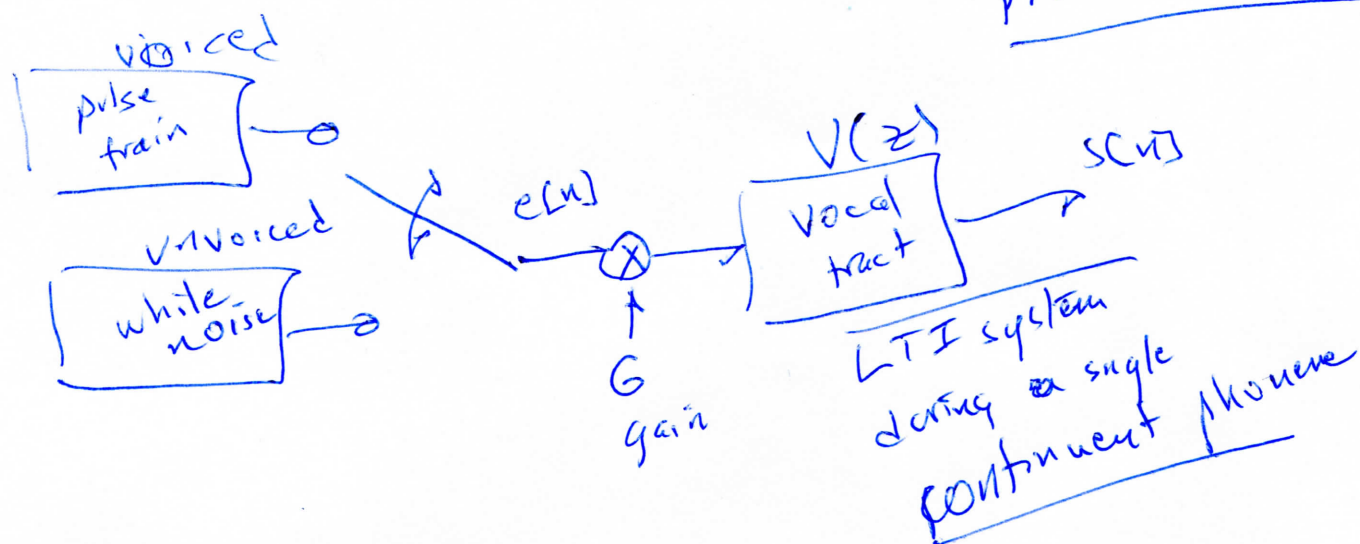


Linear Predictive Coding (LPC) of Speech (Module 4.3)

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Short-time DTFT (STDTFT)
formant frequencies

} frequency domain

time-domain

Develop a time-domain model for speech waveform

All-pole model

$$V(z) = \frac{G}{1 - \sum_{k=1}^p a_k z^{-k}}$$

Model parameters:
 a_k , $k = 1, \dots, p$ - no. of poles
 G - gain

②

true-domain model:

$$s[n] = \sum_{k=1}^p a_k s[n-k] + G e[n]$$

↑
excitation

↑
unknown

linear predictor

$$\hat{s}[n] = \sum_{k=1}^p \alpha_k s[n-k]$$

predictor coefficient

how do we judge performance of predictor?

$$f[n] = s[n] - \hat{s}[n]$$

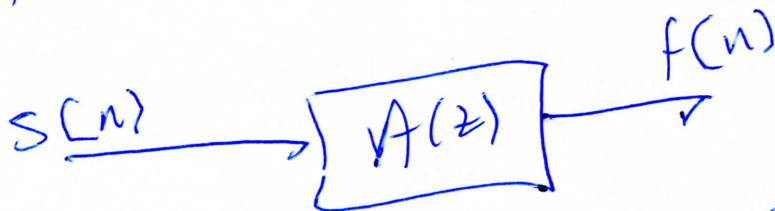
would like $f[n]$ to be small?

Choose α_k 's $k=1, \dots, p$ to minimize

$$E = \sum_n f^2[n]$$

Suppose $\alpha_k = a_k, \quad k=1, \dots, p$

$$\text{let } A(z) = 1 - \sum_{k=1}^p \alpha_k z^{-k}$$



If model is correct & we estimate

 $\alpha_k = a_k, \quad k=1, \dots, p$ then

$$f[n] = G e[n]$$

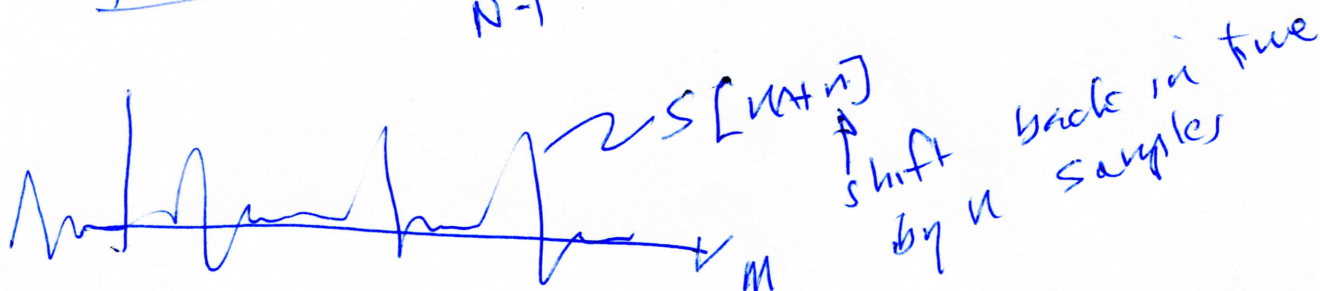
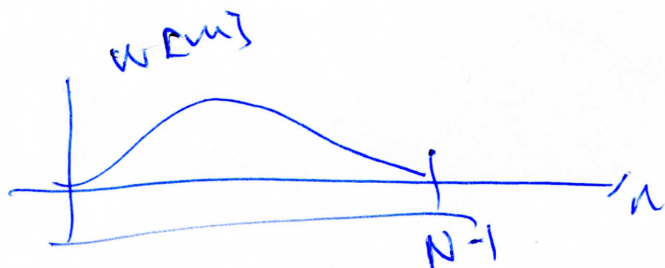
 $\Rightarrow$ we can estimate G & the pitch period from $f[n]$

Consider only short-time intervals of $s[n]$

(3)

$$\text{let } s_n[m] = w[m] s[m+n]$$

$$w[m] \neq 0 \text{ for } 0 \leq m \leq N-1$$



$$\text{let } f_n[m] = s_m[m] - \hat{s}_n[m]$$

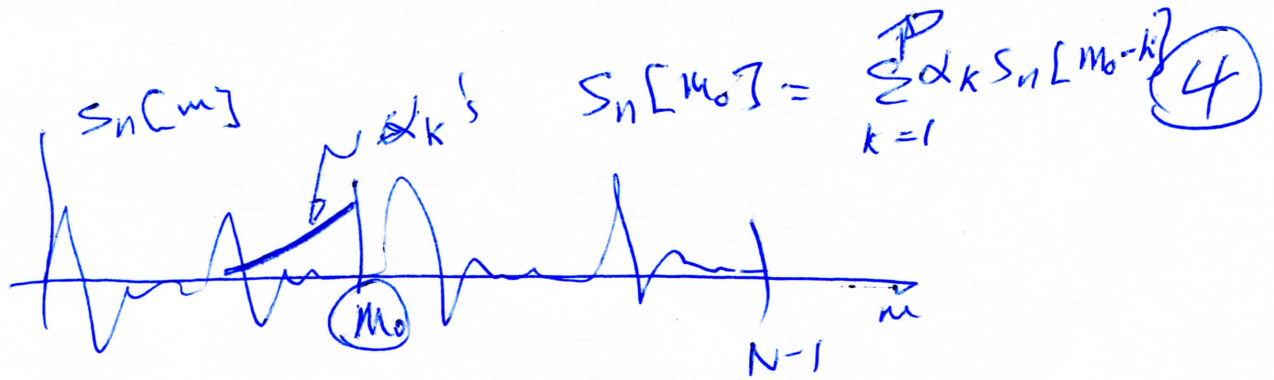
$$\text{recall } \hat{s}_n[m] = \sum_{k=1}^p \alpha_k s_n[m-k]$$

$\neq 0$ only for

$$0 \leq m \leq N+p-1$$

$$s_n[m] \neq 0 \text{ only } 0 \leq m \leq N-1$$

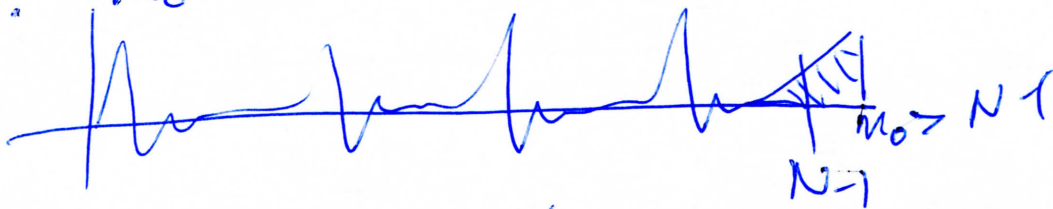
$$\therefore f_n[m] \neq 0 \text{ only for } 0 \leq m \leq N+p-1$$



Epochs in prediction error signal



- I. $0 \leq m_0 \leq P \Rightarrow$ large error because I don't have complete data
 II. ~~III~~ $P \leq m_0 \leq N-1 \Rightarrow$ small error because I have complete data
 III. $m_0 > N-1$



prediction should be zero, but we have non-zero data on which prediction based $\Rightarrow$ large error

$\Rightarrow$ should choose following limits for my error:

$$\Phi = \sum_{m=P}^{N-1} (f_n[m])^2$$

But $f_n[m] \neq 0$ for $0 \leq m \leq N-1+p$ (5)

Two solutions:

(1) let $\Phi_n = \sum_{m=p}^{N-1} (f_n[m])^2$

and solve for unknown d_k 's
 $\Rightarrow$ covariance method

(2) let $\Phi_n = \sum_{m=-\infty}^{\infty} (f_n[m])^2$

and solve for unknown d_k 's
 $\Rightarrow$ autocorrelation method

We will derive optimal d_k 's for this case, i.e. minimize Φ_n

Consider $\Phi_n = \sum_{m=-\infty}^{\infty} \left\{ s_n[m] - \sum_{k=1}^p d_k s_n[m-k] \right\}^2$ (2)

pick a particular d_k to optimize

$$\frac{\partial \Phi_n}{\partial d_k} = \sum_{m=-\infty}^{\infty} 2 \left\{ s_n[m] - \sum_{k=1}^p d_k s_n[m-k] \right\}$$

$$\left\{ 0 = s_n[m-l] \right\}$$

$$= -2 \sum_m s_n[m] s_n[m-l] + 2 \sum_m \sum_{k=1}^p d_k s_n[m-k] s_n[m-l]$$

let $m-l = m'$ in second sum (6)
 $m = m' + l$

$$\frac{\partial \Phi_n}{\partial x_l} = - \sum_m \frac{\sum_n s_n L_m s_n (m-l)}{\sum_{k=1}^p d_k \sum_{m'=-\infty}^{\infty} s_n [m-(k+l)] s_n (m')}$$

define $R_n[l] = \sum_m s_n (m) s_n (m+l)$
 $= R_n[-l]$
 $= \sum_m s_n (m) s_n (m-l)$

let $\frac{\partial \Phi_n}{\partial x_l} = 0$
 $\Rightarrow \underline{R_n[l]} = \sum_{k=1}^p d_k \underline{R_n[l-k]}$
 $l = 1, \dots, p$
 (Annotations: $R_n[l-k]$ is labeled "known data", $R_n[l]$ is labeled "unknown")

Consider matrix-vector formulation
 rows are l

$$\begin{bmatrix} R_n[0] & R_n[1] & \dots & R_n[p-1] \\ \vdots & \vdots & \ddots & \vdots \\ R_n[p-1] & R_n[p] & \dots & R_n[2p-1] \end{bmatrix} \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ d_p \end{bmatrix} = \begin{bmatrix} R_n[0] \\ R_n[1] \\ \vdots \\ R_n[p] \end{bmatrix}$$