

Lecture 06:

[Rabiner Chapter 6] Time-Domain Methods for Speech Processing

part 1. short-time energies and zero-crossing rates (ZCR)

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Original slides from Lawrence Rabiner

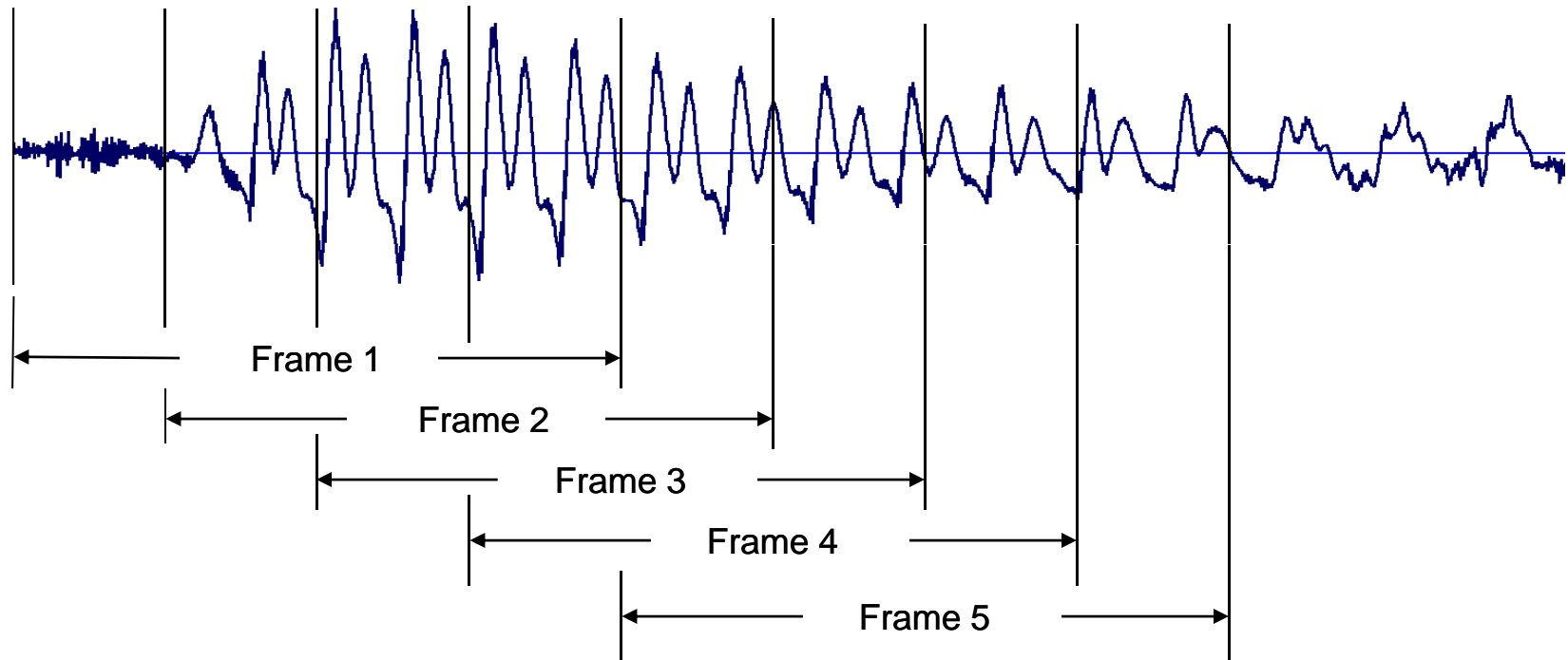
Fundamental Assumptions

- properties of the speech signal change relatively slowly with time (5-10 sounds per second)
 - over very short (5-20 msec) intervals => **uncertainty** due to small amount of data, varying pitch, varying amplitude
 - over medium length (20-100 msec) intervals => **uncertainty** due to changes in sound quality, transitions between sounds, rapid transients in speech
 - over long (100-500 msec) intervals => **uncertainty** due to large amount of sound changes
- there is **always uncertainty** in short time measurements and estimates from speech signals

Compromise Solution

- “short-time” processing methods => short segments of the speech signal are “isolated” and “processed” as if they were short segments from a “sustained” sound with fixed (non-time-varying) properties
 - this short-time processing is periodically repeated for the duration of the waveform
 - these short analysis segments, or “analysis frames” often **overlap** one another
 - the results of short-time processing can be a single number (e.g., an estimate of the pitch period within the frame), or a set of numbers (an estimate of the formant frequencies for the analysis frame)
 - the end result of the processing is a new, time-varying sequence that serves as a new representation of the speech signal

Frame-by-Frame Processing in Successive Windows



75% frame overlap \Rightarrow frame length= L , frame shift= $R=L/4$

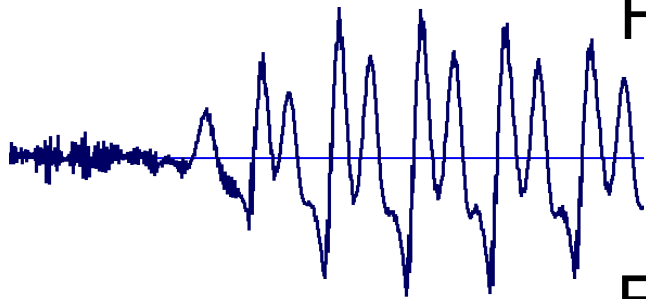
Frame1= $\{x[0],x[1],\dots,x[L-1]\}$

Frame2= $\{x[R],x[R+1],\dots,x[R+L-1]\}$

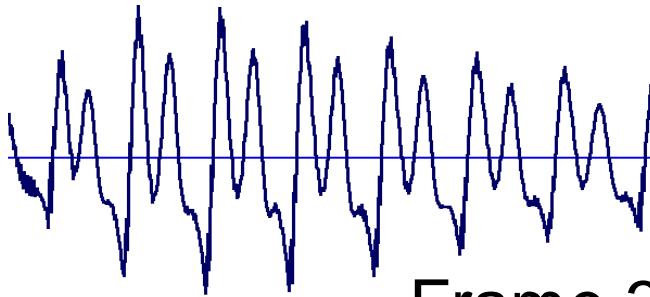
Frame3= $\{x[2R],x[2R+1],\dots,x[2R+L-1]\}$

...

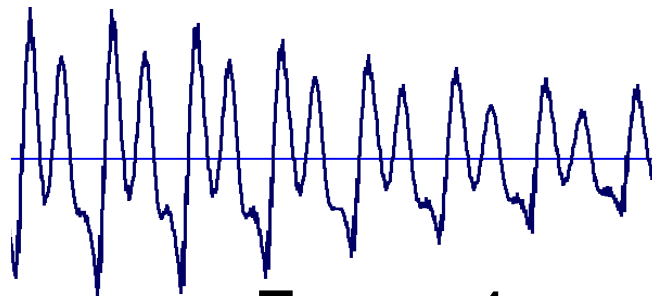
Frame 1: samples $0, 1, \dots, L-1$



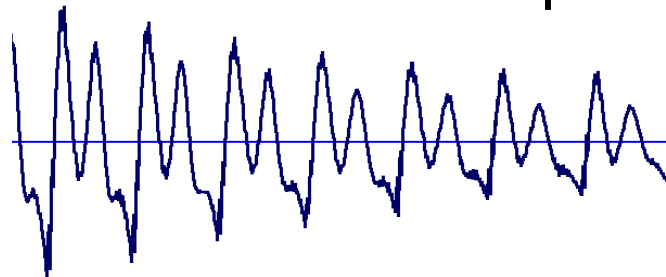
Frame 2: samples $R, R+1, \dots, R+L-1$



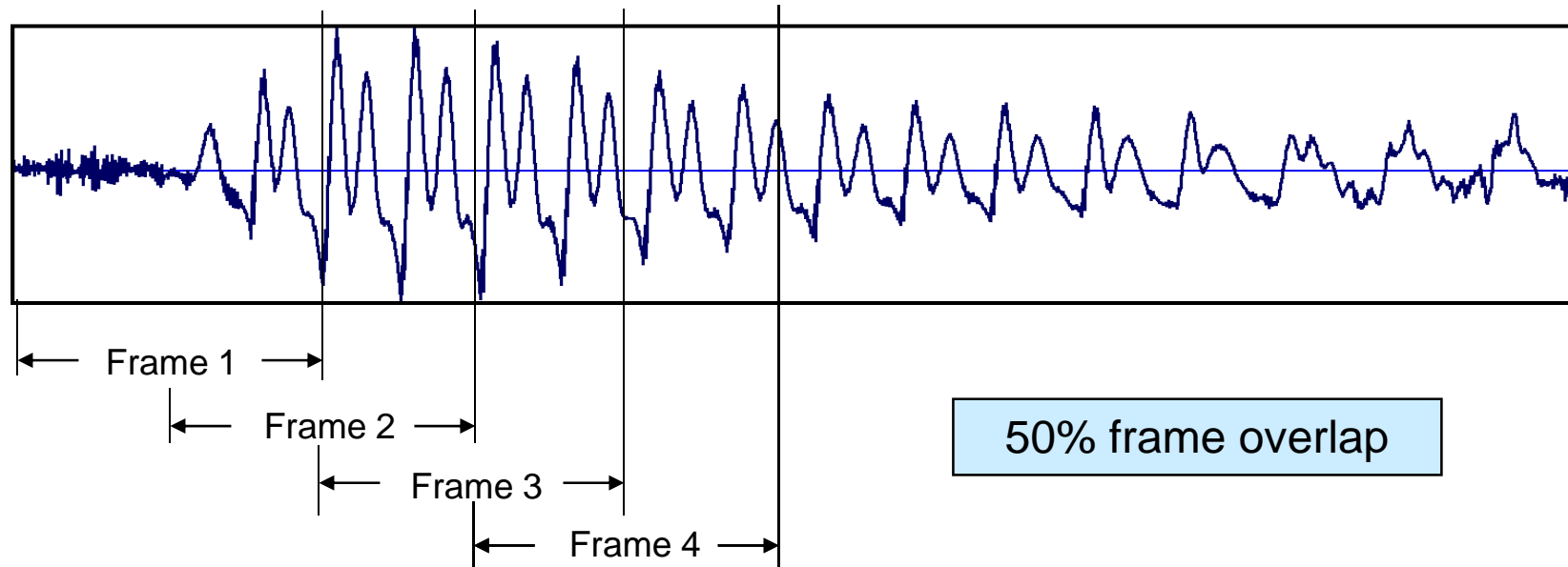
Frame 3: samples $2R, 2R+1, \dots, 2R+L-1$



Frame 4: samples $3R, 3R+1, \dots, 3R+L-1$

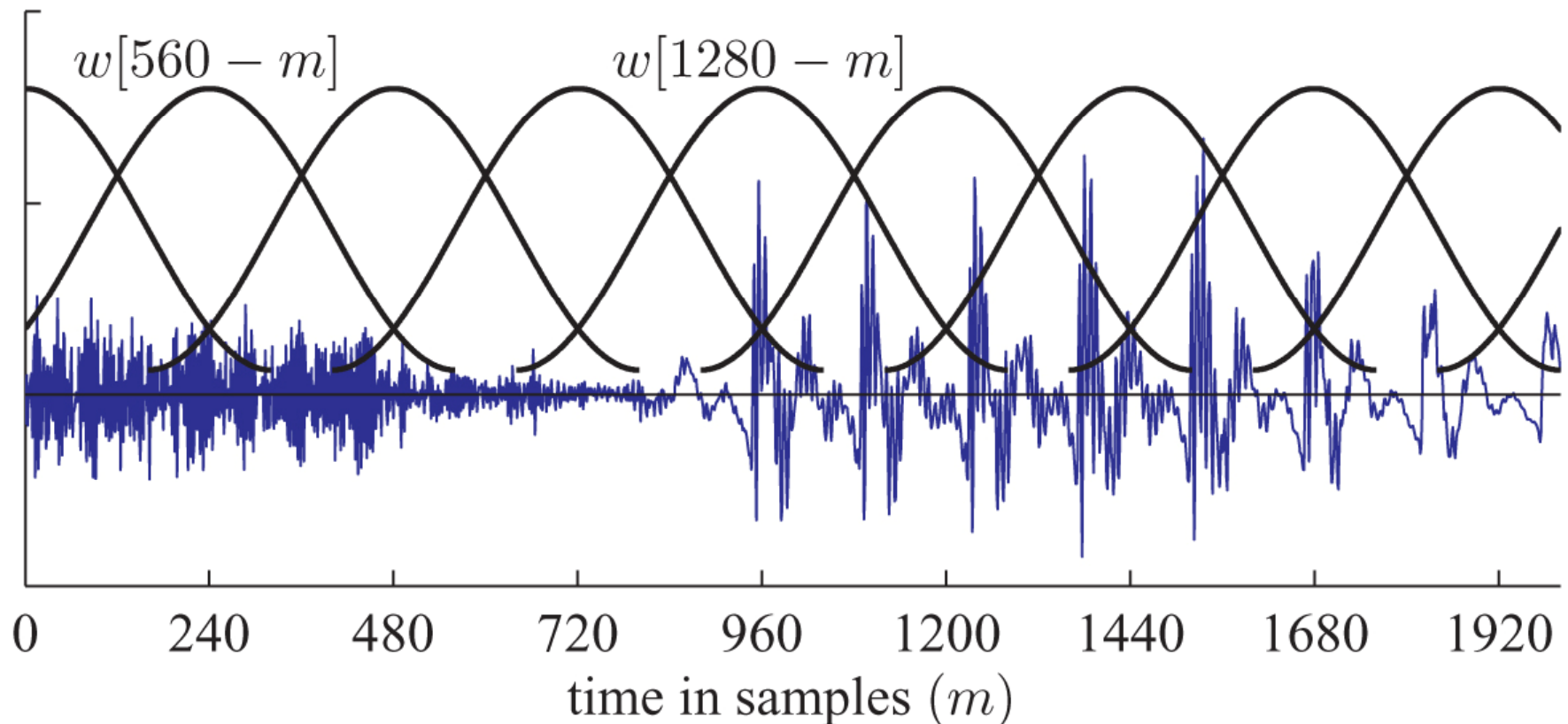


Frame-by-Frame Processing in Successive Windows



- Speech is processed frame-by-frame in overlapping intervals until entire region of speech is covered by at least one such frame
- Results of analysis of individual frames used to derive model parameters in some manner
- Representation goes from time sample $x[n]$, $n = \dots, 0, 1, 2, \dots$ to parameter vector $\mathbf{f}[m]$, $m = 0, 1, 2, \dots$ where n is the time index and m is the frame index.

Frames and Windows



$F_s = 16,000$ samples/second

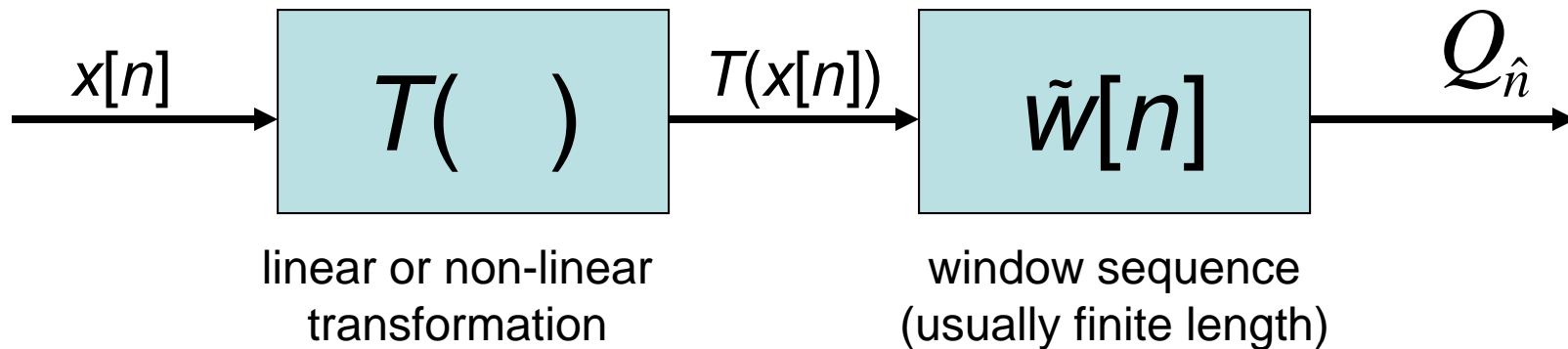
$L = 641$ samples (equivalent to 40 msec frame (window) length)

$R = 240$ samples (equivalent to 15 msec frame (window) shift)

Frame rate of 66.7 frames/second

Generic Short-Time Processing

$$Q_{\hat{n}} = \left(\sum_{m=-\infty}^{\infty} T(x[m]) \tilde{w}[n-m] \right) \Big|_{n=\hat{n}}$$



- $Q_{\hat{n}}$ is a sequence of **local weighted average values** of the sequence $T(x[n])$ at time $n = \hat{n}$

Short-Time Energy

$$E = \sum_{m=-\infty}^{\infty} x^2[m]$$

- this is the long term definition of signal energy
- there is little or no utility of this definition for time-varying signals

$$E_{\hat{n}} = \sum_{m=\hat{n}-N+1}^{\hat{n}} x^2[m] = x^2[\hat{n}-N+1] + \dots + x^2[\hat{n}]$$

- short-time energy in vicinity of time \hat{n}

$$T(x) = x^2$$

$$\begin{aligned} \tilde{w}[n] &= 1 & 0 \leq n \leq N-1 \\ &= 0 & \text{otherwise} \end{aligned}$$

Computation of Short-Time Energy

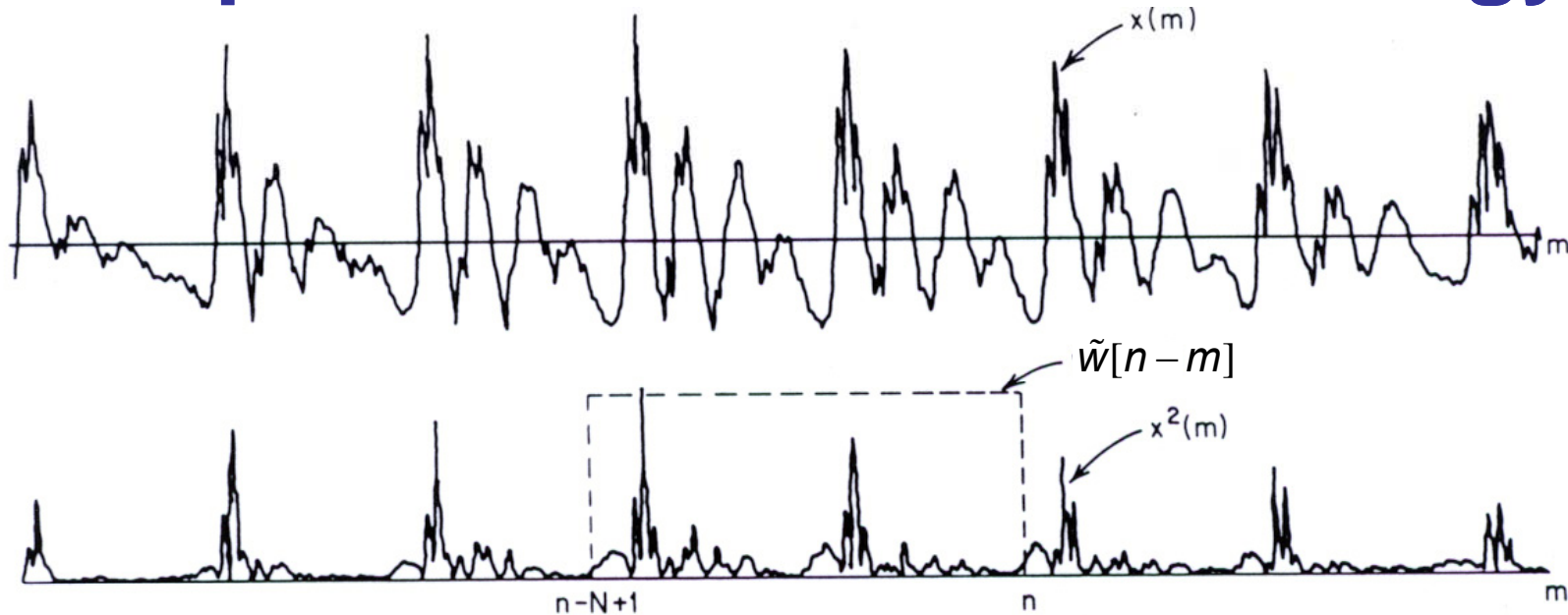


Fig. 4.2 Illustration of the computation of short-time energy.

- window jumps/slides across sequence of squared values, selecting interval for processing
- what happens to $E_{\hat{n}}$ as sequence jumps by $2, 4, 8, \dots, L$ samples ($E_{\hat{n}}$ is a lowpass function—so it can be decimated without loss of information; why is $E_{\hat{n}}$ lowpass?)
- effects of decimation depend on L ; if L is small, then $E_{\hat{n}}$ is a lot more variable than if L is large (window bandwidth changes with L !)

Short-Time Energy

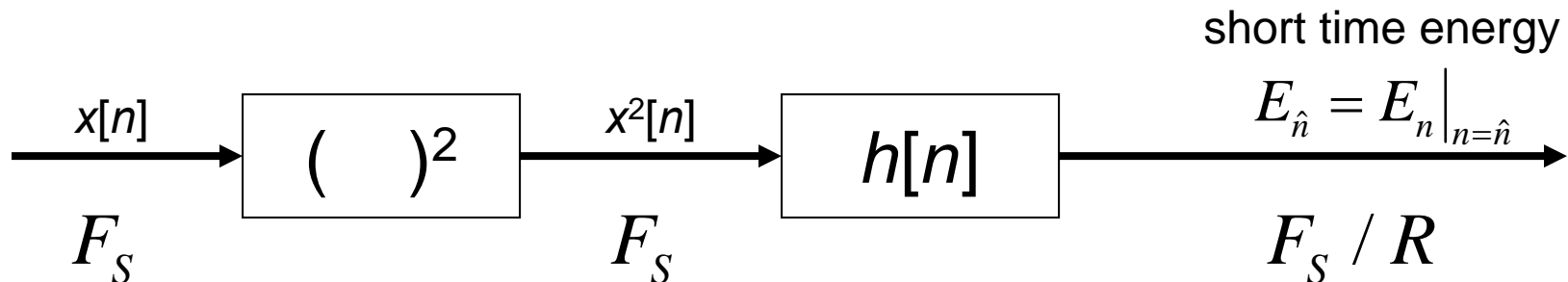
- serves to differentiate voiced and unvoiced sounds in speech from silence (background signal)
- natural definition of energy of weighted signal is:

$$E_{\hat{n}} = \sum_{m=-\infty}^{\infty} [x[m] \tilde{w}[\hat{n} - m]]^2 \text{ (sum of squares of portion of signal)}$$

-- concentrates measurement at sample \hat{n} , using weighting $\tilde{w}[\hat{n} - m]$

$$E_{\hat{n}} = \sum_{m=-\infty}^{\infty} x^2[m] \tilde{w}^2[\hat{n} - m] = \sum_{m=-\infty}^{\infty} x^2[m] h[\hat{n} - m]$$

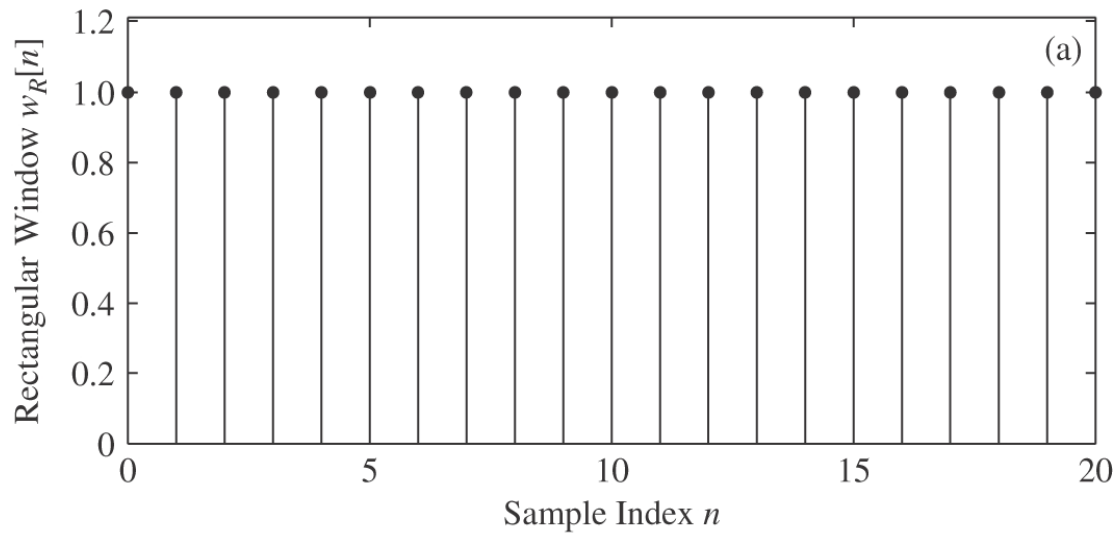
$$h[n] = \tilde{w}^2[n]$$



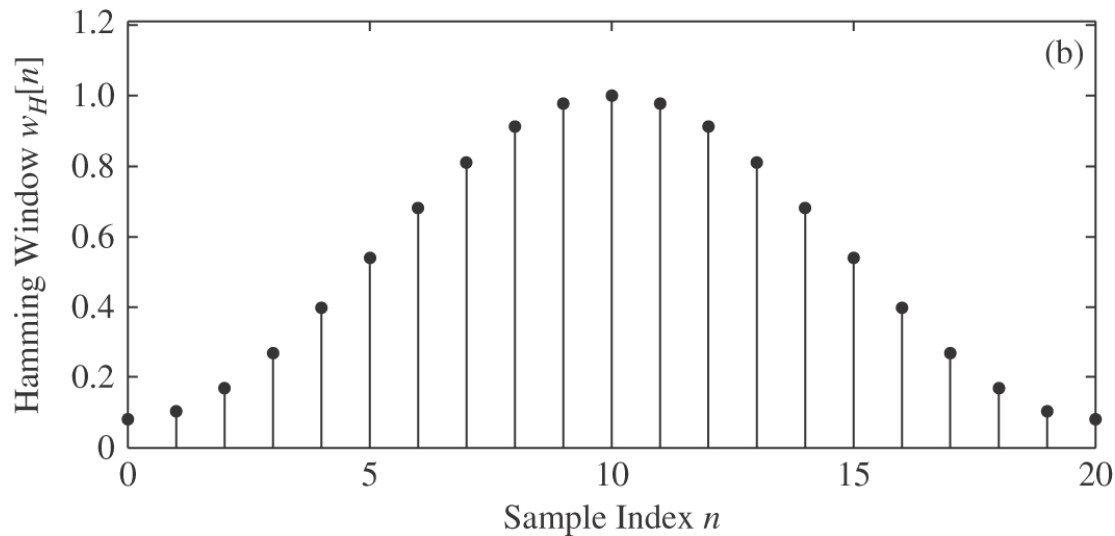
Windows

- consider two windows, $\tilde{w}[n]$
 - rectangular window:
 - $h[n]=1, 0 \leq n \leq L-1$ and 0 otherwise
 - Hamming window (raised cosine window):
 - $h[n]=0.54-0.46 \cos(2\pi n/(L-1)), 0 \leq n \leq L-1$ and 0 otherwise
 - rectangular window gives **equal weight** to all L samples in the window $(n, \dots, n-L+1)$
 - Hamming window gives **most weight** to middle samples and **tapers off** strongly at the beginning and the end of the window

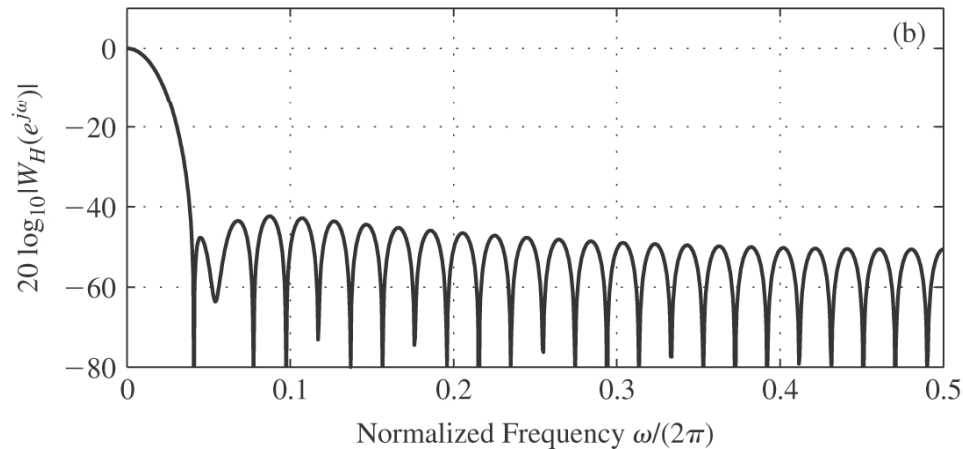
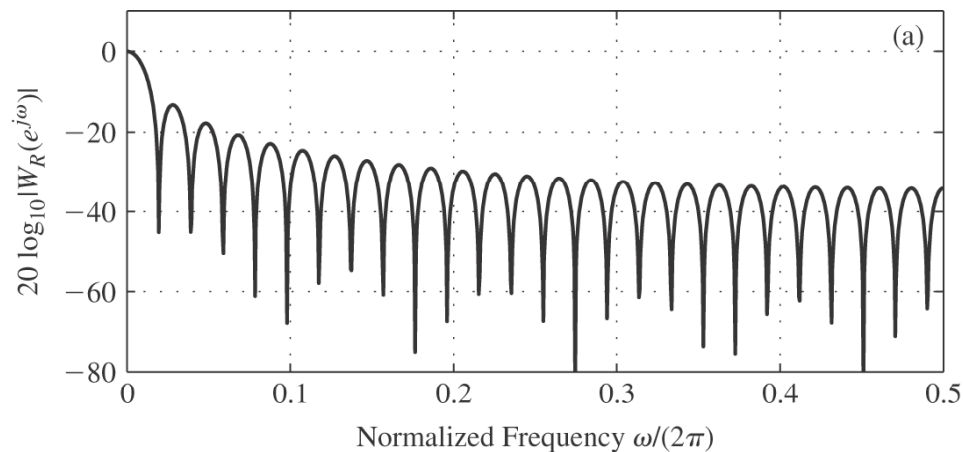
Rectangular and Hamming Windows



$L = 21$ samples



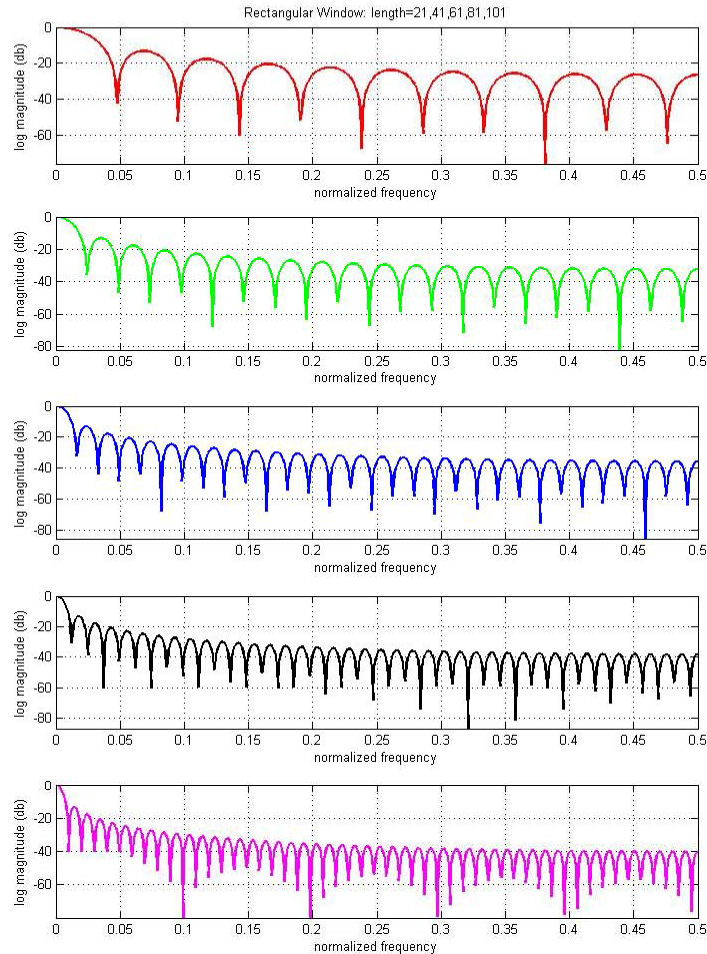
RW and HW Frequency Responses



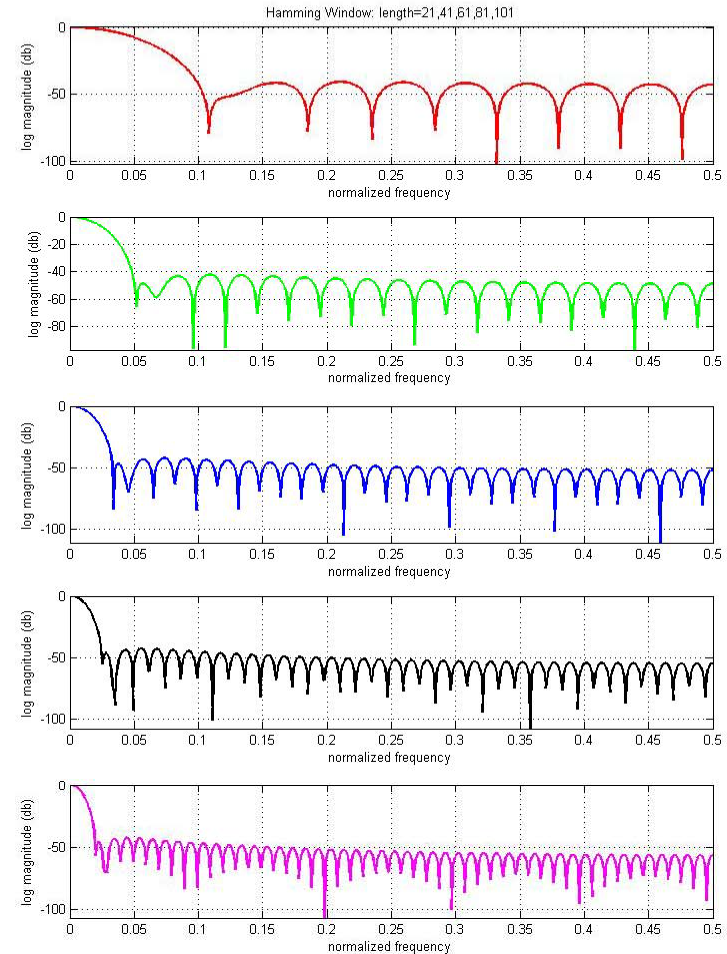
- log magnitude response of RW and HW
- **bandwidth** of HW is approximately twice the bandwidth of RW
- **attenuation** of more than 40 dB for HW outside passband, versus 14 dB for RW
- stopband attenuation is essentially **independent** of L , the window duration => increasing L simply decreases window bandwidth
- L needs to be larger than a pitch period (or severe fluctuations will occur in E_n), but smaller than a sound duration (or E_n will not adequately reflect the changes in the speech signal)

There is no perfect value of L , since a pitch period can be as short as 20 samples (500 Hz at a 10 kHz sampling rate) for a high pitch child or female, and up to 250 samples (40 Hz pitch at a 10 kHz sampling rate) for a low pitch male; a compromise value of L on the order of 100-200 samples for a 10 kHz sampling rate is often used in practice

Window Frequency Responses

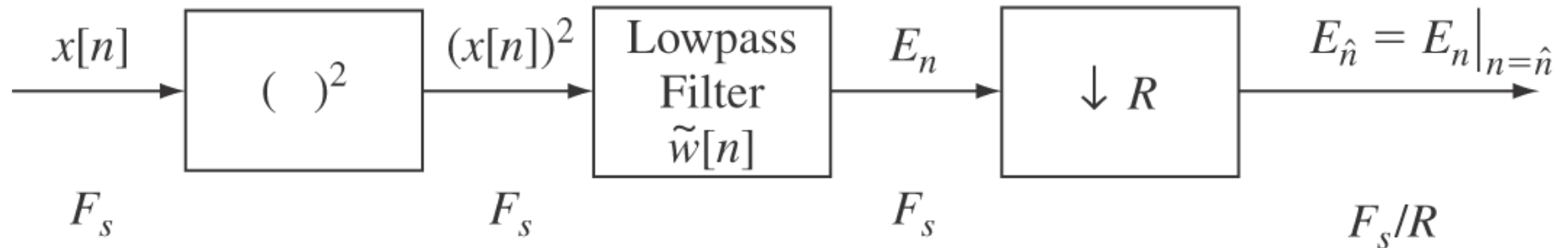


**Rectangular Windows,
L=21,41,61,81,101**



**Hamming Windows,
L=21,41,61,81,101**

Short-Time Energy



- Short-time energy computation:

$$\begin{aligned}
 E_{\hat{n}} &= \sum_{m=-\infty}^{\infty} (x[m]w[\hat{n}-m])^2 \\
 &= \sum_{m=-\infty}^{\infty} (x[m])^2 \tilde{w}[\hat{n}-m]
 \end{aligned}$$

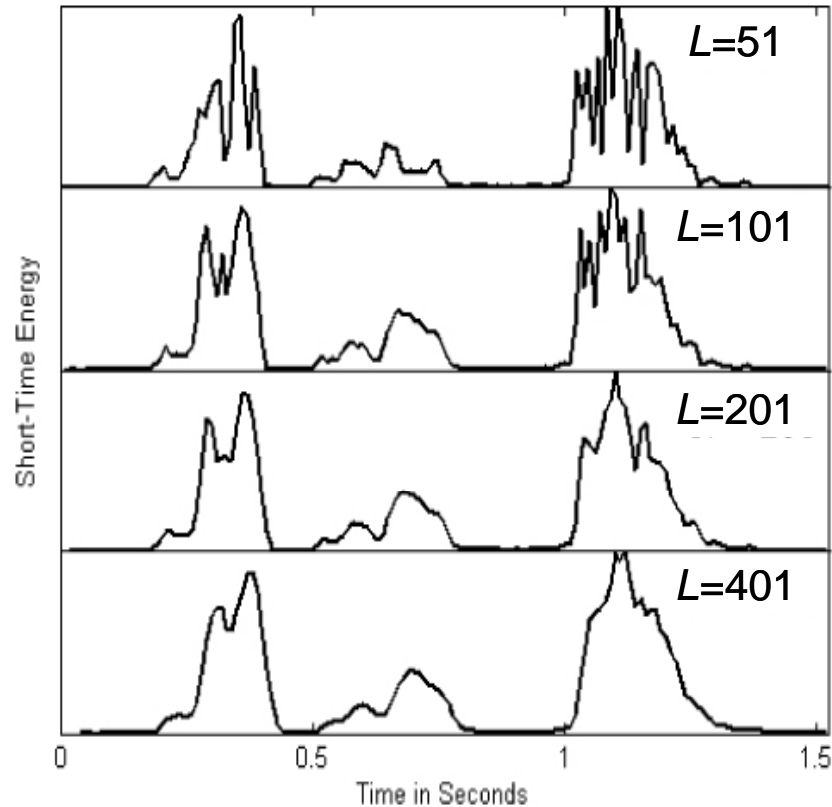
- For L -point rectangular window,
 $\tilde{w}[m] = 1, \quad m = 0, 1, \dots, L-1$

- giving

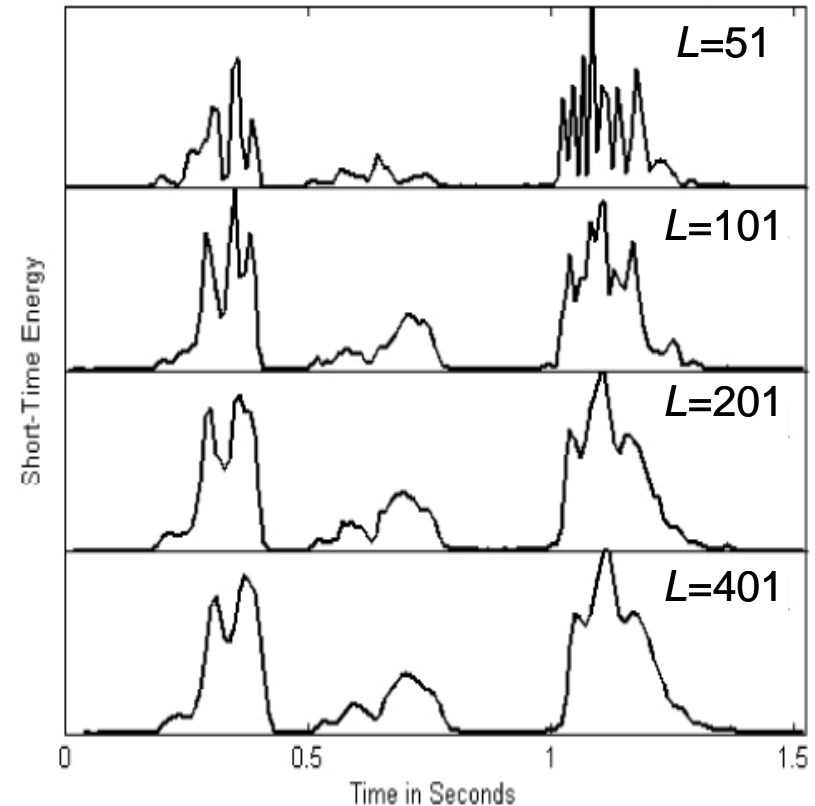
$$E_{\hat{n}} = \sum_{m=\hat{n}-L+1}^{\hat{n}} (x[m])^2$$

Short-Time Energy using RW/HW

/ What She Said / -- Rectangular Window, $E_{\hat{n}}$



/ What She Said / -- Hamming Window, $E_{\hat{n}}$



- as L increases, the plots tend to converge (however you are smoothing sound energies)
- short-time energy provides the basis for distinguishing voiced from unvoiced speech regions, and for medium-to-high SNR recordings, can even be used to find regions of silence/background signal

Short-Time Energy for AGC

Can use an IIR filter to define short-time energy, e.g.,

- time-dependent energy definition

$$\sigma^2[n] = \sum_{m=-\infty}^{\infty} x^2[m]h[n-m] / \sum_{m=0}^{\infty} h[m]$$

- consider impulse response of filter of form

$$\begin{aligned} h[n] &= \alpha^{n-1}u[n-1] = \alpha^{n-1} & n \geq 1 \\ &= 0 & n < 1 \end{aligned}$$

$$\sigma^2[n] = \sum_{m=-\infty}^{\infty} (1-\alpha) x^2[m] \alpha^{n-m-1} u[n-m-1]$$

Recursive Short-Time Energy

- $u[n - m - 1]$ implies the condition $n - m - 1 \geq 0$
or $m \leq n - 1$ giving

$$\sigma^2[n] = \sum_{m=-\infty}^{n-1} (1-\alpha) x^2[m] \alpha^{n-m-1} = (1-\alpha)(x^2[n-1] + \alpha x^2[n-2] + \dots)$$

- for the index $n-1$ we have

$$\sigma^2[n-1] = \sum_{m=-\infty}^{n-2} (1-\alpha) x^2[m] \alpha^{n-m-2} = (1-\alpha)(x^2[n-2] + \alpha x^2[n-3] + \dots)$$

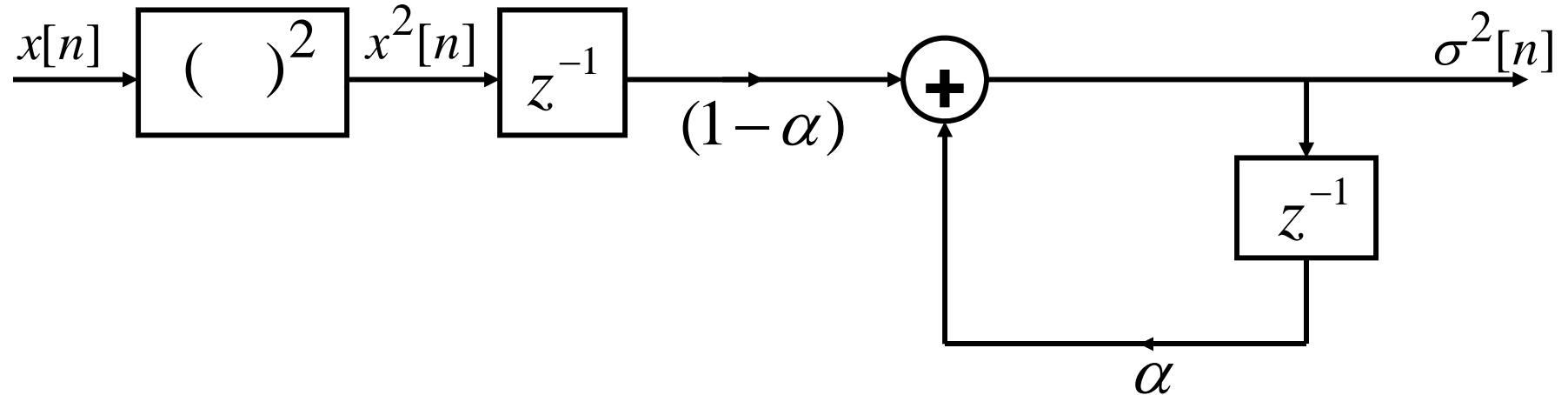
- thus giving the relationship

$$\boxed{\sigma^2[n] = \alpha \cdot \sigma^2[n-1] + x^2[n-1](1-\alpha)}$$

- and defines an Automatic Gain Control (AGC) of the form

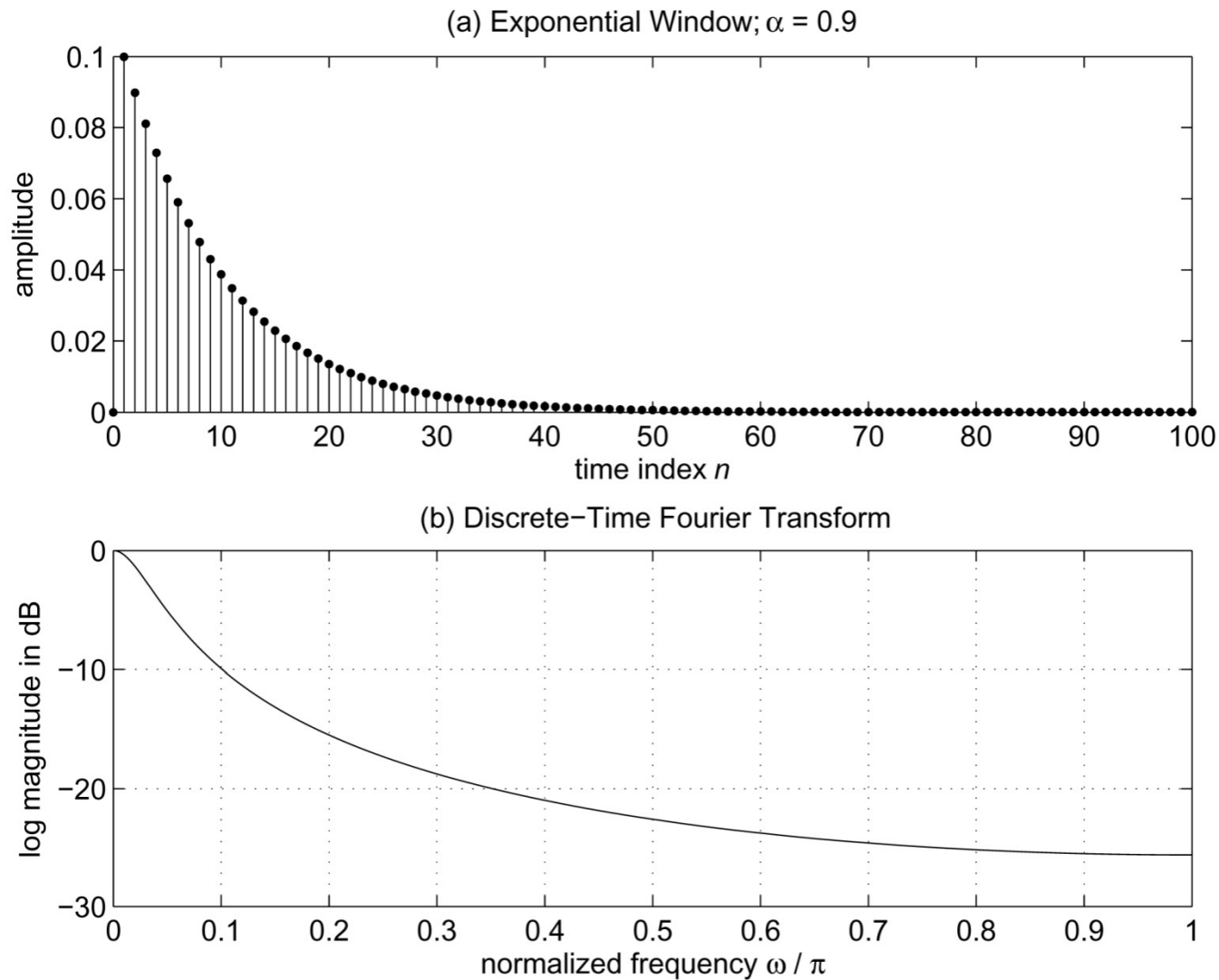
$$G[n] = \frac{G_0}{\sigma[n]}$$

Recursive Short-Time Energy



$$\sigma^2[n] = \alpha \cdot \sigma^2[n-1] + x^2[n-1](1-\alpha)$$

Recursive Short-Time Energy



Use of Short-Time Energy for AGC

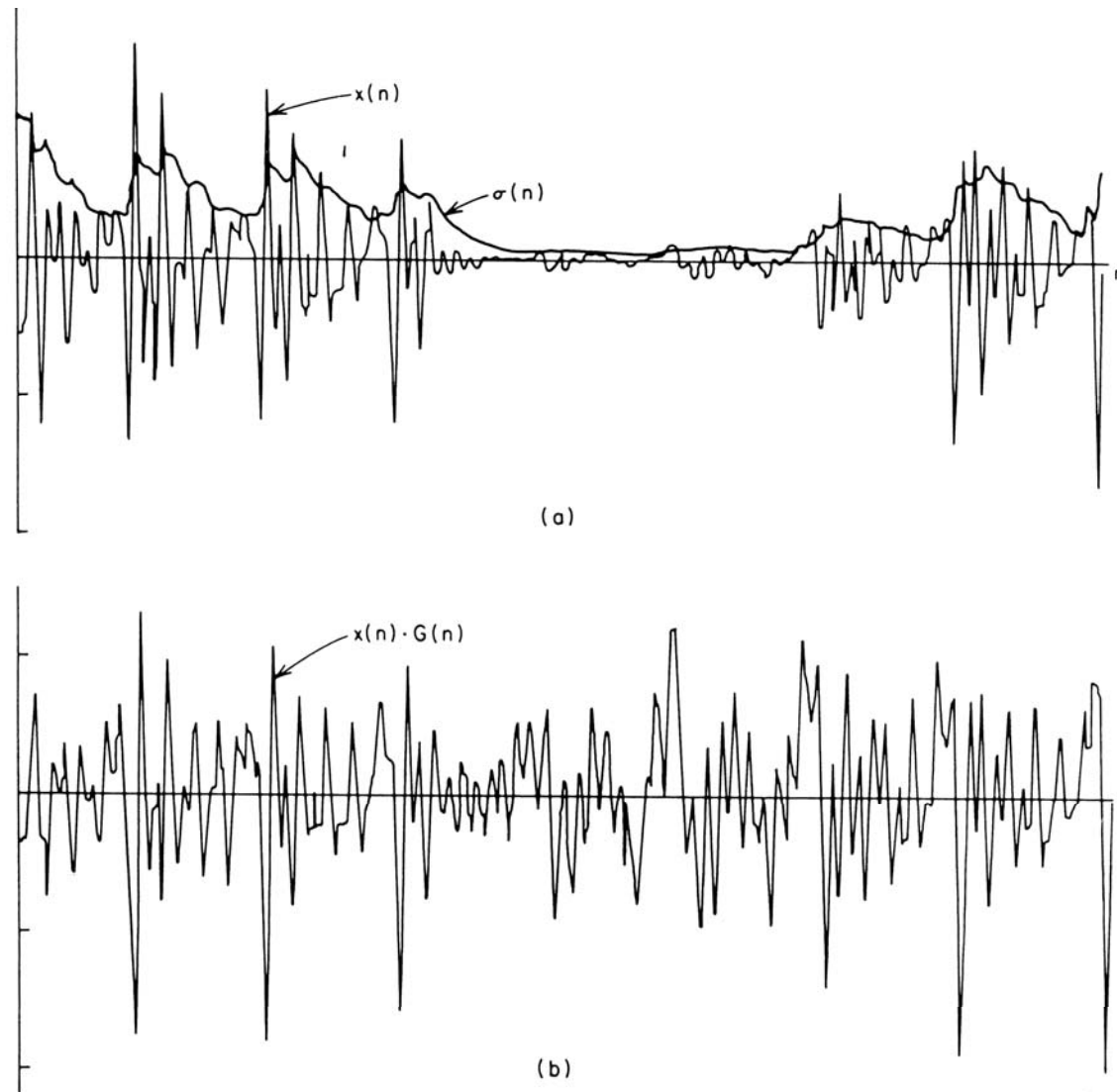
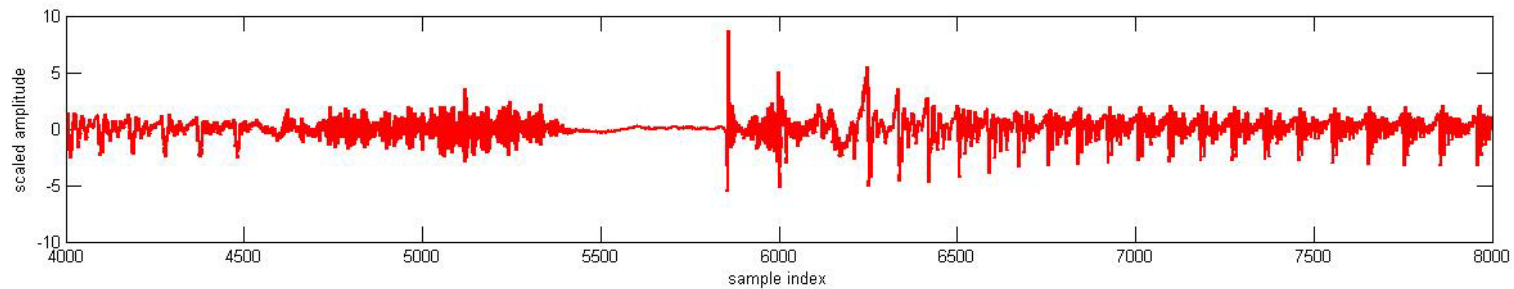
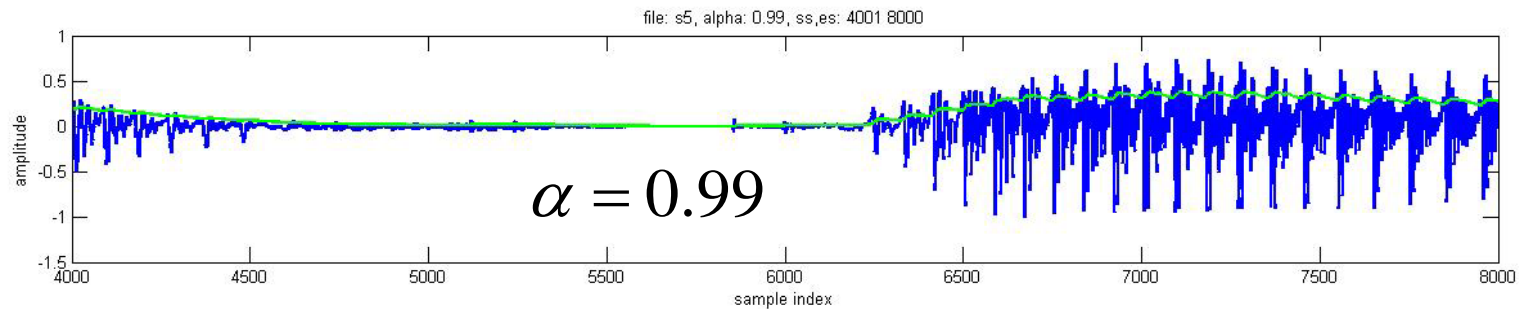
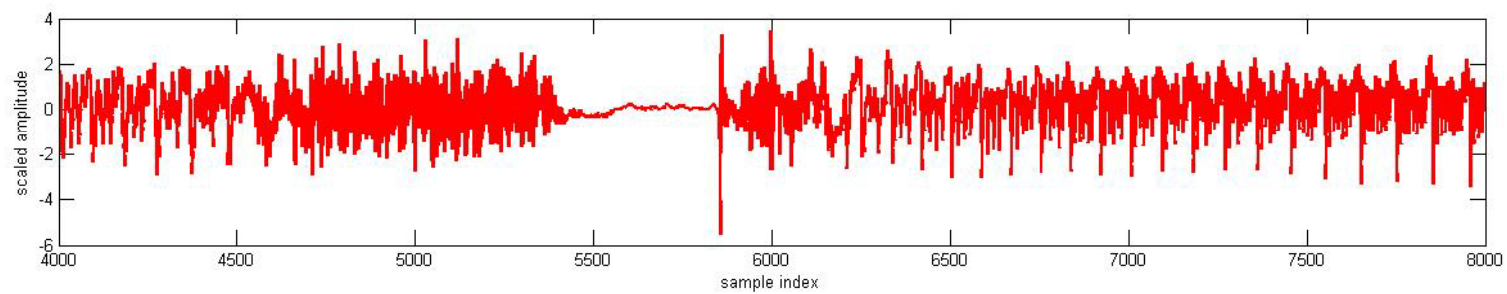
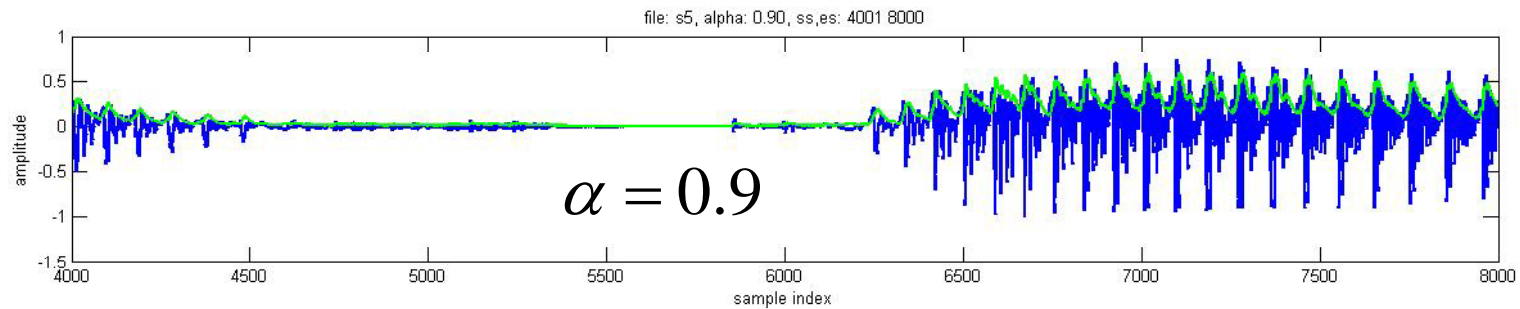


Fig. 5.26 Variance estimate using Eq. (5.56); (a) $x(n)$ and $\sigma(n)$ for $\alpha = 0.9$; (b) $x(n) G(n)$.

Use of Short-Time Energy for AGC



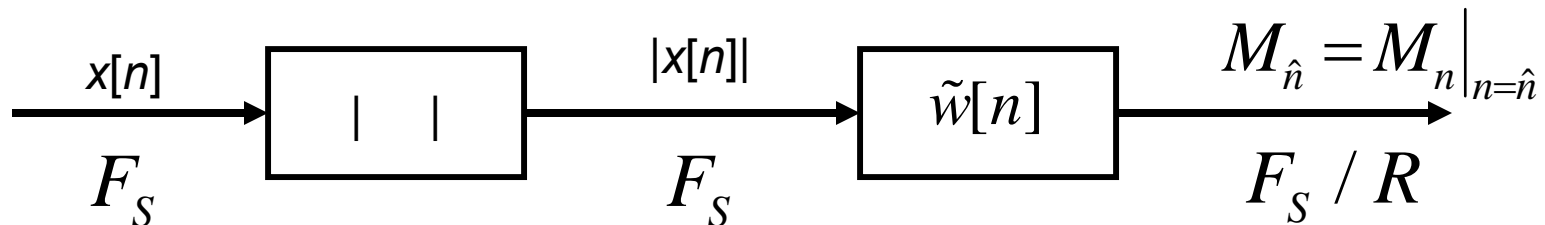
Short-Time Magnitude

Power

- short-time energy is very sensitive to large signal levels due to $x^2[n]$ terms
 - consider a new definition of ‘pseudo-energy’ based on average signal magnitude (rather than energy)

$$M_{\hat{n}} = \sum_{m=-\infty}^{\infty} |x[m]| \tilde{w}[\hat{n} - m]$$

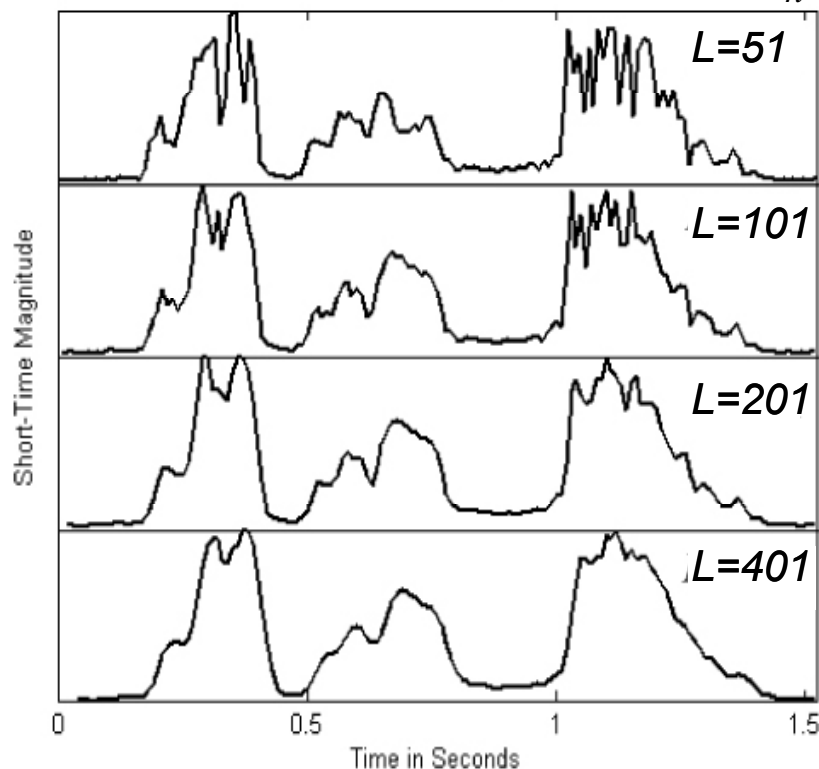
- weighted sum of magnitudes, rather than weighted sum of squares



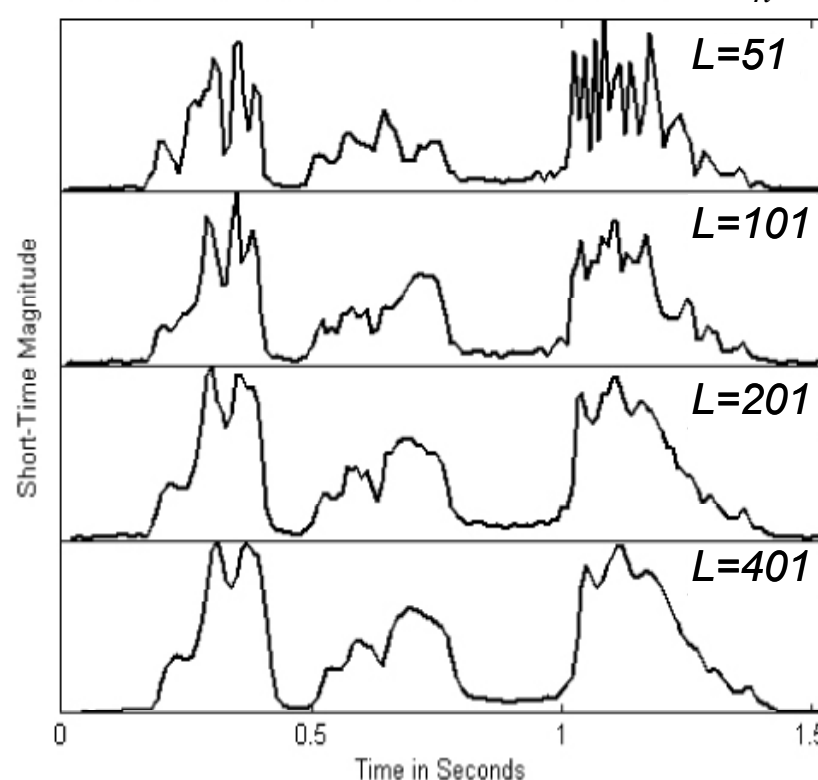
- computation avoids multiplications of signal with itself (the squared term)

Short-Time Magnitudes

/ What She Said / -- Rectangular Window, $M_{\hat{n}}$



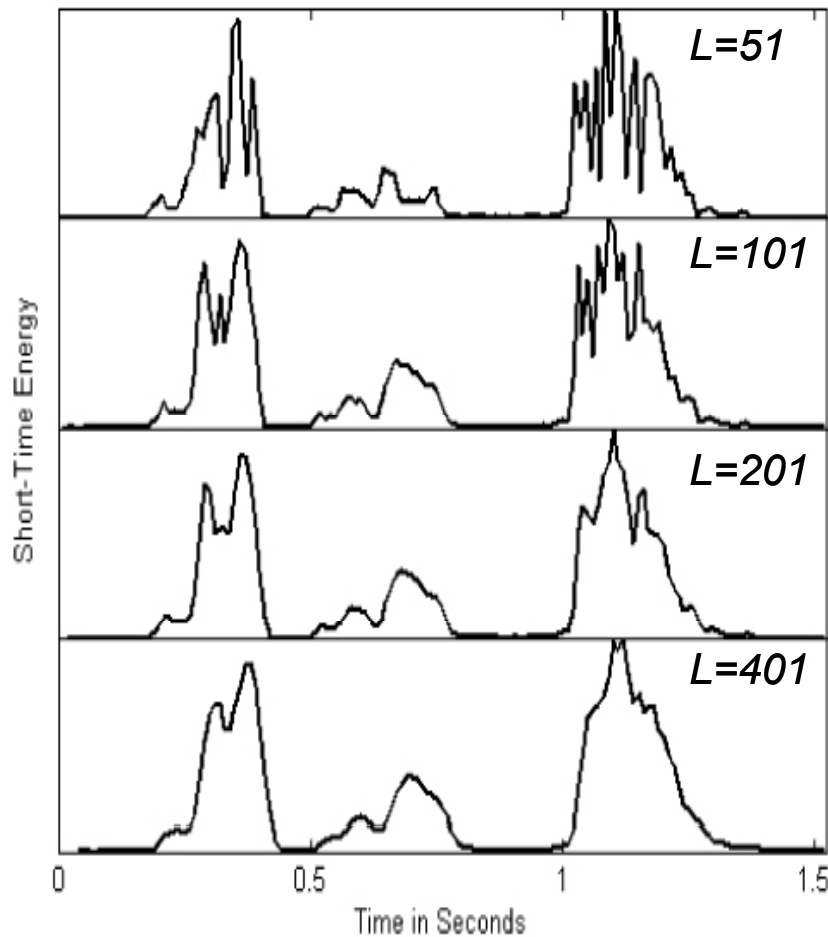
/ What She Said / -- Hamming Window, $M_{\hat{n}}$



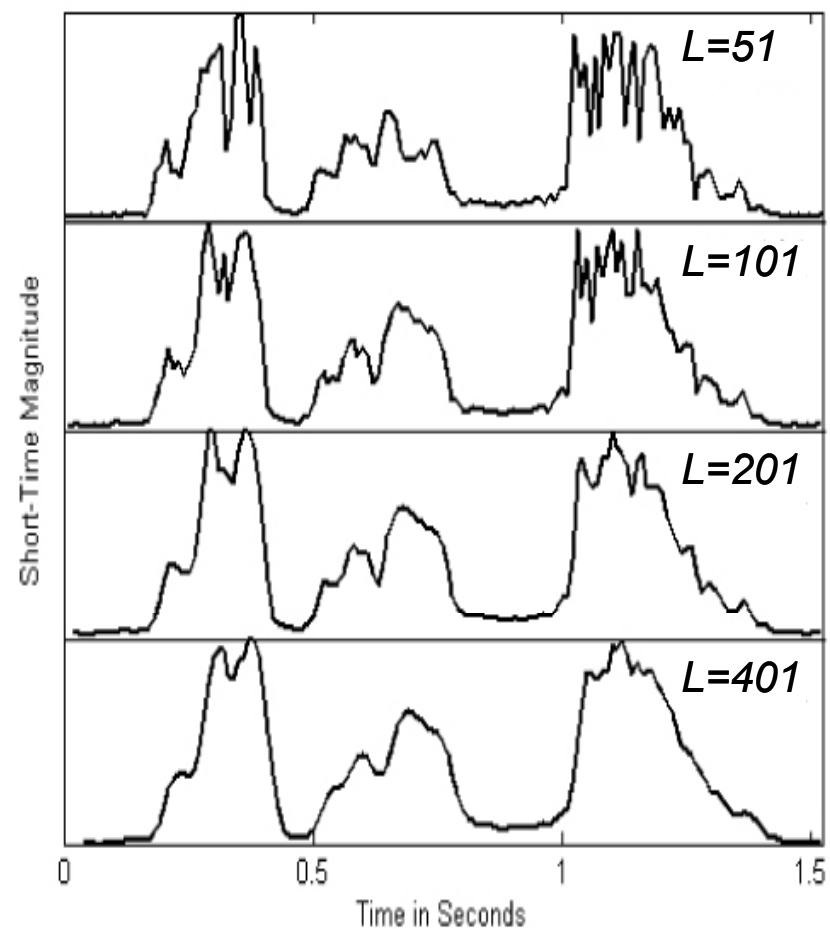
- differences between E_n and M_n noticeable in unvoiced regions
- dynamic range of $M_n \sim$ square root (dynamic range of E_n) \Rightarrow level differences between voiced and unvoiced segments are smaller
- E_n and M_n can be sampled at a rate of 100/sec for window durations of 20 msec or so \Rightarrow efficient representation of signal energy/magnitude

Short Time Energy and Magnitude— Rectangular Window

/ What She Said / -- Rectangular Window, $E_{\hat{n}}$

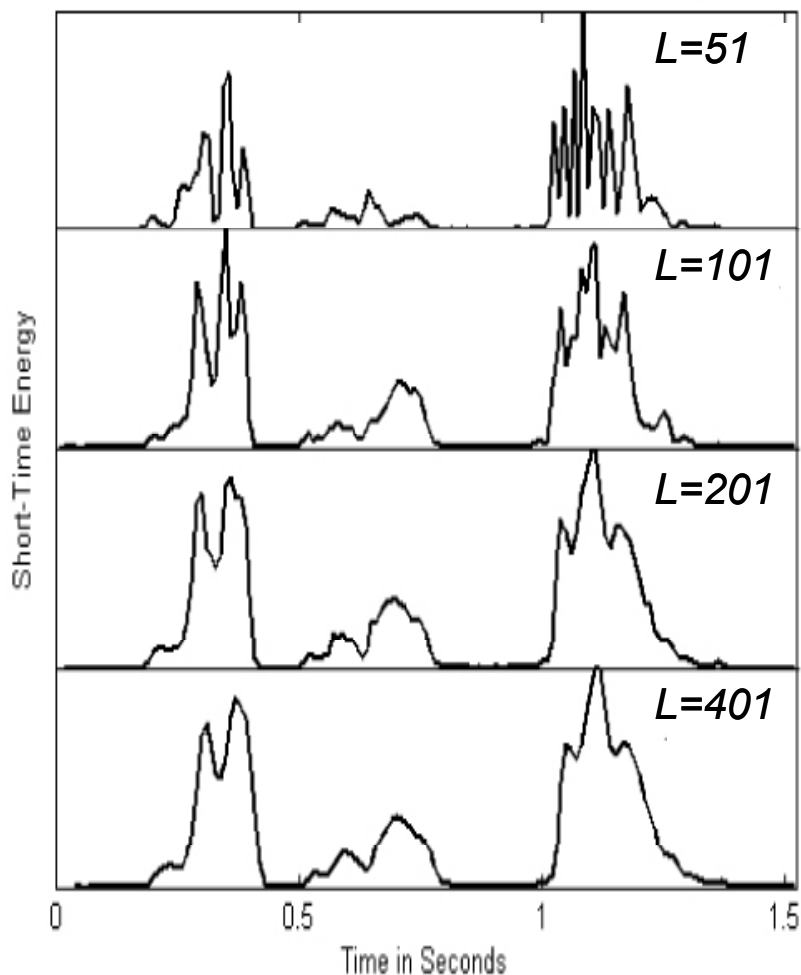


/ What She Said / -- Rectangular Window, $M_{\hat{n}}$

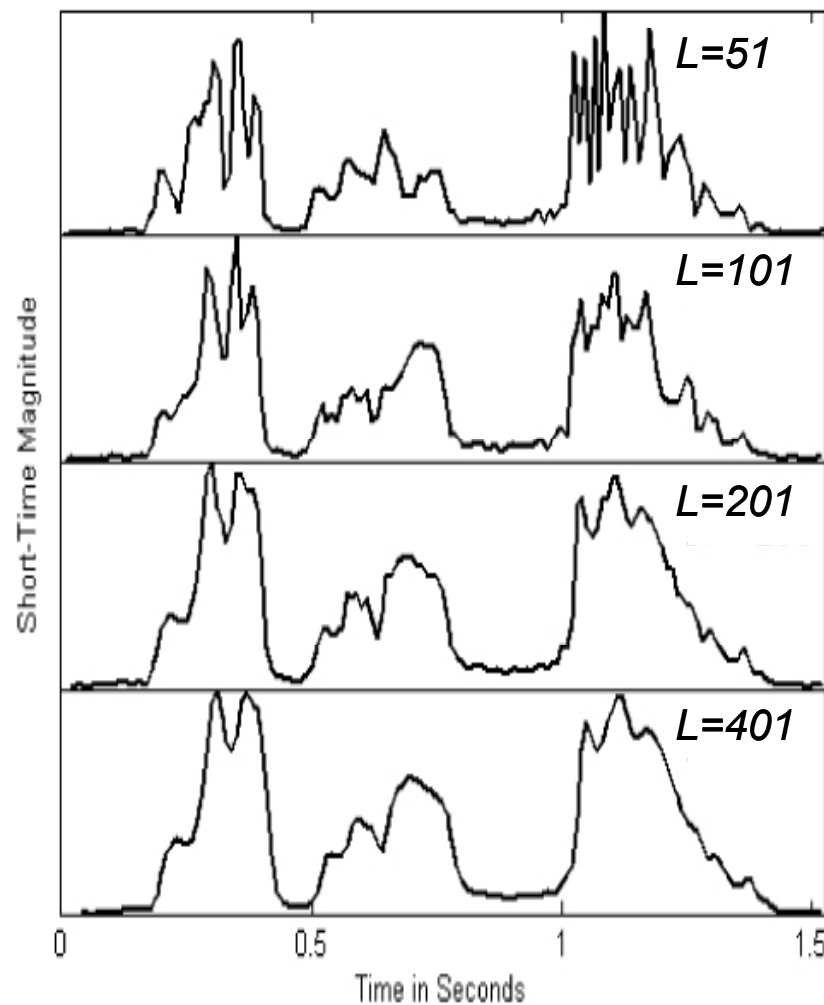


Short Time Energy and Magnitude— Hamming Window

/ What She Said / -- Hamming Window, $E_{\hat{n}}$



/ What She Said / -- Hamming Window, $M_{\hat{n}}$



Other Lowpass Windows

- can replace RW or HW with any lowpass filter
- window should be positive since this guarantees E_n and M_n will be positive
- FIR windows are efficient computationally since they can slide by L samples for efficiency with no loss of information (what should L be?)
- can even use an infinite duration window if its z -transform is a rational function, i.e.,

$$h[n] = a^n, \quad n \geq 0, \quad 0 < a < 1$$
$$= 0 \quad n < 0$$

$$H(z) = \frac{1}{1 - az^{-1}} \quad |z| > |a|$$

Other Lowpass Windows

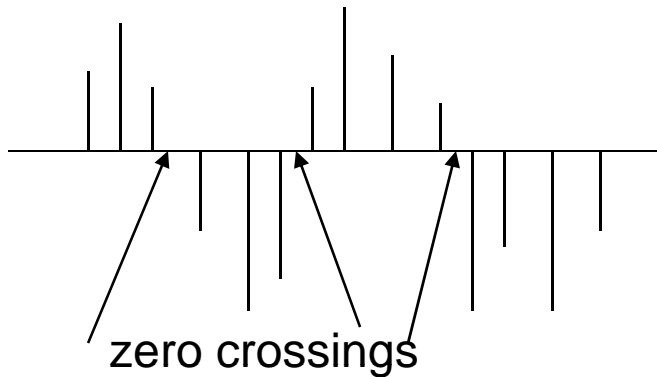
- this simple lowpass filter can be used to implement E_n and M_n recursively as:

$$E_n = a E_{n-1} + (1 - a) x^2[n] - \text{short-time energy}$$

$$M_n = a M_{n-1} + (1 - a) |x[n]| - \text{short-time magnitude}$$

- need to compute E_n or M_n every sample and then down-sample to 100/sec rate
- recursive computation has a non-linear phase, so delay cannot be compensated exactly

Short-Time Average ZC Rate



zero crossing => successive samples
have different algebraic signs

- zero crossing rate is a simple measure of the ‘frequency content’ of a signal—especially true for narrowband signals (e.g., sinusoids)
- sinusoid at frequency F_0 with sampling rate F_s has F_s/F_0 samples per cycle with two zero crossings per cycle, giving an average zero crossing rate of

$$z_1 = (2) \text{ crossings/cycle} \times (F_0 / F_s) \text{ cycles/sample}$$

$$z_1 = 2F_0 / F_s \text{ crossings/sample (i.e., } z_1 \text{ proportional to } F_0)$$

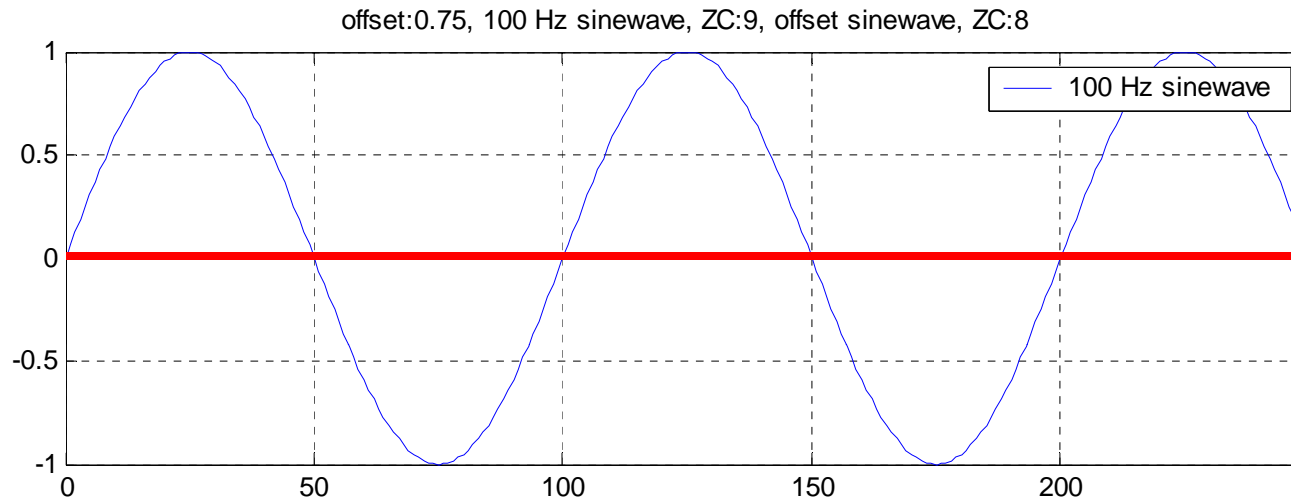
$$z_M = M (2F_0 / F_s) \text{ crossings/(} M \text{ samples)}$$

Sinusoid Zero Crossing Rates

Assume the sampling rate is $F_s = 10,000$ Hz

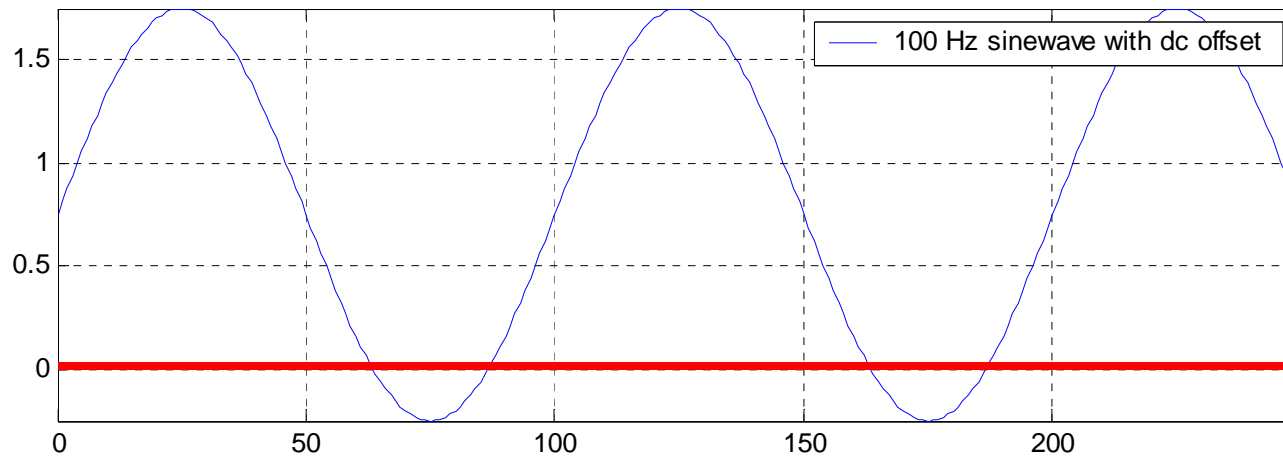
1. $F_0 = 100$ Hz sinusoid has $F_s / F_0 = 10,000 / 100 = 100$ samples/cycle;
or $z_1 = 2 / 100$ crossings/sample, or $z_{100} = 2 / 100 * 100 =$
2 crossings/10 msec interval
2. $F_0 = 1000$ Hz sinusoid has $F_s / F_0 = 10,000 / 1000 = 10$ samples/cycle;
or $z_1 = 2 / 10$ crossings/sample, or $z_{100} = 2 / 10 * 100 =$
20 crossings/10 msec interval
3. $F_0 = 5000$ Hz sinusoid has $F_s / F_0 = 10,000 / 5000 = 2$ samples/cycle;
or $z_1 = 2 / 2$ crossings/sample, or $z_{100} = 2 / 2 * 100 =$
100 crossings/10 msec interval

Zero Crossing for Sinusoids



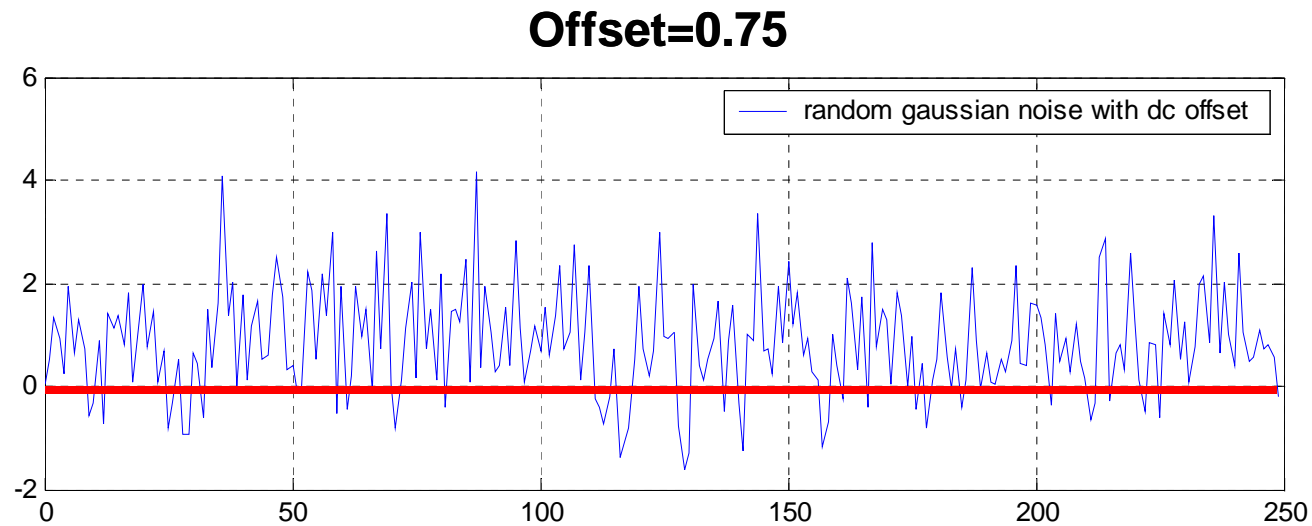
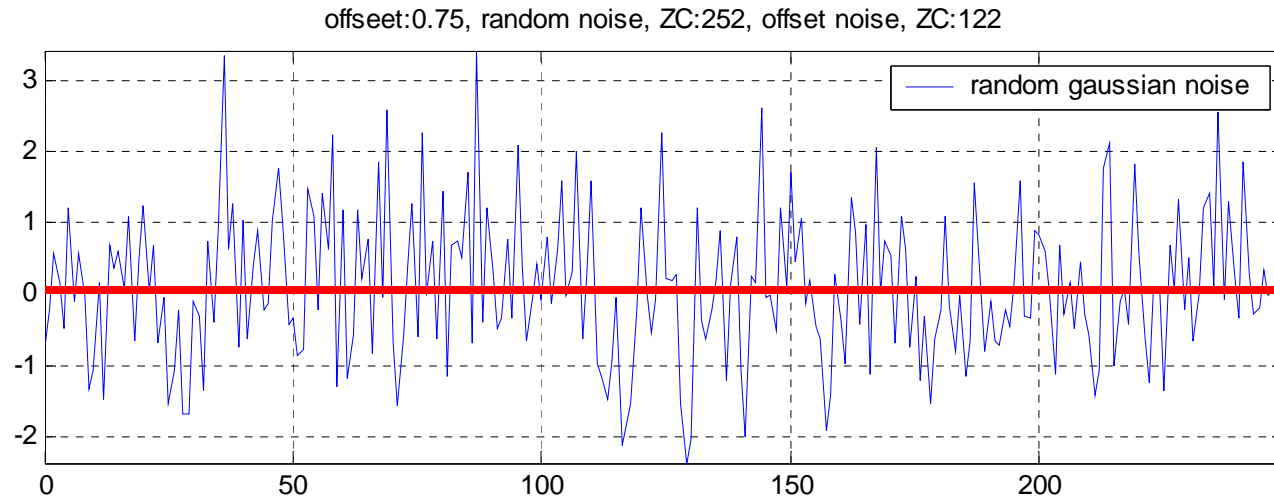
ZC=9

Offset=0.75

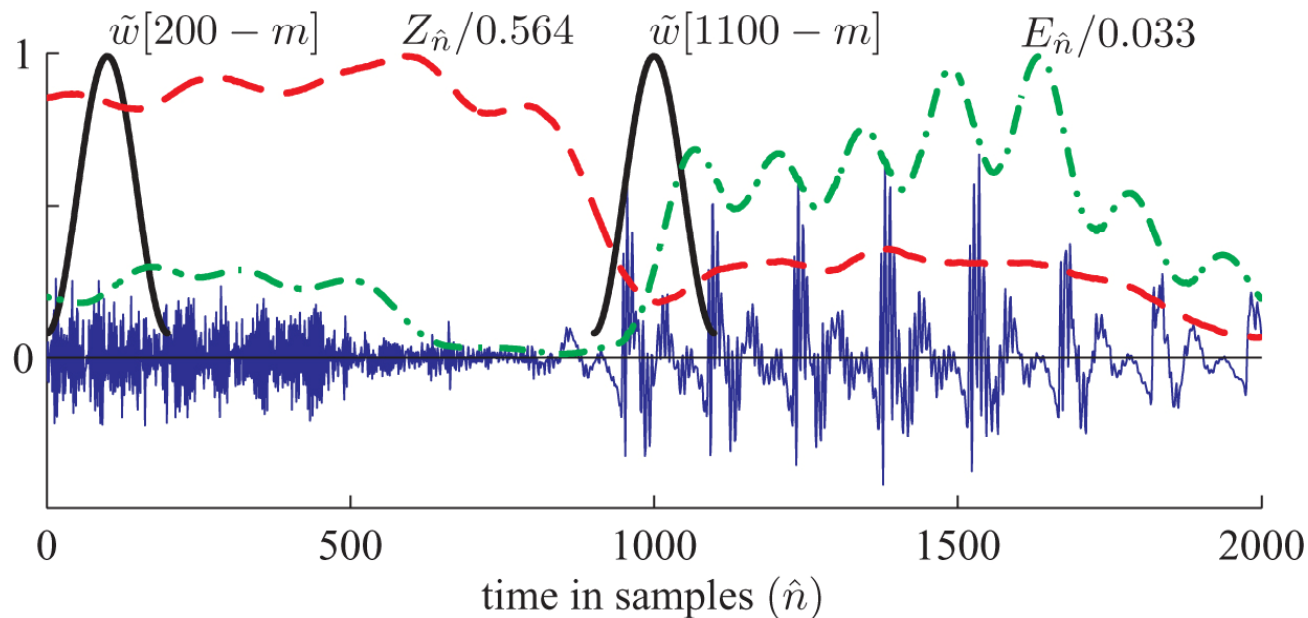


ZC=8

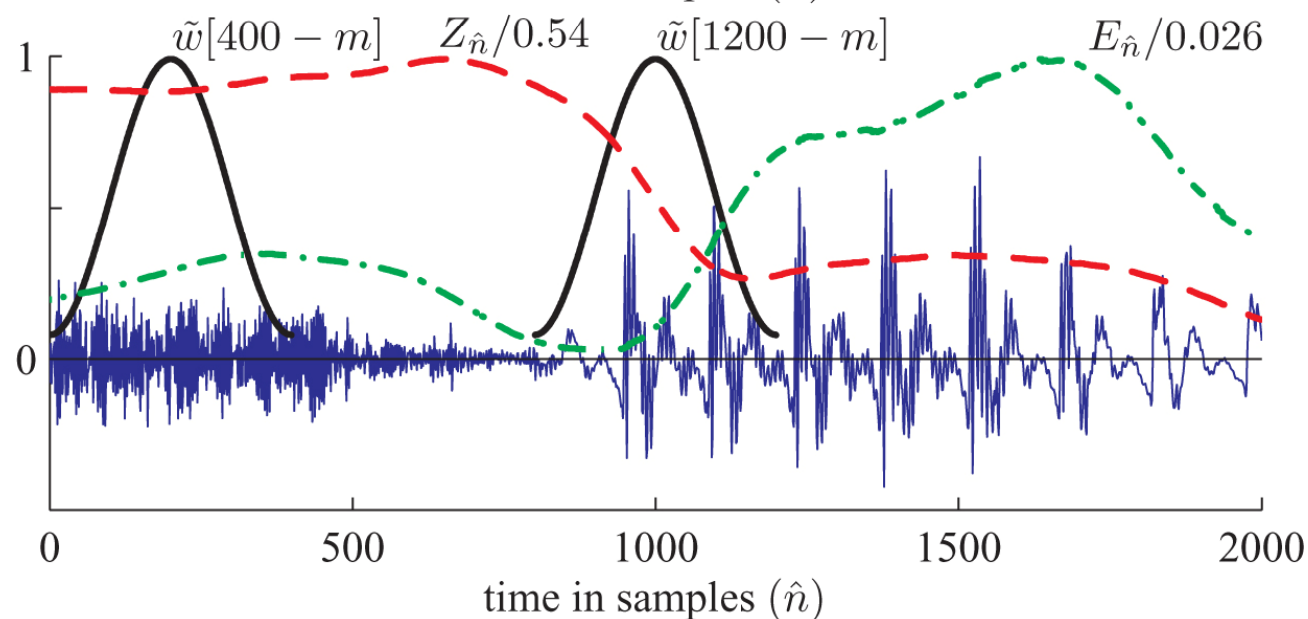
Zero Crossings for Noise



ZC and Energy Computation

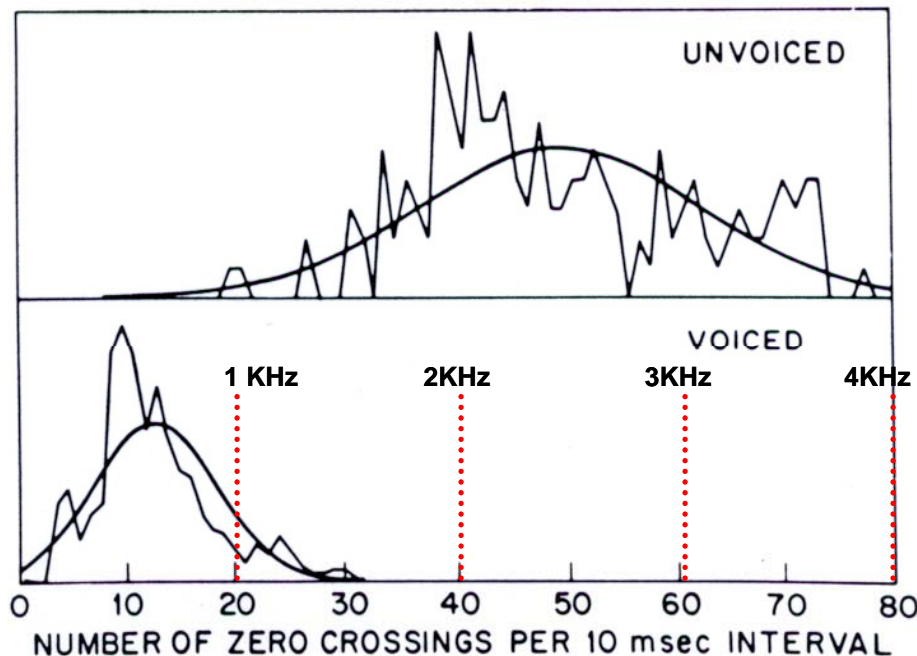


Hamming window
with duration
 $L=201$ samples
(12.5 msec at
 $F_s=16$ kHz)



Hamming window
with duration
 $L=401$ samples
(25 msec at
 $F_s=16$ kHz)

ZC Rate Distributions



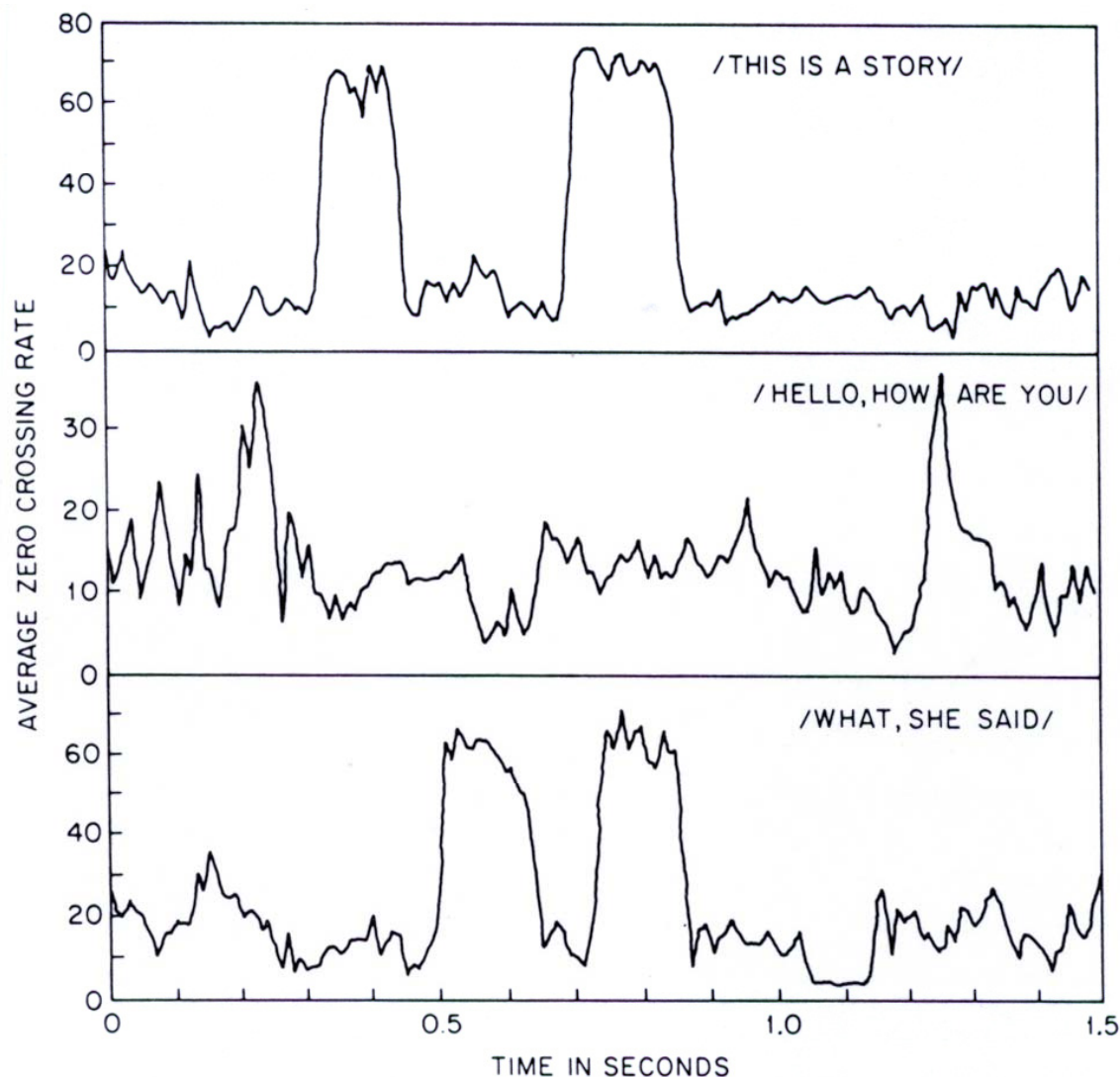
Unvoiced Speech:
the dominant energy
component is at
about 2.5 kHz

Voiced Speech: the
dominant energy
component is at
about 700 Hz

Fig. 4.11 Distribution of zero-crossings for unvoiced and voiced speech.

- for voiced speech, energy is mainly below 1.5 kHz
- for unvoiced speech, energy is mainly above 1.5 kHz
- mean ZC rate for unvoiced speech is 49 per 10 msec interval
- mean ZC rate for voiced speech is 14 per 10 msec interval

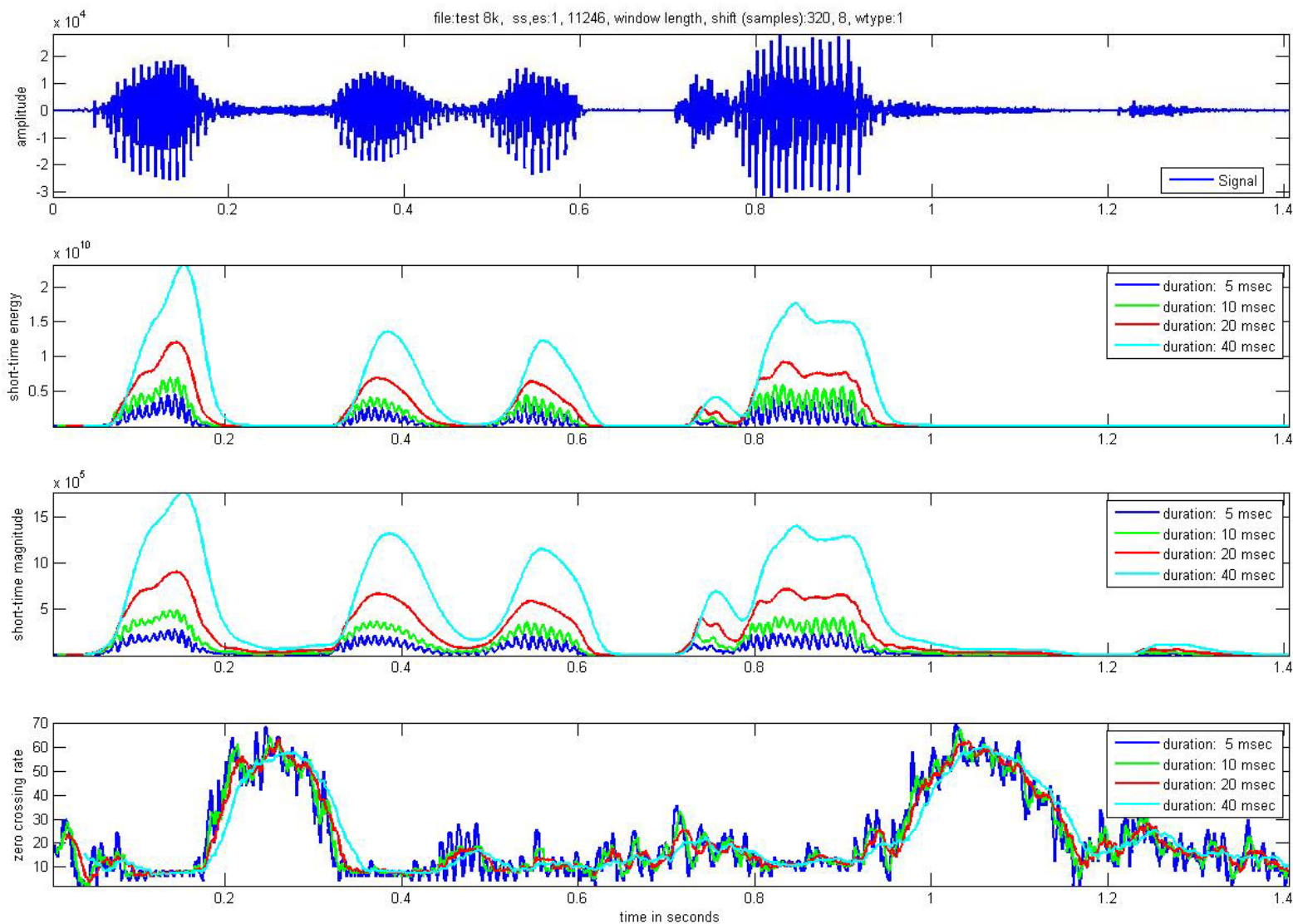
ZC Rates for Speech



- 15 msec windows
- 100/sec sampling rate on ZC computation

Fig. 4.12 Average zero-crossing rate for three different utterances.

Short-Time Energy, Magnitude, ZC



Issues in ZC Rate Computation

- for zero crossing rate to be accurate, need zero DC in signal => need to remove offsets, hum, noise => use bandpass filter to eliminate DC and hum
- can quantize the signal to 1-bit for computation of ZC rate
- can apply the concept of ZC rate to bandpass filtered speech to give a 'crude' spectral estimate in narrow bands of speech (kind of gives an estimate of the strongest frequency in each narrow band of speech)

Summary of Simple Time Domain Measures



$$Q_{\hat{n}} = \sum_{m=-\infty}^{\infty} T(x[m]) \tilde{w}[\hat{n} - m]$$

1. Energy:

$$E_{\hat{n}} = \sum_{m=\hat{n}-L+1}^{\hat{n}} x^2[m] \tilde{w}[\hat{n} - m]$$

- can downsample $E_{\hat{n}}$ at rate commensurate with window bandwidth

2. Magnitude:

$$M_{\hat{n}} = \sum_{m=\hat{n}-L+1}^{\hat{n}} |x[m]| \tilde{w}[\hat{n} - m]$$

3. Zero Crossing Rate:

$$Z_{\hat{n}} = z_1 = \sum_{m=\hat{n}-L+1}^{\hat{n}} |\text{sgn}(x[m]) - \text{sgn}(x[m-1])| \tilde{w}[\hat{n} - m]$$

where $\text{sgn}(x[m]) = 1 \quad x[m] \geq 0$
 $\quad \quad \quad = -1 \quad x[m] < 0$

Summary

- Short-time parameters in the domain
 - short-time energy
 - short-time average magnitude
 - Short-time zero crossing rate (ZCR)
- Can be used in distinguishing fore/background

DEEE725 Speech Signal Processing Lab

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END OF LECTURE 06

CHAPTER 6. TIME-DOMAIN METHODS FOR SPEECH PROCESSING