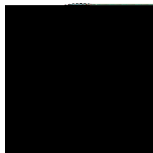


# Information Rates for Phase Noise Channels

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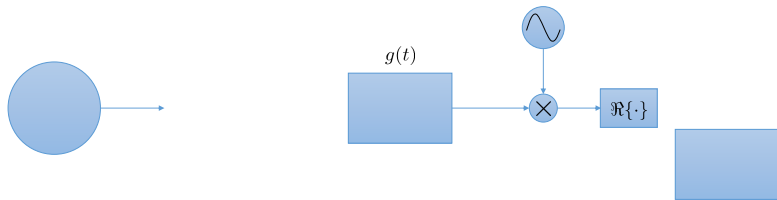
# Outline

- 1 Motivation
- 2 From continuous to discrete time
- 3 Finite Resolution Receivers
- 4 Capacity bounds
- 5 Conclusions

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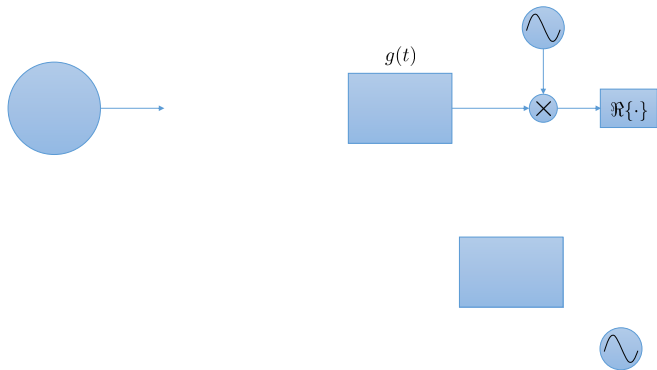
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# A Classic Communication Scheme





# The AWGN Channel

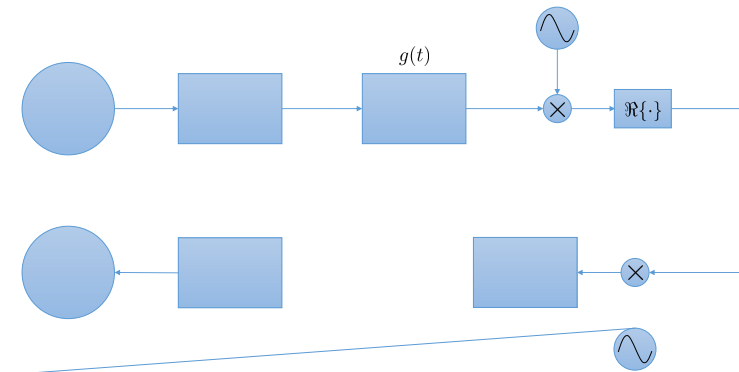


$$Y_k = X_k + W_k$$

# The Actual

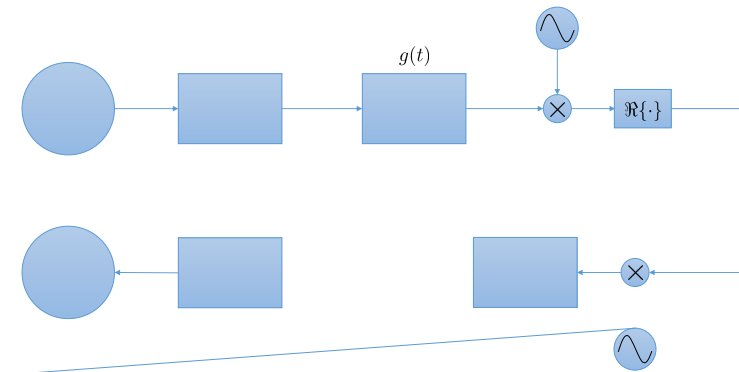


# The Actual AWGN Channel



Phase noise processes  $t_x$  and  $t_r$

# The Actual AWGN Channel



Phase noise processes  $\phi_{tx}$  and  $\phi_{rx}$   
Sampling at  $kT_{\text{symb}}$  is no longer optimal!

# Phase Noise Channels

Phase noise arises due to

- Imperfections in the oscillator circuits at the transceivers

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Phase noise arises due to

- Imperfections in the oscillator circuits at the transceivers
  - Even for high-quality oscillators: if the continuous-time waveform is processed by long filters at the receiver (e.g., long symbol time, OFDM systems), the phase uncertainty accumulates!

# Phase Noise Channels

Phase noise arises due to



# Phase Noise Channels

Questions:

- Models for phase noise channels

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# Phase Noise Channels

Questions:

- Models for phase noise channels
- Impact of phase noise on channel capacity
- Signal and code design

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## Representation of continuous-time waveforms

- Assume input waveform  $fX(t)g_{t=0}^T$  is square integrable:

$$X(t) \in L^2[0; T] \quad ! \quad \int_0^T |X(t)|^2 dt < 1$$



## Representation of continuous-time waveforms

- Assume input waveform  $fX(t)g_t^T$



## Mutual information for random waveforms

- The average mutual information between  $fX(t)g_{t=0}^T$  and  $fY(t)g_{t=0}^T$  is [Gallager, 1968]

$$I(fX(t)g_{t=0}^T; fY(t)g_{t=0}^T) = \lim_{n \rightarrow \infty} \frac{1}{n} I(X_1, \dots, X_n; Y_1, \dots, Y_n)$$

(if it exists)

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## Example: mutual information for a phase noise channel

- Input-output relation:

$$Y(t) = X(t)e^{j\phi(t)} + W(t)$$

## Example: mutual information for a phase noise channel

- Input-output relation:

$$Y(t) = X(t)e^{j\theta(t)} + W(t)$$

- Choose an incomplete orthonormal basis as

$$p_m(t) = \frac{1}{\sqrt{T}} \text{rect} \left( \frac{t - mT}{T} \right) ; \quad m = 1 \dots n; \quad T = T = n$$



## Example: mutual information for a phase noise channel

- Discretized model:

$$Y_m = X_m \int_{(m-1)}^m e^{j\theta(t)} dt + W_m$$

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- Both amplitude fading and phase noise!
- Commonly used discrete-time phase noise channel model:

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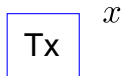
$$Y_m = X_m e^{j\phi_m} + W_m; \quad \phi_m = \int_{(m-1)}^m \phi(t) dt$$

- How different are the two models in terms of capacity?

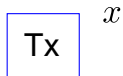




# Receivers with finite time resolution

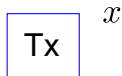


# Receivers with finite time resolution



- How small should  $\epsilon$  be?

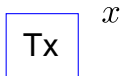
# Receivers with finite time resolution



- How small should  $\tau$  be?
  - It depends on the statistics of  $f(t)g$

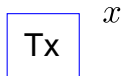


## Receivers with finite time resolution



- How small should  $\Delta t$  be?
  - It depends on the statistics of  $f(t)g$
  - In general, as small as possible
- Oversampling helps!  $\Delta t \rightarrow 0 \Rightarrow I(X_1, X_n; Y_1, Y_n) \rightarrow I(X; Y)$

# Receivers with finite time resolution



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- **Oversampling helps!**  $\epsilon \Rightarrow I(X_1 \dots X_n; Y_1 \dots Y_n) \%$

# Oversampled channel model

$$Y_{mL+\ell} = X_m F_{mL+\ell} + W_{m\ell}; \quad \ell = 1; \dots; L$$

$$m = 1; \dots; n$$

$$F_{mL+\ell} = \int_{(mL+\ell-1)T_{\text{symp}}}^{(mL+\ell)T_{\text{symp}}} e^{j2\pi f_c t} x_m(t) dt; \quad = \frac{T_{\text{symp}}}{L}$$





## Wiener phase noise

- Widely used for modeling oscillators
- Also known as Brownian motion:

$$\phi(t) = \phi(0) + \int_0^t Z(t') dt'$$

where  $Z$  is a white Gaussian process



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- Samples are not independent:  $E[\phi(t)\phi(s)] = 2 \min\{t, s\}$
- Process with memory!
- Oversampling, i.e.  $L > 1$ , increases information rates

## Wiener phase noise channel

Define  $\theta_k = ((k-1) \rho)$  and  $N_k \sim N(0; 1)$ :

$$\theta_k = \theta_{k-1} + \rho N_k$$

## Wiener phase noise channel

Define  $\theta_k = ((k-1) \Delta\theta)$  and  $N_k \sim N(0; \sigma^2)$ :

$$\theta_k = \theta_{k-1} + \sqrt{\rho} N_k$$

$$Y_{mL+\Delta} = X_m e^{j \int_{(mL+\Delta-1)\Delta}^{(mL+\Delta)\Delta} \theta(t) dt} + W_{mL+\Delta}$$



## Wiener phase noise channel

Define  $\theta_k = ((k-1)\theta)$  and  $N_k \sim N(0;1)$ :

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Contour plot of the unnormalized fading pdf for  $\alpha = 6$  and  $\beta = 1$ . (Y. Wang *et al.*, TCOM 2006, vol. 54, no. 5)

# Oversampled Discrete-time Wiener Phase Noise Channel

- Let us study the capacity of a simpler model

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# Oversampled Discrete-time Wiener Phase Noise Channel

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$$Y_{mL+\cdot} = X_m e^{j\theta_{mL+\cdot}} + W_{mL+\cdot}$$

- Capacity under an average power constraint:

$$\lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T |X(t)|^2 dt \leq P$$



# Oversampled Discrete-time Wiener Phase Noise Channel

- Let us study the capacity of a simpler model

$$X_k = X_{k-1} + \sqrt{\rho} N_k$$

$$Y_{mL+1} = X_m e^{j\theta_{mL+1}} + W_{mL+1}$$

- Capacity under an average power constraint:

$$E \left[ \frac{1}{T} \int_0^T |jX(t)|^2 dt \right] \leq P \Rightarrow E [ |X_m|^2 ] \leq P$$





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Challenges:

- Channel with memory



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# How to compute capacity

Challenges:

- Channel with memory
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We will see how to:

- Get rid of the memory
- Compute an upper bound to capacity
- We assume iid  $X_m$ 's with  $\underline{X}_m \sim U[0; 2)$

## A capacity upper bound

Define  $X_1^n = X_1 \dots X_n$

$$\frac{1}{n} I(X_1^n; \mathbf{Y}_1^n) = \frac{1}{n} \sum_{m=1}^n I(X_1^n; \mathbf{Y}_m | \mathbf{Y}_1^{m-1})$$

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$$\text{(Stationary)} = I(X_1; \mathbf{Y}_{1:j} \mathbf{Y}_{1:L+1}) + \frac{1}{n} \sum_{m=1}^n I(\mathbf{Y}_{m:L+1}; \mathbf{Y}_{m:j} \mathbf{Y}_1^{m-1})$$







# A capacity upper bound

Assumption: iid  $X_m$ 's with  $\angle X_m \sim U[0; 2\pi)$

$$\begin{aligned}
 & I_{mL+1; \mathbf{Y}_m | \mathbf{Y}_1^{m-1}} \\
 \text{(DPI)} \quad & I_{mL+1; mL+1} \angle X_m \stackrel{p}{\sim} N_{mL+1} | \mathbf{Y}_1^{m-1} \\
 & = 0
 \end{aligned}$$



# Polar decomposition

$$\begin{aligned}
 I(X_1; \mathbf{Y}_1^{j_{L+1}}) &= I(jX_1j; \underline{\angle X_1}; \mathbf{Y}_1^{j_{L+1}}) \\
 &= \underbrace{I(jX_1j; \mathbf{Y}_1^{j_{L+1}})}_{\text{amplitude mod.}} + \underbrace{I(\underline{\angle X_1}; \mathbf{Y}_1^{j_{L+1}}; jX_1j)}_{\text{phase mod.}}
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- Different bounding techniques are used for the two terms
  - Reveal all phase noise samples to the receiver: amplitude mod. on AWGN channel
  - Application of the I-MMSE formula to the phase mod. term

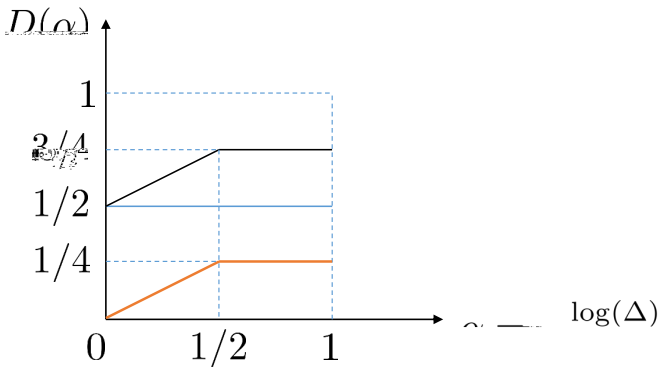
$$C \approx \frac{1}{2} \log \left( 1 + \frac{P}{2} \right) + \log(2) + \frac{1}{2} \log \left( P \frac{S}{1 + \frac{4}{2P}} \right) \quad !!$$



# Degrees of freedom

Define the degrees of freedom as

$$D(\alpha) = \lim_{P \rightarrow \infty} \frac{C(P; \alpha = P^{-\alpha})}{\log(P)}$$





## Conclusions

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- If  $\rho = \frac{1}{P}$ , an asymptotic capacity pre-log of 0.75 can be achieved, but not surpassed
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  - For any  $\rho > 0$ ! Even for very high-quality oscillators!

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  - For any  $\rho > 0$ ! Even for very high-quality oscillators!
- Conjectures:
  - Simplifying the model by discarding the amplitude fading is too much
  - The fundamental tension between additive noise and phase noise limits the degrees of freedom

Thanks for your attention!

## Derivation of the average power constraint

$$\lim_{T \rightarrow \infty} \frac{1}{T}$$