



## **Sinyaller ve Sistemler**

“Convolutuon,

Filtre,

Dalgacık (Wavelet),

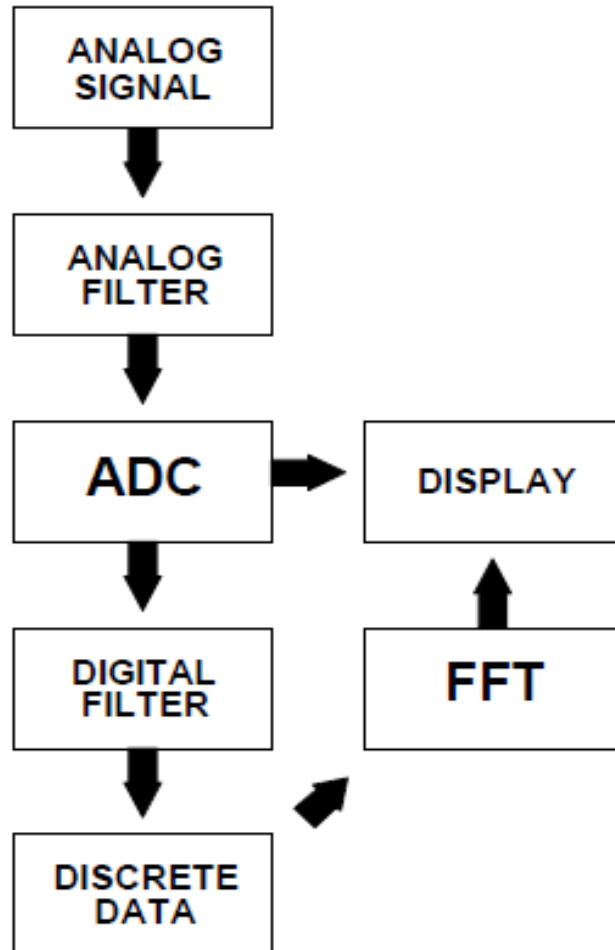
Örtüşme (Aliasing),

Gürültü Arındırma (Denoising),

Hilbert Dönüşümü”

**Dr. Cahit Karakuş, 2020**

# The Anatomy of the FFT Analyzer



*The FFT Analyzer can be broken down into several pieces which involve the digitization, filtering, transformation and processing of a signal.*

*Several items are important here:*

- Digitization and Sampling*
- Quantization of Signal*
- Aliasing Effects*
- Leakage Distortion*
- Windows Weighting Functions*
- The Fourier Transform*
- Measurement Formulation*

# Convolution

# Convolution

- Sinyal üzerinde yapılan tüm işlemler “Sinyal İşleme” olarak adlandırılan geniş bir inceleme alanı oluşturmaktadır. Sinyallerin işlenmesindeki karmaşıklığa bağlı olarak sinyal işlemlerini iki geniş kategoride sınıflandırabiliriz;
  - ► Matematiksel temel sinyal işlemleri
  - ► Korelasyon ve filtreleme gibi gelişmiş sinyal işlemleri
- Matematiksel olarak konvolüsyon denklemi korelasyon denklemiyle büyük benzerlik göstermektedir. Bununla birlikte, korelasyondan farklı olarak konvolüsyon, sinyallerden birini ters çevirmeyi içerir. Bu zaman dönüşümü ( $t - \tau$ ) olarak temsil edilebilir. Burada  $\tau$  zamanı anında düşünülür.

# Convolution

- Sürekli zaman sinyalleri için  $x_1(t)$  ve  $x_2(t)$ 'nin konvolusyon işlemini aşağıdaki gibi ifade edebiliriz:

$$y(t) = \int_{-\infty}^{\infty} x_1(\tau) x_2(t - \tau) d\tau$$

veya

$$y(t) = \int_{-\infty}^{\infty} x_1(t - \tau) x_2(\tau) d\tau$$

# Convolution

- Eş zamanlı olarak, ayrık zaman sinyalleri için,

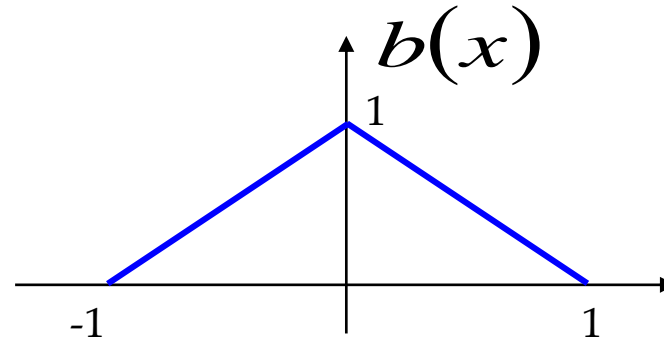
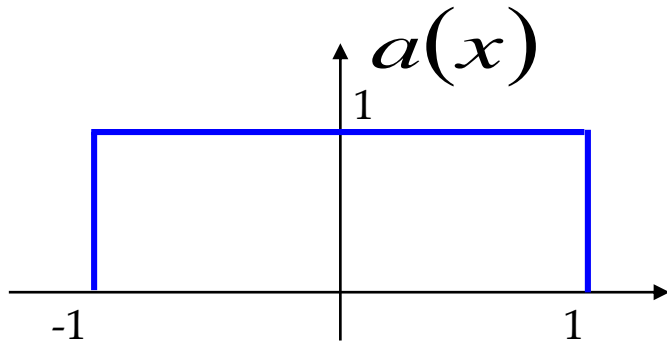
$$y[n] = \sum_{-\infty}^{\infty} k = \{x1 [k] x2 [n - k]\}$$

veya

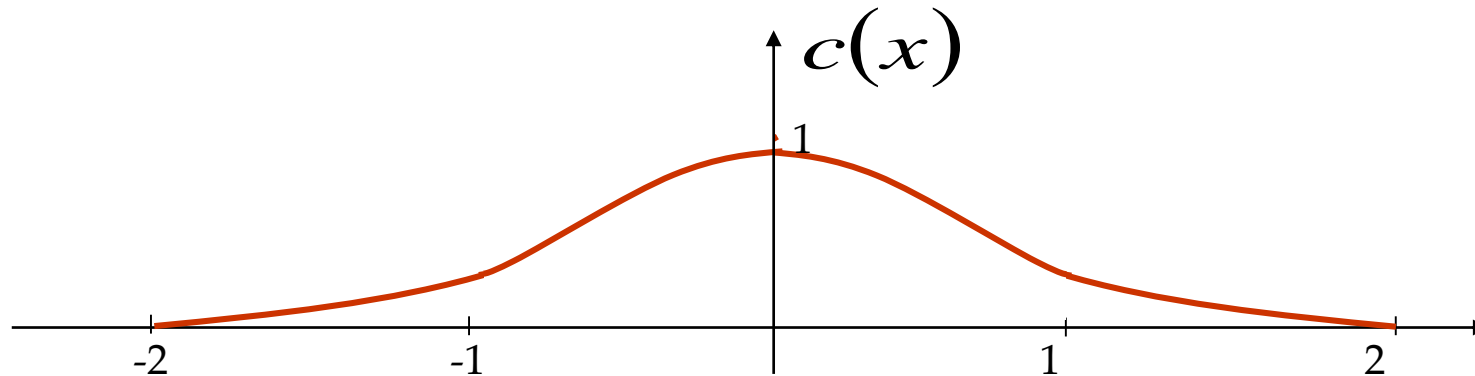
$$y[n] = \sum_{-\infty}^{\infty} k = \{x1 [n - k] x2 [k]\}$$

# Convolution - Example

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↓  $c = a * b$



# Properties of Convolution

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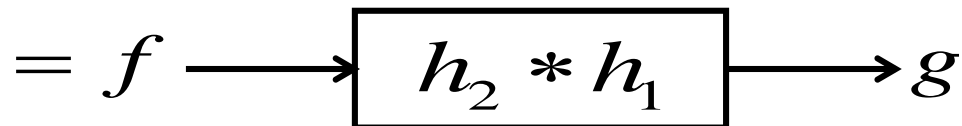
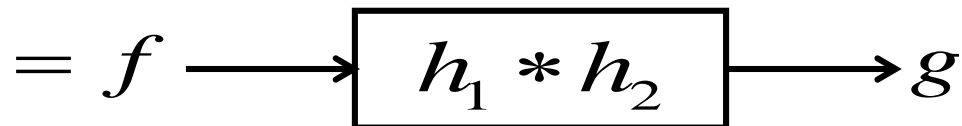
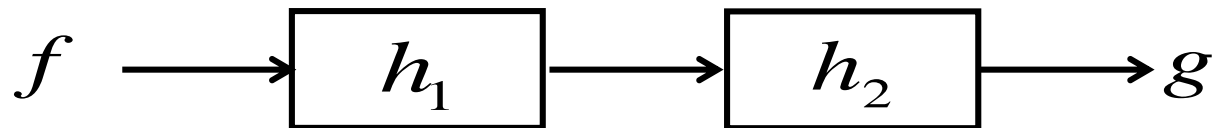
- Commutative

$$a * b = b * a$$

- Associative

$$(a * b) * c = a * (b * c)$$

- Cascade system

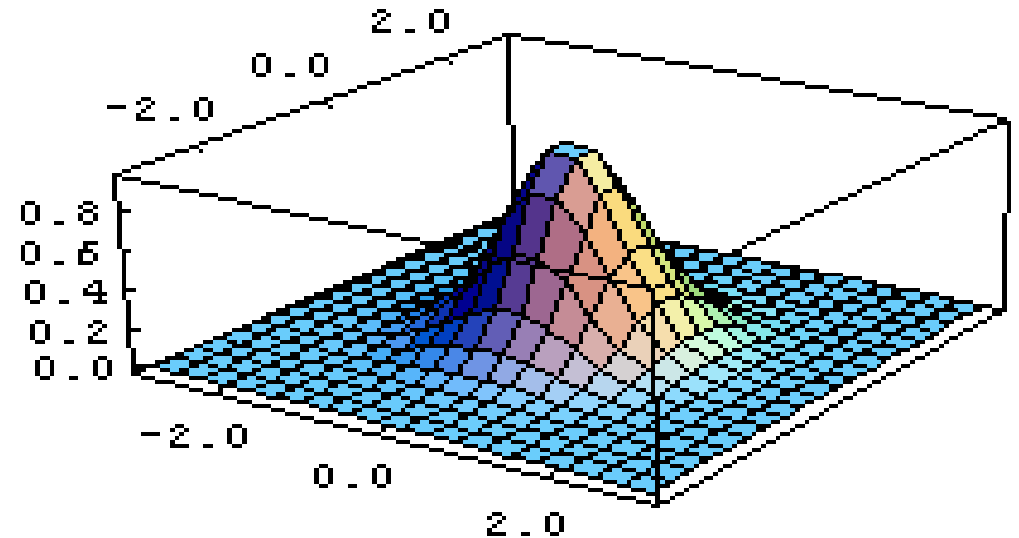




# Gaussian filtering

- A Gaussian kernel gives less weight to pixels further from the center of the window
- This kernel is an approximation of a Gaussian function:

$$h(u, v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{\sigma^2}}$$



# Convolution

- **cross-correlation:** 
$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i + u, j + v]$$

- A **convolution** operation is a cross-correlation where the filter is flipped both horizontally and vertically before being applied to the image:

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i - u, j - v]$$

- It is written:

$$G = H \star F$$

- Suppose H is a Gaussian or mean kernel. How does convolution differ from cross-correlation?

# Convolution is nice!

$$b = c \star a$$

- Notation:

- Convolution is a multiplication-like operation

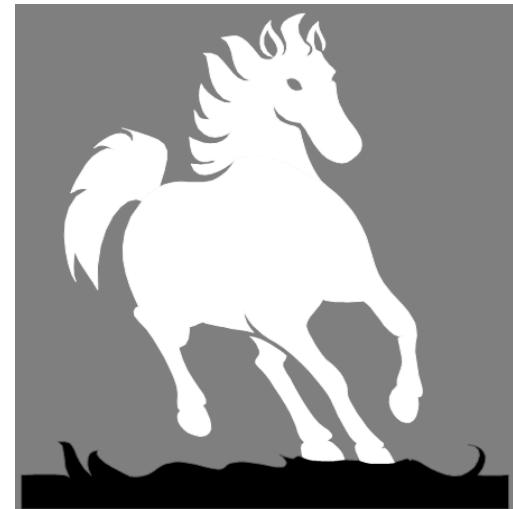
- commutative  $a \star b = b \star a$
- associative  $a \star (b \star c) = (a \star b) \star c$
- distributes over addition  $a \star (b + c) = a \star b + a \star c$
- scalars factor out  $\alpha a \star b = a \star \alpha b = \alpha(a \star b)$
- identity: unit impulse  $e = [\dots, 0, 0, 1, 0, 0, \dots]$

$$a \star e = a$$

- Conceptually no distinction between filter and signal

- Usefulness of associativity

- often apply several filters one after another:  $((a \star b_1) \star b_2) \star b_3$
- this is equivalent to applying one filter:  $a \star (b_1 \star b_2 \star b_3)$



# Image Processing



# Image processing

- Image compression
- Noise reduction
- Edge extraction
- Contrast enhancement
- Segmentation
- Thresholding
- Morphology
- Image restoration

# General commands

- `imread`: Read an image
- `figure`: creates a figure on the screen.
- `imshow(g)`: which displays the matrix `g` as an image.
- `imread(i, j)`: the command returns the value of the pixel `(i,j)`
- `iminfo`: Information about the image.

# Basic Filters

- Convolution/correlation/Linear filtering
- Gaussian filters
- Smoothing and noise reduction
- First derivatives of Gaussian
- Second derivative of Gaussian: Laplacian
- Oriented Gaussian filters
- Steerability

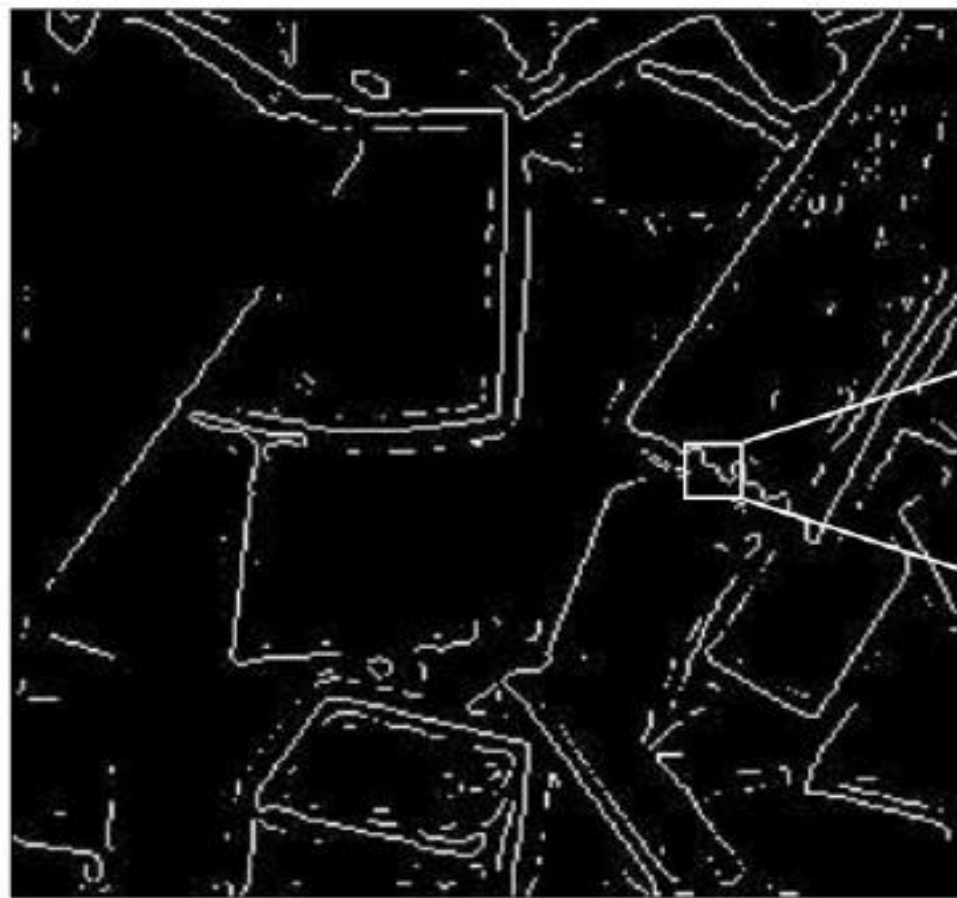


# Dijital Görüntü Türleri

- İkilik: Her piksel sadece siyah veya beyazdır. Her piksel için sadece iki olası değer olduğundan (0,1), sadece piksel başına bir bit gerekir.
- Gri Tonlama: Her piksel, gri (normalde 0 (siyah) ila 255 (beyaz) arasında bir değerdir. Bu aralık, her pikselin sekiz bit veya tam olarak bir bayt ile temsil edilebileceği anlamına gelir. Diğer gri tonlama aralıkları kullanılır, ancak genellikle  $2^n$ 'dir.
- Gerçek Renk veya RGB: Her piksel belirli bir renge sahiptir; Bu renk, içindeki kırmızı, yeşil ve mavi miktarıyla açıklanır. Bu bileşenlerin her biri 0–255 aralığına sahipse, bu toplam 256<sup>3</sup> farklı olası renk verir. Böyle bir görüntü üç matrisin “yığını”dır; Her piksel için kırmızı, yeşil ve mavi değerleri temsil eder. Bu, her piksel için 3 değere tekabül ettiği anlamına gelir.



## Binary Image



1	1	0	0	0	0
0	0	1	0	0	0
0	0	1	0	0	0
0	0	0	1	0	0
0	0	0	1	1	0
0	0	0	0	0	1

## Grayscale Image



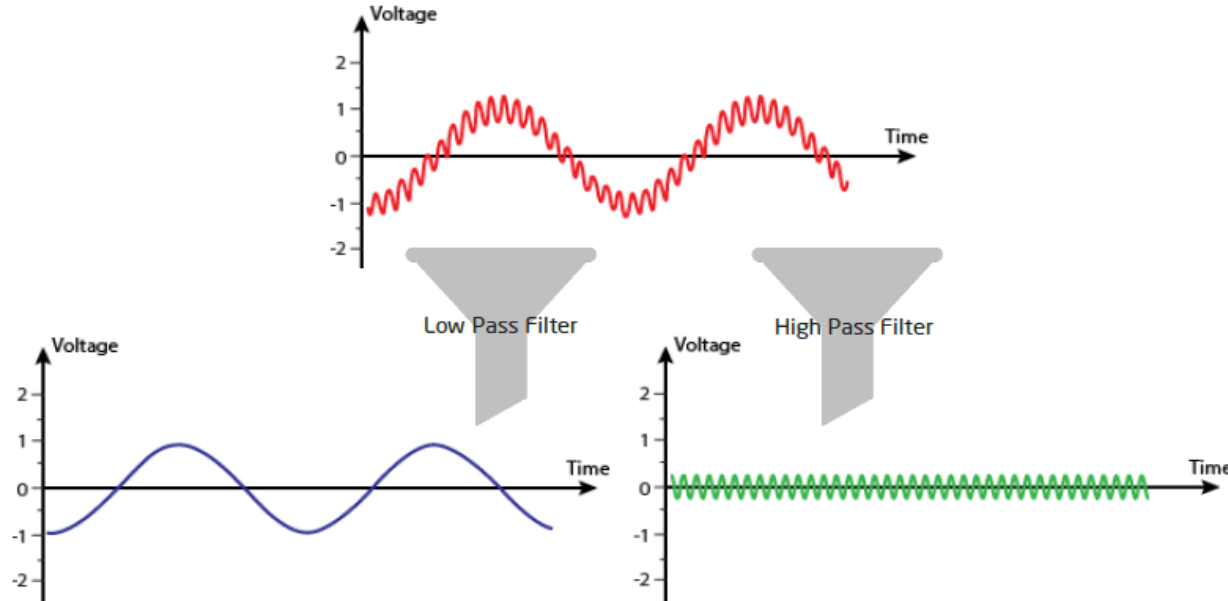
230	229	232	234	235	232	148
237	236	236	234	233	234	152
255	255	255	251	230	236	161
99	90	67	37	94	247	130
222	152	255	129	129	246	132
154	199	255	150	189	241	147
216	132	162	163	170	239	122

# Filtering

# Filtered Signal

- The function introduces the implementation of fft and ifft in filtering and cleaning of signals.
- The function plots
  - 1. the original signal,
  - 2. its transform,
  - 3. the reconstructed (filtered) signal.

# Filterleme



- Analog sinyal çok sayıda sinüsoidal sinyallerin karışımından oluşur.
- Fourier dönüşümü çok sayıdaki sinüsoidal sinyali frekanslarına göre ayrıştırır. Genliklerini de verir.
- FFT ile frekans domenindeki frekanslarına göre sinyalleri ayrıştırır.
- LPF, Alçak geçiren filtre üst frekanslar söndürülür. HPF, yüksek geçiren filte alt frekanslar söndürülür.
- BPF, Band geçiren filtre istenilen frekans aralığındaki sinyalleri geçirir, diğerlerini söndürür.
- Gürültü yüksek frekans bileşenleri içerir.

# Örnek-1

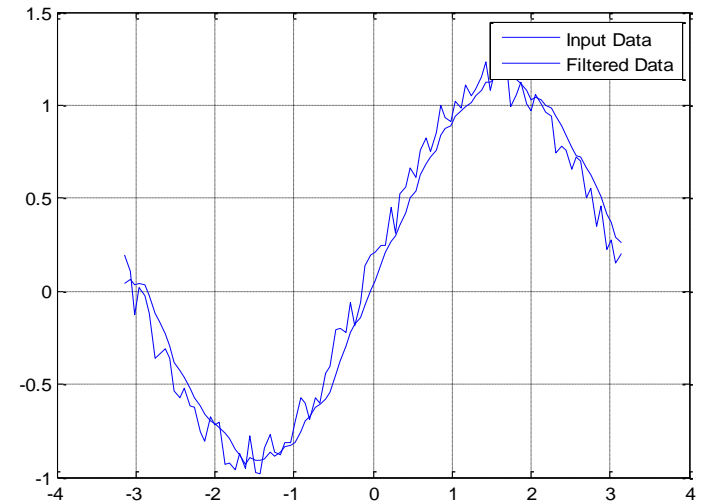
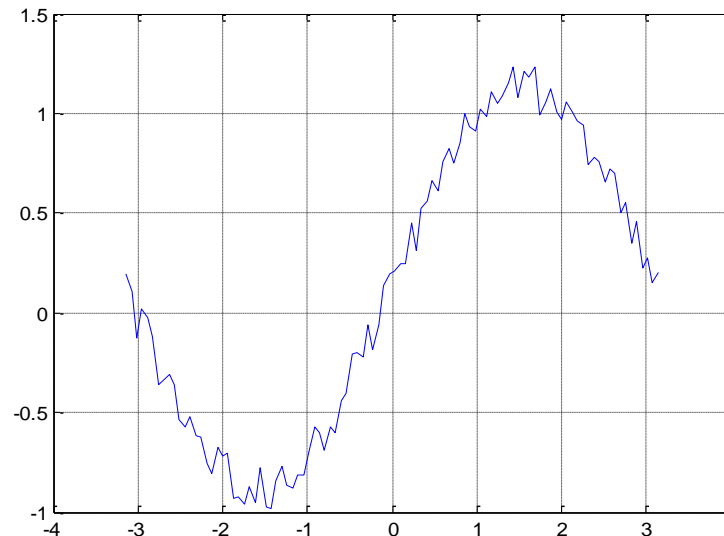
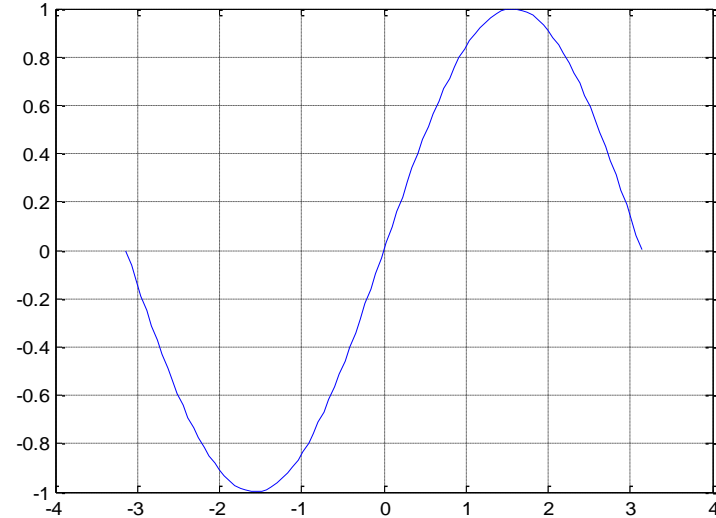
```
clear all  
close all
```

```
t = linspace(-pi,pi,100);  
M=length(t)  
x1 = sin(t);
```

```
figure, plot(t,x1)  
grid on  
x = sin(t) + 0.25*rand(size(t));
```

```
figure, plot(t,x)  
grid on  
windowSize = 5;  
b = (1/windowSize)*ones(1,windowSize);  
a = 1;
```

```
y = filter(b,a,x);  
grid on  
figure, plot(t,x)  
hold on  
plot(t,y)  
grid on  
legend('Input Data','Filtered Data')
```



# Örnek-1

```
ya=fft(x);  
figure, plot(fftshift(abs(ya)))  
grid on
```

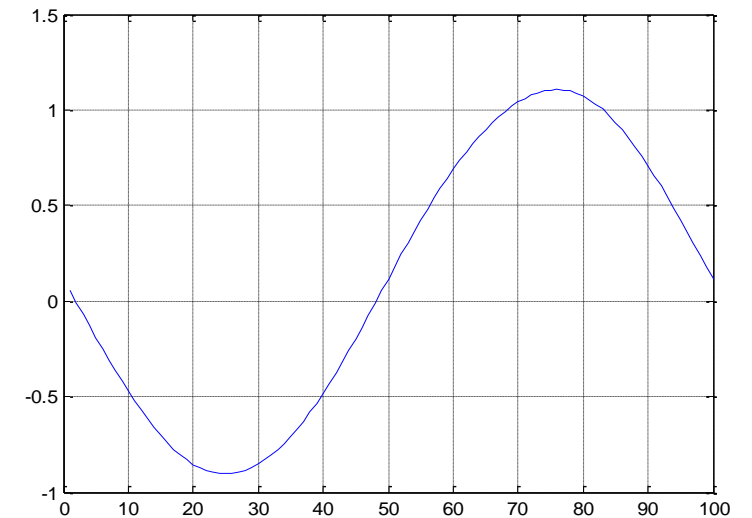
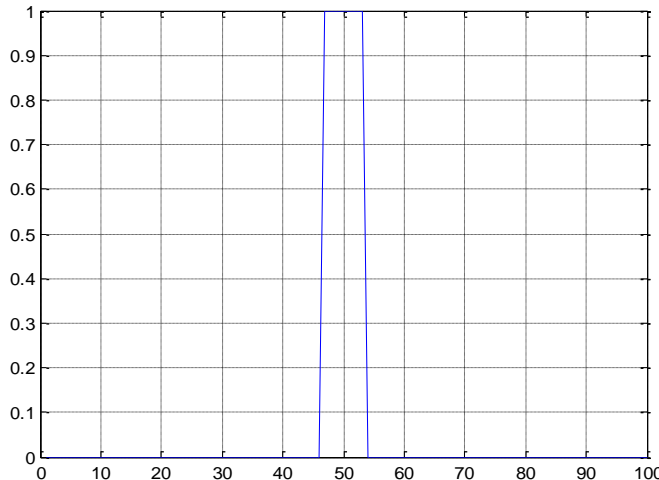
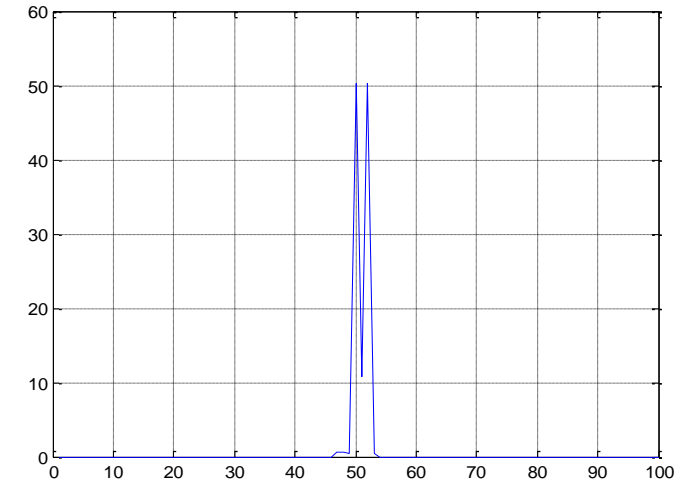
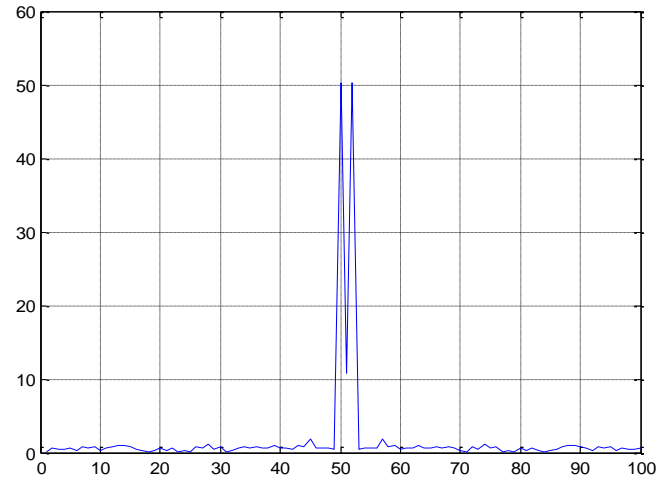
```
for i=1:100  
yb(i)=1;  
end  
for i=4:96  
yb(i)=0;  
end
```

```
figure, plot((abs(fftshift(yb))))  
grid on
```

```
yc=ya.*yb;  
figure, plot((abs(fftshift(yc))))  
grid on
```

```
yb=ifft(yc);
```

```
figure, plot((real(yb)))  
grid on
```



# Wavelet



# Wavelet – Aliasing - Denoising

Wavelet – Dalgacık

Aliasing – Örtüşme

Denoising – Gürültü arındırma

# Wavelet

- Dalgacık, sıfırdan başlayan, artan ve sonra sıfıra azalan bir genliğe sahip dalga benzeri bir salınımdır.
- Bu tür sinyallerin ana sinyale içerisinde aranması işlemidir.
- Bir sinyalin ayrıştırılması için Fourier dönüşümünde kullanılan sinüslerin aksine, dalgacıklar genellikle zaman içinde çok daha yoğunlaşır. Genellikle zaman ve frekansta lokalize olan sinyalin bir analizini sağlarken, Fourier dönüşümü sadece frekansta lokalizedir. Dalgacıklara örnekler Şekil'de verilmiştir.

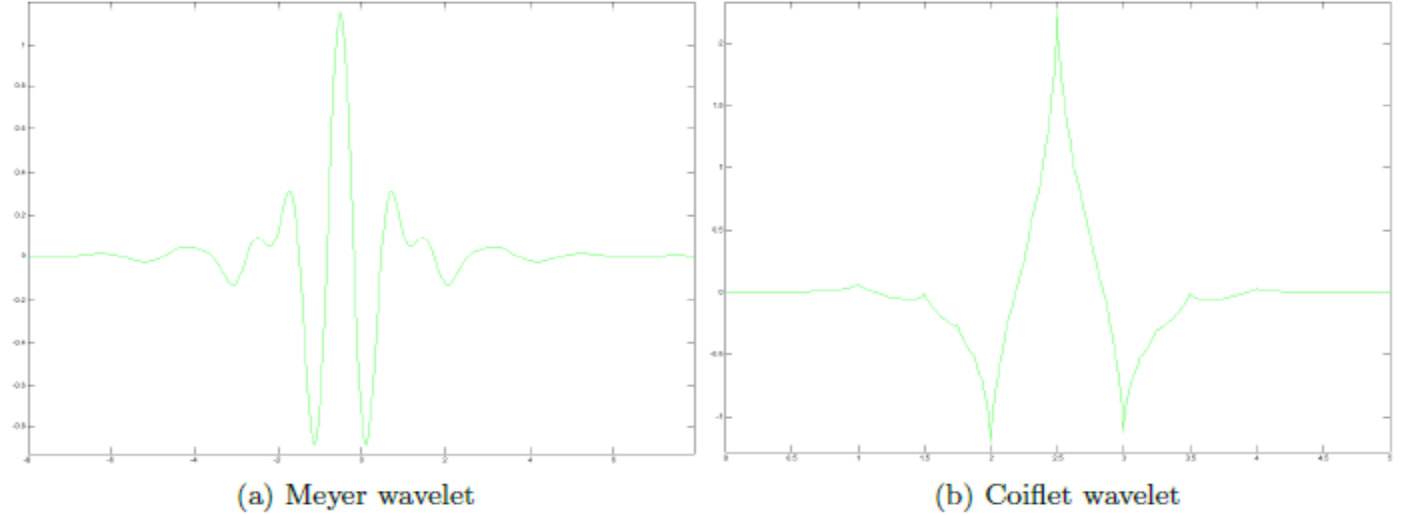


Figure : Wavelets - examples

Given a *mother wavelet*  $\psi(t)$  is defined as:

$$X(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} \psi\left(\frac{t-b}{a}\right) x(t) dt$$

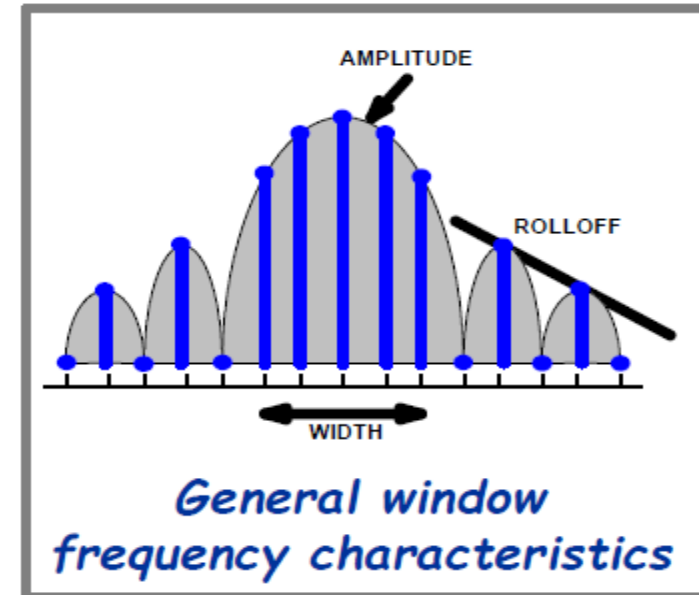
# Wavelet Analysis

- Dalgacık Analizi –Değişken boyutlu bölgelere sahip bir pencere tekniği
- Daha hassas düşük frekanslı bilgiye ihtiyaç duyduğumuz uzun zaman aralıklarının kullanılmasına ve yüksek frekanslı bilgi istediğimiz kısa bölgelerin kullanılmasına izin verir

# **Time weighting functions**

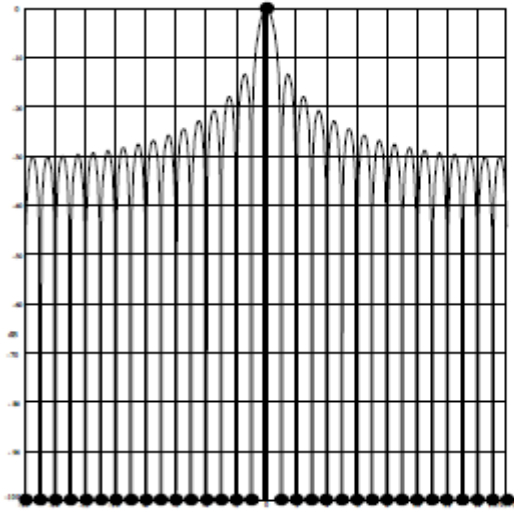
# Windows - Rectangular/Hanning/Flattop

- Time weighting functions are applied to minimize the effects of leakage.
- Rectangular
- Hanning
- Flat Top and many others

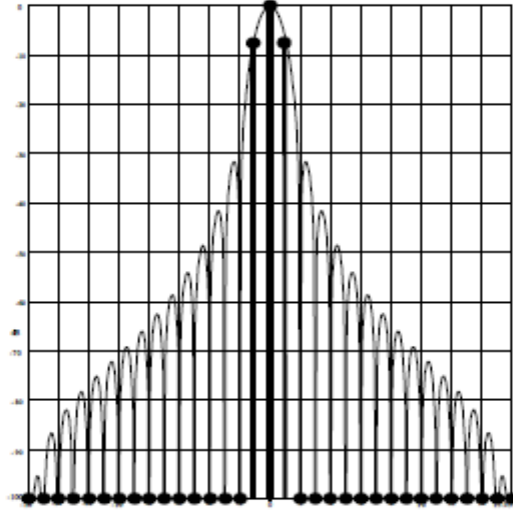


## *Windows*

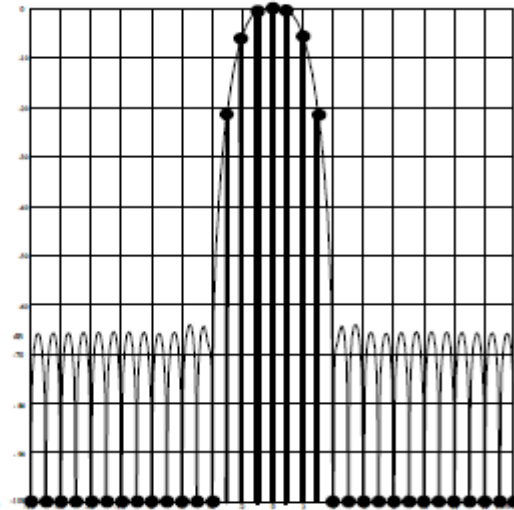
### *Rectangular*



### *Hanning*



### *Flat Top*





# Aliasing - Örtüşme

# Aliasing

- Analog sinyal örneklenirken, örnek alma sinyal frekansı yanlış tanımlanırsa, bozulmaya (distorsiyon) veya hataya (Aliasing)neden olur.
- Farklı sinyaller örneklendiğinde ayırt edilemez (veya birbirinin örtüğü) olmasına neden olan bir etkidir.
- Aynı zamanda, örneklemeden elde edilen değerlerden yeniden yapılandırılan bir sinyal orijinal sürekli sinyalden farklı olduğunda ortaya çıkan bozulmayı da ifade eder.
- Örneklemeden önce ve bir sinyali daha yüksek bir örneklemeden daha düşük bir örnekleme oranına dönüştürürken, giriş sinyaline alçak geçiren filtreler veya kenar yumuşatma filtreleri (AAF) uygulanarak örtüşme önlenir.

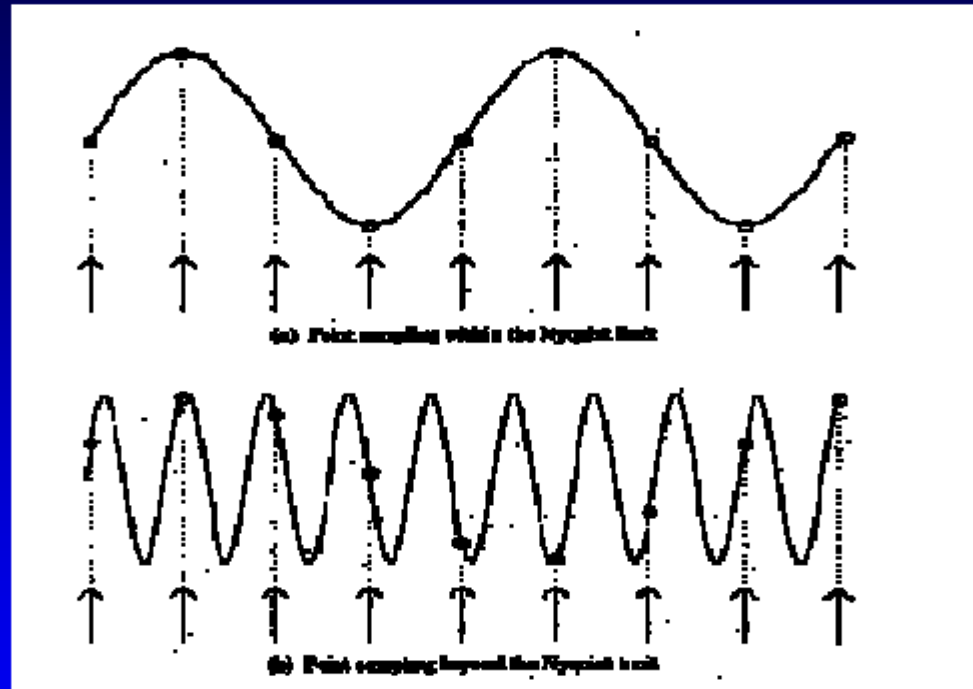


# Aliasing

- Fourier dönüşümünde işareti oluşturan frekanslar belirlendiğinde, örtüşerek kaybolan sinyali belirlemek için bir periyotta alınan örnek sayısı artırılarak analiz edilir.

# Aliasing

## Sampling and Aliasing



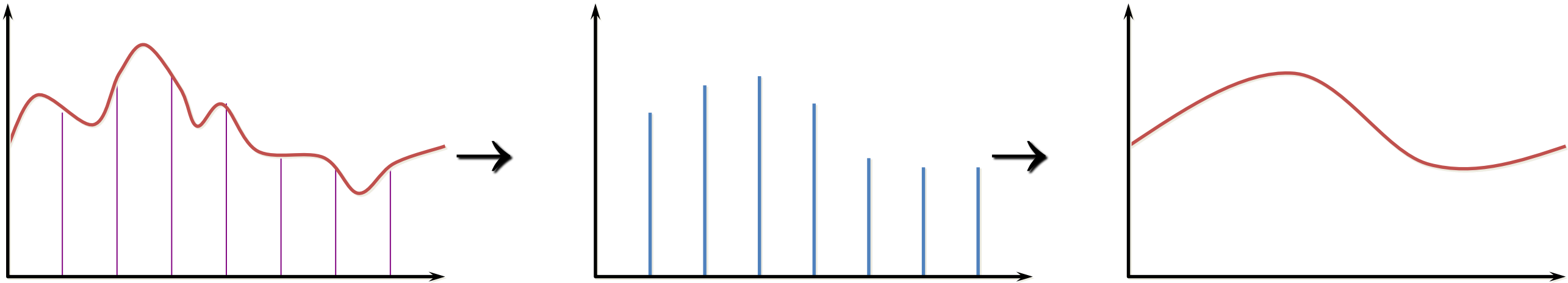
The top signal is sampled at the Nyquist limit and is not aliased.

The bottom signal is sampled beyond the Nyquist limit and is aliased.

*Aliasing occurs when higher frequencies are folded into lower frequencies.*

# Aliasing

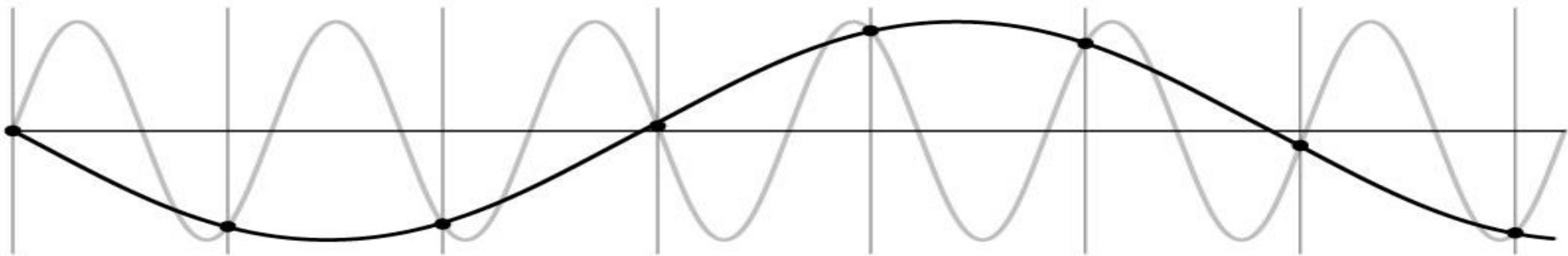
- Reconstructed signal might be very different from original: “aliasing”



- Solution: smooth the signal *before* sampling

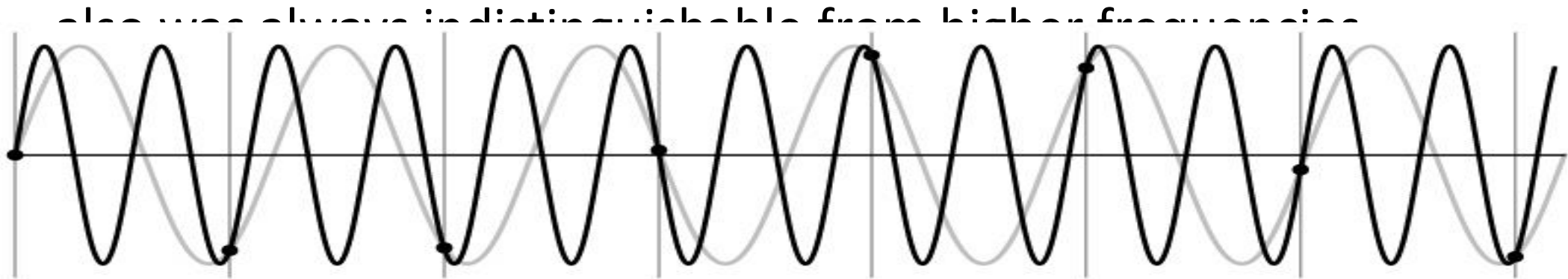
# Undersampling

- What if we “missed” things between the samples?
- Simple example: undersampling a sine wave
  - unsurprising result: information is lost
  - surprising result: indistinguishable from lower frequency



# Undersampling

- What if we “missed” things between the samples?
- Simple example: undersampling a sine wave
  - unsurprising result: information is lost
  - surprising result: indistinguishable from lower frequency



# **Denoising**

## **Gürültü Arındırma**

# Denoising

- Analog sinyaller ile çevrili dünya verileriyle çalışan herhangi bir bilim adamı ve mühendis tarafından iyi bilinir.
- Belirli koşullar altında ihmal edilebilecek düzeyde (örn. yüksek SNR – İşaretin Gürültüye Oranı) gürültü olmadan var olamazlar. Analog sinyalin var olduğu her yerde gürültü vardır.
- Bununla birlikte, gürültünün sinyalleri önemli ölçüde bozduğu birçok durum vardır ve daha ileri veri analizine devam edebilmek için gürültünün verilerden çıkarılması gerekir.
- Gürültü giderme işlemine genellikle sinyal gürültüsünü giderme veya basitçe gürültüyü giderme (Denoising) adı verilir.
- Gürültülü bir sinyalin örneği ve gürültüsü giderilmiş versiyonu Şekilde görülebilir.
- Gürültünün, düzgün olan orijinal sinyale yüksek frekanslı bileşenler eklediği görülebilir. Bu gürültünün karakteristik bir etkisidir.
- Bir analog sinyal Fourier dönüşümü ile genlikleri ile birlikte frekanslarına ayrıştırılır. Gürültülü olan filtreleme ile söndürülür.

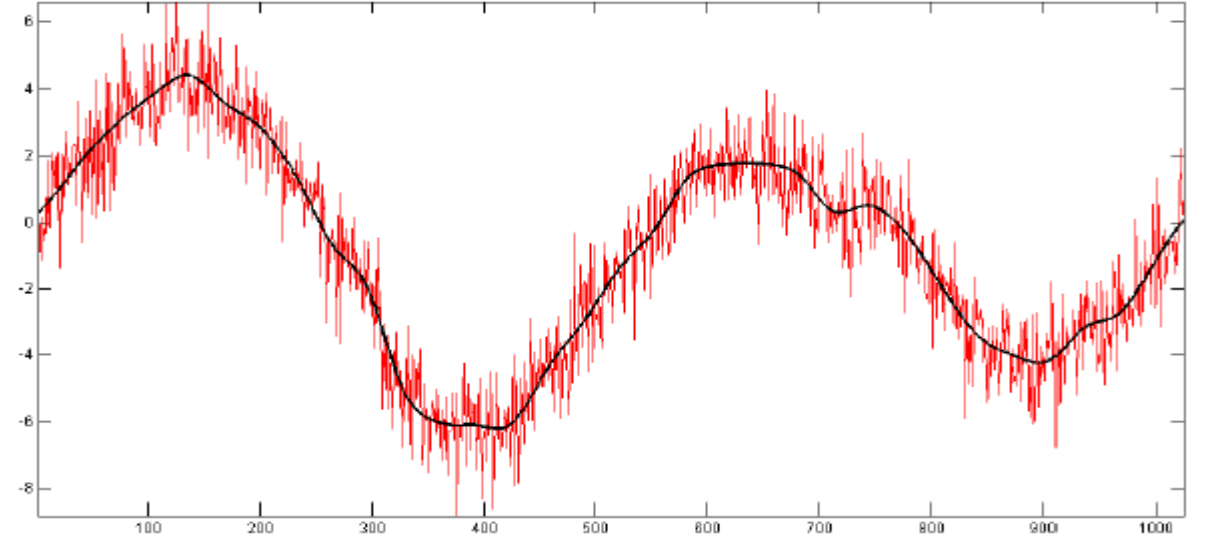


Figure : Noisy sine and its denoised version (solid line)

# **HILBERT HUANG TRANSFORMATION**



# Nerede kullanılır?

- Yapay zeka uygulamalarında, aşırı uyumu önlemede...

# Outline of Presentation

1. Motivation
2. Basic design of UWB radar system for through-wall human activity characterization
3. Hilbert Huang transform
4. Some results and notes on the development of the algorithm
5. Future work
6. Summary

# 1. Motivation

- Doppler etkileri gözlemlenerek ortamdaki deęişimlerin algılanması
  - İnsan yaşamının duvardan algılanması,
  - Yüzeydeki gerilmelerin algılanması,
  - Yüzey üzerindeki deęişimlerin algılanması,
  - Sınır ötesi tehditleri algılama.
- Mikrodalga radar, düşük dalga boyu, yüksek enerji, katı bariyerleri geçebilmesi, düşük zayıflama nedeniyle uygun bir seçimdir.
- Depremlerin önceden tespit edilebilmesi
- Askeri: Yurt güvenliği, şehir savaşı.
- Sağlık sektörü: hastaneler için uzaktan sağlık izleme sistemleri vb.
- Askeri uygulamalar için tasarlıyoruz - gizlilięi tasarım hedeflerinden biri olarak görüyoruz.

# Hilbert Huang Transform

- Hilbert Huang Transform algoritması hesaplama açısından pahalıdır.
- Algoritmanın asimptotik karmaşıklığını belirlemek mümkün değildir, çünkü algoritmanın doğası giriş sinyaline çok duyarlıdır, en kötü durumu ve en iyi durumu açıkça tanımlayamayız.
- Ortalama olarak, algoritma doğrusal olarak ölçeklenir.
- En önemli adım, en zayıf halka enterpolasyondur. Deneylerden kübik enterpolasyonun en iyi sonuçları verdiğini bulduk.
- Daha basit enterpolasyon teknikleri için, algoritmanın IMF'lere yakınsaması daha uzun sürer, daha karmaşık enterpolasyon teknikleri gereksizdir ve hesaplama açısından çok pahalıdır.

## 2. Basic design of the system

- Military operations require low probability of interception (LPI), low probability of exploitation (LPE), low probability of detection (LPD), and anti-jam characteristics.
- Traditional communication and radar systems use deterministic waveforms.
- Deterministic waveforms do not have these desirable properties.

# 2. Basic design of the system

## ➤ Moving person

- Position change
- Doppler shift
- Polarization change
- Gait

## ➤ Non-moving person

- Breathing
- Heartbeat and Respiration
- Talking
- Shaking
- Hands moving

# 2. Basic design of the system

## Waveform Design

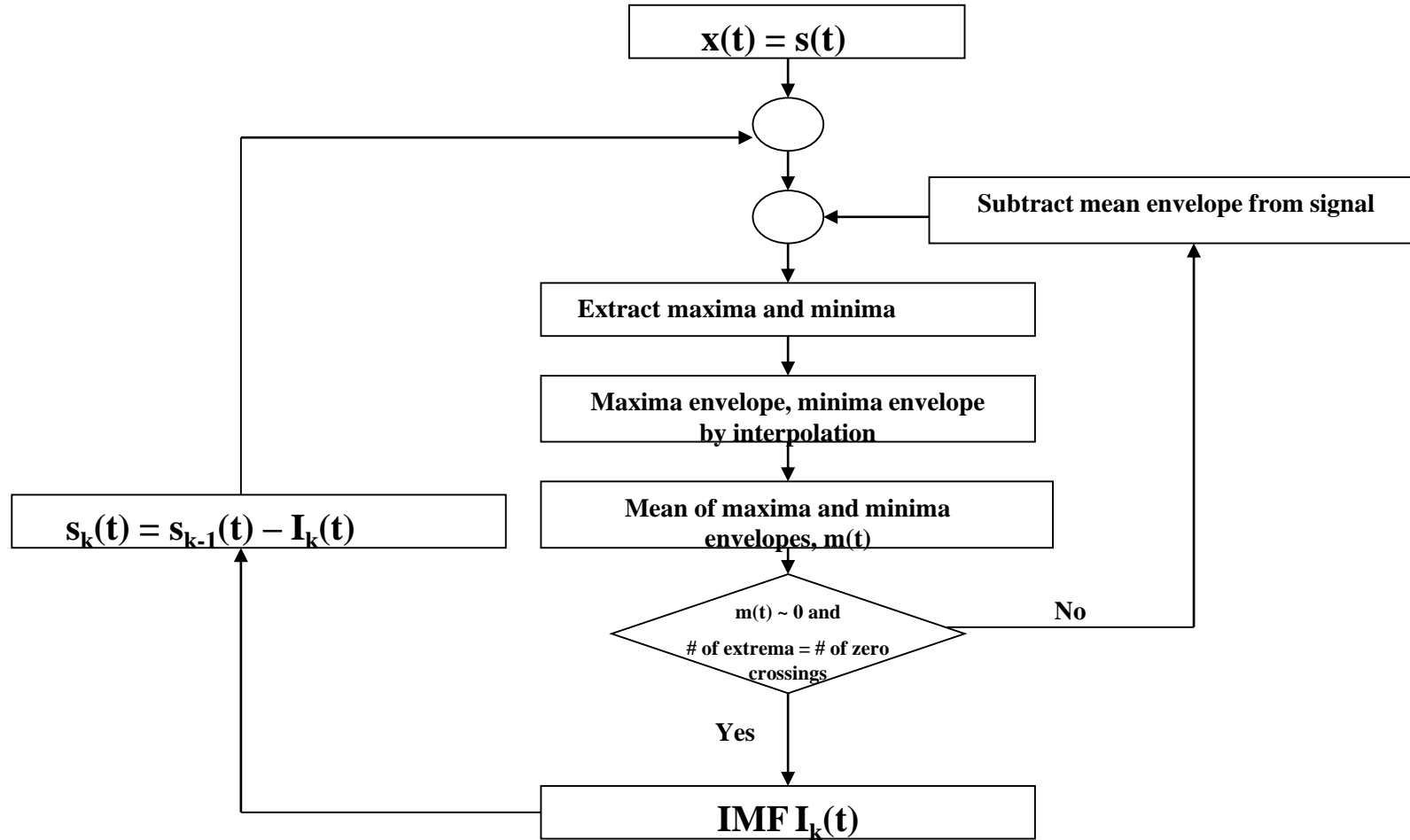
- Start with ultra-wideband (UWB) noise waveform.
- Insert low energy single tone waveform, such that, the single tone is 'masked' by the noise waveform.
- Doppler signatures of human movement can be inferred from the modulations of the single tone present in the reflected waveform.
- We propose to use the Hilbert-Huang Transform method for analyzing the Doppler return signal.

# Hilbert Huang Transform

- *Sinyal, sinyale özgü farklı zaman ölçeklerinin bileşenlerine ( İçsel Mod İşlevleri denir: IMF-Intrinsic Mode Functions) uyarlanabilir şekilde ayrıştırılır.*
- *Dönüşüm doğrusal değildir - doğrusal olmayan olaylardan kaynaklanan veriler için uygundur.*
- *IMF'ler "tek bileşenlidir" ve "anlık frekansı" rahatça tanımlamak için uygundur, bu da HHT'yi hızlı değişen frekans profilli sabit olmayan sinyaller için uygun hale getirir.*
- *IMF'ler, sıfır ortalaması olan ve maksimum veya minimum kadar sıfır geçişe sahip fonksiyonlar olarak tanımlanır.*

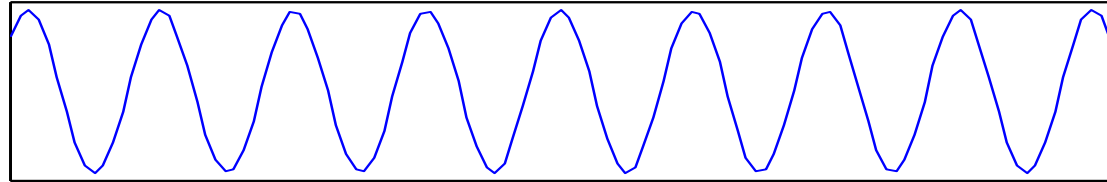


# 3. Hilbert Huang Transform-3

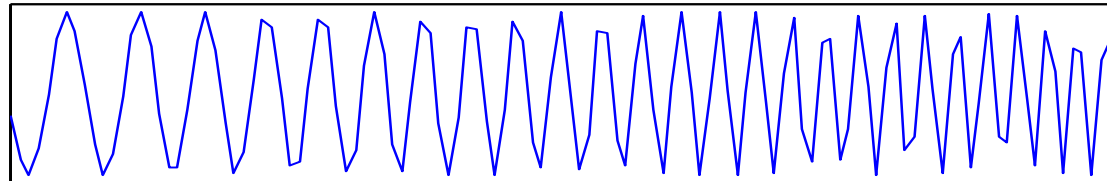


# 3. Hilbert Huang Transform-4

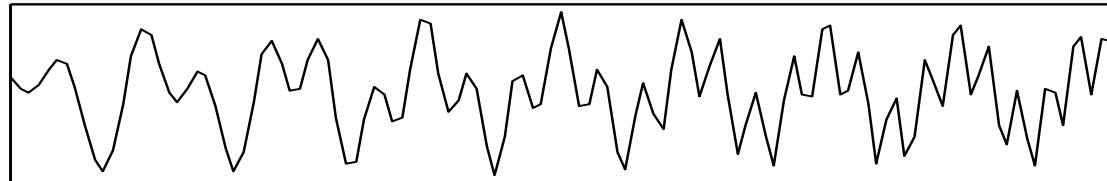
tone



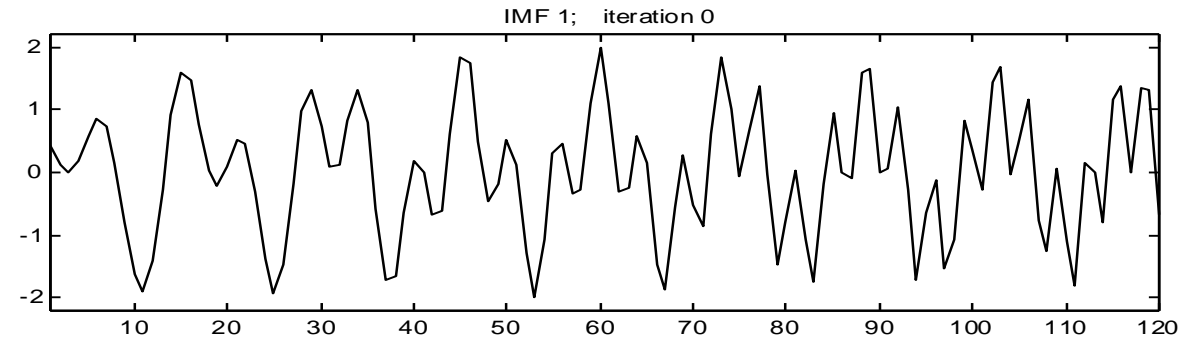
chirp



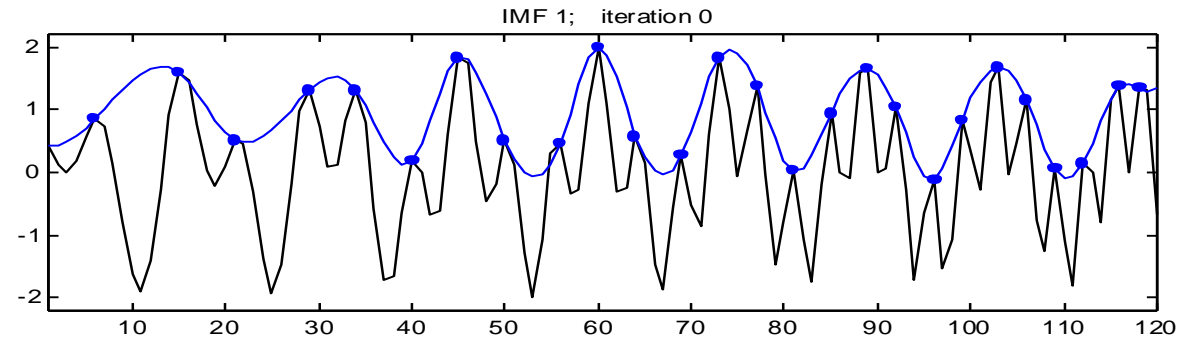
tone + chirp



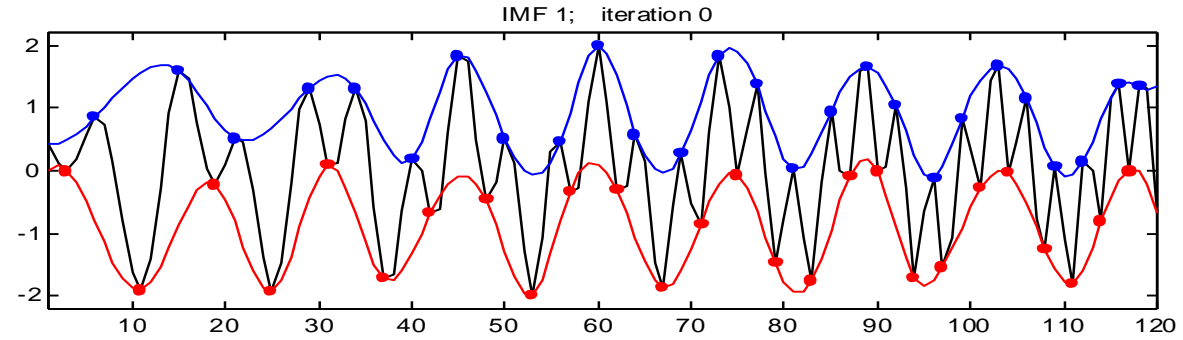
# 3. Hilbert Huang Transform-4



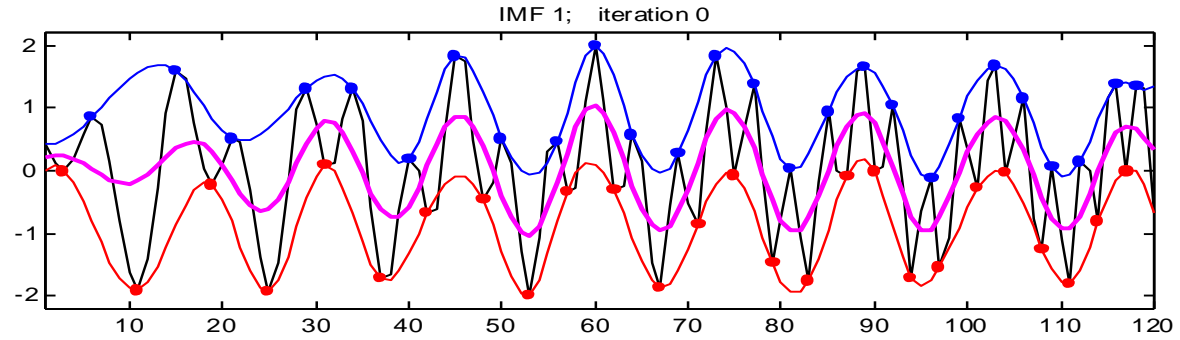
# 3. Hilbert Huang Transform-4



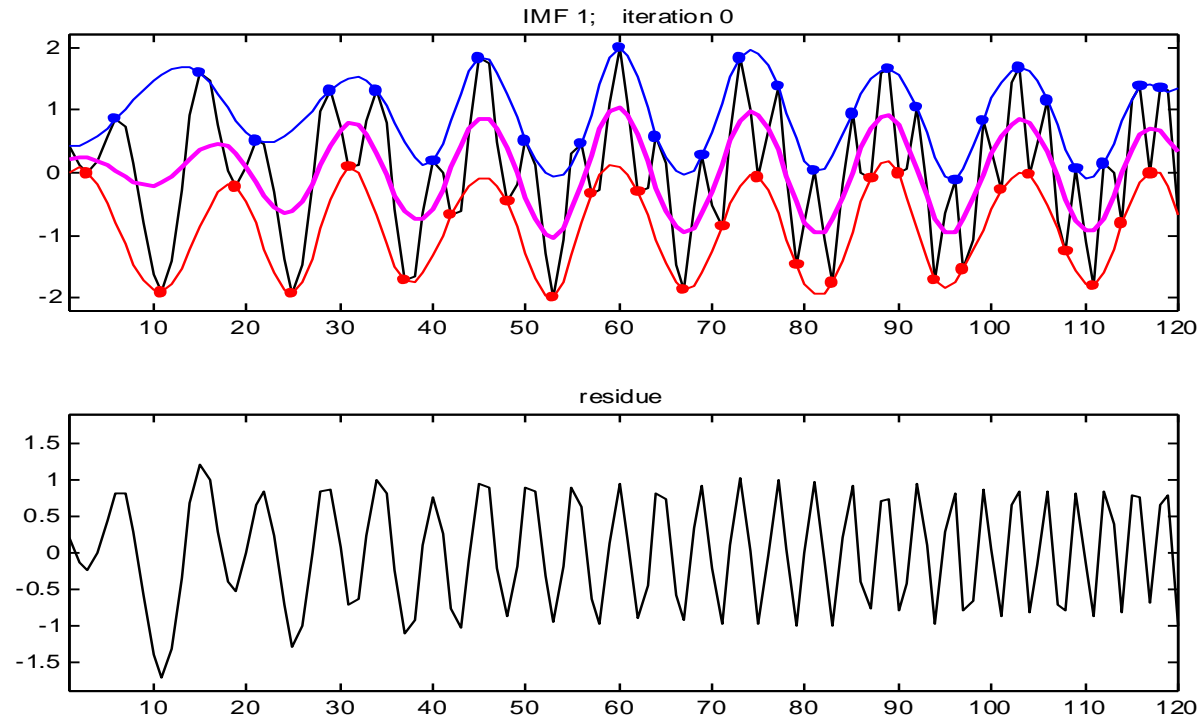
# 3. Hilbert Huang Transform-4



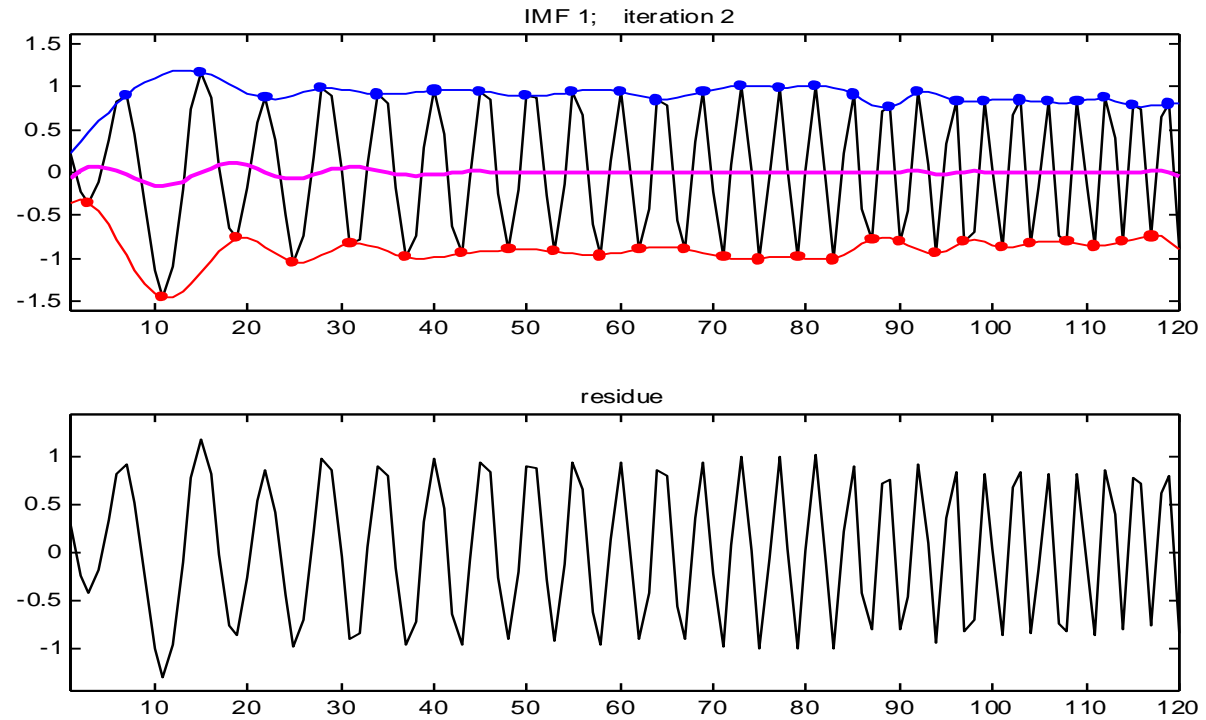
# 3. Hilbert Huang Transform-4



# 3. Hilbert Huang Transform-4

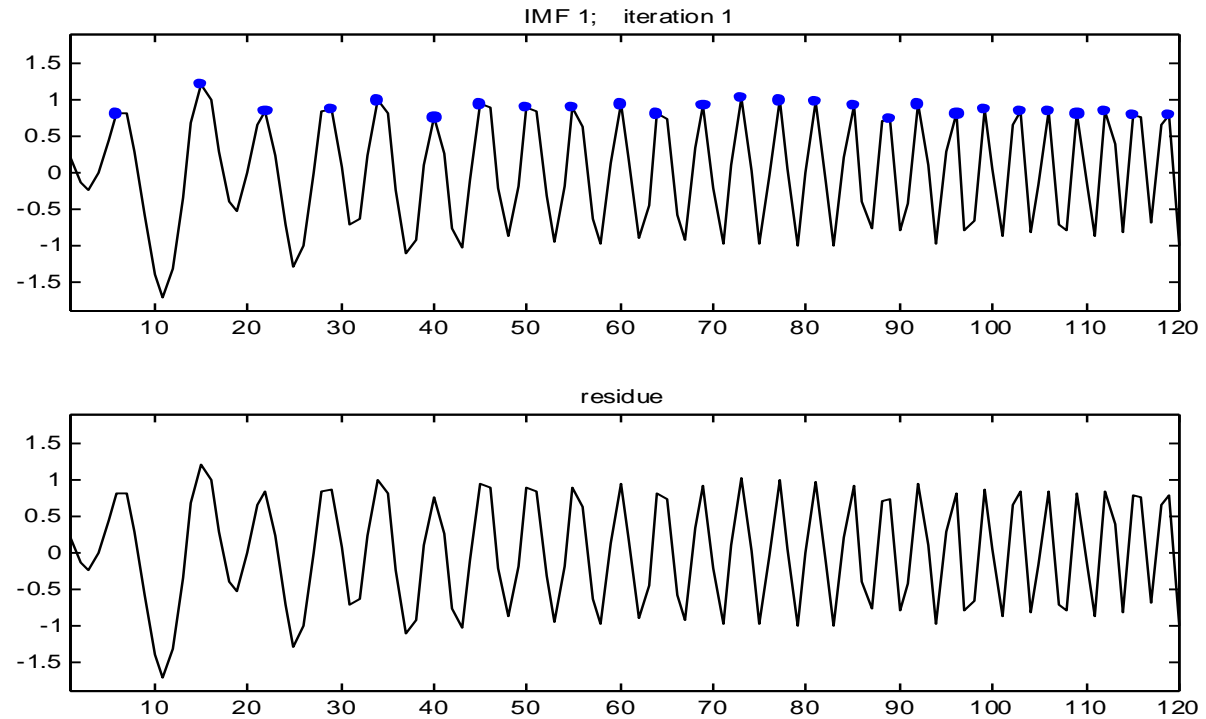


# 3. Hilbert Huang Transform-4

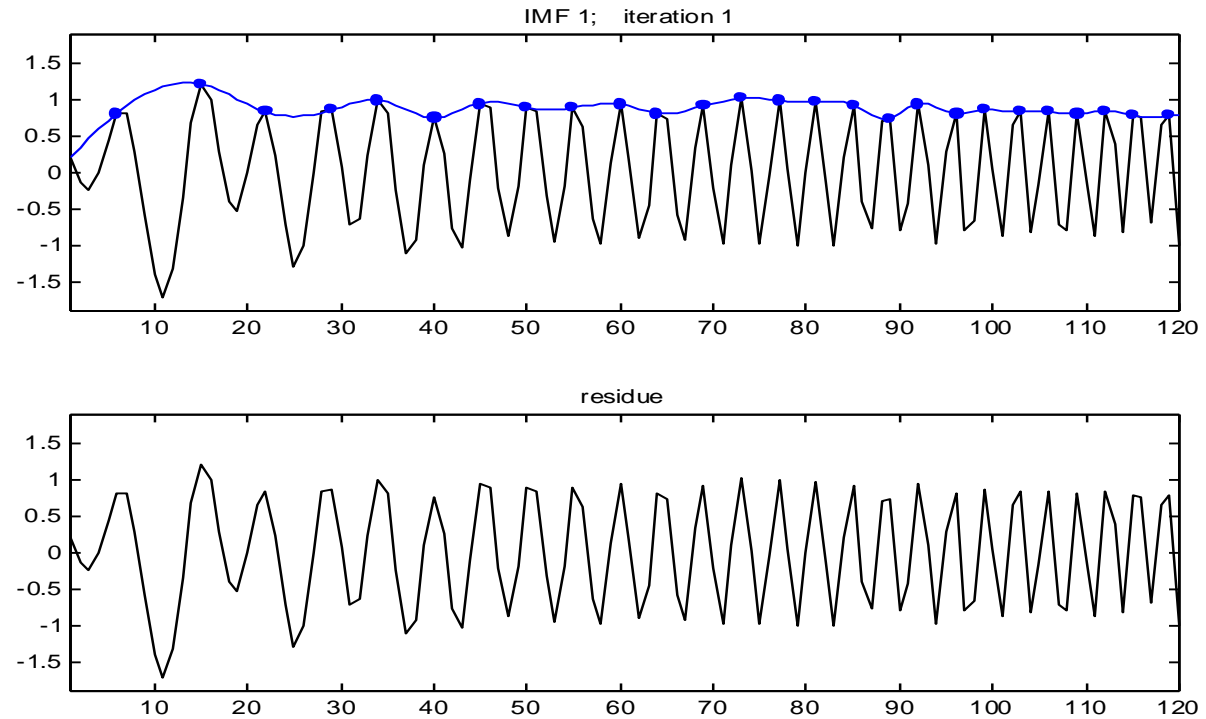




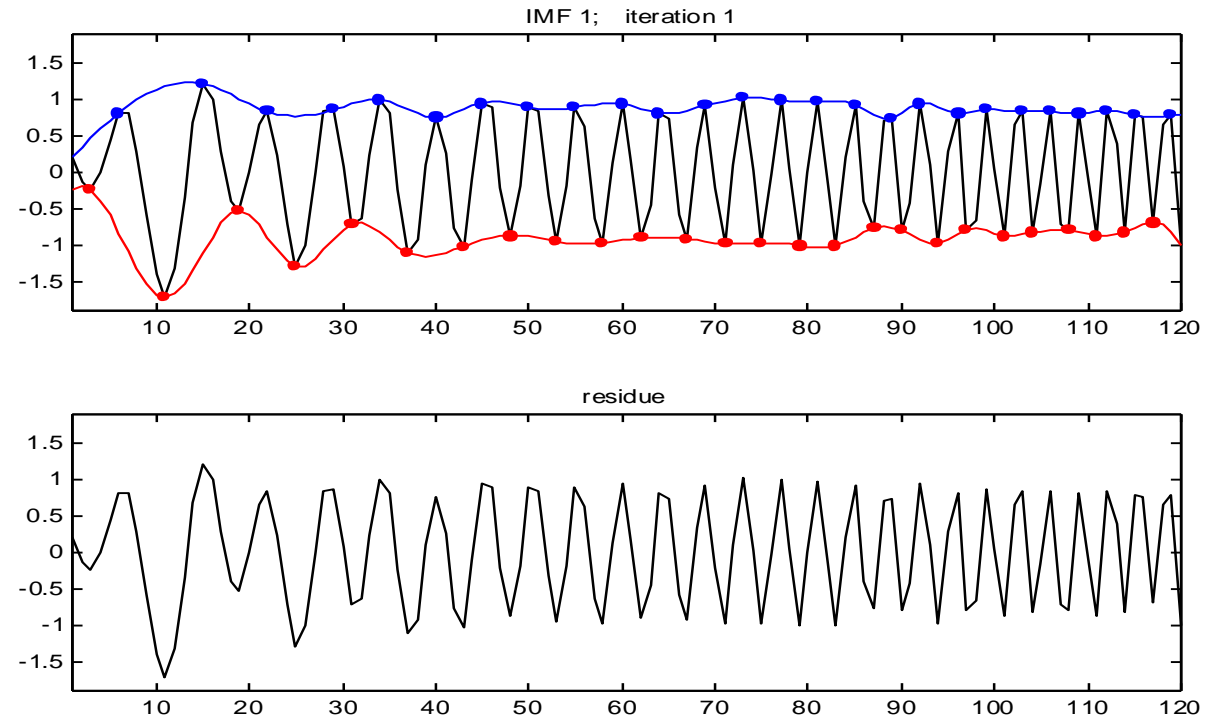
# 3. Hilbert Huang Transform-4



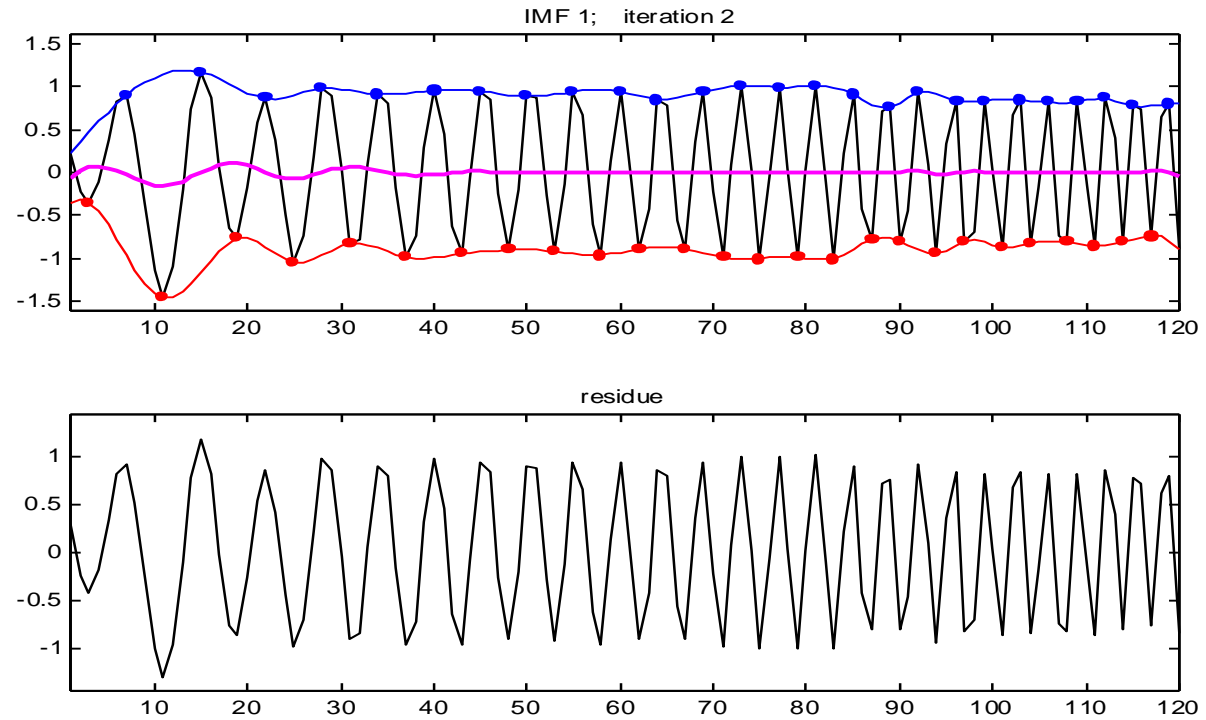
# 3. Hilbert Huang Transform-4



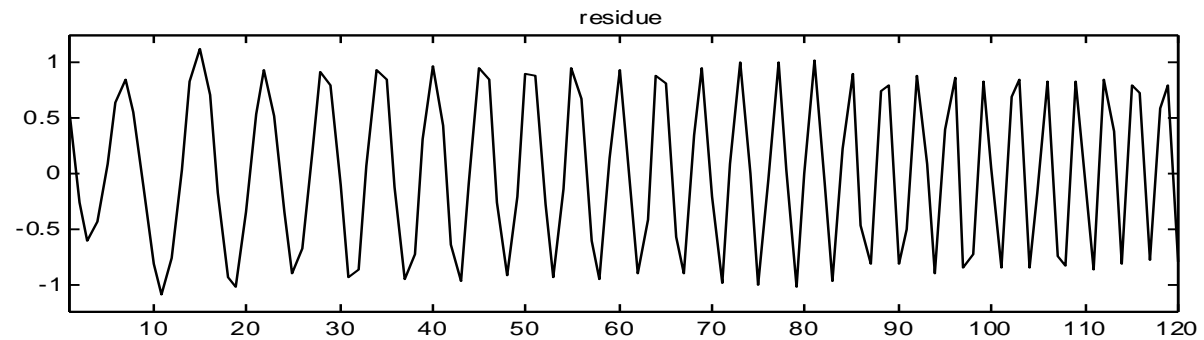
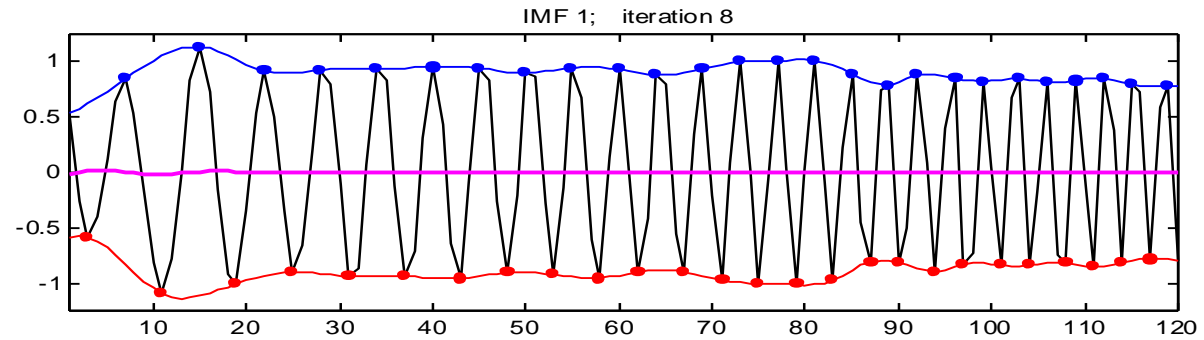
# 3. Hilbert Huang Transform-4



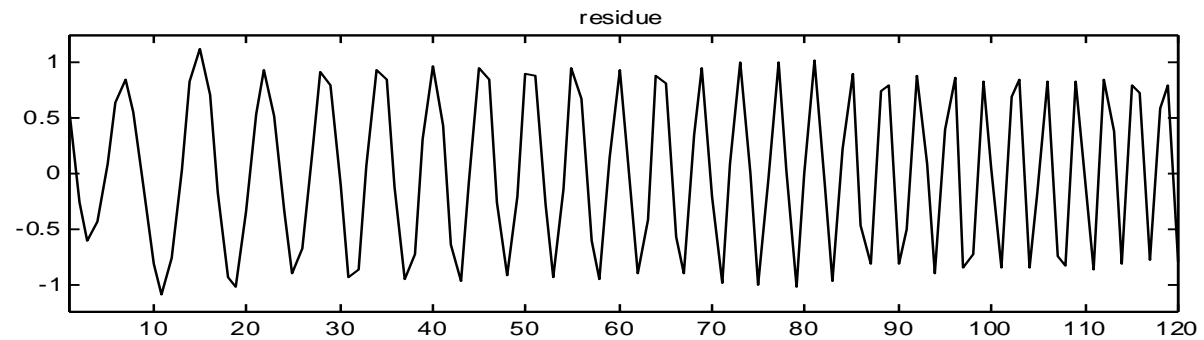
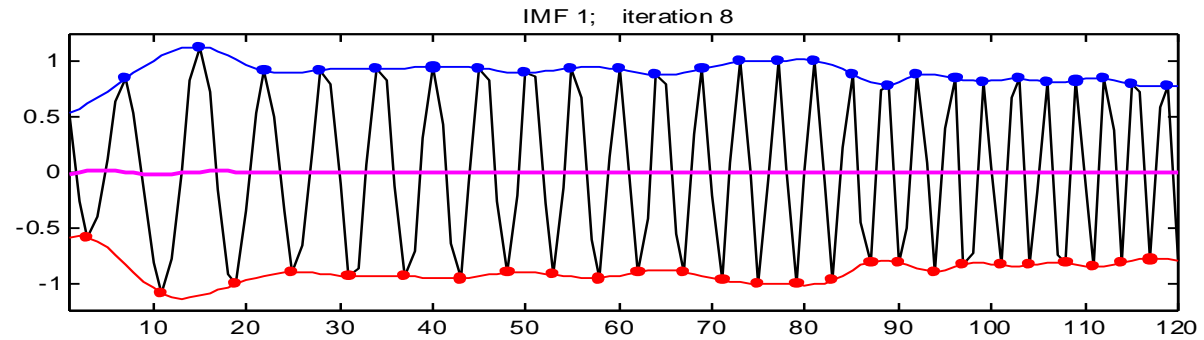
# 3. Hilbert Huang Transform-4



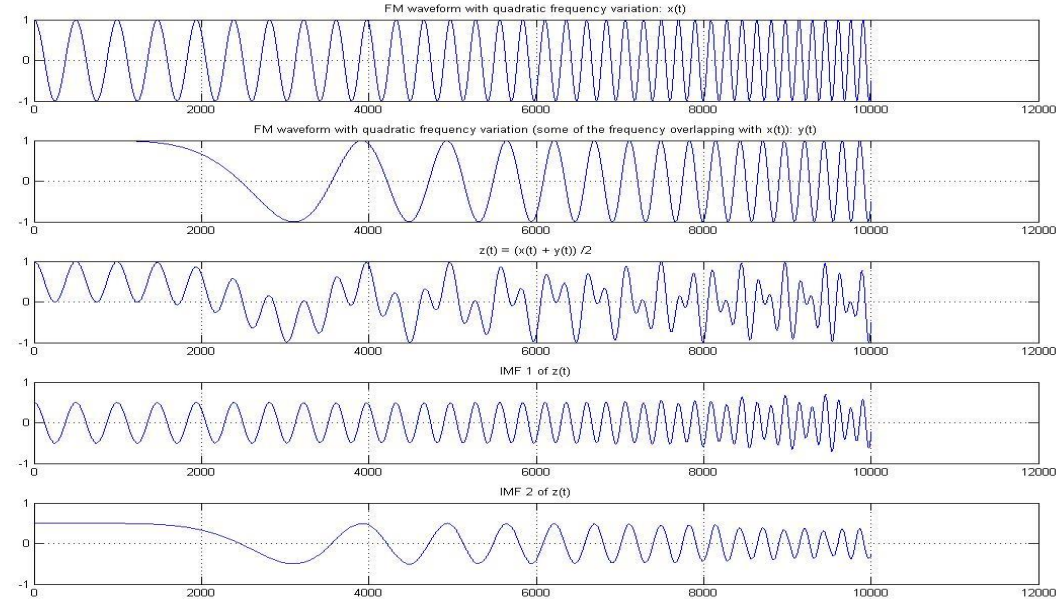
# 3. Hilbert Huang Transform-4



# 3. Hilbert Huang Transform-4



# 3. Hilbert Huang Transform-4



IMF 1 and 2 show an accurate decomposition of the original signal into relevant components.

# 3. Hilbert Huang Transform-5

## The Hilbert Spectrum

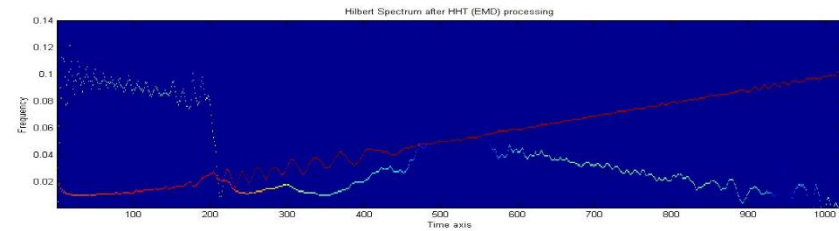
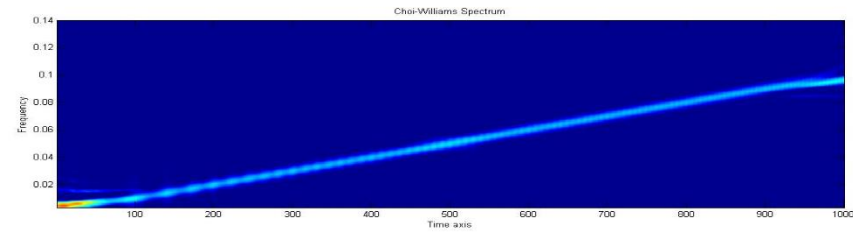
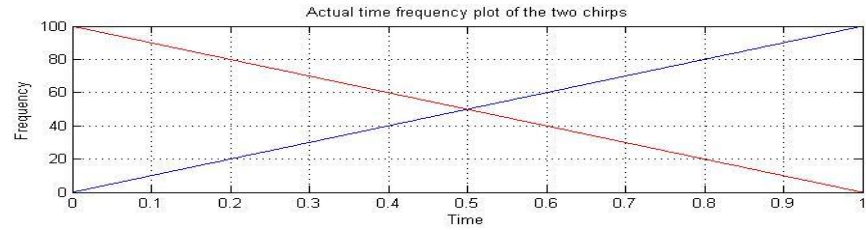
- The second part of HHT is the Hilbert spectrum.
- The IMF's are suitable for applying the Hilbert transform [1]
- We construct the analytical signal from the IMF's,  
$$Y(t) = X(t) + j H(X(t))$$
where  $H$  denotes the Hilbert transform
- The phase is computed as  
$$\phi = \arctan(H(X(t))/X(t))$$
- The instantaneous frequency is defined as  $d\phi/dt$
- The Hilbert Spectrum refers to the plot of the 'instantaneous frequency' of the signal versus time.
- Using the Hilbert transform to analyze the frequency profile of the signal means that we do not encounter the time-frequency uncertainty associated with Fourier-based transforms.



# 3. Hilbert Huang Transform-5

	<b>Fourier</b>	<b>STFT</b>	<b>Wavelet</b>	<b>HHT</b>
<b>Basis</b>	<b>Non-adaptive</b>	<b>Non-adaptive</b>	<b>Non-adaptive</b>	<b>Adaptive</b>
<b>Frequency</b>	<b>Convolution: Global</b>	<b>Convolution: Regional</b>	<b>Convolution: Regional</b>	<b>Differentiation: Local</b>
<b>Presentation</b>	<b>Energy- frequency</b>	<b>Energy-time- frequency</b>	<b>Energy-time- frequency</b>	<b>Energy-time- frequency</b>
<b>Nonlinear</b>	<b>No</b>	<b>No</b>	<b>No</b>	<b>Yes</b>
<b>Non stationary</b>	<b>No</b>	<b>No</b>	<b>Yes</b>	<b>Yes</b>
<b>Feature Extraction</b>	<b>No</b>	<b>Discrete: No Continuous: Yes</b>	<b>Discrete: No Continuous: Yes</b>	<b>Yes</b>

# 3. Hilbert Huang Transform-5



HHT vs. Choi-Williams Distribution

# 3. Hilbert Huang Transform

## Implementation Issues

- The Hilbert Huang Transform algorithm is computationally expensive.
- It is not possible to determine the asymptotic complexity of the algorithm because the nature of the algorithm is very sensitive to the input signal, we cannot clearly define a worst case and a best case.
- On an average, the algorithm scales linearly.
- Most important step, the weakest link is the interpolation. We found from experiments that cubic interpolation yields the best results.
- For simpler interpolation techniques, the algorithm take longer to converge to IMF's, more complicated interpolation techniques are redundant and are computationally very expensive.

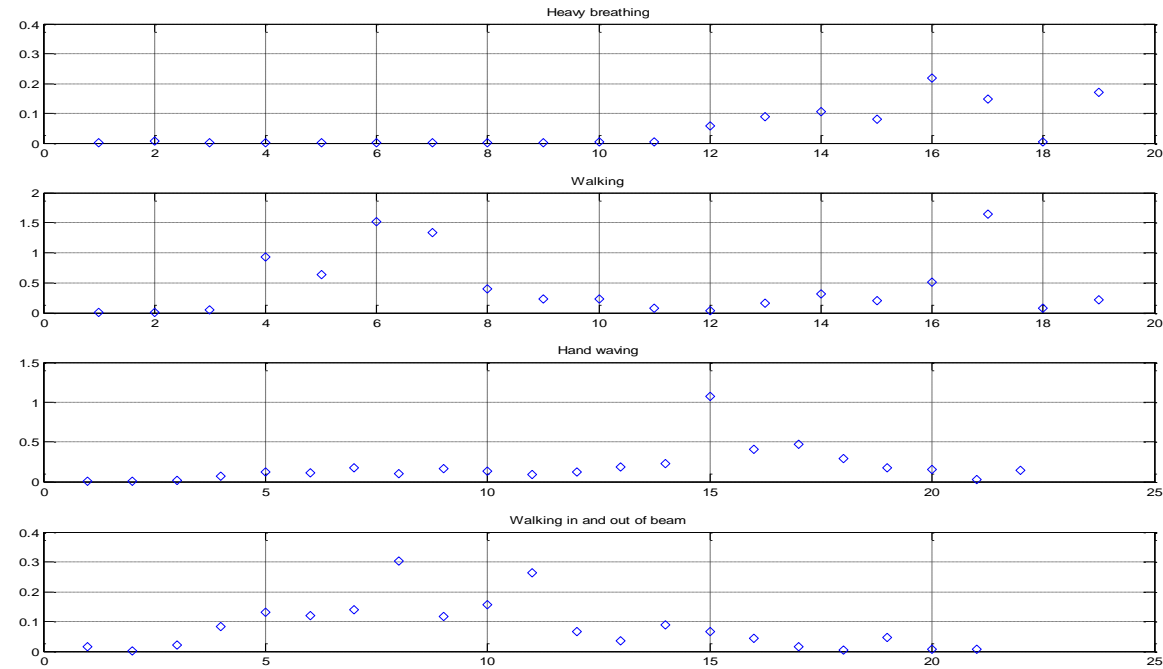
# 4. Results

- We conducted some experiments with human gait, we present the results and their analysis.
- We show the effectiveness of HHT in analyzing Doppler return for single tone transmit waveforms.
- Then we simulate the actual waveform we intend to use by adding noise to the echo signal.
- We transmit a 2 GHz single tone waveform and pass the return signal through an RF mixer which removes the 2 GHz component and retains only the Doppler shifts, which are of low frequency.
- Our system cannot differentiate between negative and positive Doppler.

# 4. Results

- We acquire the signal, subtract the dc component and run it through the EMD algorithm to extract the IMF's.
- To extract the Doppler features, we look at the IMF with the highest energy.
- Since the signal does not contain any components other than those from the Doppler, the highest energy IMF's contain the signatures.
- We considered simple human movement such as, heavy breathing, walking and waving of hand.
- The signal was acquired for a duration of 20s and in that duration, the person being observed was in only one of these states.

# 4. Results



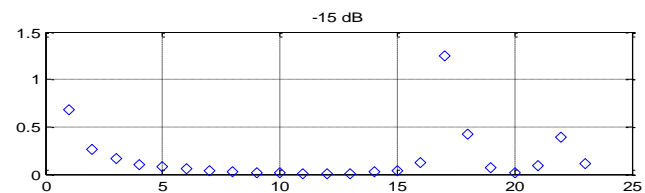
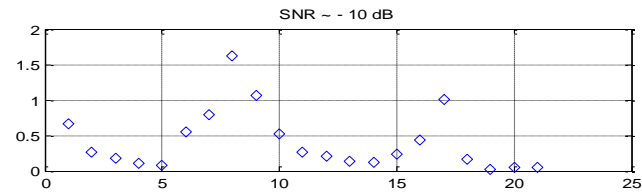
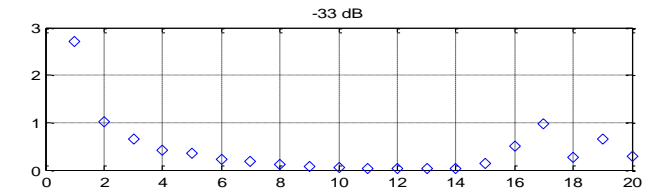
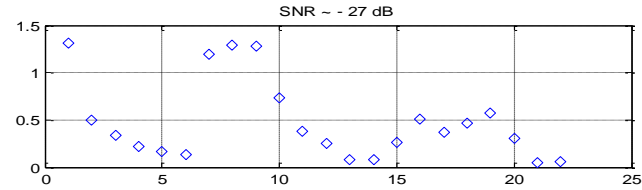
Distribution of energy across the IMF's for each of the experiments.

# 4. Results

Experiment	Highest Energy IMFs	Freq. (approx)	Comments
1. Background	-	-	All the IMF's are of comparable energy. The energy was much lower than with the presence of a human in front of the radar. Energy = 0.0203 (As a sum of squares of data points)
2. Human standing, with light breathing	Inconclusive	-	The energy of the returned signal at the analysis stage is: Energy = 1.5305 Suggests presence of Doppler
3. Breathing heavily	1. IMF 16 & 17 2. IMF 17	1. 0.3 Hz 2. 0.4 Hz	Energy = 3.0657 Higher energy than last two cases, indicating a stronger Doppler signature. And movement of larger cross-section.
4. Walking in the direction of the radar. to and fro, 20s	IMF 6, 7 and 17	10 to 15 Hz	Energy = 7.4875  Much higher than other experiments, because the moving cross section is high.
5. Stationary human, waving hands in the direction of the radar. Hand-waving: about 12 times in 20s	IMF 15	1.5 Hz	Energy = 4.2832
6. Walking in and out of the beam width of the radar.	IMF 8	7 Hz	Energy = 1.9842

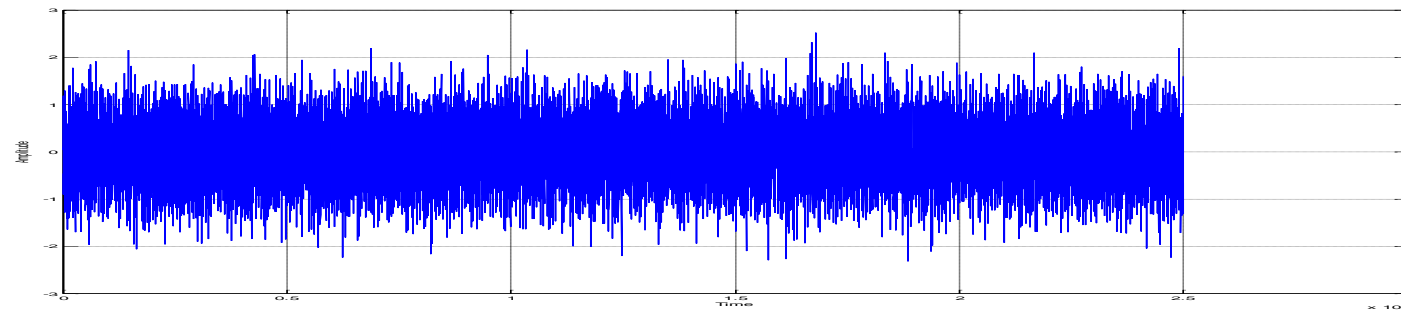
# 4. Results

## Simulated noisy signal, covert waveform



Walking

Heavy breathing

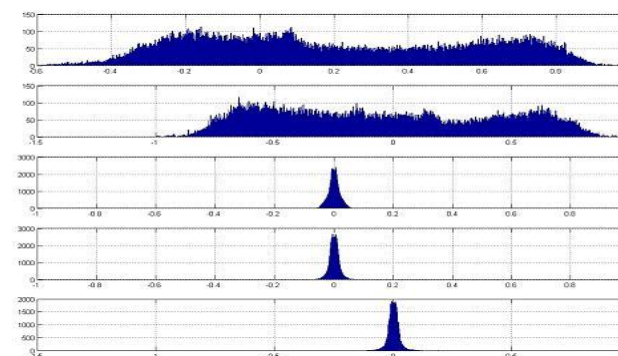
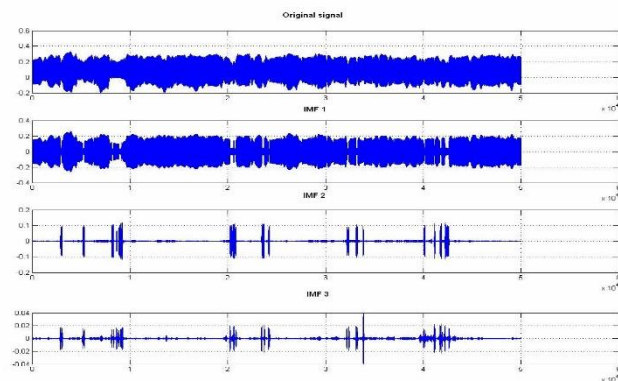




# 4. Results

## Development of Algorithms for Automatic Detection

- HHT can extract the Doppler signatures in time domain.
- We intend to use statistical classification tools to automatically detect the presence or absence of these signatures.
- The figures below show the decomposition of a hand-waving return single tone waveform, the figure on the right shows that the the corresponding distributions



# 5. Future work

- Algorithm for automatic detection of human presence.
- Through-wall experiments
- Modeling of human movement.
- Fine-tuning the system, hardware and software for through-wall detection of stationary human by detecting the Doppler changes caused by breathing.

# 6. Summary

- Described the design of a system for through wall detection using HHT.
- Introduction to the HHT algorithm.
- Applicability of HHT for detection and characterization of human Doppler.
- Long term objectives of the project:
  - Automatic detection
  - Characterization of human activity
  - Detection of stationary human

# Kaynakça

- Fast Fourier Transform and MATLAB Implementation by Wanjun Huang for Dr. Duncan L. MacFarlane
- Borrowed from <http://perso.ens-yon.fr/patrick.flandrin/emd.html> , Gabriel Rilling and Patrick Flandrin

# Usage Notes

- These slides were gathered from the presentations published on the internet. I would like to thank who prepared slides and documents.
- Also, these slides are made publicly available on the web for anyone to use
- If you choose to use them, I ask that you alert me of any mistakes which were made and allow me the option of incorporating such changes (with an acknowledgment) in my set of slides.

Sincerely,

Dr. Cahit Karakuş

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