## IIR Gradient Adaptive Filters

- IIR:fewer coefficients than FIR
- IIR:may be a function looked for
- Important class in modeling or identifying systems

$$
\begin{gathered}
H(z)=\frac{\sum_{i=0}^{N} a_{i} z^{-i}}{1-\sum_{i=1}^{N} b_{i} z^{-i}}=\frac{A(z)}{B(z)} \\
\hat{Y}(z)=H(z) X(z)
\end{gathered}
$$

## Error and Coefficient Update

$$
\begin{gathered}
e(n+1)=y(n+1)-\left[A^{T}(n) B^{T}(n)\right]\left[\begin{array}{c}
X(n+1) \\
\hat{Y}(n)
\end{array}\right] \\
{\left[\begin{array}{l}
A(n+1) \\
B(n+1)
\end{array}\right]=\left[\begin{array}{l}
A(n) \\
B(n)
\end{array}\right]-\delta \frac{\partial}{\partial c_{i}} \frac{1}{2} e^{2}(n+1)}
\end{gathered}
$$

gradient

$$
c_{i}: a_{i} \text { or } b_{i}
$$

$$
\begin{gathered}
\hat{y}(n)=\frac{1}{2 \pi j} \oint z^{n-1} H(z) X(z) d z \\
\left\{\begin{array}{l}
\frac{\partial \hat{y}(n)}{\partial a_{i}}=\frac{1}{2 \pi j} \oint z^{n-1} z^{-i} \frac{X(z)}{B(z)} d z \\
\frac{\partial \hat{y}(n)}{\partial b_{i}}=\frac{1}{2 \pi j} \oint z^{n-1} z^{-i} \frac{1}{B(z)} H(z) X(z) d z
\end{array}\right.
\end{gathered}
$$

gradient is calculated by applying $x(n)$ and $\hat{y}(n)$ to $\frac{1}{B(z)}$

## Parallel IIR Gradient Adaptive Filter


-analysis
-stability
not simple
problem

## Series-Parallel IIR Gradient Adaptive Filter

After convergence

$$
\hat{y}(n) \cong y(n)
$$

then

$$
\begin{aligned}
& e(n+1) \cong y(n+1)-\left[A^{T}(n) B^{T}(n)\right]\left[\begin{array}{c}
X(n+1) \\
Y(n)
\end{array}\right] \\
& x(n), A(z) \longrightarrow B(n)
\end{aligned}
$$

No stability problem

# Strength and Weakness of Gradient Filters 

- Strength
-Ease of design
-Simplicity of realization
-Flexibility
-Robustness against signal characteristic evolution and computation errors
- Weakness
-Dependence on signal statistics
- best for flat spectrum
- low speed or large residual errors for colored signal


# Linear Prediction Filter <br> $$
e(n)=x(n)-\sum_{i=1}^{\infty} a_{i} x(n-i)
$$ 

- coefficients are calculated to minimize the variance of $e(n)$.
- The minimization leads to

$$
\begin{array}{ll}
E[e(n) x(n-i)]=0, & i \geq 1 \\
E[e(n) e(n-i)]=0, & i \geq 1
\end{array}
$$

- $e(n)$ :white noise prediction error or innovation


# Linear Prediction Filter and Inverse 


model or
whitening filter innovation filter
$E_{a}=E\left[e^{2}(n)\right]$ : prediction error variance $S\left(e^{j \omega}\right)$ : input signal power spectrum density

$$
\begin{aligned}
E_{a} & =\frac{1}{2 \pi} \int_{-\pi}^{\pi}\left|A\left(e^{j \omega}\right)\right|^{2} S\left(e^{j \omega}\right) d \omega \\
& =\frac{1}{j 2 \pi} \oint A(z) A\left(z^{-1}\right) S(z) \frac{d z}{z}
\end{aligned}
$$

## $\boldsymbol{A}(\mathbf{z})$ is Minimum Phase

- if $z_{0}$, a zero of $A(z)$, is outside the unit circle, $\left|z_{0}\right|>1$, consider $A^{\prime}(z)$ given by

$$
\begin{gathered}
A^{\prime}(z)=A(z) \frac{\left(z-\bar{z}_{0}^{-1}\right)\left(z-z_{0}^{-1}\right)}{\left(z-z_{0}\right)\left(z-\overline{z_{0}}\right)} \\
E_{a}^{\prime}=\frac{1}{\left|z_{0}\right|^{2}} E_{a}<E_{a}
\end{gathered}
$$

which contradicts the assumption.

- Consequently, the prediction filter $A(z)$ is minimum phase.


## Prediction Error Power

$$
E_{a}=\frac{1}{j 2 \pi} \oint A(z) A\left(z^{-1}\right) S(z) \frac{d z}{z}
$$

$$
2 \pi j \ln E_{a}=\oint \ln A(z) \frac{d z}{z}+\underbrace{\oint \ln A\left(z^{-1}\right) \frac{d z}{z}}_{0}+\oint \ln S(z) \frac{d z}{z}
$$

because
$A(z)$ is minimum phase $---\ln A(z)$ is analytic for $|z|>1$ integration contour can be a circle whose radius is arbitrarily large, and $\lim _{z \rightarrow \infty} A(z)=a_{0}=1$

$$
E_{a}=\exp \left\{\frac{1}{j 2 \pi} \int_{-\pi}^{\pi} \ln S\left(e^{j \omega}\right) d \omega\right\}
$$

Kolmogoroff-Szego formula

## Linear Prediction Coefficients

$$
\begin{gathered}
e(n)=x(n)-\sum_{i=1}^{N} a_{i} x(n-i) \\
\frac{\partial}{\partial a_{j}} E\left[e^{2}(n)\right]=r(j)-\sum_{i=1}^{N} a_{i} r(j-i)=0, \quad 1 \leq j \leq N
\end{gathered}
$$

which can be completed by the power relation

$$
E_{a N}=E\left[e^{2}(n)\right]=r(0)-\sum_{i=1}^{N} a_{i} r(i)
$$

In concise form $R_{N+1}\left[\begin{array}{c}1 \\ -A_{N}\end{array}\right]=\left[\begin{array}{c}E_{a N} \\ 0\end{array}\right]$ where

$$
R_{N+1}=\left[\begin{array}{c|ccc}
r(0) & r(1) & \cdots & r(N) \\
\hline r(1) & & & \\
\vdots & & R_{N} & \\
r(n) & & &
\end{array}\right], R_{N}=E\left[X(n) X^{T}(n)\right]
$$

## First-Order FIR Predictor

$H(z)=1-a z^{-1}$
can be applied to a constant signal in white noise with power $\sigma_{b}^{2}$
$x(n)=1+b(n)$
The prediction error power

$$
\begin{aligned}
& E\left[e^{2}(n)\right]=|H(1)|^{2}+\sigma_{b}^{2}\left(1+a^{2}\right) \\
&=(1-a)^{2}+\sigma_{b}^{2}\left(1+a^{2}\right) \\
& \frac{\partial E\left[e^{2}(n)\right]}{\partial a}=0 \rightarrow a=\frac{1}{1+\sigma_{b}^{2}}
\end{aligned}
$$

## First-Order FIR Predictor (cont'd)

Residual prediction error $(1-a)^{2}$
Amplified noise power $\quad \sigma_{b}^{2}\left(1+a^{2}\right)$

## The former is much smaller

# Forward and Backward Prediction 

For finite order, the oldest sample is discarded every time a new sample is acquired. the loss of the oldest sample is characterized by backward linear prediction.
-Forward linear prediction $e_{a}(n)=x(n)-\sum_{i=1}^{N} a_{i} x(n-i)$
or $e_{a}(n)=x(n)-A_{N}^{T} X(n-1)$
-Backward linear prediction $e_{b}(n)=x(n-N)-B_{N}^{T} X(n)$

# Forward and Backward Linear Prediction Error Filter 

backward prediction

forward prediction

## Backward Prediction

Minimization of prediction error power leads to

$$
\begin{array}{cc}
R_{N+1}\left[\begin{array}{c}
-B_{N} \\
1
\end{array}\right]=\left[\begin{array}{c}
0 \\
E_{b N}
\end{array}\right] & \\
J_{N+1} R_{N+1}\left[\begin{array}{c}
-B_{N} \\
1
\end{array}\right]=\left[\begin{array}{c}
E_{b N} \\
0
\end{array}\right] & J=\left[\begin{array}{ccc}
0 & \cdots & 1 \\
\vdots & \therefore & \vdots \\
1 & \cdots & 0
\end{array}\right] \\
R_{N+1}\left[\begin{array}{c}
1 \\
-J_{N} B_{N}
\end{array}\right]=\left[\begin{array}{c}
E_{b N} \\
0
\end{array}\right] & \begin{array}{c}
\text { co-identity } \\
\text { matrix }
\end{array}
\end{array}
$$

Hence

$$
A_{N}=J_{N} B_{N}, \quad E_{a N}=E_{b N}=E_{N}
$$

## Forward and Backward Prediction

For the stationary signals, the two are equal, and the coefficients are the same. Difference appears in the transition phases.
-Forward linear prediction error filter is minimum phase. -Backward filter is maximum phase.

## Order Iterative Relations

$$
\text { Let } r_{N}^{a}=\left[\begin{array}{c}
r(1) \\
r(2) \\
\vdots \\
r(N)
\end{array}\right], r_{N}^{b}=J_{N} r_{N}^{a}
$$

$$
\begin{aligned}
& {\left[\begin{array}{c|c}
R_{N} & r_{N}^{b} \\
\left(r_{N}^{b}\right)^{T} & r(0)
\end{array}\right]\left[\begin{array}{c}
1 \\
-A_{N-1} \\
\hline 0
\end{array}\right]=\left[\begin{array}{c}
E_{N-1} \\
0 \\
\hline K_{N}
\end{array}\right]} \\
& \quad \text { where } K_{N}=r(N)-\sum_{i=1}^{N N_{1}} a_{i, N-1} r(N-i)
\end{aligned}
$$

For backward linear prediction,

$$
\left[\begin{array}{c|c}
r(0) & \left(r_{N}^{a}\right)^{T} \\
\hline r_{N}^{a} & R_{N}
\end{array}\right]\left[\begin{array}{c}
0 \\
-B_{N-1} \\
1
\end{array}\right]=\left[\begin{array}{c}
K_{N} \\
0 \\
E_{N-1}
\end{array}\right]
$$

## Order Iterative Relations

## (cont'd)

Multiplying both side by $k_{N}=K_{N} / E_{N-1}$

Subtracting this from the equation in the previous page leads to order $N$ linear prediction equation, which implies

$$
\begin{aligned}
& A_{N}=\left[\begin{array}{c}
A_{N-1} \\
0
\end{array}\right]-k_{N}\left[\begin{array}{c}
B_{N-1} \\
-1
\end{array}\right], \text { the last row is } a_{N N}=k_{N} \\
& \quad \text { and } E_{N}=E_{N-1}\left(1-k_{N}^{2}\right)
\end{aligned}
$$

This recursive solution of prediction matrix equation is called Levinson-Durbin algorithm.

# Lattice Linear Prediction 

## Filter

The coefficient $k_{n}$ establish direct relations between forward and backward prediction errors for consecutive orders.
from $\left\{\begin{array}{c}e_{a N}(n)=x(n)-A_{N}^{T} X(n-1) \\ A_{N}=\left[\begin{array}{c}A_{N-1} \\ 0\end{array}\right]-k_{N}\left[\begin{array}{c}B_{N-1} \\ -1\end{array}\right]\end{array}\right.$
we have $e_{a N}(n)=e_{a N-1}(n)-k_{N}\left[B_{N-1}^{T} \quad 1\right] X(n-1)$
backward prediction error

$$
e_{b N}(n)=x(n-N)-B_{N}^{T} X(n)
$$

for order $N-1$

$$
e_{b N-1}(n)=\left[\begin{array}{ll}
-B_{N-1}^{T} & 1
\end{array}\right] X(n)
$$

## Lattice Linear Prediction Filter

$$
\left\{\begin{array}{c}
e_{a N}(n)=e_{a N-1}(n)-k_{N} e_{b N-1}(n-1) \\
e_{b N}(n)=e_{b N-1}(n)-k_{N} e_{a N-1}(n)
\end{array}\right.
$$



Lattice linear prediction filter section

## PARCOR

## Partial autocorrelation



C: correlator

## Speech Synthesis Filter

vocal cord


## wave digital filter



## Exercise 9

1. Express the error outputs of parallel IIR gradient AF and series-parallel IIR gradient AF in $z$-domain, and compare them.
2. Calculate the first four terms of the autocorrelation function of the signal
$x(n)=\sin \frac{\pi n}{4}$.
Using the normal equations, calculate the coefficients of the predictor of order $N=3$.
3. Consider the three systems $(0<a, b<1)$
$y_{n}=x_{n}-(a+b) x_{n-1}+a b x_{n-2}$,
$y_{n}=a b x_{n}-(a+b) x_{n-1}+x_{n-2}$,
$y_{n}=a x_{n}-(a+b) x_{n-1}+b x_{n-2}$.
What are the system functions for these systems? Which system is minimum phase, which maximum phase, and which mixed phase?
Take $x_{n}$ to be a zero mean stationary white noise, with $\left\langle x_{n} x_{n+m}\right\rangle=\delta_{m}$ and $\left\langle x_{n} x_{n+m_{1}} x_{n+m_{2}}\right\rangle=\delta_{m_{1} m_{2}}$. Compare the autocorrelations of the outputs of those systems.
4. Read the following paper;
J. Makhoul,,"Linear prediction: A tutorial review", Proceedings of the IEEE, Vol.63, 4, pp. 561-580, Apr. 1975
