



Algorithms for Wireless Communications II

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OFDM Channel Estimation

Notation Conventions

Type	Notation	Example
Scalars	Lower case, italic	a, n, b, x, y
Column vectors	Lower case, bold	$\mathbf{t}, \boldsymbol{t}$
Matrices	Upper case, bold	$\mathbf{T}, \boldsymbol{\mathcal{T}}$
Time domain signals	Regular font	$\mathbf{H}, H, \mathbf{h}, h$
Frequency domain signals	Script font	$\hbar, \hbar, \mathcal{H}, \mathcal{H}, \mathcal{T}, \mathcal{T}, \boldsymbol{t}, \boldsymbol{t}$

We distinguish between

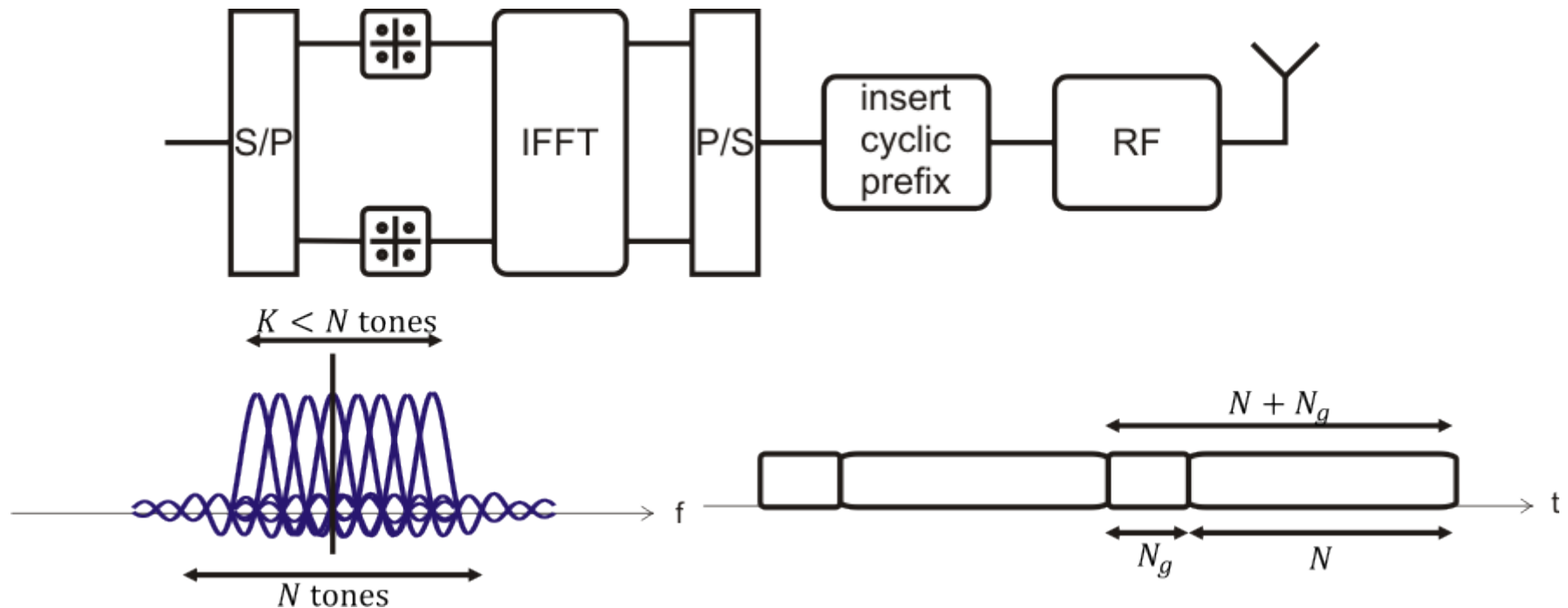
- Scalars and matrices or vectors by using regular and bold upper/lower case letters
- Time and frequency domain representation using regular and script font

We carefully distinguish between a variable \hbar and its estimate $\hat{\hbar}$ (denoted by adding a *hat*)

OFDM Reminder (1/2)

Wideband transmission using many (orthogonal) narrow-band channels

- Transmitted signal is divided into OFDM symbols, each comprising N tones
- Each tone is modulated separately with any modulation scheme
- IDFT or better IFFT generates time-domain signal
- A cyclic prefix is prepended to each OFDM symbol



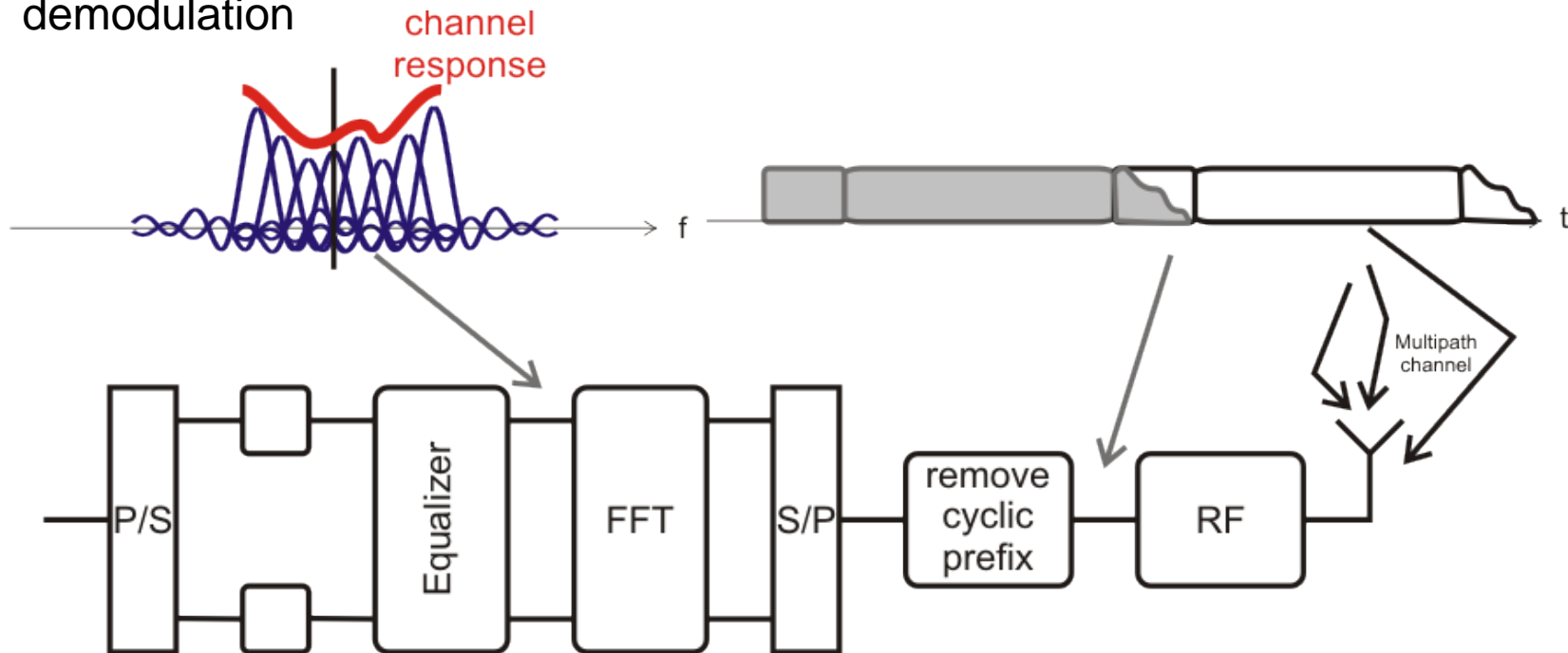
OFDM Reminder (2/2)

Transmission over multipath (frequency selective) channel

- Each tone experiences a different phase and attenuation
- Cyclic prefix captures ISI from previous symbol

Receiver

- Removes the cyclic prefix and transforms back into frequency domain (DFT or FFT)
- Per-tone equalization to undo the impact of the channel on each tone before demodulation



OFDM System Model

Recall the OFDM system model

$$\mathbf{y} = \mathbf{F}(\mathbf{H}(\mathbf{F}^{-1}\mathbf{s}) + \mathbf{n}) = \underbrace{\mathbf{F}\mathbf{H}\mathbf{F}^{-1}}_{\text{diag}(\mathbf{F}\mathbf{h})=\mathbf{h}} \mathbf{s} + \mathbf{F}\mathbf{n}$$

- $\mathbf{F}^{-1}\mathbf{s}$: Frequency domain modulated data signal after IFFT
 \mathbf{H} : Circulant matrix with time-domain channel coefficients
 \mathbf{F} : FFT matrix
 \mathbf{n} : i.i.d. Gaussian noise samples $\mathbb{E}\{\mathbf{n}\mathbf{n}^H\} = \mathbf{I}\sigma_n^2$

Frequency domain representation

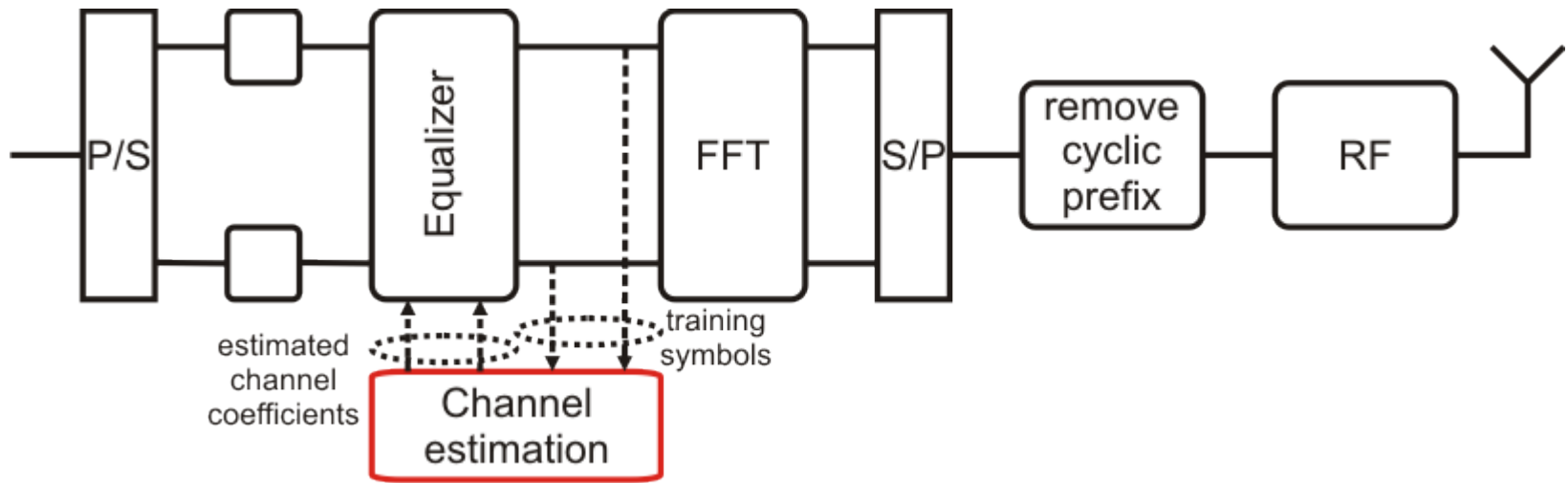
$$\mathbf{y} = \mathcal{H}\mathbf{s} + \mathbf{n} \quad \text{with} \quad \mathcal{H} = \begin{bmatrix} h_0 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & h_{N-1} \end{bmatrix} = \text{diag}(\mathbf{F}\mathbf{h})$$

$$y_f = h_f s_f + n_f$$

- Note: noise properties remain unchanged $\mathbb{E}\{\mathbf{n}\mathbf{n}^H\} = \sigma_n^2 \mathbf{I}$ since \mathbf{F} is an orthonormal transform

Channel Estimation

Task: obtain knowledge (estimate) of the channel coefficients in the frequency domain h_f based on the received signal y_f



Estimation strategies

- Training/Pilot based: Transmitter sends known data (training/pilot symbols) so that h_f and n_f are the only unknown parameters
 - Overhead: training/pilot symbols do not carry data!!
- Data aided: channel estimation based on feedback of detected data
- Blind: Estimation only based on statistical properties

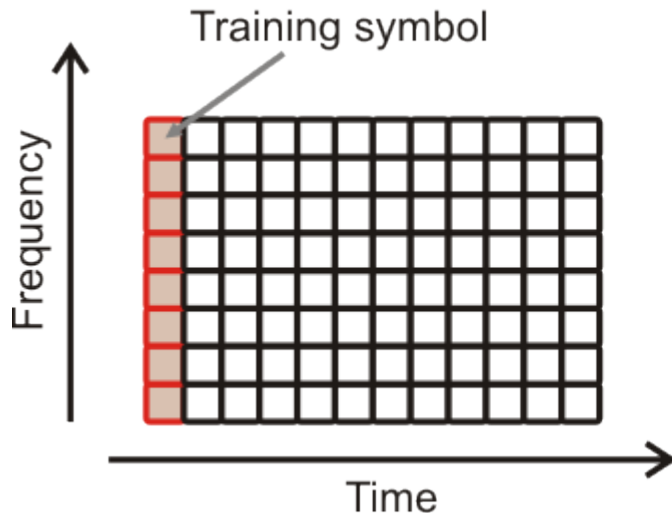
Here, we consider only training/pilot based channel estimation

- Most frequently used approach (very robust)
- Overhead is usually low when channels do not change too quickly

Common Training/Pilot Patterns

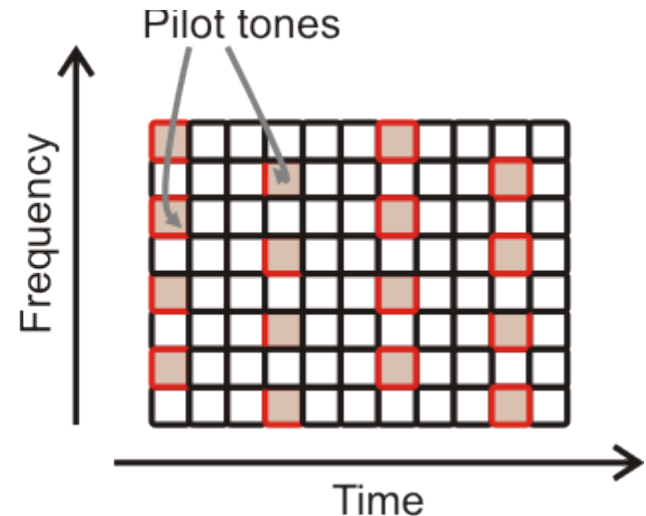
OFDM-training structures differ by how training/pilot symbols are distributed across time and frequency

Block type training (e.g., 802.11a/g/n)



- Dedicated OFDM training symbol
- Used in systems with relatively static channel conditions
- Packet based systems (burst traffic)

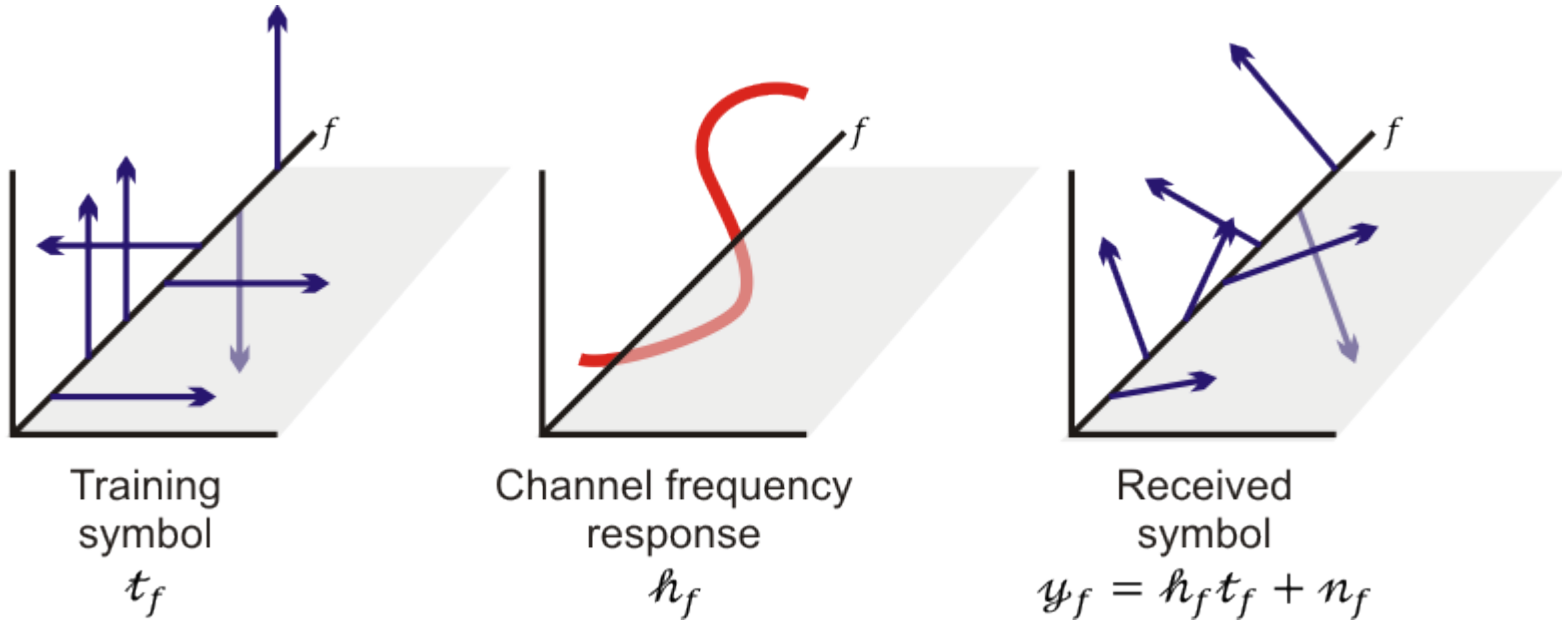
Comb type training (e.g., DVB-T, 3GPP LTE)



- Pilot tones interleaved with data
- Pilot location varies to cover all tones
- Used in rapidly time-varying channels
- Streaming (continuous transmission)

Input Output Relationship for Channel Estimation

Consider the transmission of a single training symbol t



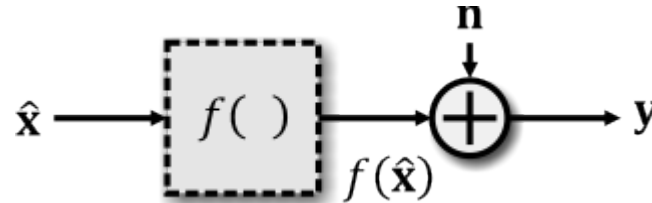
- Two options to formulate the input-output relationship

$$\begin{bmatrix} y_0 \\ \vdots \\ y_{N-1} \end{bmatrix} = \begin{bmatrix} h_0 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & h_{N-1} \end{bmatrix} \begin{bmatrix} t_0 \\ \vdots \\ t_{N-1} \end{bmatrix} + \begin{bmatrix} n_0 \\ \vdots \\ n_{N-1} \end{bmatrix} = \boxed{\begin{bmatrix} t_0 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & t_{N-1} \end{bmatrix} \begin{bmatrix} h_0 \\ \vdots \\ h_{N-1} \end{bmatrix} + \begin{bmatrix} n_0 \\ \vdots \\ n_{N-1} \end{bmatrix}}$$

For our purposes (estimate t) the 2nd expression is more appropriate

Estimation Theory Basics

Problem statement: consider the following simplified system model



- Observation y is some function of an unknown parameter \hat{x} distorted by noise
 - Often, $f(x)$ is a linear function of x
 - Often, the observation is distorted by additive Gaussian noise
- Objective: estimate x from y using some cost metric
- We may consider different types of prior knowledge on the variable to be estimated
 - A priori probabilities
 - Knowledge on 1st and 2nd order statistics
- OFDM channel estimation:
 - Observation: received training symbol/tones
 - $f()$: Impact of the channel on the (known) transmitted training symbol
 - Noise: thermal noise, additive Gaussian
 - A priori knowledge: **what can we say about the channel ??**

Estimation Theory Basics

Maximum likelihood estimation: Maximize likelihood of the observation under hypothesis \hat{x}

$$\hat{\mathbf{x}} = \underset{\hat{\mathbf{x}}}{\operatorname{argmax}} p(\mathbf{y}|\hat{\mathbf{x}})$$

Least squares estimation: Minimize distance between observation and noise free observation under hypothesis \hat{x}

$$\hat{\mathbf{x}} = \underset{\hat{\mathbf{x}}}{\operatorname{argmin}} |\mathbf{y} - f(\hat{\mathbf{x}})|^2$$

- Linear least squares approach: $\hat{\mathbf{x}} = \mathbf{W}_{LS}\mathbf{y}$
- No assumptions on 2nd order statistics
- For additive Gaussian noise: equivalent to ML estimation

Minimum mean squared error (MMSE) estimation

$$\hat{\mathbf{x}} = \underset{\hat{\mathbf{x}}}{\operatorname{argmin}} \mathbb{E}\{|\mathbf{x} - \hat{\mathbf{x}}|^2\}$$

- Linear least squares approach: $\hat{\mathbf{x}} = \mathbf{W}_{MMSE}\mathbf{y}$

Per Tone (Linear) Least Squares Method

Linear least squares estimation: obtain the estimate \hat{h} of h according to

$$\hat{h} = \underset{\hat{h}}{\operatorname{argmin}} \left\{ |\mathbf{y} - \mathcal{T}\hat{h}|^2 \right\} \text{ with } \mathcal{T} = \begin{bmatrix} t_0 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & t_{N-1} \end{bmatrix}$$

- Minimize Euclidean distance between \mathbf{y} and $\mathcal{T}\hat{h}$
- Gaussian noise: least squares solution corresponds to the maximum likelihood solution

No assumptions are made on correlation of the individual tones:

- Treat all tones as if they had an independent channel coefficient
- Since \mathcal{T} is diagonal, tones can be estimated independently (locally optimal solutions leads to a global optimal solution)

$$\hat{h} = \mathcal{T}^{-1}\mathbf{y} \text{ or } \hat{h}_f = \frac{1}{t_f} y_f$$

Estimation Error for Per Tone Least Squares Estimation

- Define the per tone estimation error as

$$\Delta h_f = h_f - \hat{h}_f$$

We are interested in the mean squared error

- Mean: taken over many noise realizations (average error we expect over many independent channel estimations)

$$\sigma_{h_f}^2 = \mathbb{E} \left\{ |\Delta h_f|^2 \right\} = \mathbb{E} \left\{ \left| h_f - \frac{1}{t_f} y_f \right|^2 \right\}$$

- Substitute the signal model $y_f = h_f t_f + n_f$

$$\sigma_{h_f}^2 = \mathbb{E} \left\{ \left| h_f - \frac{1}{t_f} (h_f t_f + n_f) \right|^2 \right\} = \frac{\mathbb{E} \left\{ |n_f|^2 \right\}}{|t_f|^2} = \frac{\sigma_n^2}{|t_f|^2}$$

Per Tone Least Squares: remember from part 1 of the course

Channel Estimation

Quality of the channel estimate

$$\frac{r_k}{t} = h + \frac{w_k}{t}$$

Noise component
on the channel est.

$$\frac{\mathcal{E}\{|h|^2\}}{\mathcal{E}\{|w_k/t|^2\}} = \frac{\mathcal{E}\{|h|^2\}}{\sigma_n^2}$$

Improving the channel estimate by averaging

- If the channel is static, we can use multiple training symbols and average

$$\hat{h} = \frac{1}{N} \sum_{k=1}^N \frac{r_k}{t} = \frac{1}{N} \sum_{k=1}^N h + \frac{1}{N} \sum_{k=1}^N \frac{w_k}{t}$$

N-fold averaging reduces
noise on the channel
estimate by a factor of N

If the channel is time varying, averaging is replaced by a low-pass filter

- Filter bandwidth determined by the Doppler frequency
- Remove the frequency components outside the Doppler bandwidth (noise!!)

Design of the Training Symbol

Quality metric: average estimation MSE (across tones)

$$\sigma_k^2 = \frac{\sigma_n^2}{N} \sum \frac{1}{|\tau_f|^2}$$

- Average power constraint: $\sum |\tau_f|^2 = NP_t$ with P_t : transmit power during training

Distribution of power across tones has an impact on the average channel estimation error

Optimum power allocation

- Distribute power equally to all tones of the training symbol

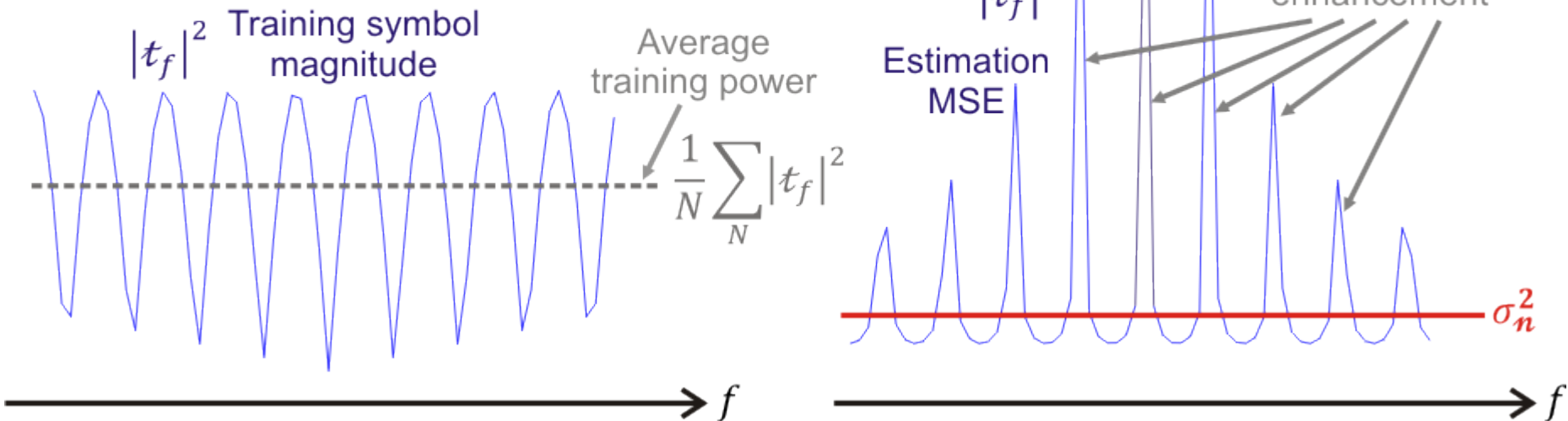
$$|\tau_f|^2 \equiv P_t$$

Channel estimation MSE: $\sigma_k^2 = \sigma_{h_f}^2 = \sigma_n^2/P_t$

Implication for the Design of the Training Sequence

Example: training sequence with uneven power allocation across tones

- System constraints limit only the average (across tones) transmit power
- **Example:** training sequence designed in time domain (e.g., for good PAPR)

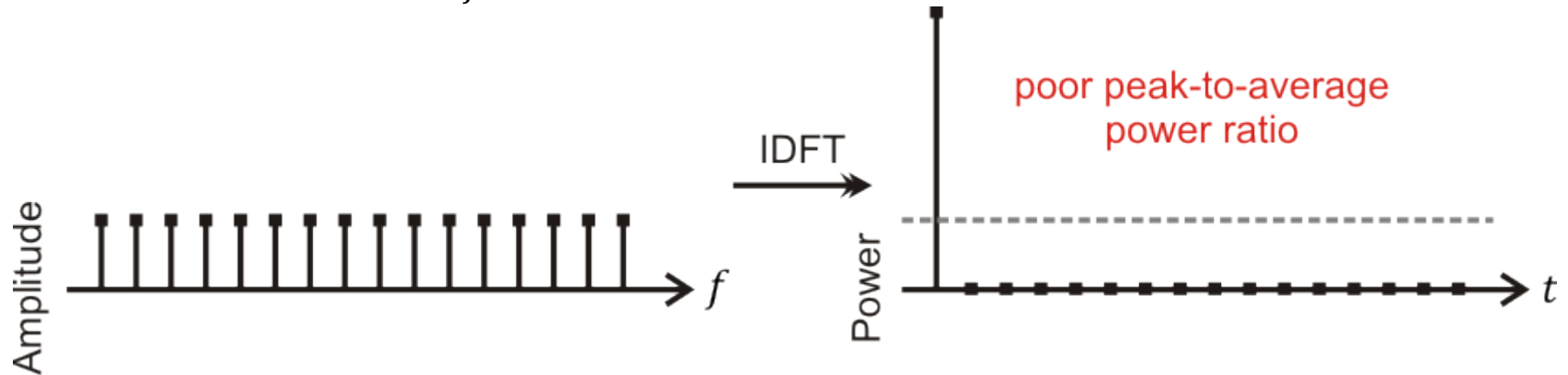


- MSE depends on the power allocated to each pilot tone
- Unequal power allocation -> unequal distribution of the MSE across tones

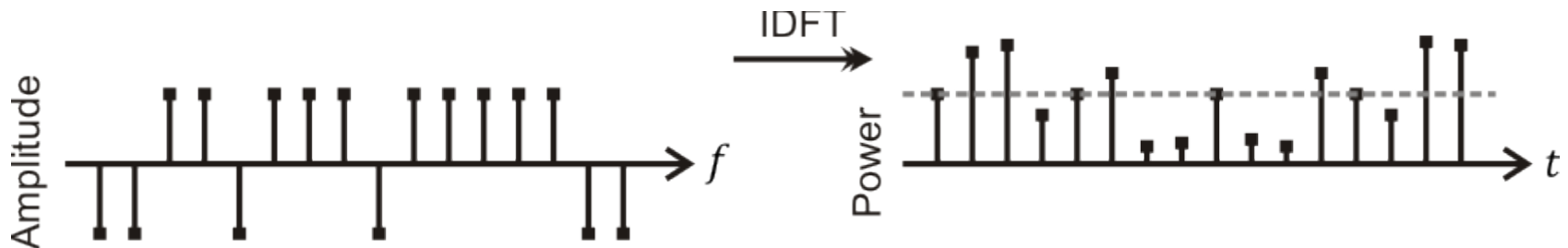
Distribute power equally across tones!

Design of the Training Symbol

Straightforward design: $\tau_f \equiv 1$



Solution: choose the phase of τ_f to achieve an approximately constant envelope (PAPR ≈ 1)



- Real-world example: IEEE 802.11a long training symbol (tones -26 to +26)

$$\tau_f = ++-++-++-++++-++-+++++0+---++-++-++++-++-+++++$$

Impact of Channel Estimation Error on BER

- Channel estimation error $\Delta h_f = h_f - \hat{h}_f$
- Input-output relationship $y_f = h_f s_f + n_f$ (data symbols)

Express the real channel h_f as function of its estimate \hat{h}_f and the error Δh_f

$$h_f = \hat{h}_f + \Delta h_f$$

$$y_f = (\hat{h}_f + \Delta h_f) s_f + n_f$$

Treat all unknown terms as noise

$$\check{n}_f = \Delta h_f s_f + n_f$$

$$\sigma_{\check{n}}^2 = \mathbb{E} \left\{ |\check{n}_f|^2 \right\} = \underbrace{\mathbb{E} \left\{ |\Delta h_f|^2 \right\}}_{\sigma_n^2 / P_t} \underbrace{\mathbb{E} \left\{ |s_f|^2 \right\}}_{P_s} + \underbrace{\mathbb{E} \left\{ |n_f|^2 \right\}}_{\sigma_n^2} = \left(\frac{P_s}{P_t} + 1 \right) \sigma_n^2$$

Impact of Channel Estimation Error on BER

- Assume training and data have equal power (usually the case) : $P_s = P_t$

$$\sigma_{\tilde{n}}^2 = 2\sigma_n^2$$

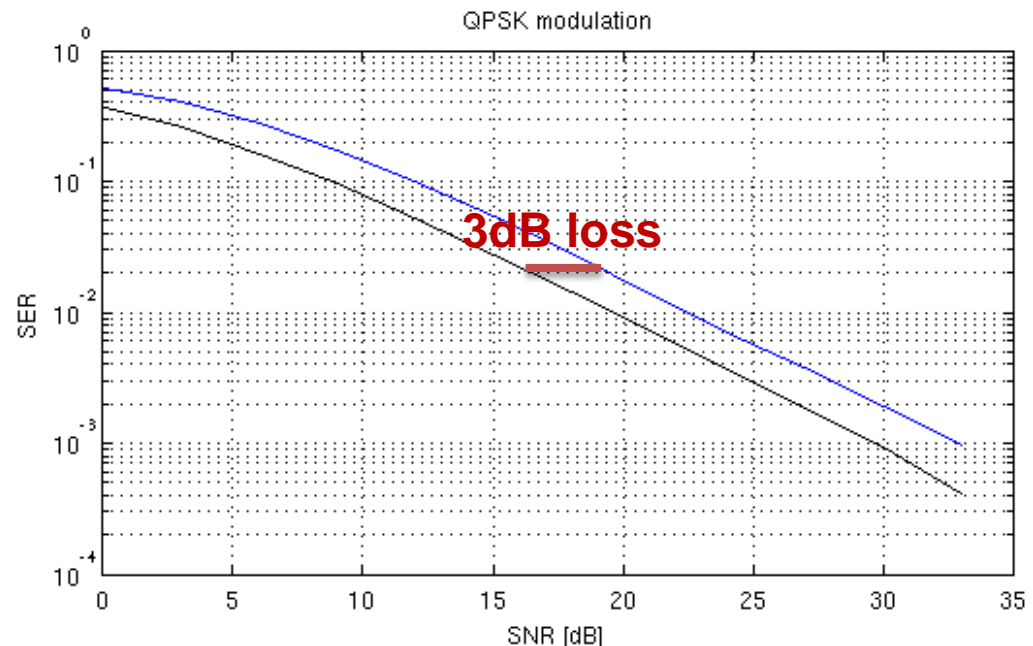
Channel estimation doubles the noise on the signal

Impact on bit error rate

- Approximation: ignore the fact that $\Delta h_f s_f$ is *data dependent* and *not necessarily, but often Gaussian*

Example

- QPSK modulation
- With perfect channel state information (CSI): blue
- With estimated channel: black



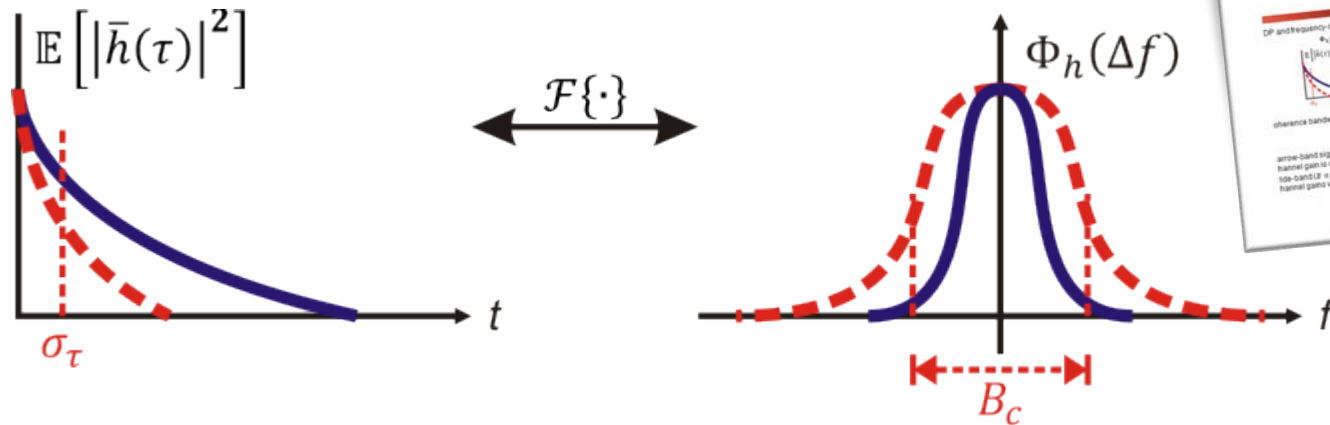
Suboptimality of Per Tone Channel Estimation

Assumes independence between channel coefficients across all tones

Remember:

- Correlation across tones measured by the **coherence bandwidth** and quantified by

$$\Phi_h(\Delta f) = \mathbb{E}[\bar{H}^*(f)\bar{H}(f + \Delta f)] = \mathcal{F}\left\{\mathbb{E}\left[|\bar{h}(\tau)|^2\right]\right\}$$



- Coherence bandwidth is inverse proportional to the channel delay spread
- OFDM** (by design): coherence bandwidth \gg carrier spacing

Independence assumption is wrong (->pessimistic)

Least Squares Estimation (Freq. Domain View)

- Vector of channel coefficients spans an N -dimensional space

$$\mathbf{h} = [h_0 \ h_1 \ \cdots \ h_{N-1}]^T$$

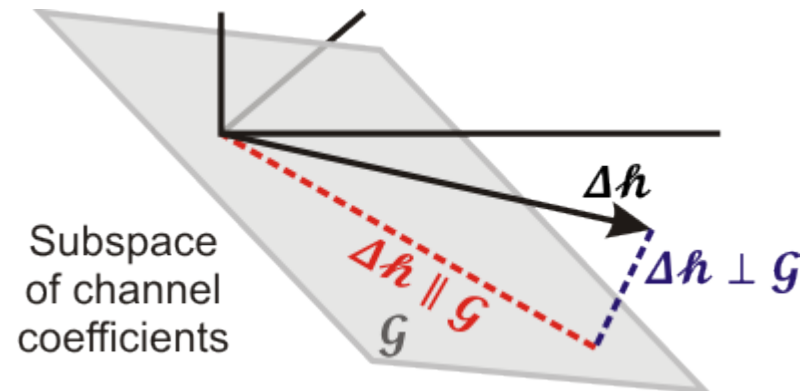
Per-tone channel estimation has two main signal components

$$\hat{\mathbf{h}} = \mathbf{h} + \Delta\mathbf{h}$$

- Uncorrelated (=independent) across tones noise $\Delta\mathbf{h}$
- *Correlated* channel across tones channel coefficients \mathbf{h}

The desired signal \mathbf{h} lies in a lower dimensional subspace \mathcal{G} (support)

- Two noise components
 - Orthogonal to the channel subspace $\Delta\mathbf{h} \perp \mathcal{G}$
 - Within the channel subspace $\Delta\mathbf{h} \parallel \mathcal{G}$
- Per tone estimation: no noise filtering
- But, if we know \mathcal{G} , we can remove $\Delta\mathbf{h} \perp \mathcal{G}$ completely => better estimate

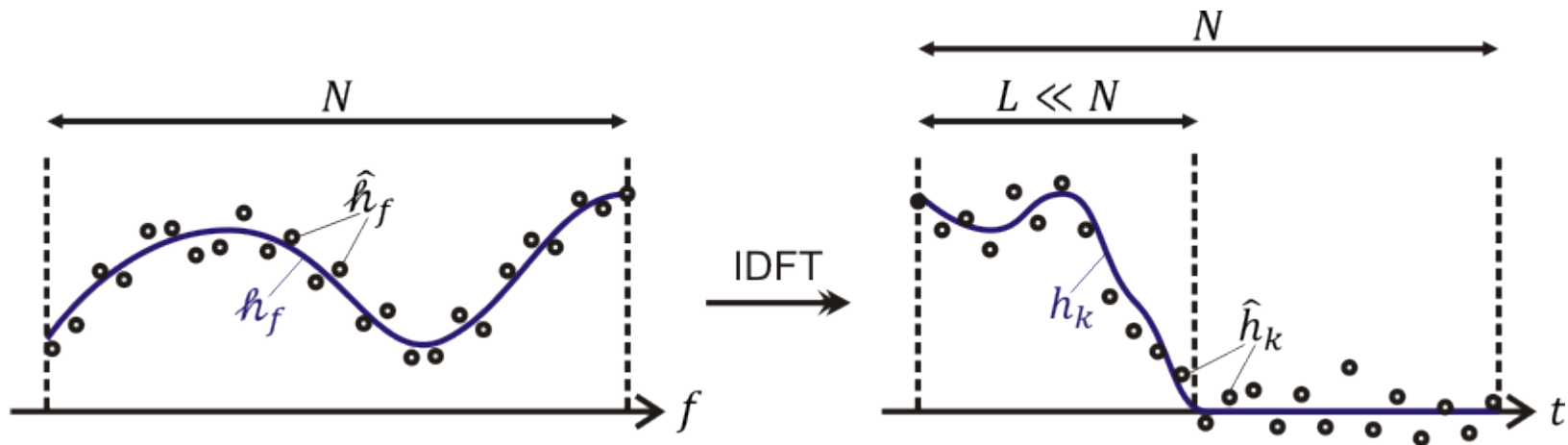


Least Squares Estimation (Time Domain View)

Frequency domain: subspace of the channel is not immediately obvious

- **OFDM** (by design): delay spread $L \ll$ number of carriers N

Consider the time domain representation



$$\mathbf{h} = [h_0 \quad \dots \quad h_{L-1} \quad 0 \quad \dots \quad 0]^T$$

$$\mathcal{G} = \mathbf{F}\mathbf{G}$$

DFT

$$\mathbf{G} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & 1 \\ 0 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 0 \end{bmatrix}$$

Least Squares Estimation (Time Domain View)

- Write $\hat{\mathbf{h}}$ in terms of its (non-zero) time-domain representation \mathbf{h}_L

$$\hat{\mathbf{h}} = \mathbf{F}\mathbf{G}\hat{\mathbf{h}}_L = \mathbf{F}_{NxL}\hat{\mathbf{h}}_L$$

$$\begin{array}{ll} \hat{\mathbf{h}}_L & = [\hat{h}_0 \quad \cdots \quad \hat{h}_{L-1}]^T \quad (\hat{\mathbf{h}} = \mathbf{G}\hat{\mathbf{h}}_L) \\ \mathbf{F}_{NxL} & : \text{Truncated Fourier matrix (only first } L \text{ columns)} \end{array}$$

$$\mathbf{y} = \mathcal{F}\mathbf{F}_{NxL}\mathbf{h}_L + \mathbf{n}$$

**Overdetermined
system!!**

Least squares solution

$$\hat{\mathbf{h}}_L = \underset{\hat{\mathbf{h}}_L}{\operatorname{argmin}} \left\{ \|\mathbf{y} - \mathcal{F}\mathbf{F}_{NxL}\hat{\mathbf{h}}_L\|^2 \right\}$$

- Pseudo inverse yields impulse response

$$\hat{\mathbf{h}}_L = (\mathbf{F}_{NxL}^H \mathcal{F}^H \mathcal{F} \mathbf{F}_{NxL})^{-1} \mathbf{F}_{NxL}^H \mathcal{F}^H \mathbf{y}$$

Least Squares Estimation (Time Domain View)

Back to frequency domain ($\hat{\mathbf{h}} = \mathbf{F}_{NxL} \hat{\mathbf{h}}_L$)

$$\hat{\mathbf{h}} = \mathbf{F}_{NxL} (\mathbf{F}_{NxL}^H \mathcal{T}^H \mathcal{T} \mathbf{F}_{NxL})^{-1} \mathbf{F}_{NxL}^H \mathcal{T}^H \mathbf{y}$$

- $\mathcal{T}^H \mathcal{T} = P_t \mathbf{I}$ is a scaled identity matrix

- $\mathbf{F}_{NxL}^H \mathbf{F}_{NxL} = \mathbf{I}_L$

$$\hat{\mathbf{h}} = \mathbf{F}_{NxL} \underbrace{\mathbf{F}_{NxL}^H (\mathcal{T}^H \mathcal{T})^{-1} \mathcal{T}^H \mathbf{y}}_{\text{per-tone estimate}}$$

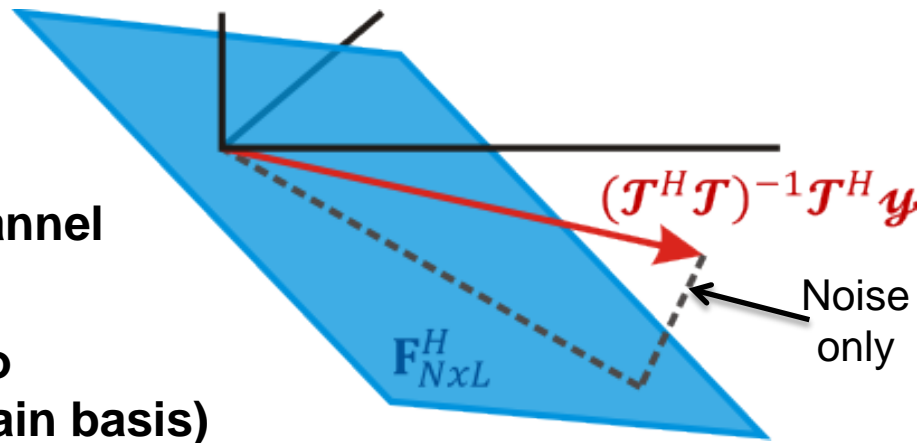
support of the channel

Assume $P_t = 1$

1. Per tone estimate

2. Projection onto the support \mathbf{F}_{NxL}^H of the channel

3. Transformation back to the original (freq. domain basis)



Interpretation in the Frequency Domain

$$\hat{\mathbf{h}} = \mathbf{F}_{NxL} \mathbf{F}_{NxL}^H (\mathcal{T}^H \mathcal{T})^{-1} \mathcal{T}^H \mathbf{y}$$

- $(\mathcal{T}^H \mathcal{T})^{-1} \mathcal{T}^H \mathbf{y}$: Per-tone channel estimation
- $\mathbf{F}_{NxL} \mathbf{F}_{NxL}^H$: Low-pass filter in frequency domain

$$\mathbf{F}_{NxL} \mathbf{F}_{NxL}^H = \mathbf{F} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & 1 \\ 0 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 & \dots & 0 \\ 0 & \ddots & 0 & \vdots & \ddots & \vdots \\ 0 & 0 & 1 & 0 & \dots & 0 \\ 0 & \ddots & 0 & \vdots & \ddots & \vdots \\ 0 & 0 & 1 & 0 & \dots & 0 \end{bmatrix} \mathbf{F}^H = \mathbf{F} \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & \dots & 0 \\ 0 & \ddots & 0 & \vdots & \ddots & \vdots \\ 0 & 0 & 1 & 0 & \dots & 0 \\ 0 & \dots & 0 & 0 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & 0 & \dots & 0 \end{bmatrix}}_{\text{diag}\{[1 \dots 1 \ 0 \dots 0]\}} \mathbf{F}^H$$

$\underbrace{\hspace{10em}}_L \quad \underbrace{\hspace{10em}}_N$

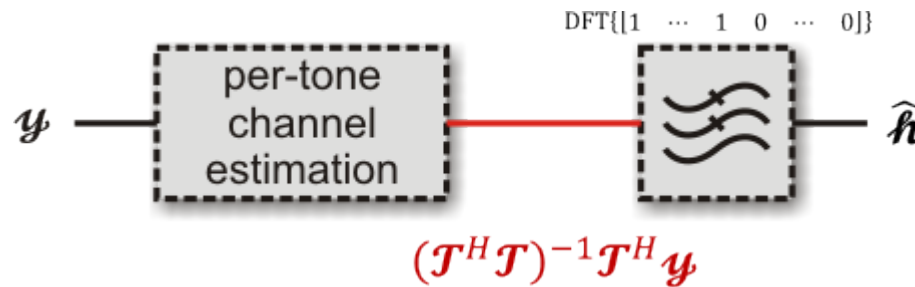
- $\mathbf{F} \mathbf{D} \mathbf{F}^H$: Circulant matrix
- First row given by $\text{DFT}\{\text{diag}\{\mathbf{D}\}\}$
- Multiplication with a circulant matrix = cyclic convolution with its first row

Multiplication of the per-tone estimate with $\mathbf{F}_{NxL} \mathbf{F}_{NxL}^H$ corresponds to a cyclic convolution in frequency domain

Interpretation in the Frequency Domain

Multiplication of the per-tone estimate with $\mathbf{F}_{N \times L} \mathbf{F}_{N \times L}^H$ corresponds to a cyclic convolution in frequency domain

Convolution with $\text{DFT}\{[1 \ \dots \ 1 \ 0 \ \dots \ 0]\}$ of the per-tone estimates corresponds to **low-pass filter in the frequency domain**



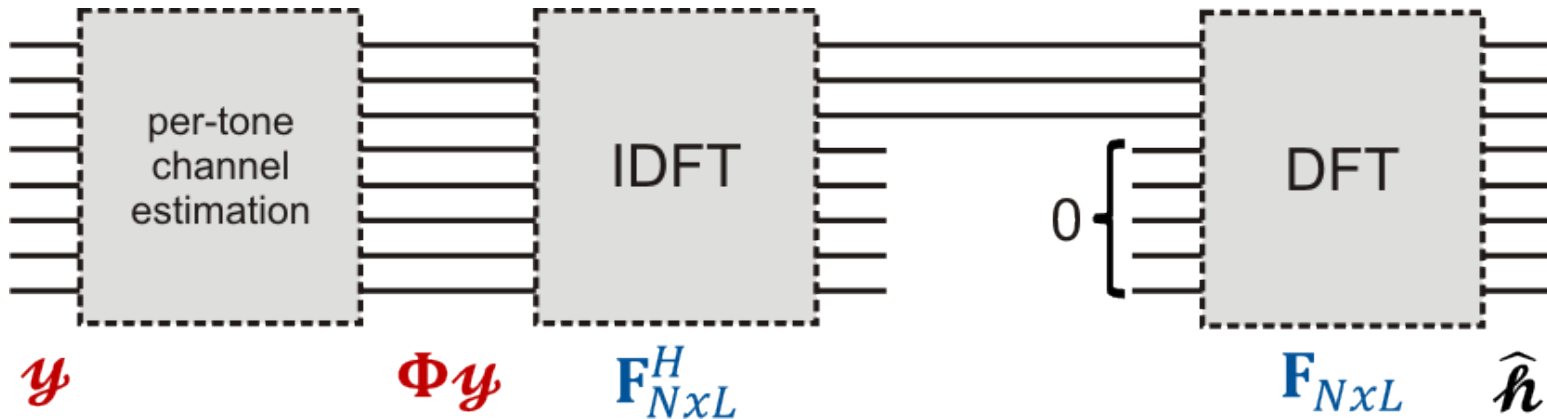
- Computational complexity (multiplications) $\propto N^2$

Low Complexity Implementation

More economic implementation

$$\hat{\mathbf{h}} = \mathbf{F}_{NxL} \mathbf{F}_{NxL}^H \underbrace{(\mathbf{T}^H \mathbf{T})^{-1} \mathbf{T}^H}_{\Phi} \mathbf{y}$$

- \mathbf{F}_{NxL}^H : Truncated IFFT (keep only L of N outputs)
- \mathbf{F}_{NxL} : Zero-padded FFT (Only first L coefficients are non-zero)



- Computational complexity (multiplications) $\propto N \log N$ (complexity of an FFT/IFFT)

Impact on Channel Estimation Error

Reminder: total channel estimation error with per-tone estimation

$$(\mathcal{T}^H \mathcal{T})^{-1} \mathcal{T}^H \mathbf{y} = \mathbf{h} + \Delta \mathbf{h}$$

$$\mathbb{E}\{|\Delta \mathbf{h}|^2\} = N \sigma_{\mathbf{h}}^2 = N \sigma_{h_f}^2 = N \sigma_n^2 / P_t$$

Time-domain least squares $\hat{\mathbf{h}} = \mathbf{F}_{NxL} \mathbf{F}_{NxL}^H (\mathbf{h} + \Delta \mathbf{h})$

- Consider the noise $\Delta \mathbf{h}$ after projection onto the support of the channel \mathbf{F}_{NxL}^H

$$\mathbb{E}\{|\mathbf{F}_{NxL}^H \Delta \mathbf{h}|^2\} = \mathbb{E}\{|\Delta \mathbf{h}|^2\} \text{ with } \Delta \mathbf{h} = \mathbf{F}_{NxL}^H \Delta \mathbf{h}$$

- Since \mathbf{F}_{NxL}^H is an orthonormal transform: $\sigma_{h_k}^2 = \sigma_{h_f}^2 = \sigma_n^2 / P_t$ and all Δh_k are independent

$$\mathbb{E}\{|\Delta \mathbf{h}|^2\} = \sum_{k=1}^L \mathbb{E}\{|\Delta h_k|^2\} = L \sigma_n^2 / P_t$$

- Transformation back to frequency domain only re-distributes the noise across tones

$$\mathbb{E}\{|\hat{\mathbf{h}} - \mathbf{h}|^2\} = \frac{L \sigma_n^2}{P_t} = \frac{L}{N} \mathbb{E}\{|\Delta \mathbf{h}|^2\}$$

Improvement compared to per-tone estimation

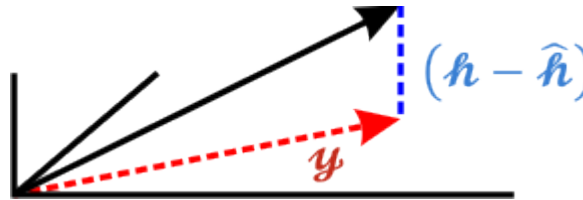
Linear MMSE Channel Estimation (Frequ. Domain View)

$$\hat{\mathbf{h}} = \underset{\hat{\mathbf{h}}}{\operatorname{argmin}} \mathbb{E} \left\{ |\mathbf{h} - \hat{\mathbf{h}}|^2 \right\}$$

- Linear MMSE estimator : $\hat{\mathbf{h}} = \mathbf{W}\mathbf{y}$

Solving the MMSE estimation problem:

- Orthogonality principle:** *residual error must be orthogonal to the observation*



$$\mathbb{E} \{ (\mathbf{h} - \hat{\mathbf{h}}) \mathbf{y}^H \} = 0$$

- Substitute \mathbf{y} and $\hat{\mathbf{h}} = \mathbf{W}\mathbf{y}$, then take the expectation

$$\mathbb{E} \{ (\mathbf{h} - \hat{\mathbf{h}}) \mathbf{y}^H \} = \mathbb{E} \{ (\mathbf{h} - \mathbf{W}\mathbf{y}) \mathbf{y}^H \} = 0$$

$$\mathbb{E} \{ \mathbf{h} \mathbf{y}^H \} = \mathbf{W} \mathbb{E} \{ \mathbf{y} \mathbf{y}^H \}$$

Φ_{yh} (red arrow pointing to $\mathbb{E} \{ \mathbf{h} \mathbf{y}^H \}$)
 Φ_{yy} (red arrow pointing to $\mathbb{E} \{ \mathbf{y} \mathbf{y}^H \}$)

$$\mathbf{W} = \Phi_{hh} \mathcal{T}^H (\mathcal{T} \Phi_{hh} \mathcal{T}^H + \Phi_{nn})^{-1}$$

Covariance matrix
of the channel coeffs

$$\Phi_{hh} = \mathbb{E} \{ \mathbf{h} \mathbf{h}^H \} = ?$$

$$\mathbf{W} = \Phi_{yh} \Phi_{yy}^{-1}$$

Covariance matrix
of the thermal noise

$$\Phi_{nn} = \mathbb{E} \{ \mathbf{n} \mathbf{n}^H \} = \sigma_n^2 \mathbf{I}$$

Linear MMSE Channel Estimation

How do we know the frequency domain covariance matrix of the channel?

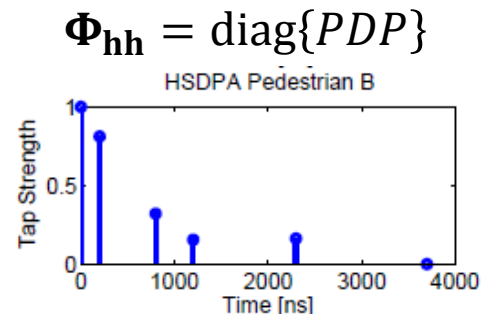
- Start from the time-domain representation of the channel and substitute

$$\begin{aligned}\mathbf{h} &= \mathbf{F}\mathbf{h} \\ \Phi_{hh} &= \mathbf{F}\mathbb{E}\{\mathbf{h}\mathbf{h}^H\}\mathbf{F}^H = \mathbf{F}\Phi_{hh}\mathbf{F}^H\end{aligned}$$

We can write the frequency domain channel covariance matrix in terms of the covariance matrix of the channels time-domain coefficients

Remember from discussion of channel models:

- In many models, individual taps are *uncorrelated* $\Rightarrow \Phi_{hh}$: diagonal
- Power-delay-profile specifies variance of the individual taps
- Length of the PDP (including trailing zeros is given by the OFDM symbol duration!!
- Φ_{hh} is a circulant matrix by construction



Comb-Type Training

Only P out of N tones are used for training

Per tone channel estimation only for P pilot tones

- Set of pilot tone indices $\mathcal{P} = \{p_0, p_1, \dots, p_{P-1}\}$

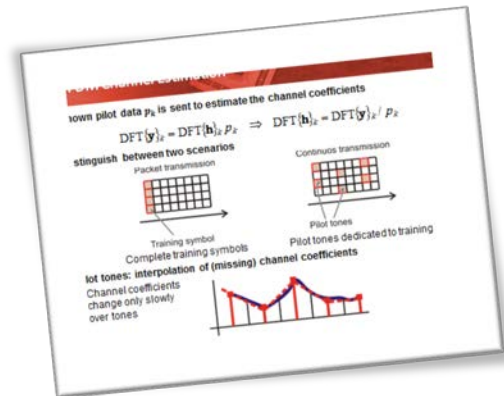
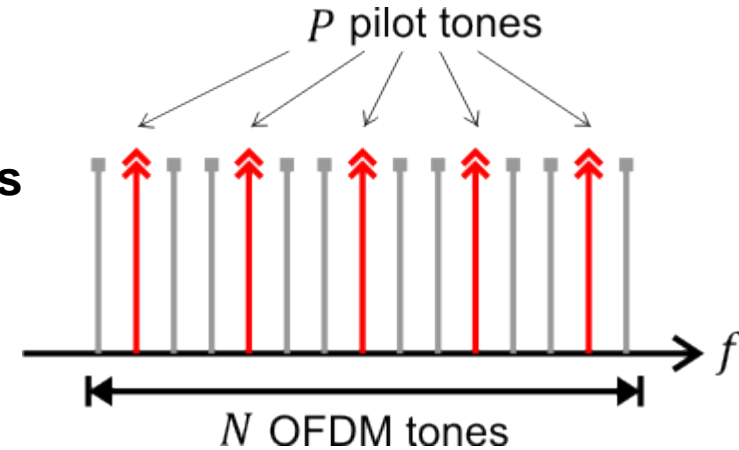
$$y_{p_k} = h_{p_k} t_k + n_{p_k}$$

- $\mathbf{h}_{\mathcal{P}} = [h_{p_0} \ h_{p_1} \ \dots \ h_{p_{P-1}}]^T$

- $\mathbf{y}_{\mathcal{P}} = [y_{p_0} \ y_{p_1} \ \dots \ y_{p_{P-1}}]^T$

$$\mathbf{T}_{\mathcal{P}} = \begin{bmatrix} t_0 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & t_{P-1} \end{bmatrix}$$

$$\mathbf{y}_{\mathcal{P}} = \mathbf{T}_{\mathcal{P}} \mathbf{h}_{\mathcal{P}} + \mathbf{n}_{\mathcal{P}}$$



How can we estimate the channel for all tones?

Time Domain Channel Estimation for Comb-Training

- Write channel frequency response in terms of the channels impulse response
- Consider only the tones occupied by pilot symbols
- Example $N = 8, L = 4$

$$\begin{bmatrix} h_0 \\ h_{p_0} \\ h_2 \\ h_{p_1} \\ h_4 \\ h_{p_2} \\ h_6 \\ h_{p_3} \end{bmatrix} = \begin{bmatrix} f_{0,0} & f_{0,1} & f_{0,2} & f_{0,3} & f_{0,4} & f_{0,5} & f_{0,6} & f_{0,7} \\ & f_{1,0} & & f_{1,3} & f_{1,4} & & & \\ & f_{2,0} & & f_{2,3} & f_{2,4} & & & \\ & f_{3,0} & & f_{3,3} & f_{3,4} & & & \\ & f_{4,0} & & f_{4,3} & f_{4,4} & & & \\ & f_{5,0} & & f_{5,3} & f_{5,4} & & & \\ & f_{6,0} & & f_{6,3} & f_{6,4} & & & \\ & f_{7,0} & & f_{7,3} & f_{7,4} & & & \end{bmatrix} \begin{bmatrix} h_0 \\ h_1 \\ h_2 \\ h_3 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

- $\mathbf{F}_{\mathcal{P} \times L}$: Truncated Fourier matrix (only first L columns)
keeping only the rows with indices in \mathcal{P} (only pilot tones)

Time Domain Channel Estimation for Comb-Training

- System model for pilot subcarriers based on channel impulse response of length L

$$\mathbf{y}_{\mathcal{P}} = \mathbf{T}_{\mathcal{P}} \mathbf{F}_{\mathcal{P}xL} \mathbf{h}_L + \mathbf{n}_{\mathcal{P}}$$

Solve for the time domain impulse response

$$\widehat{\mathbf{h}}_L = (\mathbf{F}_{\mathcal{P}xL}^H \mathbf{T}_{\mathcal{P}}^H \mathbf{T}_{\mathcal{P}} \mathbf{F}_{\mathcal{P}xL})^{-1} \mathbf{F}_{\mathcal{P}xL}^H \mathbf{T}_{\mathcal{P}}^H \mathbf{y}_{\mathcal{P}}$$

- Necessary condition: $(\mathbf{F}_{\mathcal{P}xL}^H \mathbf{T}_{\mathcal{P}}^H \mathbf{T}_{\mathcal{P}} \mathbf{F}_{\mathcal{P}xL})$ must be invertible
- **Note:** condition of $(\mathbf{F}_{\mathcal{P}xL}^H \mathbf{T}_{\mathcal{P}}^H \mathbf{T}_{\mathcal{P}} \mathbf{F}_{\mathcal{P}xL})$ depends on $\mathcal{P} \Rightarrow$ improper selection of tones leads to ill conditioned estimator (noise enhancement)
- With $\widehat{\mathbf{h}}_L$ we can easily find $\widehat{\mathbf{h}}$ according to

$$\widehat{\mathbf{h}} = \mathbf{F}_{NxL} \widehat{\mathbf{h}}_L$$

Time Domain Channel Estimation for Comb-Training

Consider a frequently used special case: $P > L$ training tones are distributed equally spaced in frequency domain

- In this case: $\mathbf{F}_{\mathcal{P} \times L}^H \mathbf{F}_{\mathcal{P} \times L} = \mathbf{I}_P$

$$\hat{\mathbf{h}} = \mathbf{F}_{N \times L} \left(\mathbf{F}_{\mathcal{P} \times L}^H \mathbf{T}_{\mathcal{P}}^H \mathbf{T}_{\mathcal{P}} \mathbf{F}_{\mathcal{P} \times L} \right)^{-1} \mathbf{F}_{\mathcal{P} \times L}^H \mathbf{T}_{\mathcal{P}}^H \mathbf{y} = \mathbf{F}_{N \times L} \mathbf{F}_{\mathcal{P} \times L}^H \underbrace{\left(\mathbf{T}_{\mathcal{P}}^H \mathbf{T}_{\mathcal{P}} \right)^{-1} \mathbf{T}_{\mathcal{P}}^H \mathbf{y}}_{\text{per-tone estimate}}$$

- $\mathbf{F}_{\mathcal{P} \times L}^H$: P -point DFT results in a P -periodic impulse response, truncated to the first $L < P$ coefficients
- $\mathbf{F}_{N \times L} \mathbf{F}_{\mathcal{P} \times L}^H$ is a low-pass (interpolation) filter in the frequency domain (cf. Slide 26)

For equally spaced pilot tones, channel estimation corresponds to
interpolation of channel coefficients