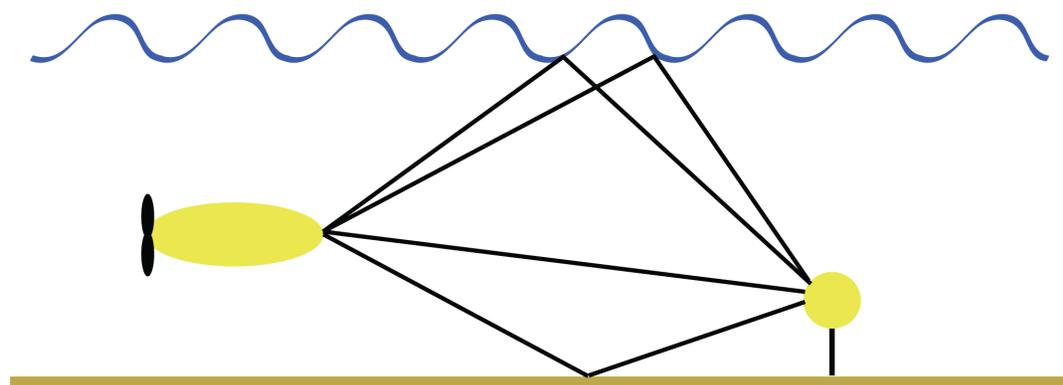


Comparison and Analysis of Equalization Techniques for the Time-Varying Underwater Acoustic Channel



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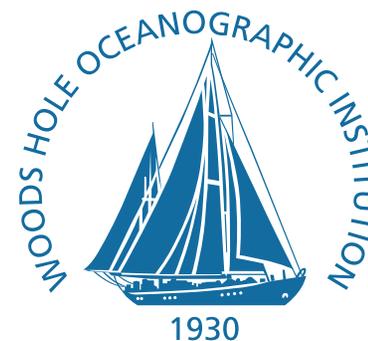
MIT/WHOI Joint Program

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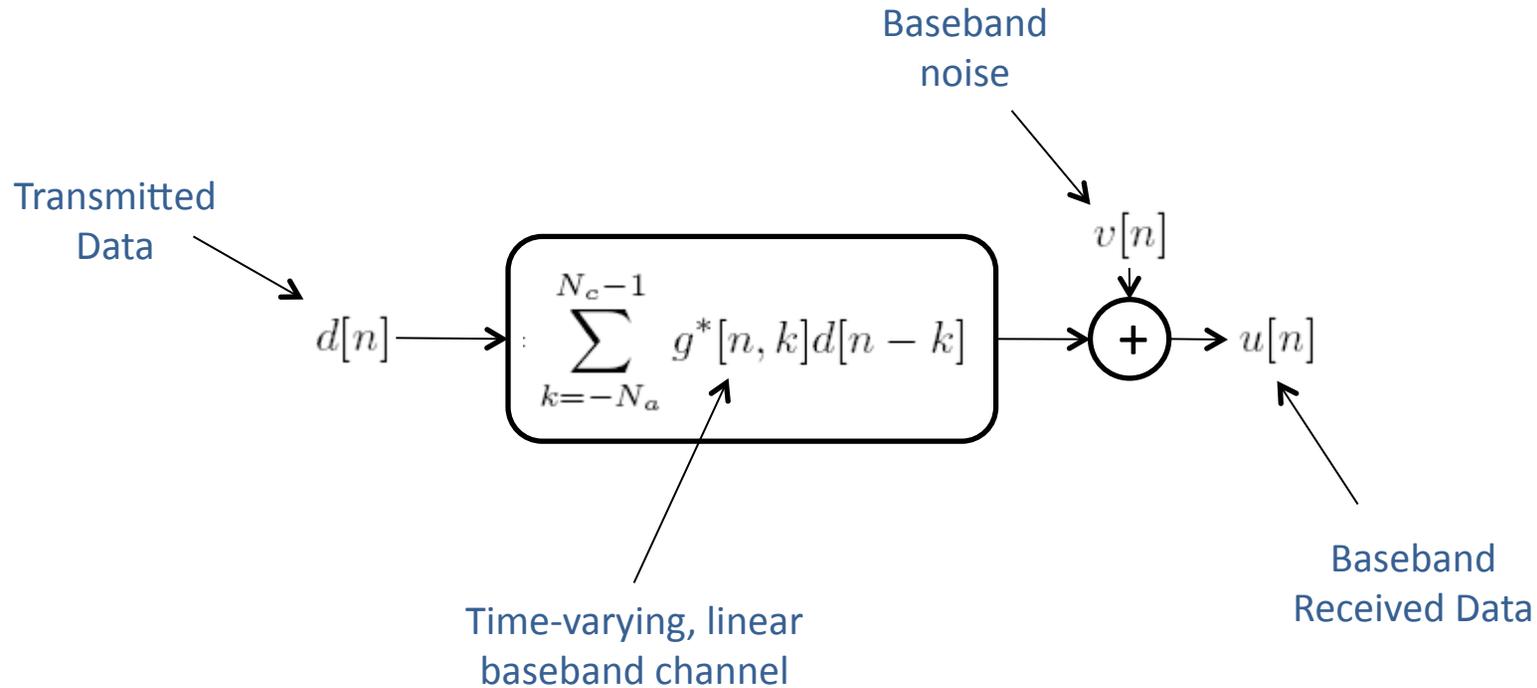


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Matrix-vector Form:

$$\mathbf{u}[n] = \mathbf{G}[n]\mathbf{d}[n] + \mathbf{v}[n] = \overbrace{\mathbf{G}_{fb}[n]\mathbf{d}_{fb}[n] + \mathbf{G}_0[n]\mathbf{d}_0[n]}^{\text{Split Channel Convolution Matrix}} + \mathbf{v}[n]$$



Decision Feedback Equalizer (DFE)



- Problem Setup: $\hat{\mathbf{h}}_{\text{opt}} = \arg \min_{\mathbf{h}'} E\{|\mathbf{h}^H \mathbf{z} - d|^2\}$

- Estimate using RX data and TX data estimates

$$\mathbf{z}[n] = [u[n - L_c + 1] \dots u[n] \dots u[n + L_a], \hat{d}[n - 1] \dots \hat{d}[n - L_{fb}]]^T$$

- DFE Eq: $\hat{d}[n] = \hat{\mathbf{h}}_{\text{opt}}^H[n] \mathbf{z}[n] = \mathbf{h}_{\text{ff}}^H \mathbf{u}[n] + \mathbf{h}_{\text{fb}}^H \hat{\mathbf{d}}_{\text{fb}}$

Solution to
Weiner-Hopf Eq.

$$\begin{aligned} \hat{\mathbf{h}}_{\text{opt}}[n] &= \mathbf{R}_{\mathbf{z}}^{-1}[n] \mathbf{r}_{\mathbf{z}d}[n] \\ \mathbf{R}_{\mathbf{z}}[n] &= E\{\mathbf{z}\mathbf{z}^H\} \\ \mathbf{r}_{\mathbf{z}d} &= E\{\mathbf{z}d^*\} \end{aligned}$$

MMSE Sol. Using Channel Model

$$\begin{aligned} \mathbf{h}_{\text{ff}} &= [\mathbf{G}_0 \mathbf{G}_0 + \mathbf{R}_{\mathbf{v}}]^{-1} \mathbf{g}_0 \\ \mathbf{h}_{\text{fb}} &= -\mathbf{G}_{\text{fb}} \mathbf{h}_{\text{ff}} \end{aligned}$$

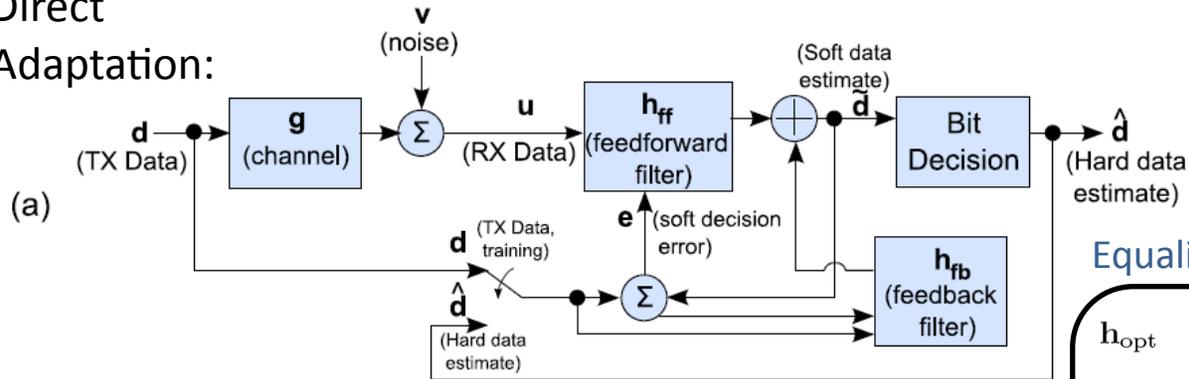
- Two Parts:
 - (Linear) feed-forward filter (of RX data)
 - (Linear) feedback filter (of data estimates)



DFE Strategies



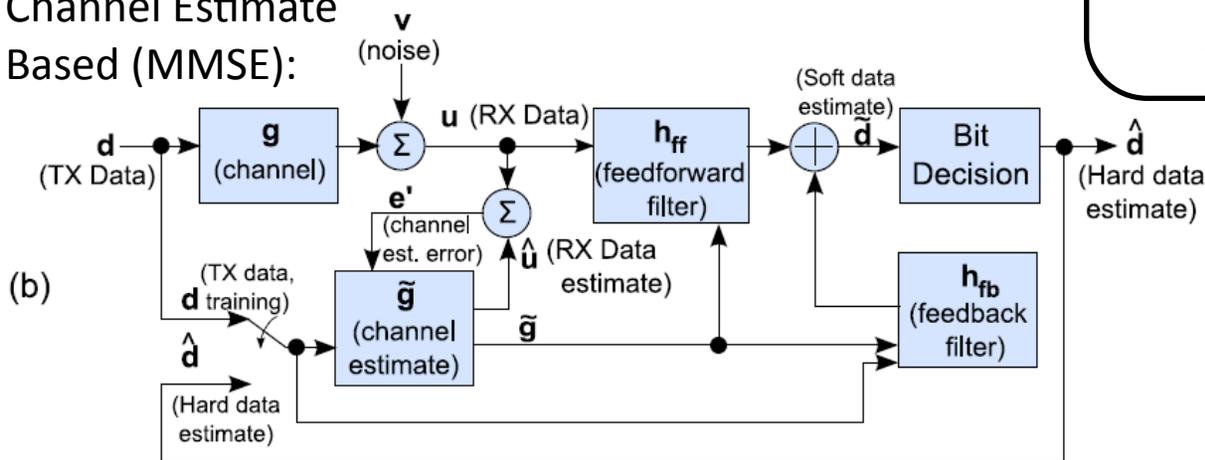
Direct
Adaptation:



Equalizer Tap Solution:

$$\begin{aligned}
 \mathbf{h}_{\text{opt}} &= \begin{bmatrix} \mathbf{h}_{\text{ff}} \\ \mathbf{h}_{\text{fb}} \end{bmatrix} \\
 &= (\mathbf{E}[\mathbf{z}\mathbf{z}^H])^{-1} \mathbf{E}[\mathbf{z}d^*] \\
 &= \left(\mathbf{E} \begin{bmatrix} \mathbf{u} \\ \mathbf{d}_{\text{fb}} \end{bmatrix} \begin{bmatrix} \mathbf{u} \\ \mathbf{d}_{\text{fb}} \end{bmatrix}^H \right)^{-1} \mathbf{E} \begin{bmatrix} \mathbf{u} \\ \mathbf{d}_{\text{fb}} \end{bmatrix} d^* \\
 &= \begin{bmatrix} \mathbf{G}_0 \mathbf{G}_0 + \mathbf{R}_v & -\mathbf{g}_0 \\ -\mathbf{G}_{\text{fb}} \mathbf{h}_{\text{ff}} & \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{g}_0 \\ \end{bmatrix}
 \end{aligned}$$

Channel Estimate
Based (MMSE):



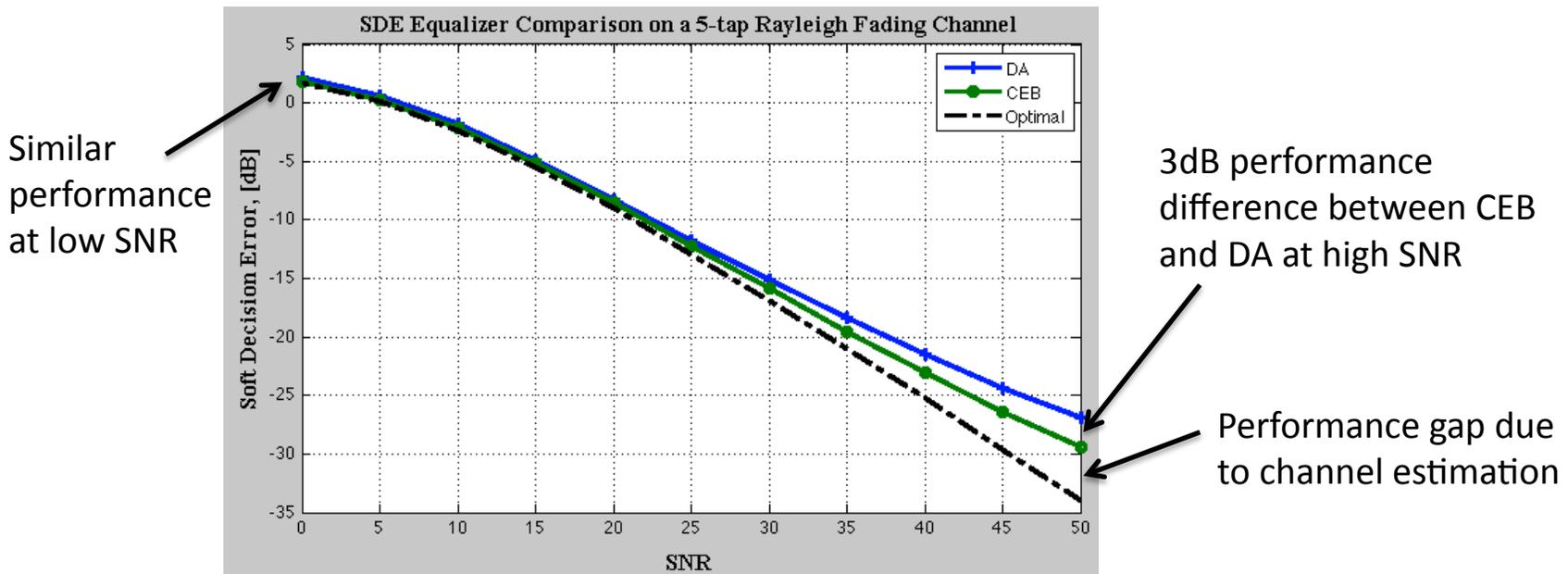


Central Question:



Why is the performance of a channel estimate based equalizer different than a direct adaptation equalizer?

- In the past, CEB methods empirically shown to have lower mean squared error at high SNR
- Reasons for difference varied:
 - Condition number of correlation matrix
 - Num. of samples required to get good estimate





Comparison between DA and CEB



- Our analysis shows the answer is:
Longer corr. time for channel coefficients than MMSE equalizer coefficients at high SNR
- Will examine low SNR and high SNR regimes
 - Use simulation to show transition of correlation time for the equalizer coefficients from low to high is smooth

Update eqn. for feed-forward equalizer coefficients (AR model assumed):

$$\begin{aligned}
 \mathbf{h}_{\text{ff}}[n+1] &= (\mathbf{G}_0[n+1]\mathbf{G}_0^H[n+1] + \mathbf{R}_v)^{-1}(\mathbf{g}_0[n+1]) \\
 &\approx \mathbf{R}_v^{-1}(\alpha\mathbf{g}_0[n] + \mathbf{w}[n]) \\
 &\approx \alpha\mathbf{h}_{\text{ff}}[n] + \mathbf{R}_v^{-1}\mathbf{w}[n]
 \end{aligned}$$

Approximation:

$$\mathbf{R}_v + \mathbf{G}[n]\mathbf{G}^H[n] \approx \mathbf{R}_v$$

Has same correlation structure
as channel coefficients

$$\mathbf{h}_{\text{ff}}[n+1] = (\mathbf{G}_0[n+1]\mathbf{G}_0^H[n+1] + \mathbf{R}_v)^{-1}(\mathbf{g}_0[n+1])$$

Approximation:

$$\mathbf{G}_0[n]\mathbf{G}_0^H[n] + \mathbf{R}_v \approx \mathbf{G}_0[n]\mathbf{G}_0^H[n] \implies (\mathbf{G}_0[n]\mathbf{G}_0^H[n])\mathbf{h}_{\text{ff}}[n] = \mathbf{g}_0[n]$$

Reduced Channel Convolution Matrix:

$$\mathbf{G}_0 = \begin{bmatrix} g_0^*[n-L+1] & 0 & 0 & \cdots & 0 \\ g_1^*[n-L+2] & g_0^*[n-L+2] & 0 & \cdots & 0 \\ g_2^*[n-L+3] & g_1^*[n-L+3] & g_0^*[n-L+3] & \cdots & 0 \\ \vdots & & & \ddots & \vdots \\ g_L^*[n] & g_{L-1}^*[n] & g_{L-2}^*[n] & \cdots & g_0^*[n] \end{bmatrix}$$

Matrix Product:

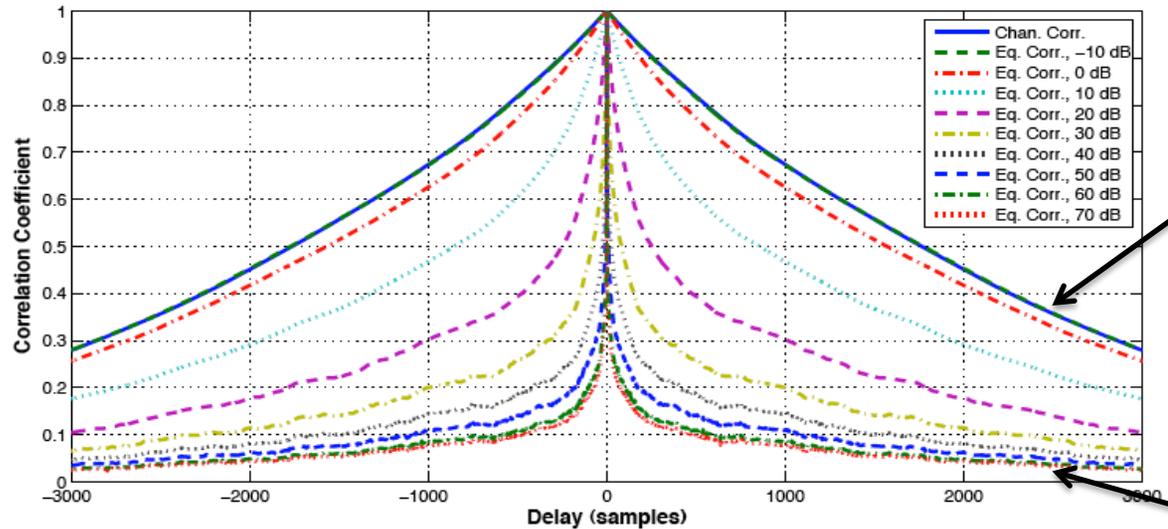
$$\mathbf{G}_0\mathbf{G}_0^H = \begin{bmatrix} |g_0|^2 & \cdots \\ g_0g_1^* & \cdots \\ g_0g_2^* & \cdots \\ \vdots & \vdots \\ g_0g_L & \cdots \end{bmatrix}$$

Reduces to single tap:

$$\mathbf{h}[n] = [1/g_0 \ 0 \ 0 \ \cdots \ 0]^T$$

Correlation over SNR – 1-tap

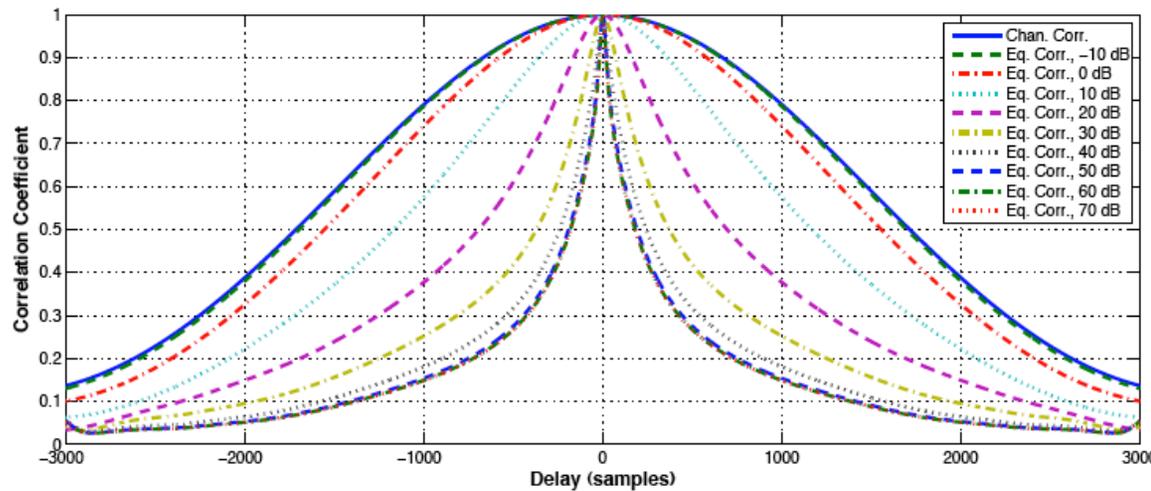
AR(1)
model



Channel and Equalizer Coeff. Correlation the Same at low SNR

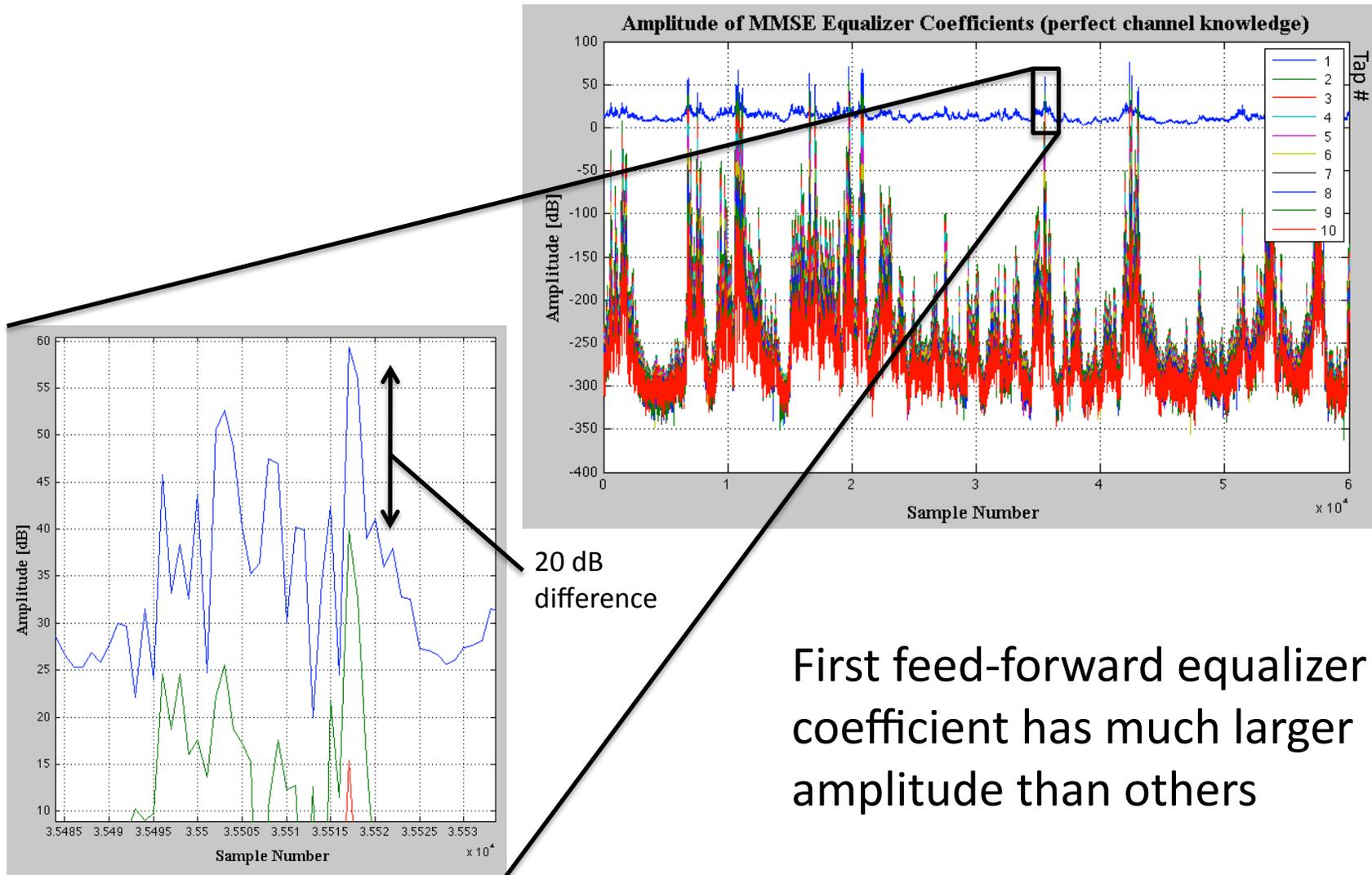
Equalizer Coeff. Correlation reduces as SNR increases

Gaussian
model



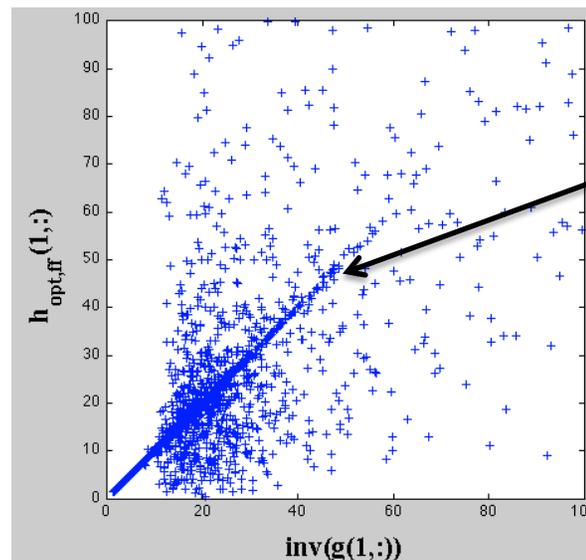
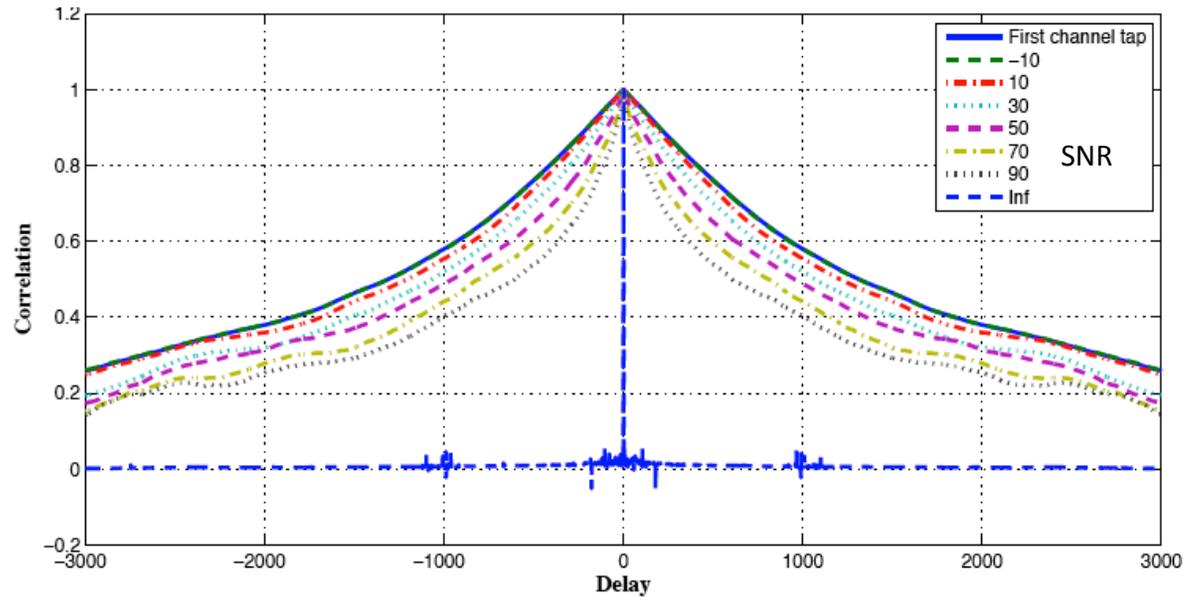


Amplitude of MMSE Eq. Coeff.



Multi-tap correlation

Multi-tap
AR(1)
model



Strong linear
correlation between
inverse of first
channel tap and first
MMSE Eq. tap



Take-home Message



- Channel impulse-response taps have longer correlation time than MMSE equalizer taps
 - DA has greater MSE than CEB
- For time-invariant statistics, CEB and DA algorithms have similar performance
 - Low-SNR regime (assuming stationary noise)
 - Underwater channel operates in low SNR regime (<35dB)

Questions?





Backup Slides



- Unit variance, white transmit data

$$E\{\mathbf{d}[n]\mathbf{d}^H[n]\} = \mathbf{I}$$

- TX data and obs. noise are uncorrelated

$$E\{\mathbf{v}[n]\mathbf{d}^H[m]\} = \mathbf{0}$$

- Obs. Noise variance:

$$\mathbf{R}_v = E\{\mathbf{v}[n]\mathbf{v}^H[n]\}$$

- Perfect data estimation (for feedback)

$$\hat{\mathbf{d}} = \mathbf{d}$$

- Equalizer Length = Estimated Channel Length

$$N_a + N_c = L_a + L_c$$

- MMSE Equalizer Coefficients have form:

$$\mathbf{h}_{ff} = [\mathbf{G}_0\mathbf{G}_0^H + \mathbf{R}_v]^{-1}\mathbf{G}_0\mathbf{s}$$

$$\mathbf{h}_{fb} = -\mathbf{G}_{fb}^H\mathbf{h}_{ff}$$



WSSUS AR channel model



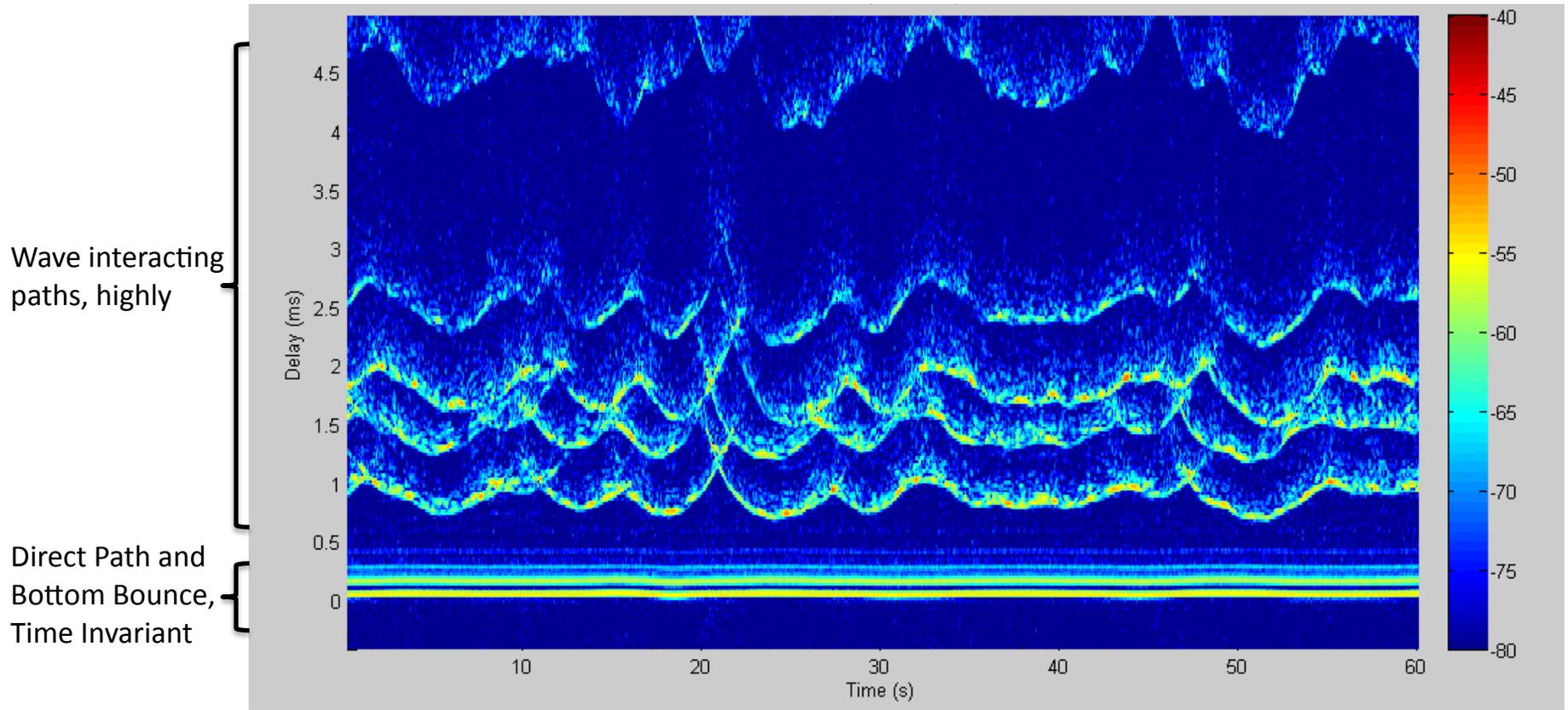
- Simple channel model to analyze
- Similar to encountered situations

$$g[n + 1] = \alpha g[n] + w[n]$$

$$R_{gg}[k] = \mathbb{E}\{g[n]g^*[n + k]\} = \begin{cases} \sigma_w^2 \left(\frac{(\alpha^*)^k}{1 - |\alpha|^2} \right) & k \geq 0 \\ \sigma_w^2 \left(\frac{\alpha^{-k}}{1 - |\alpha|^2} \right) & k < 0 \end{cases}$$



Time Varying Impulse Response



Wavefronts II Experiment from San Diego, CA



Future Work



- Reduce time needed to update channel model
 - Sparsity
 - Physical Constraints
 - Optimization Techniques
- Combine DA and CEB equalizers
 - Better performance at lower complexity