbf{U}\mathbf{h}}_{\underline{\beta}} = \sum_{i=1}^{r} \lambda_i |\beta_i|^2$ with $\underline{\beta} = [\beta_1, \ldots, \beta_{N_T}]$

$$
\begin{aligned}
\Pr\{\mathbf{x}_i \to \mathbf{x}_j\} &= \frac{1}{2}\mathcal{E}_{\underline{\beta}}\left\{ \exp\left(-\frac{\sum_{i=1}^{r} \lambda_i |\beta_i|^2}{4\sigma_n^2} \right) \right\} \\
&= \frac{1}{2}\mathcal{E}_{\underline{\beta}}\left\{ \prod_{i=1}^{r} e^{-\frac{\lambda_i}{4\sigma_n^2}|\beta_i|^2} \right\} \\
&= \frac{1}{2} \prod_{i=1}^{r} \mathcal{E}_{\beta_i}\left\{ e^{-\frac{\lambda_i}{4\sigma_n^2}|\beta_i|^2} \right\} \\
&= \frac{1}{2} \prod_{i=1}^{r} \mathcal{E}_{|\beta_i|^2}\left\{ e^{-\frac{\lambda_i}{4\sigma_n^2}|\beta_i|^2} \right\} \,\hat{=}\, \text{MGF of exponentially distributed variable } \alpha_i = |\beta_i|^2
\end{aligned}
$$

$\to P_{\alpha_i}(x) = e^{-x}, \; x \geq 0$

$$
\to \Pr\{\mathbf{x}_i \to \mathbf{x}_j\} \leq \frac{1}{2} \prod_{i=1}^{r} \frac{1}{1 + \frac{\lambda_i}{4\sigma_n^2}}
$$

$$
\leq \prod_{i=1}^{r} \frac{1}{\frac{\lambda_i}{4\sigma_n^2}} = 2^{2r-1} \frac{1}{\prod_{i=1}^{r} \lambda_i} \left(\underbrace{\frac{1}{\sigma_n^2}}_{\hat{=}SNR} \right)^{-r}
$$

- upper bound on P_e:

$$
\begin{aligned}
\lambda_n(i,j) &= n\text{th eigenvalue of } (\mathbf{x}_i - \mathbf{x}_j)^H (\mathbf{x}_i - \mathbf{x}_j) \\
r(i,j) &= \text{ rank of } (\mathbf{x}_i - \mathbf{x}_j)^H (\mathbf{x}_i - \mathbf{x}_j)
\end{aligned}
$$

$$
\to P_e \leq \frac{1}{|\mathscr{X}|} \sum_{i=1}^{|\mathscr{X}|} \sum_{j=1}^{|\mathscr{X}|} 2^{2r(i,j)-1} \frac{1}{\prod_{n=1}^{r(i,j)} \lambda_n(i,j)} \left(\frac{1}{\sigma_n^2} \right)^{-r(i,j)}
$$

- generally loose bound but offers significant insight for code design

<u>Two criteria:</u>

Rank criterion: The diversity gain of a ST code is given by
$$G_d = \min_{i,j}(r(i,j)) = \min_{i,j} \text{rank}\left((\mathbf{x}_i - \mathbf{x}_j)^H(\mathbf{x}_i - \mathbf{x}_j)\right)$$
$\rightarrow$ Design code such that minimum rank of all possible matrices $(\mathbf{x}_i - \mathbf{x}_j)^H(\mathbf{x}_i - \mathbf{x}_j)$ is maximized

$$T \updownarrow \overset{N_T}{\overleftrightarrow{\mathbf{X}_i}} \Rightarrow r(i,j) = N_T \qquad \forall i \neq j$$

Determinant criterion: To maximize the coding gain among all codes with $r(i,j) = N_T$, we need to maximize $\max \min_{i,j} \prod_{n=1}^{N_T} \lambda_n(i,j) = \max \min_{i,j} \left|(\mathbf{x}_i - \mathbf{x}_j)^H(\mathbf{x}_i - \mathbf{x}_j)\right| \qquad \forall i \neq j$

- Rank and determinant criterion can be used for the search for good space-time block codes and space-time trellis codes. These two criteria were first derived by Tarokh, et. al. 1998.

- diversity increases to $N_T N_R$ if N_K receive antennas are available

- Example: see Bäro, Bauch, Hansmann: Improved codes for space-time trellis coded modulation. IEEE Comm. Letters, 2000.

2.4 Partial or Imperfect CSI at the Transmitter

- In practice, the CSI cannot be perfect. Channel estimation, quantization and noisy feedback channels introduce errors.

- If the system is optimized for perfect CSI (*e.g.* using MRT or EGT), the performance for imperfect CSI may be worse than for a system designed for no CSI(*e.g.* space-time coding)

- In this case, it is advantageous to use a hybrid approach and combine beamforming and space-time coding.
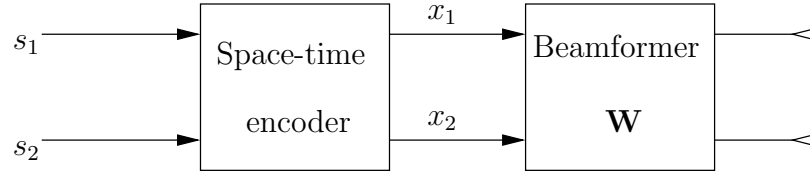
- $\mathbf{W}$ is the beamforming matrix which depends on the reliability of the CSI

- CSI is modeled as
$$\hat{h}_i = \rho h_i + \sqrt{1 - \rho^2} e_i$$
where:
  - $\hat{h}_i$ is the CSI estimate
  - ρ is the correlation between $\hat{h}_i$ and h_i

- e_i is the CSI error modeled as AWGN

extreme cases:

- $\rho = 0 : \hat{h}_i$ independent of $h_i \rightarrow$ no CSI ($\mathbf{W} = \mathbf{I}$)

- $\rho = 1 : \hat{h}_i = h_i \rightarrow$ perfect CSI ($\mathbf{W}$ performs MRT)

- $\mathbf{W}$ can be optimized under the assumptions for given ρ and $\hat{h}_i$
  $\rightarrow$ see for details: Jöngren, Skorglund and Ottersten: "Combining Beamforming and Orthogonal Space-time Block Coding", IEEE on IT, 2002.

3 MIMO Systems without CSI at the transmitter

- We consider $N_T \times N_R$ MIMO system and assume that the channel matrix $\mathbf{H}$ is not known at the transmitter
  $\rightarrow$ no CSI at the transmitter (CSIT)

- signal model:

$$N_R \updownarrow \mathbf{y} = N_R \updownarrow \overset{\overset{N_T}{\longleftrightarrow}}{\mathbf{H}} \mathbf{x} \updownarrow N_T + \mathbf{n} \updownarrow N_R$$
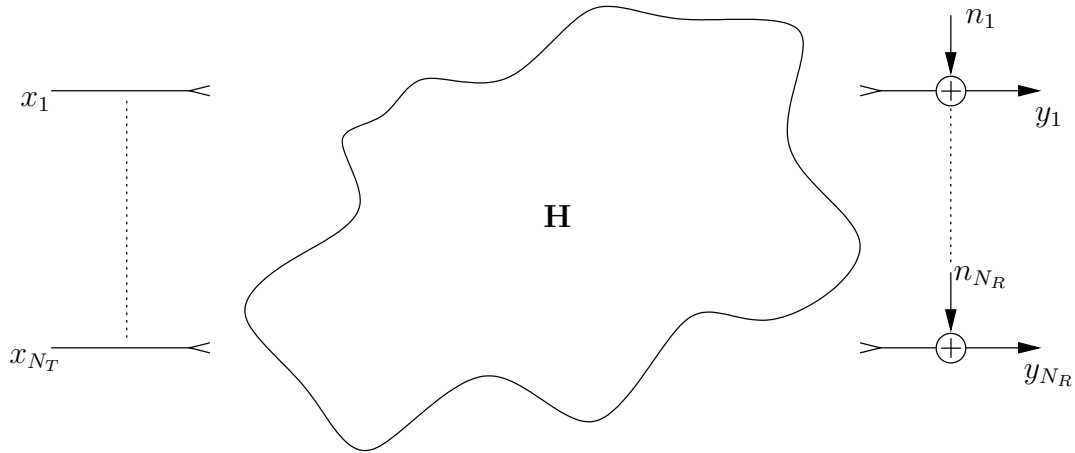
- x_n are M-ary i.i.d. scalar symbols taken $e.g$ from an M-PSK or M-QAM symbol alphabet $\mathscr{A}$

- This scheme is often called "spatial multiplexing"

- We transmit N_T symbols per symbol interval
  $\rightarrow$ rate $R = \log_2(M) \cdot N_T$ for uncoded transmission

- Problem: How to detect $\mathbf{x}$ at the receiver considering

  - performance

  - complexity

3.1 Optimum Detection

- Elements of $\mathbf{n}$ are gaussian random variables with variance σ_n^2

- $\mathbf{H}$ is known at the receiver

$$p(\mathbf{y}|\mathbf{x}) = \frac{1}{\pi^{N_R}\sigma_n^2 \mathbf{I}_{N_R \times N_R}} \exp\left(-(\mathbf{y}-\mathbf{Hx})^H (\sigma_n^2 \mathbf{I}_{N_R \times N_R})^{-1}(\mathbf{y}-\mathbf{Hx})\right)$$

$$= \frac{1}{\pi^{N_R}\sigma_n^{2N_R}} \exp\left(-\frac{1}{\sigma_n^2}||\mathbf{y}-\mathbf{xH}||^2\right)$$

- ML-Detection

$$\hat{x} = \operatorname*{argmin}_{\mathbf{x}\in\mathscr{A}^{N_T}}||\mathbf{y}-\mathbf{xH}||^2 = \operatorname*{argmax}_{\mathbf{x}\in\mathscr{A}^{N_T}} \; p(\mathbf{y}|\mathbf{x})$$

  $\rightarrow M^{N_T}$ metric calculations $\rightarrow$ complexity is exponential in N_T!!

  $\rightarrow$ in general too complex in practice

- Performance

  - consider worst case pairwise error probability (PEP) to evaluate <u>diversity gain</u>

  - PEP $\rightarrow x_i$ is transmitted but $x_j \neq x_i$ is detected
    this happens if $||\mathbf{y}-\mathbf{Hx}_i||^2 > ||\mathbf{y}-\mathbf{Hx}_j||^2$
    $\rightarrow ||\mathbf{n}||^2 > ||\mathbf{H}(\mathbf{x}_i - \mathbf{x}_j) + \mathbf{n}||^2$

  - the "worst case" is if $\mathbf{x}_i$ & $\mathbf{x}_j$ differ only in one element $i.e.,$

$$\mathbf{x}_i - \mathbf{x}_j = (x_{ni} - x_{nj}) = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \\ 0 \end{bmatrix} \leftarrow \text{"1" in position } n$$

  where $\mathbf{x}_i = [x_{1i}, x_{2i}, \ldots, x_{N_T i}]$

  - $||\mathbf{n}||^2 > || \underbrace{\mathbf{h}_n}_{n\text{th column of } \mathbf{H}} \underbrace{(x_{ni} - x_{nj})}_{\Delta x_n(i,j)} + \mathbf{n}||^2$

  - $||\mathbf{n}||^2 > \mathbf{h}_n^H \mathbf{n}\Delta x_n^*(i,j) + \mathbf{n}^H \mathbf{h}_n \Delta x_n(i,j) + ||\mathbf{n}||^2 + ||\mathbf{h}_n||^2 - |\Delta x_n(i,j)|^2$

    $||\mathbf{h}_n||^2|\Delta x_n(i,j)|^2 < \underbrace{-\mathbf{h}_n^H \mathbf{n}\Delta x_n(i,j) - \mathbf{n}^H \mathbf{h}_n \Delta x_n(i,j)}_{\text{Gaussian random variable with variance } \sigma_{eq}^2 = 2\sigma_n^2|\Delta x_n(i,j)|^2||\mathbf{h}_n||^2}$

  - $\Pr\{\mathbf{x}_i \rightarrow \mathbf{x}_j || \mathbf{H}\} = Q\left(\sqrt{\frac{||\mathbf{h}_n||^2|\Delta x_n(i,j)|^2}{2\sigma_n^2}}\right)$

– $\Pr\{\mathbf{x}_i \to \mathbf{x}_j\} = \mathcal{E}\left\{Q\left(\sqrt{\frac{||\mathbf{h}_n||^2|\Delta x_n(i,j)|^2}{2\sigma_n^2}}\right)\right\}$

$\to$ use same approach as for space-time code design to get diversity order
or : SNR is

$$\gamma_t = \frac{||\mathbf{h}_n||^2|\Delta x_n(i,j)|^2}{2\sigma_n^2} = \frac{|\Delta x_n(i,j)|^2}{2\sigma_n^2}(|h_{1n}|^2 + |h_{2n}^2 + \cdots + |h_{N_R n}|^2)$$

– same form as SNR of MRC with N_R receive antennas

– diversity gain of spatial multiplexing wit ML-decoding is

$$G_d = N_R$$

– diversity of N_T transmit antennas is not exploited with spatial multiplexing

– to exploit this additional gain, coding across space is required (at the expense of rate)
(Hier gehören die detection performance kurven für BPSK hin)

3.2 Linear Receivers

- How can we avoid the complexity associated wit the joint detection of the elements of $\mathbf{x}$?

- Idea: Employ linear filter (matrix) to seperate the elements of $\mathbf{x}$

- Requires: $N_T \leq N_R$

- We form

$$\mathbf{r} = N_T \updownarrow \overset{\overset{N_R}{\longleftrightarrow}}{\mathbf{F}} \mathbf{y} = [r_1, \ldots, r_{N_T}]^T$$
where $\mathbf{F}$ is the filter matrix and $\mathbf{y}$ is the received vector

such that x_n can be obtained from

$$\hat{x}_n = \underset{x_n \in \mathscr{A}}{\operatorname{argmin}} |r_i - x_n|^2 \qquad\qquad \text{where } \mathbf{F} \in \mathbb{C}^{N_T \times N_R}$$

- Two popular design criteria for $\mathbf{F}$
    – Zero-forcing (ZF) criterion
    – minimum mean squared error (MMSE) crtiterion

3.2.1 ZF Detection

$$\mathbf{r} = \mathbf{F}\mathbf{y} = \mathbf{F}(\mathbf{H}\mathbf{x} + \mathbf{n}) = \mathbf{F}\mathbf{H}\mathbf{x} + \mathbf{F}\mathbf{n}$$

ZF $\leftrightarrow$ we require $\mathbf{F}\mathbf{H} = \mathbf{I}_{N_T \times N_T}$

- noise covariance matrix

$$\Phi_{ee} = \mathcal{E}\{\mathbf{Fn}(\mathbf{Fn})^H\} = \sigma_n^2 \mathbf{FF}^H$$

- $N_T = N_R \rightarrow \mathbf{FH} = \mathbf{I}_{N_T \times N_T} \rightarrow \mathbf{F} = \mathbf{H}^{-1}$ assuming $\mathbf{H}$ is invertible

- $\rightarrow N_T \leq N_R \rightarrow$ which one of the many $\mathbf{F}$ that yield $\mathbf{FH} = \mathbf{I}_{N_T \times N_T}$?

- choose $\mathbf{F}$ that leads to the smallest noise enhancement

- optimal $\mathbf{F}$ is the solution to the following problem:

$$\min_{\mathbf{F}} \text{tr}\{\sigma_n^2 \mathbf{FF}^H\}$$

$$\text{s.t } \mathbf{FH} = \mathbf{I}_{N_T \times N_T}$$

the constraint is equivalent to $\text{tr}\{(\mathbf{FH} - \mathbf{I})(\mathbf{FH} - \mathbf{I})^H\} = 0$

Lagrangian:

$$L(\mathbf{F}) = \text{tr}\{\sigma_n^2 \mathbf{FF}^H\} + \lambda \text{tr}\{\mathbf{FHH}^H\mathbf{F} - \mathbf{FH} - \mathbf{H}^H\mathbf{F}^H + \mathbf{I}\}$$
$$= \sigma_n^2 \text{tr}\{\mathbf{FF}^H\} + \lambda \text{tr}\{\mathbf{FHH}^H\mathbf{F}^H\} - \lambda \text{tr}\{\mathbf{FH}\} - \lambda \text{tr}\{\mathbf{H}^H\mathbf{F}^H\} + \lambda N_T$$

- use rules for complex matrix differentiation in Table IV in paper by Hjörunges & Gesbert

$$\frac{\delta L(\mathbf{F})}{\delta \mathbf{F}^*} = \sigma_n^2 \mathbf{F} + \lambda \mathbf{FHH}^H - \lambda \mathbf{H}^H = 0$$

$$\rightarrow \mathbf{F}(\sigma_n^2 \mathbf{I} + \lambda \mathbf{HH}^H) = \lambda \mathbf{H}^H$$

$$\rightarrow \mathbf{F} = \lambda \mathbf{H}^H(\sigma_n^2 \mathbf{I} + \lambda \mathbf{HH}^H)^{-1}$$

use matrix inversion lemma

$$(\mathbf{A} + \mathbf{UBV})^{-1} = \mathbf{A}^{-1} - \mathbf{A}^{-1}\mathbf{U}(\mathbf{B}^{-1} + \mathbf{VA}^{-1}\mathbf{U})^{-1}\mathbf{VA}^{-1}$$

$$\rightarrow \mathbf{F} = \lambda \mathbf{H}^H \left[\frac{1}{\sigma_n^2}\mathbf{I} - \frac{1}{\sigma_n^2}\mathbf{H}\left[\frac{1}{\lambda}\mathbf{I} + \frac{1}{\sigma_n^2}\mathbf{H}^H\mathbf{H}\right]^{-1}\mathbf{H}^H \frac{1}{\sigma_n^2}\right]$$

$$= \frac{\lambda}{\sigma_n^2}\left[\underbrace{\mathbf{I}}_{\left(\frac{1}{\lambda}\mathbf{I}+\frac{1}{\sigma_n^2}\mathbf{H}^H\mathbf{H}\right)\left(\frac{1}{\lambda}\mathbf{I}+\frac{1}{\sigma_n^2}\mathbf{H}^H\mathbf{H}\right)^{-1}} - \frac{1}{\sigma_n^2}\mathbf{H}^H\mathbf{H}\left[\frac{1}{\lambda}\mathbf{I} + \frac{1}{\sigma_n^2}\mathbf{H}^H\mathbf{H}\right]\right]\mathbf{H}^H$$

$$= \frac{\lambda}{\sigma_n^2}\left[\frac{1}{\lambda}\mathbf{I} + \frac{1}{\lambda}\mathbf{H}^H\mathbf{H} - \frac{1}{\sigma_n^2}\mathbf{H}^H\mathbf{H}\right]\left(\frac{1}{\lambda}\mathbf{I} + \frac{1}{\sigma_n^2}\mathbf{H}^H\mathbf{H}\right)^{-1}\mathbf{H}^H$$

$$= \frac{1}{\sigma_n^2}\left(\frac{1}{\lambda}\mathbf{I} + \frac{1}{\sigma_n^2}\mathbf{H}^H\mathbf{H}\right)\mathbf{H}^H$$

- How to choose λ

$$\mathbf{FH} = \frac{1}{\sigma_n^2}\left(\frac{1}{\lambda}\mathbf{I} + \frac{1}{\sigma_n^2}\mathbf{H}^H\mathbf{H}\right)^{-1}\mathbf{H}^H\mathbf{H} = \mathbf{I}$$

$$\frac{1}{\sigma_n^2}\mathbf{H}^H\mathbf{H} = \frac{1}{\lambda}\mathbf{I} + \frac{1}{\sigma_n^2}\mathbf{H}^H\mathbf{H}$$

$$\Rightarrow \lambda \rightarrow \infty$$

$$\Rightarrow \boxed{\mathbf{F} = (\mathbf{H}^H \mathbf{H})^{-1}} \,\widehat{=}\, \text{Moore-Penrose pseudoinverse}$$

noise covariance:

$$\Phi_{ee} = \sigma_n^2 \mathbf{F}\mathbf{F}^H = \sigma_n^2 (\mathbf{H}^H \mathbf{H})^{-1} \underbrace{\mathbf{H}^H \mathbf{H}(\mathbf{H}\mathbf{H})^{-1}}_{\mathbf{I}} = \sigma_n^2 (\mathbf{H}^H \mathbf{H})^{-1}$$

Φ_{ee} is not in general a diagonal matrix

- effective noise $\mathbf{F}\mathbf{n}$ is spatially correlated
- "equalization of channel leads to coloring of noise

- Interpretation:
  we have

$$\mathbf{F}\mathbf{H}\mathbf{x} = \begin{bmatrix} \mathbf{f}_1 \\ \mathbf{f}_2 \\ \vdots \\ \mathbf{f}_{N_T} \end{bmatrix} \begin{bmatrix} \mathbf{h}_1 & \mathbf{h}_2 & \dots & \mathbf{h}_{N_T} \end{bmatrix} \mathbf{x} = \mathbf{x}$$

- $\mathbf{f}_i \mathbf{h}_i = 1 \quad \mathbf{f}_i \mathbf{h}_j = 0 \quad \forall i \neq j$
- $\mathbf{f}_i^T$ is orthogonal to $\begin{bmatrix} \mathbf{h}_1 & \dots \mathbf{h}_{i-1} & \mathbf{h}_{i+1} & \dots & \mathbf{h}_{N_T} \end{bmatrix} \updownarrow N_R$
- $\mathbf{f}_i^T$ is confined to an $N_R - (N_T - 1)$ dimensional subspace of the N_R dimensional space spanned by $\mathbf{H}$

- Diversity gain
  - e.g. SISO model: $r_i = \mathbf{f}_i \cdot \mathbf{h}_i \mathbf{x}_i + \mathbf{f}_i \cdot \mathbf{n}_i$

    $\rightarrow \text{SNR}_{\text{eq}} = \frac{\epsilon_s |\mathbf{f}_i \mathbf{h}_i|^2}{\sigma_n^2 \|\mathbf{f}_i\|^2} = \frac{\epsilon_s}{\sigma_n^2} \left| \tilde{\mathbf{f}}_i \cdot \mathbf{h}_i \right|, \quad \text{where } \mathbf{f}_i = \alpha \mathbf{f}_i \text{ with } \|\tilde{\mathbf{f}}_i\|^2 = 1$

    we can represent $\mathbf{f}_i$ as: $\tilde{\mathbf{f}}_i^T = \alpha \mathbf{M}\boldsymbol{\beta}$,

    where: $\mathbf{M} \in \mathbb{C}^{N_R \times (N_R - N_T + 1)}$ and $\boldsymbol{\beta} \in \mathbb{C}^{(N_R - N_T + 1) \times 1} \,\widehat{=}\,$ basis of subspace

    $\rightarrow \tilde{\mathbf{f}}_i \mathbf{M}_i = \boldsymbol{\beta}^T \mathbf{M}_i^T \mathbf{M}_i$,

    where: $\mathbf{M}^H \mathbf{M} = \tilde{\mathbf{M}}_i = \mathbf{I}$ and $\tilde{\mathbf{M}}_i \rightarrow \mathcal{CN}(0, \sigma_n^2 \mathbf{I}_{(N_R - N_T + 1)})$

    (since rows of $\mathbf{M}^T$ are orthogonal)

$$\text{SNR}_{\text{eq}} = \frac{\epsilon_s}{\sigma_n^2} \alpha^2 \left| \sum_{j=1}^{N_R - N_T + 1} \boldsymbol{\beta}_{ji} \tilde{\mathbf{h}}_j i \right|^2 ; \tilde{\mathbf{h}}_i = \begin{pmatrix} \tilde{h}_{1i}, & \tilde{h}_{2i}, & \dots, & \tilde{h}_{N_R - N_T + 1} \end{pmatrix}^T$$

$$\boldsymbol{\beta}_i = \begin{pmatrix} \beta_{1i}, & \dots, & \beta_{N_R - N_T + 1, i} \end{pmatrix}^T$$

  - $\rightarrow \text{SNR}_{\text{eq}}$ includes only $N_R - N_T + 1$ independent Gaussian RV
  - $\rightarrow$ diversity gain is limited to: $\underline{G_d = N_R - N_T + 1}$

Example:

$$N_T = N_R = 3$$
$$G_d^{ZF} = 1 \text{ but } G_d^{ML} = N_R = 3$$

$\rightarrow$ huge performance loss because of linear ZF

3.2.2   MMSE detection

- ZF criterion may be too strict and leads to noise enhancement
    - $\rightarrow$ maybe it is better to allow some interferences between signals but reduce noise enhancement
    - $\rightarrow$ What is the optimal trade-off between interference and noise?
    - $\rightarrow$ MMSE criterion
- MMSE criterion
    - error signal: $\mathbf{e} = \mathbf{Fy} - \mathbf{x}$
    - total error variance: $\sigma_e^2 = \mathcal{E}\{\|\mathbf{e}\|^2\} = \mathcal{E}\{\mathrm{tr}\{\mathbf{ee}^H\}\} = \mathrm{tr}\{\mathcal{E}\{\mathbf{ee}^H\}\} = \mathrm{tr}\{\Phi_{ee}\}$
    - Φ_{ee}: error covariance matrix
    - optimal filter: $\mathbf{F}_{\mathrm{opt}} = \underset{\mathbf{F}}{\mathrm{argmin}}\, \mathrm{tr}\{\Phi_{ee}\}$
- Deviation of $\mathbf{F}_{\mathrm{opt}}$
    - $\Phi_{ee} = \mathcal{E}\{\mathbf{ee}^H\} = \mathcal{E}\{(\mathbf{Fy}-\mathbf{x})(\mathbf{Fy}-\mathbf{x})^H\} = \mathbf{F}\cdot\Phi_{yy}\cdot\mathbf{F}^H - \mathbf{F}\cdot\Phi_{yx} - \Phi_{xx}\cdot\Phi_{xy}\cdot\mathbf{F}^H + \Phi_{xx}$

    with:

    $$\Phi_{yy} = \mathcal{E}\{\mathbf{yy}^H\} = \mathcal{E}\{(\mathbf{Hx}+\mathbf{n})(\mathbf{Hx}+\mathbf{n})^H\} = \epsilon_s \cdot \mathbf{HH}^H + \sigma_n^2 \cdot \mathbf{I}_{N_R \times N_T}$$
    $$\Phi_{yx} = \mathcal{E}\{\mathbf{yx}^H\} = \mathcal{E}\{(\mathbf{Hx}+\mathbf{n})\cdot\mathbf{x}^H\} = \epsilon_s \cdot \mathbf{H}^H = \Phi_{xy}^H$$
    $$\Phi_{xx} = \epsilon_s \cdot \mathbf{I}_{N_T \times N_R}$$

    - $\mathbf{F}_{\mathrm{opt}} \quad \rightarrow \quad \frac{d}{d\mathbf{F}^*}\Big(\mathrm{tr}\{\mathbf{F}\Phi_{yy}\mathbf{F}^H\} - \mathrm{tr}\{\mathbf{F}\Phi_{yx}\} - \mathrm{tr}\{\Phi_{xy}\mathbf{F}^H\} + \mathrm{tr}\{\Phi_{xx}\}\Big) \stackrel{!}{=} 0$

    with Table IV in paper by Hjoranges & Gesbert:

    $\Rightarrow \mathbf{F}\cdot\Phi_{yy} - \Phi_{xy} = 0$

    $\Rightarrow \mathbf{F}_{\mathrm{opt}} = \Phi_{xy}\cdot\Phi_{yy}^{-1} = \epsilon_s\mathbf{H}^H\big(\epsilon_s\mathbf{HH}^H + \sigma_n^2\mathbf{I}\big)^{-1}$

    $\phantom{\Rightarrow \mathbf{F}_{\mathrm{opt}}} = \text{(Matrix inversion Lemma)} =$

    $\phantom{\Rightarrow \mathbf{F}_{\mathrm{opt}}} = \big(\mathbf{H}^H\mathbf{H} + \frac{\sigma_n^2}{\epsilon_s}\mathbf{I}\big)^{-1}\cdot\mathbf{H}^H$

    - Comparison:

    $$\mathbf{F}_{\mathrm{MMSE}} = \big(\mathbf{H}^H\mathbf{H} + \frac{\sigma_n^2}{\epsilon_s}\mathbf{I}\big)^{-1}\cdot\mathbf{H}^H \xrightarrow[\frac{\sigma_n^2}{\epsilon}\to 0]{} \big(\mathbf{H}^H\cdot\mathbf{H}\big)^{-1}\mathbf{H}^H = \mathbf{F}_{ZF}$$

    $$\xrightarrow[\frac{\sigma_n^2}{\epsilon_s}\to\infty]{} \frac{\epsilon_s}{\sigma_n^2}\cdot\mathbf{H}^H = \mathbf{F}_{MF} \quad \widehat{=}\text{matched filter}$$

$\Rightarrow$ For high SNR, $\frac{\epsilon_s}{\sigma_n^2}$, the MMSE filter approaches the ZF-Filter, for low SNR, it approaches the matched filter.

$\rightarrow$ MMSE receiver yields the same diversity gain as the ZF receiver

$$G_d^{MMSE} = G_d^{ZF} = N_R - N_T + 1 \leq G_d^{ML} = N_R$$

- End-to-End Channel: $\mathbf{K} = \mathbf{F}\mathbf{H} = \left(\mathbf{H}^H\mathbf{H} + \frac{\sigma_n^2}{\epsilon_s} \cdot \mathbf{I}\right)^{-1} \cdot \mathbf{H}^H \cdot \mathbf{H} \neq$ diagonal matrix

  $\Rightarrow$ crosstalk/interference between elements $\mathbf{x}$ in received signal after filtering $\mathbf{r}$.

  elements of $\mathbf{K} : K_{l,n}$

- Covariance for $\mathbf{F}_{\text{opt}}$

$$\mathbf{\Phi}_{ee} = \mathbf{\Phi}_{xy} \cdot \overbrace{\mathbf{\Phi}_{yy}^{-1} \cdot \mathbf{\Phi}_{yy} \cdot \mathbf{\Phi}_{yy}^{-1}}^{\mathbf{\Phi}_{yy}^{-1}} \cdot \mathbf{\Phi}_{xy}^H - \mathbf{\Phi}_{xy} \cdot \mathbf{\Phi}_{yy}^{-1} \cdot \mathbf{\Phi}_{yx} - \mathbf{\Phi}_{xy} \cdot \mathbf{\Phi}_{yy}^{-1} \cdot \mathbf{\Phi}_{xy}^H + \mathbf{\Phi}_{xx}$$

$$= \mathbf{\Phi}_{xx} - \overbrace{\mathbf{\Phi}_{xy} \cdot \mathbf{\Phi}_{yy}^{-1}}^{\mathbf{F}_{\text{opt}}} \cdot \mathbf{\Phi}_{yx}$$

$$= \epsilon_s\mathbf{I} - \epsilon_s\left(\mathbf{H}^H\mathbf{H} + \frac{\sigma_n^2}{\epsilon_s} \cdot \mathbf{I}\right)^{-1} \cdot \mathbf{H}^H\mathbf{H} = \text{(Matrix inversion Lemma)}$$

$$= \sigma_n^2\left(\mathbf{H}^H\mathbf{H} + \frac{\sigma_n^2}{\epsilon_s} \cdot \mathbf{I}\right)^{-1}$$

$$\mathbf{\Phi}_{ee} = \epsilon_s(\mathbf{I} - \mathbf{K})$$

$\rightarrow$ $0 \leq K_{m,m} \leq 1$ since main diagonal elements of $\mathbf{\Phi}_{ee}$ are $0 \leq [\mathbf{\Phi}_{ee}]_{m,m} \leq \epsilon_s$

siehe auch Abbildung 1

3.2.3 SNR (biased vs. unbiased)

a) biased SNR

$$\text{SNR}_{\text{bias,m}} = \frac{\epsilon_s}{[\mathbf{\Phi}_{ee}]_{mm}} = \frac{\epsilon_s}{\epsilon_s(1 - K_{mm})} = \frac{1}{1 - K_{mm}}, \quad 1 \leq m \leq 4$$

Anmerkung: $\mathbf{K} = \mathbf{F}_{\text{opt}} \cdot \mathbf{H} \rightarrow \text{SNR} = 1$ *falls* $\mathbf{K} = \text{zeros}() \Rightarrow$ woher SNR $= 1$ *bei keiner Uebertragung?* $\Rightarrow$ *nicht vorteilhaft: siehe: b) unbiased SNR* but:

- $\text{SNR}_{\text{bias,m}}$ does not represent the actual SNR since the main diagonal elements of $\mathbf{K}$ are smaller than 1

- $\mathbf{r} = \mathbf{F}\mathbf{H}\mathbf{x} + \mathbf{F}\mathbf{n} = \mathbf{K}\mathbf{x} + \underbrace{\mathbf{F}\mathbf{n}}_{\tilde{\mathbf{n}}=[\tilde{n}_1,...,\tilde{n}_{N_T}]^T}$

- $r_m = \underbrace{K_{mm}}_{<1}x_m + \sum\limits_{\substack{n=1 \\ n \neq m}}^{N_T} K_{mn}x_n + \tilde{n}_m$
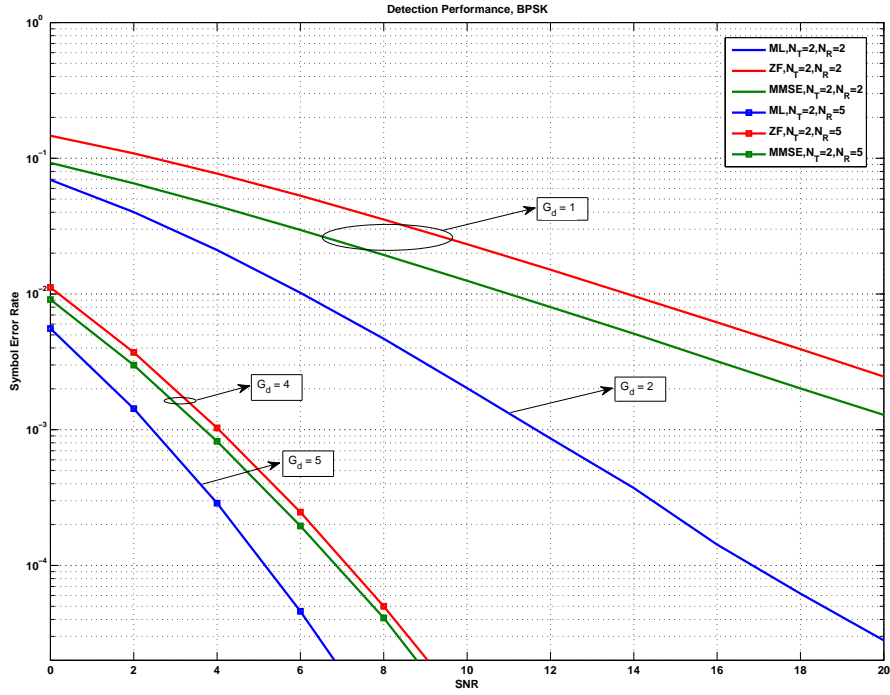
Figure 1: MMSE

b) unbiased SNR

- remove bias: $r'_m = \dfrac{r_m}{K_{mm}} = x_m + \underbrace{\dfrac{\tilde{e}_m}{K_{mm}}}_{e'_m}$

- SNR?

- scaling matrix: $\mathbf{C} = \operatorname{diag}\left\{\frac{1}{K_{11}}, \frac{1}{K_{22}}, \ldots, \frac{1}{K_{N_T N_T}}\right\}$

- $\mathbf{r'} = \mathbf{Cr} \rightarrow \mathbf{e'} = [e'_1, \ldots, e'_{N_T}]^T = \mathbf{r'} - \mathbf{x} = \mathbf{Cr} - \mathbf{x} = \mathbf{CFy} - \mathbf{x}$

- $\boldsymbol{\Phi}_{e'e'} = \mathcal{E}\left\{(\mathbf{CFy} - \mathbf{x})(\mathbf{CFy} - \mathbf{x})^H\right\} = \mathbf{CF}\boldsymbol{\Phi}_{yy}\mathbf{F}^H\mathbf{C}^H - \mathbf{CF}\boldsymbol{\Phi}_{yx} - \boldsymbol{\Phi}_{xy}\mathbf{F}^H\mathbf{C}^H + \boldsymbol{\Phi}_{xx}$

- $\mathbf{F} = \mathbf{F}_{\mathrm{opt}} \rightarrow \mathbf{F}_{\mathrm{opt}}\boldsymbol{\Phi}_{yy} = \boldsymbol{\Phi}_{xy} = \epsilon_s \cdot \mathbf{H}^H$

$\rightarrow \boldsymbol{\Phi}_{e'e'} = \epsilon_s \mathbf{C}\underbrace{\mathbf{H}^H\mathbf{F}^H}_{\mathbf{K}^H}\mathbf{C}^H - \epsilon_s\mathbf{C}\underbrace{\mathbf{FH}}_{\mathbf{K}} - \epsilon_s\underbrace{\mathbf{H}^H\mathbf{F}^H}_{\mathbf{K}^H}\mathbf{C} + \epsilon_s\mathbf{I}$

$= \epsilon_s\big[\mathbf{I} + (\mathbf{C} - \mathbf{I})\mathbf{K}^H\mathbf{C}^H - \mathbf{CK}\big]$

Anmerkung: nur Hauptdiagonalelemente interessieren, da diese die Varianz darstellen

$\rightarrow$ maindiagonal elements of $\boldsymbol{\Phi}_{e'e'}$ = variances of $e'_m \quad = \epsilon_s\Big(1 + \big(\frac{1}{K_{mm}} - 1\big)K_{mm}\frac{1}{K_{mm}} - \frac{1}{K_{mm}}K_{mm}\Big) = \epsilon_s\frac{1-K_{mm}}{K_{mm}}$

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$\rightarrow$ vgl. Abbildung 1

$\rightarrow SNR_{unbiased} = \dfrac{E_s}{[\boldsymbol{\Phi}_{e'e'}]_{mm}} = \dfrac{E_s}{E_s \dfrac{1 - K_{mm}}{K_{mm}}} = \dfrac{K_{mm}}{1 - K_{mm}}, \quad 1 \le m \le N_T$

$\rightarrow$ the SNR after bias removal is by "1" smaller than the biased SNR $\rightarrow$ general result valid for any type of MMSE estimation

3.3 Decision - Feadback Equalization (Detection)

- Also known as:

    - BLAST (Bell Laboratories space-time system)

    - successive interference cancellation

- Problem of linear receiver: Noise enhancementbecause of linear filtering $\rightarrow$ nonlinear filtering processing necessary

3.3.1 Basic Idea

- Recall (linear filter): $\mathbf{FH} = \mathbf{I}$ for linear ZF receiver $\rightarrow$ ith row of $\mathbf{F}, \mathbf{f}_i$, is orthogonal to the jth column of $\mathbf{H}, \mathbf{h}_j$, if $i \ne j$ (if $i = j$: inner product $= 1$)

- we can detect x_i, based on $r_i = \mathbf{f}_i \mathbf{y}$

- Once we have detected x_i, we can substract its contribution from $\mathbf{y}$: $\mathbf{y}_1 = \mathbf{y} - \mathbf{h}_i \hat{x}_i$ ($\hat{x}_i$ is detected symbol, we assume for now, $\hat{x}_i = x_i$)

- $\mathbf{y}_1$ can be expressed as $\mathbf{y}_1 = \mathbf{H}_i \mathbf{x}_i + \mathbf{n}$ where

$$\mathbf{H}_i = \begin{bmatrix} \mathbf{h}_1, \ldots, \mathbf{h}_{i-1}, \mathbf{h}_{i+1}, \ldots, \mathbf{h}_{N_T} \end{bmatrix}$$
$$\mathbf{x}_i = \begin{bmatrix} x_1, \ldots, x_{i-1}, x_{i+1}, \ldots, x_{N_T} \end{bmatrix}$$

    $\rightarrow$ we have reduced the number of signal streams to $N_T - 1$ (N_R bleibt gleich)

- apply now linear ZF filter for symbol to detected next, e.g. x_j, where $j \in \{1, \ldots, i-1, i+1, \ldots, N_T\}$

$\rightarrow$ $\mathbf{r}_j = \mathbf{f}_j \mathbf{y}_1$ where $\mathbf{f}_j$ is the ZF filter for $\mathbf{H}_1$

- substract contribution of x_j from $\mathbf{y}_1$: $\mathbf{y}_2 = \mathbf{y}_1 - \mathbf{h}_j x_j$

- substract until last symbol is detected

- Blockdiagram see figure2

- Observations:

    - The order in which the x_1 are detected can be freely chosen and effects the performance $\rightarrow$ $N_T!$ possible orders $\rightarrow$ cannot explore all of them

    - Practical approach: Select in each step that x_i for which the noise variance enhancement is minimum, i.e. which has the smallest $\mathcal{E}\left\{|\mathbf{f}_i \mathbf{n}|^2\right\} = \sigma_n^2 \|\mathbf{f}_i\|^2$
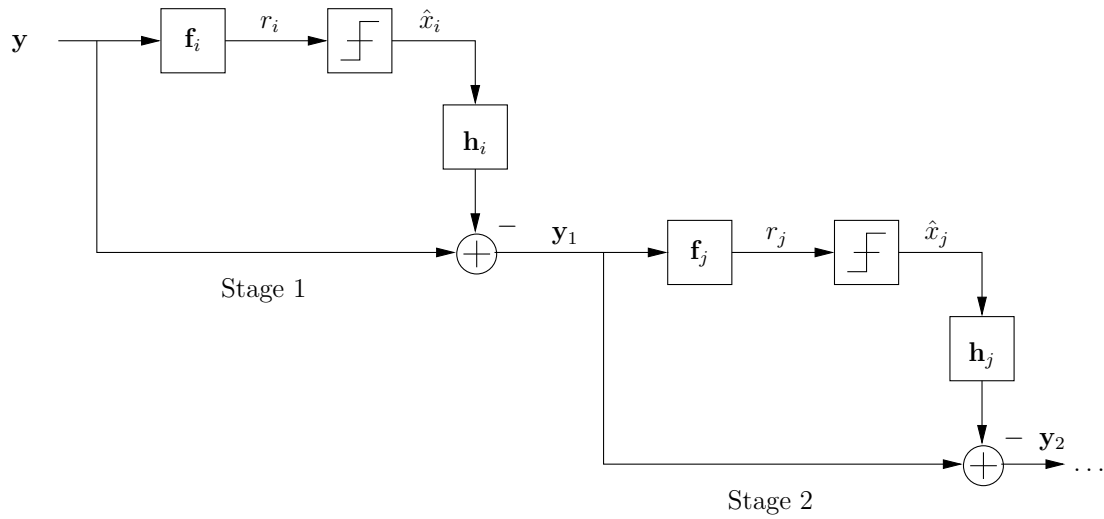
Figure 2: DFE Blockdiagram

- Diversity order:
  - stage 1: $G_d^1 = N_R - N_T + 1$
  - stage 2: $G_d^2 = G_d^1 + 1 = N_R - N_T + 2$

    $\vdots$

  - stage N_T: $G_d^{N_T} = N_R$
  - overall: $\underline{G_d = N_R - N_T + 1}$
  - *(Anmerkung: der schlechteste Fall dominiert (Stage 1), weitere koennen nur schwer beeinflussen)*

3.3.2 ZF - DFE - Matrix Model

- Signal model: $\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n} = \underbrace{\mathbf{H}\mathbf{P}}_{\tilde{\mathbf{H}}} \cdot \underbrace{\mathbf{P}^{-1}\mathbf{x}}_{\tilde{\mathbf{x}}} + \mathbf{n}$ with permutation matrix $\mathbf{P}$

- $\mathbf{P}$ has one „1" per column and row, all other elements are „0"

$\rightarrow$ can change the detection order to maximize performance

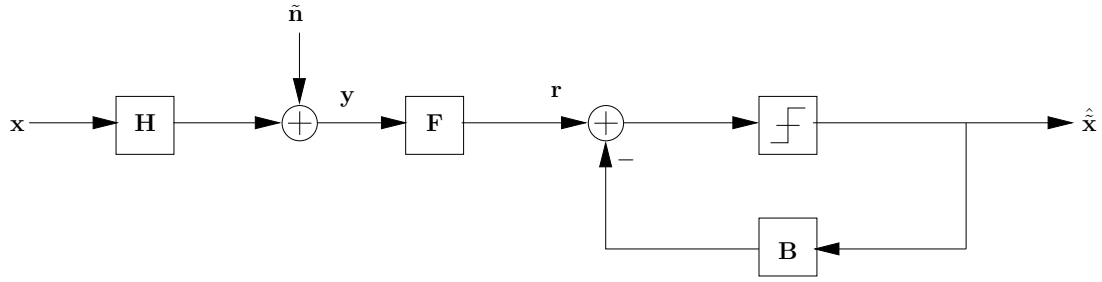- note: $\mathbf{P}^T = \mathbf{P}^{-1}$

Figure 3: ZF-DFE Matrix Model

- Example:

$$\mathbf{P} = \begin{pmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} [r] \rightarrow \mathbf{P}^{-1} = \mathbf{P}^T = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{pmatrix}$$

$$\tilde{\mathbf{x}} = \mathbf{P}^T \cdot \mathbf{x} = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} x_2 \\ x_3 \\ x_1 \end{pmatrix}$$

- Blockdiagram see figure 3

- DFE Filters:

  - $\mathbf{F}$ feedworward filter

  - $\mathbf{B}$ feedback filter

- Filter calculation

  - Cholesky factorization: $\tilde{\mathbf{H}}^H \tilde{\mathbf{H}} = \mathbf{L}^H \mathbf{D} \mathbf{L}$ with diagonal matrix $\mathbf{D}$ and lower triangular matrix $\mathbf{L}$ (maindiagonal elements of $\mathbf{L}$ are "1")

$$\mathbf{L} = \begin{bmatrix} 1 & 0 & \cdots & \cdots & 0 \\ l_{21} & 1 & \ddots & \ddots & \vdots \\ l_{31} & l_{32} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \cdots & \cdots & \cdots & 1 \end{bmatrix}$$

  - $\mathbf{F} = \mathbf{D}^{-1} \mathbf{L}^{-H} \tilde{\mathbf{H}}^H$

$$\rightarrow \mathbf{r} = \mathbf{F} \mathbf{y} = \mathbf{D}^{-1} \mathbf{L}^{-H} \underbrace{\underbrace{\tilde{\mathbf{H}}^H \tilde{\mathbf{H}}}_{\mathbf{L}^H \mathbf{D} \mathbf{L}} \tilde{\mathbf{x}}}_{\mathbf{L}} + \underbrace{\mathbf{D}^{-1} \mathbf{L}^{-H} \tilde{\mathbf{H}}^H \mathbf{n}}_{\tilde{\mathbf{n}}}$$

– $\mathbf{B} = \mathbf{L} - \mathbf{I}$ = lower triangular matrix with maindiagonal elements "0"

$$\mathbf{B} = \begin{bmatrix} 0 & 0 & \cdots & \cdots & 0 \\ l_{21} & 0 & \ddots & \ddots & \vdots \\ l_{31} & l_{32} & 0 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \cdots & \cdots & \cdots & 0 \end{bmatrix}$$

- Interpretation:
  - after feedforward filter

$$\mathbf{r} = \begin{bmatrix} 1 & 0 & \cdots & \cdots & 0 \\ l_{21} & 1 & \ddots & \ddots & \vdots \\ l_{31} & l_{32} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \cdots & \cdots & \cdots & 1 \end{bmatrix} \begin{bmatrix} \tilde{x}_1 \\ \tilde{x}_2 \\ \vdots \\ \tilde{x}_{N_T} \end{bmatrix} + \tilde{\mathbf{n}}$$

- from feedback filter

$$\tilde{\mathbf{r}} = \begin{bmatrix} 0 & 0 & \cdots & \cdots & 0 \\ l_{21} & 0 & \ddots & \ddots & \vdots \\ l_{31} & l_{32} & 0 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \cdots & \cdots & \cdots & 0 \end{bmatrix} \begin{bmatrix} \hat{\tilde{x}}_1 \\ \hat{\tilde{x}}_2 \\ \vdots \\ \hat{\tilde{x}}_{N_T} \end{bmatrix} \quad \hat{\tilde{x}}_n : \text{decision on } \tilde{x}_n$$

$$\to \mathbf{r} - \tilde{\mathbf{r}} = \begin{bmatrix} \tilde{x}_1 + 0 \\ l_{21}(\tilde{x}_1 - \hat{\tilde{x}}_1) + \tilde{x}_2 + 0 \\ l_{31}(\tilde{x}_1 - \hat{\tilde{x}}_2) + l_{32}(\tilde{x}_2 - \hat{\tilde{x}}_2) + \tilde{x}_3 + 0 \\ \vdots \end{bmatrix} + \tilde{\mathbf{n}}$$
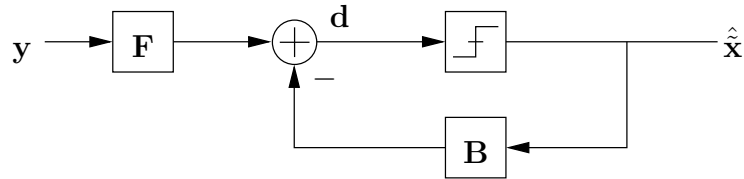
MMSE-DFE

Figure 4: MMSE-DFE Blockdiagram

- $\mathbf{B} = \mathbf{L} - \mathbf{I}$ has to be lower triangular matrx with all-zero main diagonal elements because of causality.

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- $\mathbf{d} = \mathbf{F}\mathbf{y} - \mathbf{B}\hat{\tilde{\mathbf{x}}} \quad \rightarrow \mathbf{e} = \mathbf{d} - \hat{\mathbf{x}} = \mathbf{F}\mathbf{y} - \underbrace{(\mathbf{B} + \mathbf{I})}_{\mathbf{L}}\tilde{\mathbf{x}}$

  where we assume $\hat{\tilde{\mathbf{x}}} = \tilde{\mathbf{x}}$ for filter optimization

- Optimal $\mathbf{F}$ for given $\mathbf{L}$

$$\sigma_e^2 = \mathrm{tr}\left\{\underbrace{\mathcal{E}\{\mathbf{e}\mathbf{e}^H\}}_{\mathbf{\Phi}_{ee}}\right\} = \mathrm{tr}\left\{\mathbf{F}\mathbf{\Phi}_{yy}\mathbf{F}^H\right\} - \mathrm{tr}\left\{\mathbf{F}\mathbf{\Phi}_{y\tilde{x}}\mathbf{L}^H\right\} - \mathrm{tr}\left\{\mathbf{L}\mathbf{\Phi}_{\tilde{x}y}\mathbf{F}^H\right\} + \mathrm{tr}\left\{\mathbf{L}\mathbf{\Phi}_{\tilde{x}\tilde{x}}\mathbf{L}^H\right\}$$

$$\frac{\delta}{\delta\mathbf{F}^*}\sigma_e^2 = \mathbf{F}\mathbf{\Phi}_{yy} - \mathbf{L}\mathbf{\Phi}_{\tilde{x}y} = 0 \quad \rightarrow \mathbf{F} = \mathbf{L}\mathbf{\Phi}_{\tilde{x}y}\mathbf{\Phi}_{yy}^{-1}$$

  where

$$\mathbf{\Phi}_{yy} = \mathcal{E}_s\tilde{\mathbf{H}}\tilde{\mathbf{H}}^H + \sigma_n^2\mathbf{I}$$
$$\mathbf{\Phi}_{\tilde{x}y} = \mathcal{E}_s\tilde{\mathbf{H}}^H$$

$$\rightarrow \mathbf{F} = \mathbf{L}\tilde{\mathbf{H}}^H(\tilde{\mathbf{H}}\tilde{\mathbf{H}}^h + \frac{\sigma_n^2}{\mathcal{E}_s}\mathbf{I})^{-1} = \mathbf{L}\overbrace{(\tilde{\mathbf{H}}^H\tilde{\mathbf{H}} + \frac{\sigma_n^2}{\mathcal{E}_s}\mathbf{I})^{-1}\tilde{\mathbf{H}}^H}^{\text{MMSE Linear Equalizer}}$$
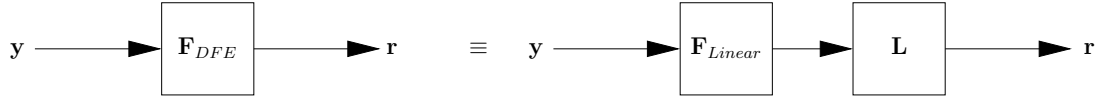

Figure 5: MMSE-DFE Equivalence

- Optimal $\mathbf{L}$:

$$\mathbf{\Phi}_{ee} = \mathbf{L}\mathbf{\Phi}_{\tilde{x}y}\mathbf{\Phi}_{yy}^{-1}\mathbf{\Phi}_{yy}\mathbf{\Phi}_{yy}^{-1}\mathbf{\Phi}_{\tilde{x}y}^H\mathbf{L}^H - \mathbf{L}\mathbf{\Phi}_{xy}\mathbf{\Phi}_{yy}^{-1}\mathbf{\Phi}_{yz}\mathbf{L}^H - \mathbf{L}\mathbf{\Phi}_{\tilde{x}y}\mathbf{\Phi}_{yy}^{-1}\mathbf{\Phi}_{\tilde{x}y}^H\mathbf{H}^H + \mathbf{L}\mathbf{\Phi}_{\tilde{x}\tilde{x}}\mathbf{L}^H$$
$$= \mathbf{L}(\mathbf{\Phi}_{\tilde{x}\tilde{x}} - \mathbf{\Phi}_{\tilde{x}y}\mathbf{\Phi}_{yy}^{-1}\mathbf{\Phi}_{\tilde{x}y}^H)\mathbf{L}^H$$

= MMSE covariance matrix for a linear MMSE filter

$\rightarrow \mathbf{\Phi}_{ee} = \sigma_n^2\mathbf{L}(\tilde{\mathbf{H}}^H\tilde{\mathbf{H}} + \frac{\sigma_n^2}{\mathcal{E}_s}\mathbf{I})^{-1}\mathbf{L}^H$

$\rightarrow$ need lower triangular matrix $\mathbf{L}$ which minimizes $\mathrm{tr}\{\mathbf{\Phi}_{ee}\}$

$\rightarrow$ the optimum $\mathbf{L}$ whitenes $\mathbf{\Phi}_{ee} \rightarrow \mathbf{\Phi}_{ee}$ becomes diagonal matrix i.e. $\mathbf{L}$ exploits the correlation after linear MMSE filtering to reduce noise variance!

$\rightarrow$ $\mathbf{L}$ is obtained via Cholesky factorization

$$\tilde{\mathbf{H}}^H\tilde{\mathbf{H}} + \frac{\sigma_n^2}{\mathcal{E}_s}\mathbf{I} = \mathbf{L}\mathbf{D}\mathbf{L}^H$$

$\rightarrow$ $\mathbf{\Phi}_{ee} = \sigma_n^2\mathbf{L}(\mathbf{L}\mathbf{D}\mathbf{L}^H)^{-1}\mathbf{L} = \sigma_n^2\mathbf{L}\mathbf{L}^{-1}\mathbf{D}^{-1}\mathbf{L}^{-H}\mathbf{L} = \sigma_n^2\mathbf{D}^{-1} \,\hat{=}\,$ diagonal matrix

- Summary of MMSE calculation

  - $\mathbf{B} = \mathbf{L} - \mathbf{I}$ where $\mathbf{H}^H \mathbf{H} + \dfrac{\sigma_n^2}{\mathcal{E}_s} \mathbf{I} = \mathbf{L} \mathbf{D} \mathbf{L}^H$

  - $\mathbf{F} = \mathbf{L} \underbrace{(\mathbf{H}^H \mathbf{H} + \dfrac{\sigma_n^2}{\mathcal{E}_s} \mathbf{I})^{-1} \tilde{\mathbf{H}}}_{\mathbf{F}_{Linear}}$

  - $\mathbf{L}$ is a prediction error filter, which whitenes the error signal $\mathbf{e}$

  - SNR:

  $$\mathbf{D} = \mathrm{diag}\{\xi_1, \ldots, \xi_{N_T}\}$$
  $$\mathbf{\Phi}_{ee} = \mathrm{diag}\{\frac{\sigma_n^2}{\xi_1}, \ldots, \frac{\sigma_n^2}{\xi_{N_T}}\}$$

  - end-to-end channel

  $$
  \begin{aligned}
  \mathbf{K} &= \mathbf{F}\tilde{\mathbf{H}} \\
  &= \mathbf{L} \underbrace{(\tilde{\mathbf{H}}^H \tilde{\mathbf{H}} + \frac{\sigma_n^2}{\mathcal{E}_s} \mathbf{I})^{-1} \mathbf{L}^H}_{\frac{1}{\sigma_n^2} \mathbf{\Phi}_{ee}} \mathbf{L}^{-H} \tilde{\mathbf{H}}^H \tilde{\mathbf{H}} \\
  &= \frac{1}{\sigma_n^2} \mathbf{\Phi}_{ee} \mathbf{L}^{-H} (\tilde{\mathbf{H}}^H \tilde{\mathbf{H}} + \frac{\sigma_n^2}{\mathcal{E}_s} \mathbf{I} - \frac{\sigma_n^2}{\mathcal{E}_s} \mathbf{I}) \mathbf{L}^{-1} \mathbf{L} \\
  &= \frac{1}{\sigma_n^2} [\underbrace{\mathbf{L}^{-H} (\tilde{\mathbf{H}}^H \tilde{\mathbf{H}} + \frac{\sigma_n^2}{\mathcal{E}_s} \mathbf{I}) \mathbf{L}^{-1}}_{\sigma_n^2 \mathbf{\Phi}_{ee}^{-1}} \mathbf{L} - \frac{\sigma_n^2}{\mathcal{E}_s} \mathbf{L}^{-H}] \\
  &= \mathbf{L} - \frac{1}{\mathcal{E}_s} \mathbf{\Phi}_{ee} \mathbf{L}^{-H}
  \end{aligned}
  $$

  $\rightarrow$ main diagonal of $\mathbf{K}$:

  $$K_{mm} = 1 - \frac{\sigma_n^2}{\mathcal{E}_s \xi_m} < 1$$

  - biased SNR

  $$SNR_{m,bias} = \frac{\mathcal{E}_S}{[\mathbf{\Phi}_{ee}]_{mm}} = \frac{\mathcal{E}_s}{\sigma_n^2} \xi_m = \frac{1}{1 - K_{mm}}, \quad 1 \leq m \leq N_T$$

  - unbiased SNR

  $$SNR_{m,unbiased} = SNR_{m,bias} - 1 = \frac{1}{1 - K_{mm}} - 1 = \frac{K_{mm}}{1 - K_{mm}}, \quad 1 \leq m \leq N_T$$

3.3.3 Sphere Decoding

- Linear and DFE receivers cannot approach performance of ML‑detector

- ML‑detector: $\hat{\mathbf{x}} = \underset{\mathbf{x}\in A^{N_T}}{\text{argmin}}||\mathbf{y} - \mathbf{Hx}||^2$

$\rightarrow$ high complexity for brute force search

Main Idea

- can we search ML metric in a "smarter" way, akin to the smart search of the viterbi algorithm for problems with a trellis structure

- we need to find a way to prune/dismiss non‑ML sequences/vectores early on

$\rightarrow$ this is accomplished by sphere decoding

Step 1 Bring metric into a suitable form:

- real represantation: $||\mathbf{y} - \mathbf{Hx}||^2 = ||\tilde{\mathbf{y}} - \tilde{\mathbf{H}}\tilde{\mathbf{x}}||^2$

- where:

$$\tilde{\mathbf{y}} = \begin{bmatrix} \text{Re}\{\mathbf{y}^T\} & \text{Im}\{\mathbf{y}^T\} \end{bmatrix}^T$$
$$\tilde{\mathbf{x}} = \begin{bmatrix} \text{Re}\{\mathbf{x}^T\} & \text{Im}\{\mathbf{x}^T\} \end{bmatrix}^T$$
$$\tilde{\mathbf{H}} = \begin{bmatrix} \text{Re}\{\mathbf{H}\} & -\text{Im}\{\mathbf{H}\} \\ \text{Im}\{\mathbf{H}\} & \text{Re}\{\mathbf{H}\} \end{bmatrix}^T$$

$\rightarrow$ QAM: $\tilde{\mathbf{x}}$ defines points in an $2N_T$ dimensional lattice

- QL decomposition: $\tilde{\mathbf{H}} = \mathbf{QL}$ with

  - orthogonal matrix $\mathbf{Q} \in \mathbb{R}^{2N_T \times 2N_T}; \quad \mathbf{QQ}^T = \mathbf{I}$

  - and lower triangular matrix $\mathbf{L} \in \mathbb{R}^{2N_T \times 2N_T}$

$$\begin{aligned}
||\tilde{\mathbf{y}} - \mathbf{QL}\tilde{\mathbf{x}}||^2 &= ||\mathbf{QQ}^T(\tilde{\mathbf{y}} - \mathbf{QL}\tilde{\mathbf{x}})||^2 + ||(\mathbf{I} - \mathbf{QQ}^T)(\tilde{\mathbf{y}} - \mathbf{QL}\tilde{\mathbf{x}})||^2 \\
&= ||\mathbf{Q}(\mathbf{Q}^T\tilde{\mathbf{y}} - \mathbf{L}\tilde{\mathbf{x}})||^2 + ||(\mathbf{I} - \mathbf{QQ}^T)\tilde{\mathbf{y}} - \underbrace{(\mathbf{Q} - \mathbf{Q})}_{=0}\mathbf{L}\tilde{\mathbf{x}}||^2 \\
&= ||\mathbf{Q}^T\tilde{\mathbf{y}} - \mathbf{L}\tilde{\mathbf{x}}||^2 + \underbrace{||(\mathbf{I} - \mathbf{QQ}^T)\tilde{\mathbf{y}}||^2}_{\text{unabhängig von } \tilde{\mathbf{x}}}
\end{aligned}$$

$\Rightarrow \underset{\tilde{\mathbf{x}}\in A^{2N_T}}{\text{argmin}}||\tilde{\mathbf{y}} - \tilde{\mathbf{H}}\tilde{\mathbf{x}}||^2 = \underset{\tilde{\mathbf{x}}\in A^{2N_T}}{\text{argmin}}||\underbrace{\mathbf{Q}^T\tilde{\mathbf{y}}}_{\bar{\mathbf{y}}} - \mathbf{L}\tilde{\mathbf{x}}||^2$

  where A^{2N_T} contains all M^{N_T} possible vectors $\tilde{\mathbf{x}}$

- Observation:

  - with

$$\mathbf{L} = \begin{bmatrix} l_{11} & 0 & \cdots & & 0 \\ l_{21} & l_{22} & \ddots & & \vdots \\ \vdots & & \ddots & & 0 \\ l_{2N_T\,1} & \cdots & & & l_{2N_T\,2N_T} \end{bmatrix}$$
$$\bar{\mathbf{y}} = \begin{bmatrix} \bar{y}_1 & \cdots & \bar{y}_{2N_T} \end{bmatrix}^T ; \quad \tilde{\mathbf{x}} = \begin{bmatrix} \tilde{x}_1 & \cdots & \tilde{x}_{2N_T} \end{bmatrix}$$

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– we have

$$||\bar{\mathbf{y}} - \mathbf{L}\tilde{\mathbf{x}}||^2 = (\bar{y} - l_{11}\tilde{x}_1)^2 + (\bar{y}_2 - l_{21}\tilde{x}_1 - l_{22}\tilde{x}_2)^2 + (\bar{y}_3 - l_{31}\tilde{x}_1 - l_{32}\tilde{x}_2 - l_{33}\tilde{x}_3)^2 + \ldots \tag{1}$$

$\rightarrow$ the n-th term in the above sum contains only $\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_n$

**Step 2** Sphere decoding algorithm
<u>**Define:**</u>

$$d(\tilde{\mathbf{x}}) = \sum_{n=1}^{2N_T} f_n(\tilde{\mathbf{x}}_n) \; ; \quad \text{with } f_n(\tilde{\mathbf{x}}_n) = \left(\bar{y}_n - \sum_{i=1}^{n} l_{ni}\tilde{x}_i\right)^2 \; ; \quad \tilde{\mathbf{x}}_n = \begin{bmatrix} \tilde{x}_1 & \ldots & \tilde{x}_n \end{bmatrix}^T$$

$$d_n(\tilde{x}_n) = \sum_{m=1}^{n} f_n(\tilde{\mathbf{x}}_m)$$

<u>**Main Idea:**</u>

- Assume we know that $d(\tilde{\mathbf{x}}) \leq R$ holds for some $\tilde{\mathbf{x}}$, where R is the so called "sphere radius" $\rightarrow$ any $\tilde{\mathbf{x}}$ with $d(\tilde{\mathbf{x}}) \geq R$ cannot be the ML solution and can be discarded

- since $d_{n+1}(\tilde{\mathbf{x}}'_n, \tilde{x}_{n+1}) \geq d_n(\tilde{\mathbf{x}}'_n)$, we can easily discard $\mathbf{x}'_n$ and all
  possible $\tilde{\mathbf{x}} = \begin{bmatrix} \tilde{\mathbf{x}}'_n & \tilde{x}_{n+1} & \tilde{x}_{n+2} & \ldots & \tilde{x}_{2N_T} \end{bmatrix}^T$ if we find $d_n(\tilde{\mathbf{x}}'_n) > R$
  $\Rightarrow$ we can exclude many possible vectors $\tilde{\mathbf{x}}$ without evaluating any metrics for them

- How to find a suitable R?

  - Initial R: $R = d(\tilde{\mathbf{x}}_{\text{subopt}})$ where $\tilde{\mathbf{x}}_{\text{subopt}}$ was obtained with some suboptimum receiver

  - R is updated as $R = R_{\text{new}} = d(\tilde{\mathbf{x}}_{\text{cand}})$ where $\tilde{\mathbf{x}}_{\text{cand}}$ is an $\tilde{\mathbf{x}}$ which yields $d(\tilde{\mathbf{x}}_{\text{cand}}) < R_{\text{old}} = R$

- Use tree structure to represent all possible $\tilde{\mathbf{x}}$

Example: <u>BPSK = 2, $N_T = 2$</u>
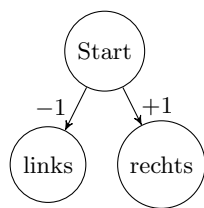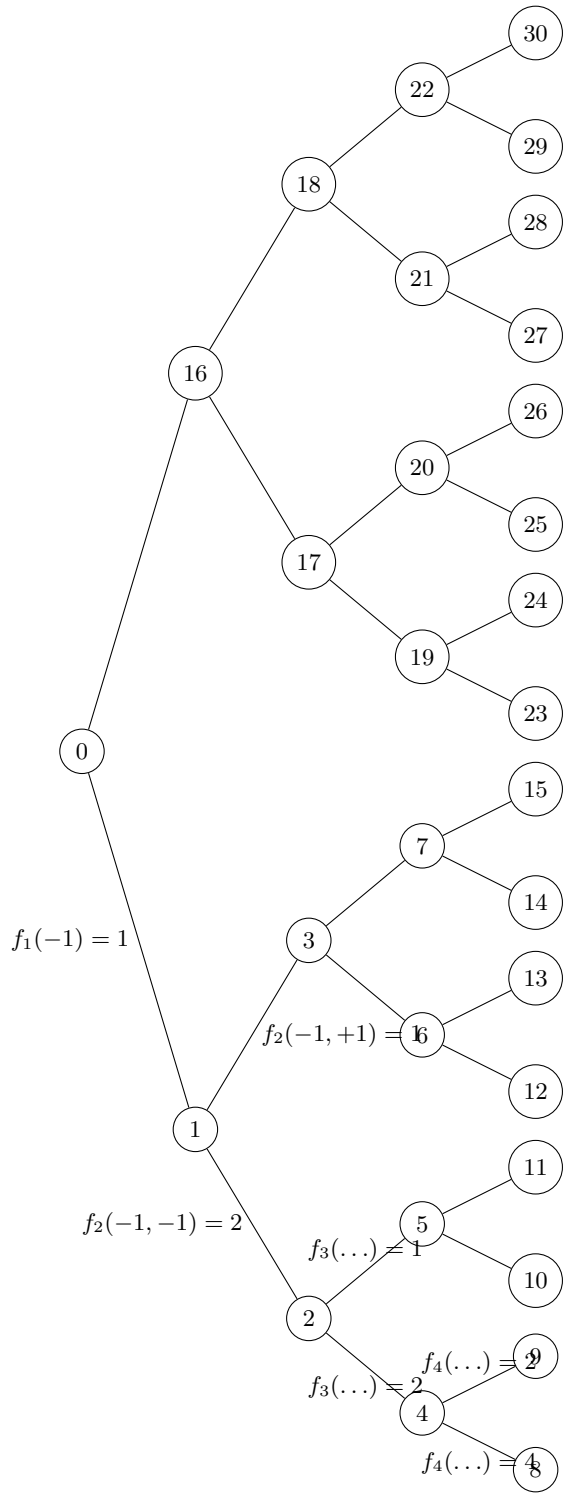
- Assume $\tilde{\mathbf{x}}_{\text{subopt}} = \begin{bmatrix} -1 & -1 & -1 & 1 \end{bmatrix}^T$
  $\Rightarrow d(\tilde{x}_{\text{subopt}} = 1 + 2 + 2 + 2 = 7 = R$

- For $\tilde{x}_1 = 1$ we find $d_2(1,1) = 5 + 3 = 8 > R$ and $d(1,-1) = 5 + 4 > R$
  $\Rightarrow$ we don't have to calculate metrics for remaining branches, i.e., for nodes $19, \ldots, 31$

- For $\tilde{x}_1 = -1$ and $\tilde{x}_2 = 1$, we find that $d_3(-1,1,-1) = 8 > R$ and $d_3(-1,1,1) = 9 > R$
  $\Rightarrow$ remaining branches emerging from nodes 6 and 7 can be discarded

- For the ML solution we find $d(-1,-1,1,-1) = 5 < R$

- Different strategies exist, regarding in which order the nodes in the tree (points in the lattice) are investigated

    - Pohst strategy

    - Schnoir - Enchner strategy

    - rich literature on lattice decoding algorithms