## Detailed Derivations

Mean Ergodicity
A w.s.s. process $\{u[n]\}$ is mean ergodic in the mean square error sense if $\lim _{N \rightarrow \infty} \mathbb{E}\left[|m-\hat{m}(N)|^{2}\right]=0$
Question: under what condition will this be satisfied?

$$
\begin{aligned}
& E\left[|\hat{m}(N)-m|^{2}\right]=E\left[\left|\frac{1}{N} \sum_{n=0}^{N-1} u[n]-m\right|^{2}\right] \\
& =\frac{1}{N^{2}} E\left[\left|\sum_{n=0}^{N-1}(u[n]-m)\right|^{2}\right] \\
& =\frac{1}{N^{2}} \sum_{n=0}^{N-1} \sum_{k=0}^{N-1} E\left[(u[n]-E(u[n]))(u[k]-E(u[k]))^{*}\right] \\
& =\frac{1}{N^{2}} \sum_{n=0}^{N-1} \sum_{k=0}^{N-1} c(n-K) \\
& l \triangleq n-K \\
& =\frac{1}{N} \sum_{l=-N+1}^{N-1}\left(1-\frac{|l|}{N}\right) c(l)
\end{aligned}
$$

Therefore, the necessary and sufficient condition for $\{u[u]\}$ to be mean ergodic in MSE sense is

$$
\lim _{N \rightarrow \infty} \frac{1}{N} \sum_{l=-N+1}^{N-1}\left(1-\frac{|l|}{N}\right) c(l)=0 \quad[* *]
$$

## Properties of $\mathbf{R}$

$\mathbf{R}$ is Hermitian, i.e., $\mathbf{R}^{H}=\mathbf{R}$
Proof $r(k) \triangleq \mathbb{E}\left[u[n] u^{*}[n-k]\right]=\left(E\left[u[n-k] u^{*}[n]\right]\right)^{*}=[r(-k)]^{*}$
Bring into the above $\mathbf{R}$, we have $\mathbf{R}^{H}=\mathbf{R}$
$\mathbf{R}$ is Toeplitz.
A matrix is said to be Toeplitz if all elements in the main diagonal are identical, and the elements in any other diagonal parallel to the main diagonal are identical.
$\mathbf{R}$ Toeplitz $\Leftrightarrow$ the w.s.s. property.

## Properties of $\mathbf{R}$

$\mathbf{R}$ is non-negative definite, i.e., $\underline{x}^{H} \mathbf{R} \underline{x} \geq 0, \forall \underline{x}$
Proof
Recall $\mathbf{R} \triangleq \mathbb{E}\left[\underline{u}[n] \underline{u}^{H}[n]\right]$. Now given $\forall \underline{x}$ (deterministic):
$\underline{x}^{H} \mathbf{R} \underline{x}=\mathbb{E}\left[\underline{x}^{H} \underline{u}[n] \underline{u}^{H}[n] \underline{x}\right]=\mathbb{E}[\underbrace{\left(\underline{x}^{H} \underline{u}[n]\right)}_{|x| \text { scalar }}\left(\underline{x}^{H} \underline{u}[n]\right)^{*}]=$
$\mathbb{E}\left[\left|\underline{x}^{H} \underline{u}[n]\right|^{2}\right] \geq 0$

- eigenvalues of a Hermitian matrix are real. (similar relation in FT analysis: real in one domain becomes conjugate symmetric in another)
- eigenvalues of a non-negative definite matrix are non-negative.

Proof choose $\underline{x}=\mathbf{R}$ 's eigenvector $\underline{v}$ s.t. $\mathbf{R} \underline{v}=\lambda \underline{v}$,
$\underline{v}^{H} \underline{R} \underline{v}=\underline{v}^{H} \lambda \underline{v}=\lambda \underline{v}^{H} \underline{v}=\lambda|v|^{2} \geq 0 \Rightarrow \lambda \geq 0$

Properties of $\mathbf{R}$

Recursive relations: correlation matrix for $(M+1) \times 1 \underline{u}[n]$ :

$$
\begin{aligned}
& =\left[\begin{array}{c|c}
N^{(0)} & \underline{I}^{H} \\
\hline \Sigma & R_{M}
\end{array}\right]=\left[\begin{array}{c|c}
R_{M} & \left(I^{B}\right)^{*} \\
\hline\left(\Gamma^{B}\right)^{\top} & r^{(0)}
\end{array}\right]
\end{aligned}
$$

where $I=\left[\begin{array}{c}r^{*}(1) \\ \vdots \\ r^{*}(M)\end{array}\right], I^{B}=\left[\begin{array}{c}r^{*}(M) \\ \vdots \\ r^{*}(1)\end{array}\right]$

## (4) Example: Complex Sinusoidal Signal

$x[n]=A \exp \left[j\left(2 \pi f_{0} n+\phi\right)\right]$ where $A$ and $f_{0}$ are real constant, $\phi \sim$ uniform distribution over $[0,2 \pi$ ) (i.e., random phase)

We have:
$\mathbb{E}[x[n]]=0 \forall n$

$\mathbb{E}\left[x[n] x^{*}[n-k]\right]$
$=\mathbb{E}\left[A \exp \left[j\left(2 \pi f_{0} n+\phi\right)\right] \cdot A \exp \left[-j\left(2 \pi f_{0} n-2 \pi f_{0} k+\phi\right)\right]\right]$
$=A^{2} \cdot \exp \left[j\left(2 \pi f_{0} k\right)\right]$
$\therefore x[n]$ is zero-mean w.s.s. with $r_{x}(k)=A^{2} \exp \left(j 2 \pi f_{0} k\right)$.

## Example: Complex Sinusoidal Signal with Noise

Let $y[n]=x[n]+w[n]$ where $w[n]$ is white Gaussian noise uncorrelated to $x[n], w[n] \sim N\left(0, \sigma^{2}\right)$
Note: for white noise, $\mathbb{E}\left[w[n] w^{*}[n-k]\right]= \begin{cases}\sigma^{2} & k=0 \\ 0 & o . w .\end{cases}$
$r_{y}(k)=\mathbb{E}\left[y[n] y^{*}[n-k]\right]$
$=\mathbb{E}\left[(x[n]+w[n])\left(x^{*}[n-k]+w^{*}[n-k]\right)\right]$
$=r_{x}[k]+r_{w}[k] \quad(\because \mathbb{E}[x[\cdot] w[\cdot]]=0$ uncorrelated and $w[\cdot]$ zero mean $)$
$=A^{2} \exp \left[j 2 \pi f_{0} k\right]+\sigma^{2} \delta[k]$
$\therefore \mathbf{R}_{y}=\mathbf{R}_{x}+\mathbf{R}_{w}=A^{2}{\underline{e e^{H}}}^{H}+\sigma^{2} \mathbb{I}$, where $\underline{e}=$

$$
\left[\begin{array}{c}
1 \\
e^{-j 2 \pi f_{0}} \\
e^{-j 4 \pi f_{0}} \\
\vdots \\
e^{-j 2 \pi f_{0}(M-1)}
\end{array}\right]
$$

## Rank of Correlation Matrix

## Questions:

The rank of $\mathbf{R}_{X}=1$
( $\because$ only one independent row/column, corresponding to only one frequency component $f_{0}$ in the signal)

The rank of $\mathbf{R}_{w}=M$

The rank of $\mathbf{R}_{y}=M$

Filtering a Random Process

(1)

$$
\begin{aligned}
& y[n]=x[n] * h[n]=\sum_{k=-\infty}^{+\infty} x[n-k] h[k] \\
& E[y[n]]=m_{x} \sum_{k=-\infty}^{+\infty} h[k]=m_{x} H(\omega) / \omega=0
\end{aligned}
$$

(2) $\Gamma_{y_{x}}(n+K, n) \triangleq E\left[y[n+K] x^{*}[n]\right]=E\left[\sum_{l=-\infty}^{+\infty} x[n+K-l] h[l] x^{*}[n]\right]$
$=\sum_{l=-\infty}^{+\infty} r_{x}(k-l) h[l]$ i.e. $r_{y x}(n+k, n)$ depends only on $k$ and not on $n$.

$$
\Rightarrow r_{y x}(k)=r_{x}(k) * h[k]
$$

Filtering a Random Process

(3)

$$
\begin{aligned}
& r_{y}(n+k, n)=E\left[y[n+k] y^{*}[n]\right]=E\left[y[n+k] \sum_{l=-\infty}^{+\infty} x^{*}[n-l] h^{*}[l]\right] \\
& =\sum_{l=-\infty}^{+\infty} r_{y x}(k+l) h^{*}[l]=\sum_{l^{\prime}=-\infty}^{+\infty} r_{y x}\left(k-l^{\prime}\right) h^{*}\left[-l^{\prime}\right]
\end{aligned}
$$

i.e. $E(y[n])$ \& $M^{(-)}$is not a funk. of $n \Rightarrow\{y[n]\}$ is w.s.s.

$$
\begin{aligned}
\Rightarrow r_{y}(k) & =r_{y x}(k) * h^{*}[-k]=r_{x}(k) * h[k] * h^{*}[-k] \\
& =\sum_{l=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} h[l] h^{*}[-m] r_{x}(k-l-m)
\end{aligned}
$$

Filtering a Random Process

deterministic autocorrelation of filter's impulse response

