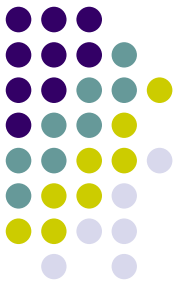


# Detection of R Waves in ECG Signals

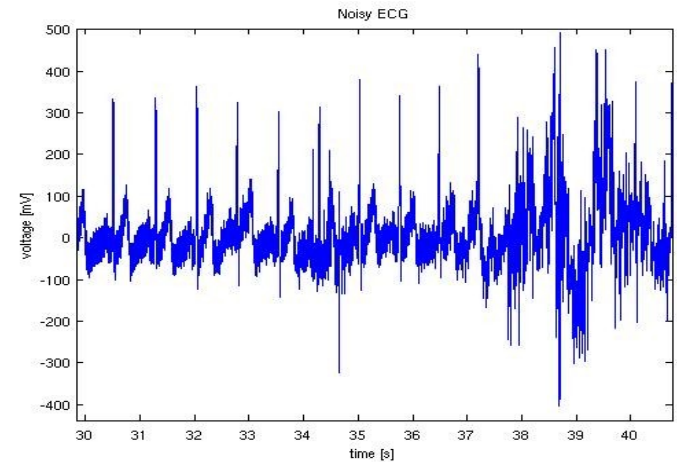
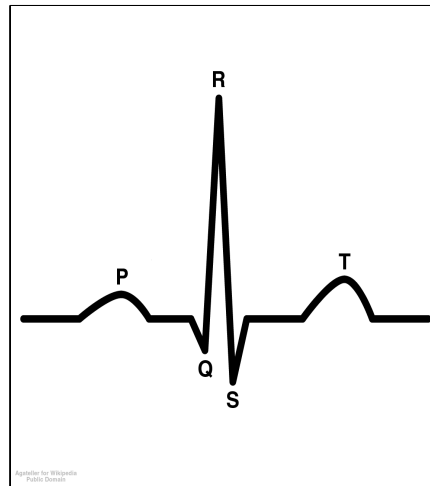
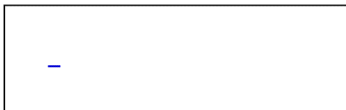
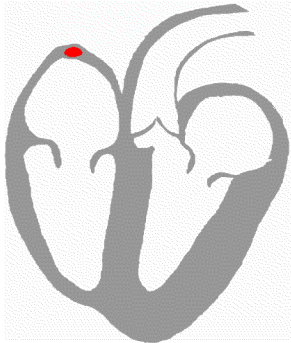
J.M. Lina, M. Hennessy, M. Morfin, E. Prosk,  
O. Rousseau, B. Borek

Industry : Stellate, Montreal

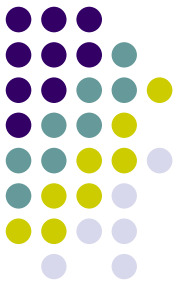
# Introduction: The Heart, ECG, and R Waves



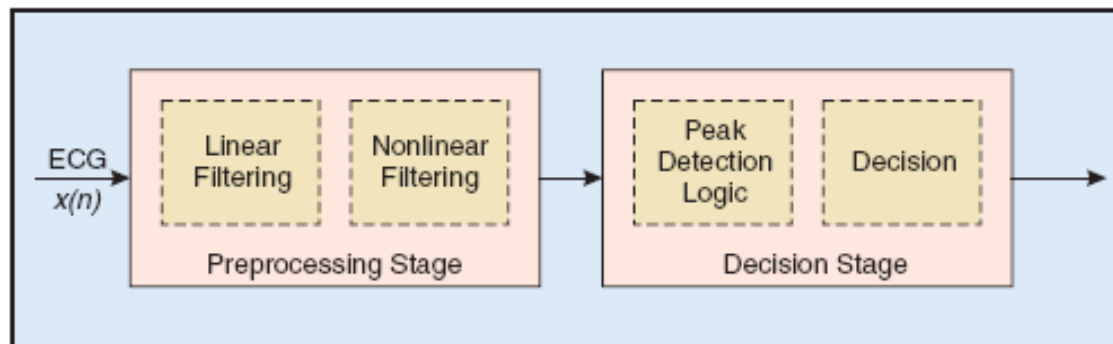
- the heart produces a wave of electrical activity to contract and pump blood throughout the body
- the electrical field produced by this wave is detected by the ECG
- the problem is to detect R wave times in order to calculate instantaneous heart rate.
- this is non-trivial because the signals are heterogeneous and noisy



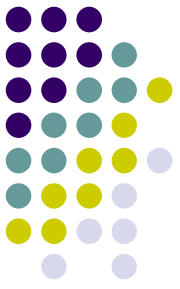
# Overview of Methodologies



- historically the QRS complex detection was done manually but in the last 30 years many software algorithms have been designed to automate the process.
- the preprocessing stage can be approached in many ways:
  - linear filtering
  - neural network-based transformations
  - Hilbert transformation
  - Wavelet coefficient estimation
  - Model-based approaches
  - etc.
- the decision stage usually consists of some form of threshold detection.



# The Hilbert and Wavelet Transforms



- Given a signal  $f$ , we can define its Hilbert Transform as follows:

$$\hat{f}(t) = \frac{1}{\pi} \int f(s) \frac{1}{(t-s)} ds$$

- The Hilbert transform is used to define the Analytic Representation of a signal

$$A(t) = f(s) + i \hat{f}(s) = R(t) e^{i\phi(t)}$$

- The amplitude of  $A(t)$  gives the signal's amplitude and slope information, but the measure is still susceptible to noise

- A wavelet transform convolves a signal with a wavelet,  $\phi_{a,b} = \frac{1}{\sqrt{a}} \phi\left(\frac{(t-b)}{a}\right)$

such that

$$w(a, b) = f * \phi = \int f(s) \overline{\phi_{a,b}}(s) ds$$

- $w(a,b)$  gives information about frequency variations in time, but this projection depends on the wavelet used.

# Analytic Wavelets

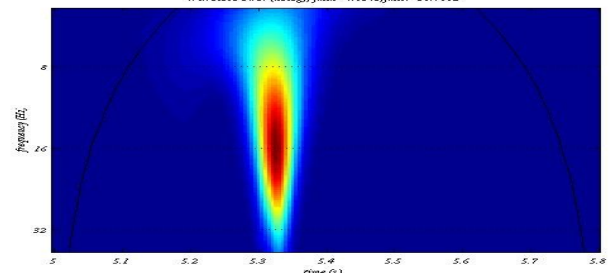
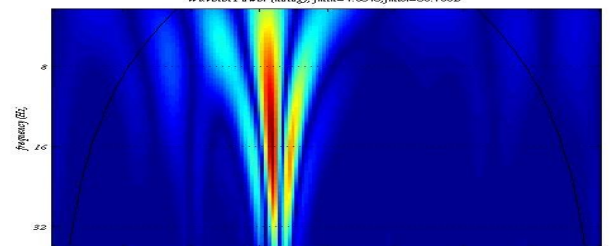
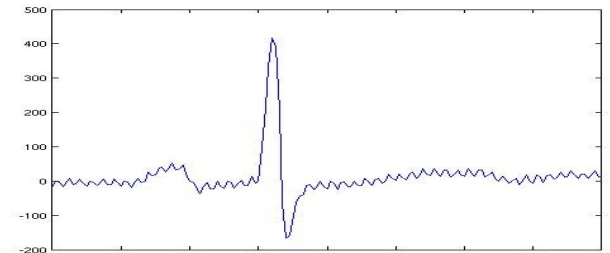


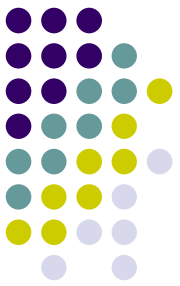
- We can combine the advantages of the Hilbert and wavelet transforms by using a complex analytic wavelet

$$\phi(\omega) = \omega^n e^{-\omega}, \omega \geq 0$$

$$\phi(\omega) = 0, \omega < 0$$

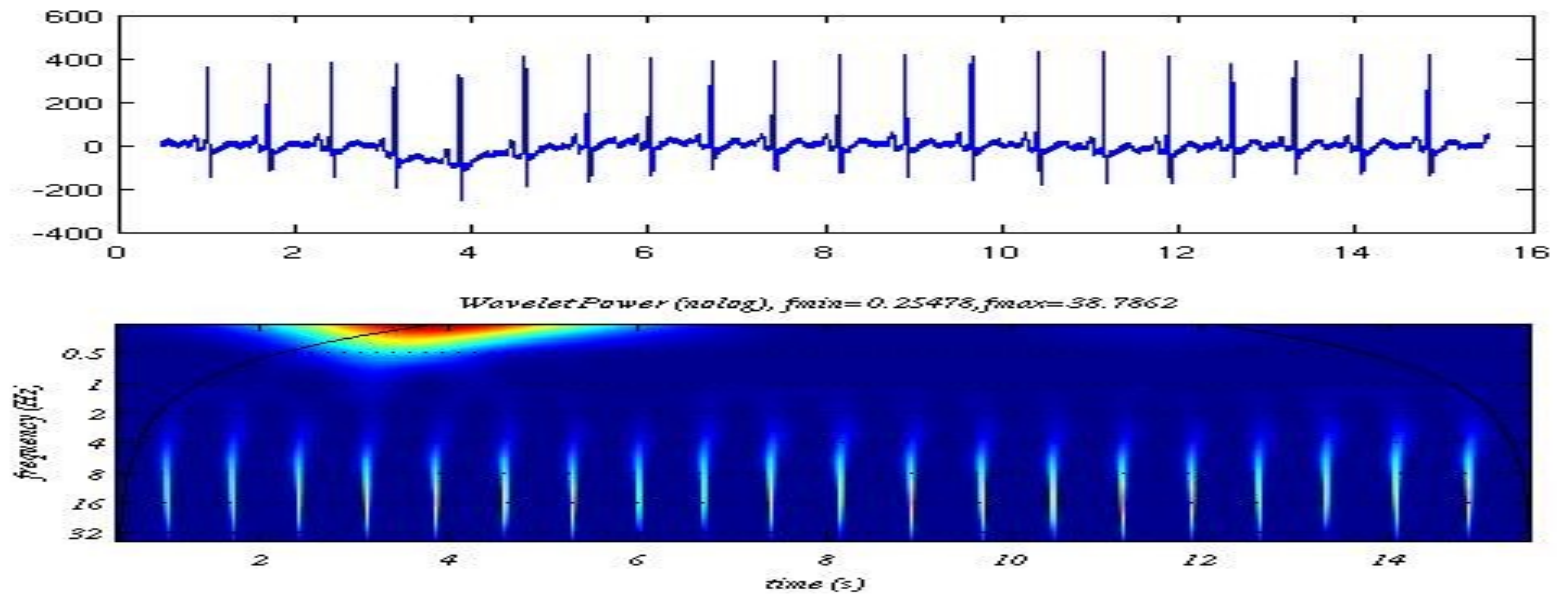
- This has the advantage of combining the time frequency localization of a wavelet transform with information about the local slope of the signal.

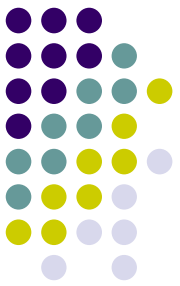




## METHODOLOGY:

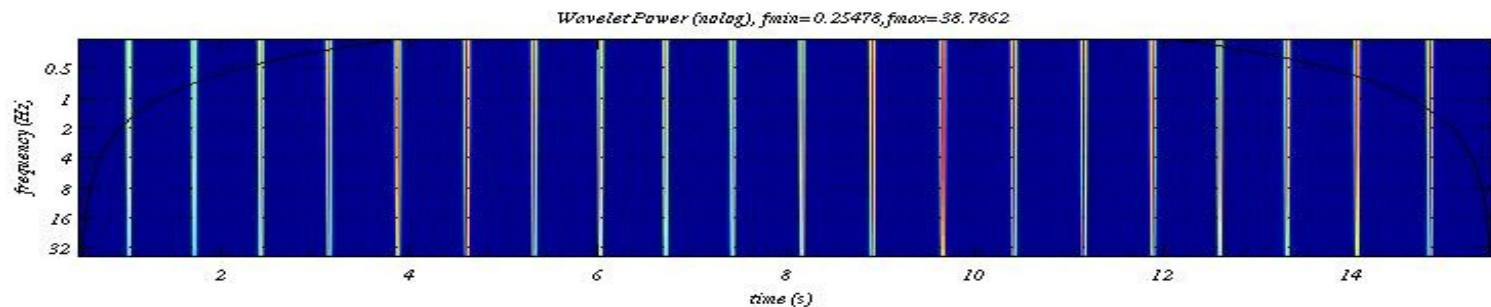
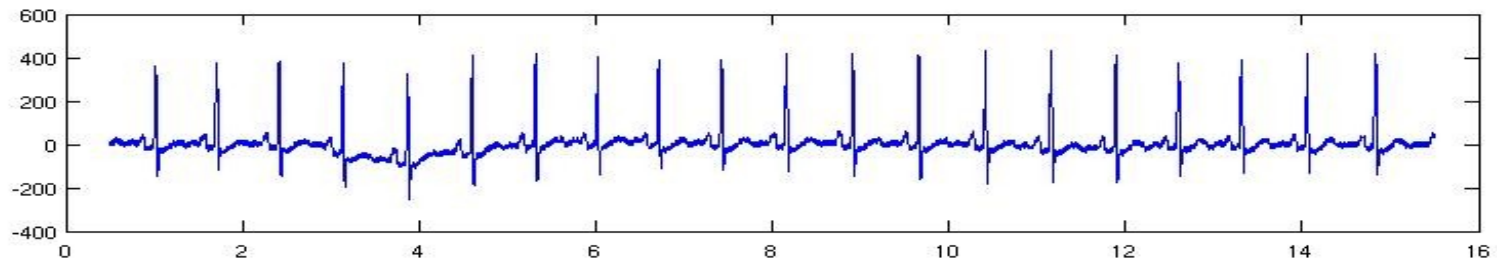
1. Compute analytical wavelet transform





## METHODOLOGY:

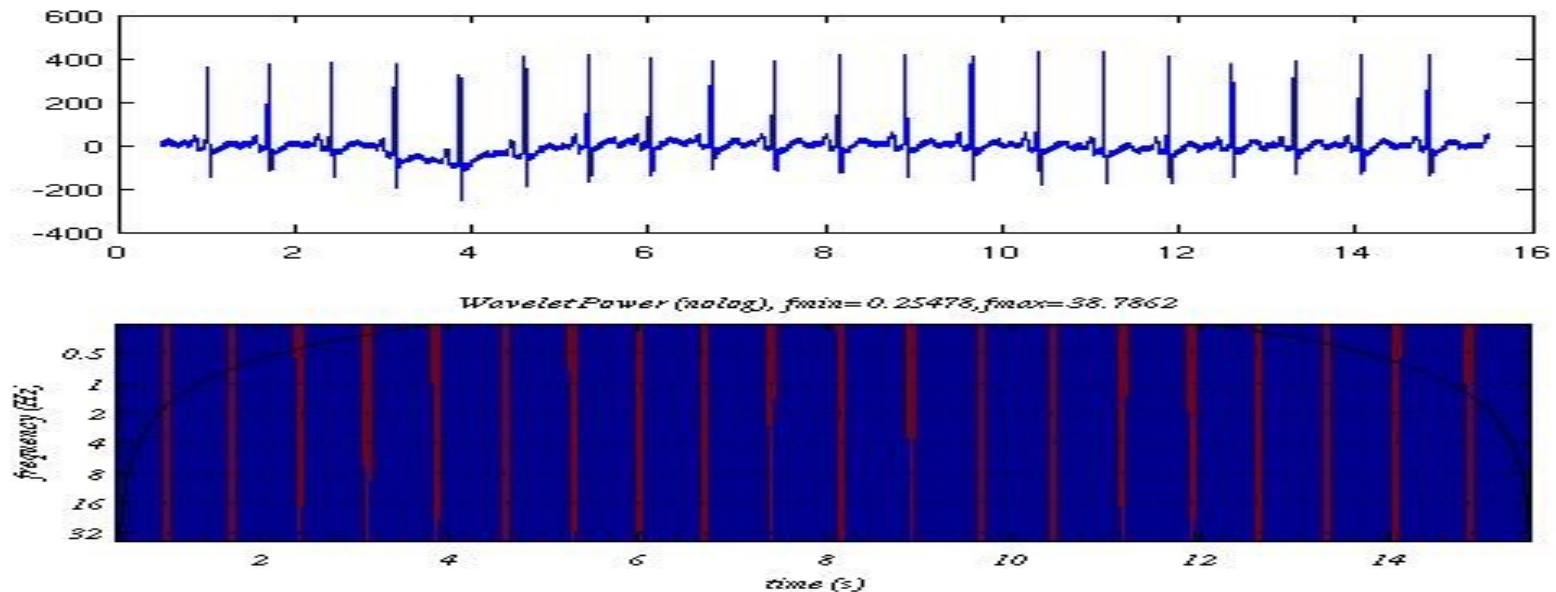
1. Compute analytical wavelet transform
2. Select band of interest (8Hz-16Hz)

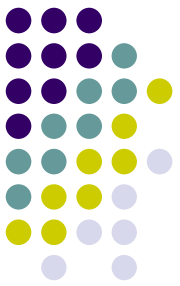




## METHODOLOGY:

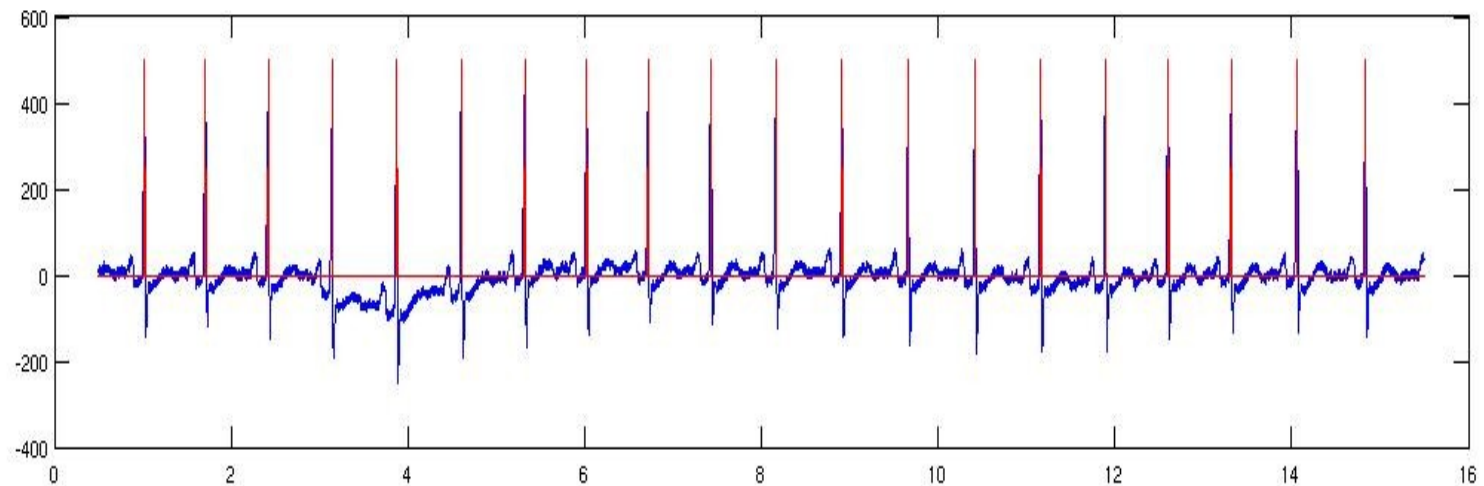
1. Compute analytical wavelet transform
2. Select band of interest (8Hz-16Hz)
3. Threshold and look for persistent lines

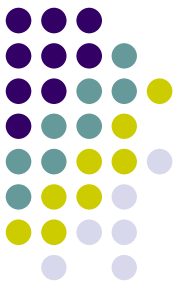




## METHODOLOGY:

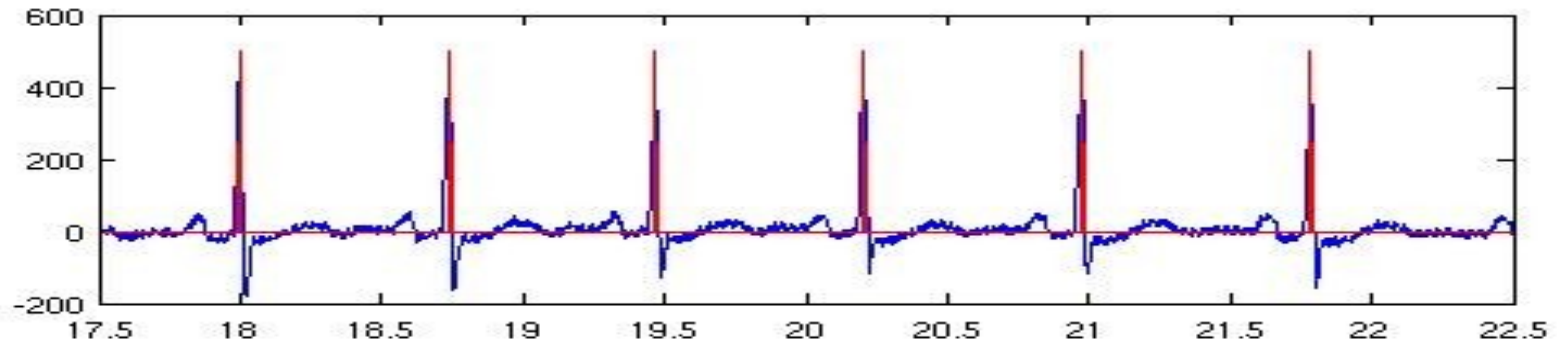
1. Compute analytical wavelet transform
2. Select band of interest (8Hz-16Hz)
3. Threshold and look for persistent lines
4. Locate the local maximums of the wavelet transform



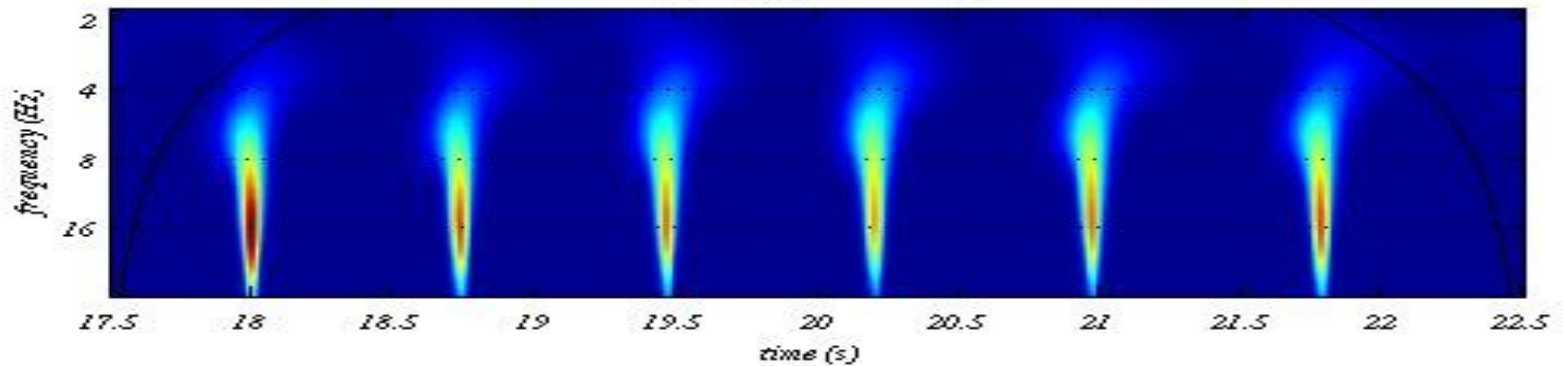


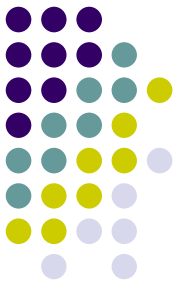
## RESULTS:

Clean signal:



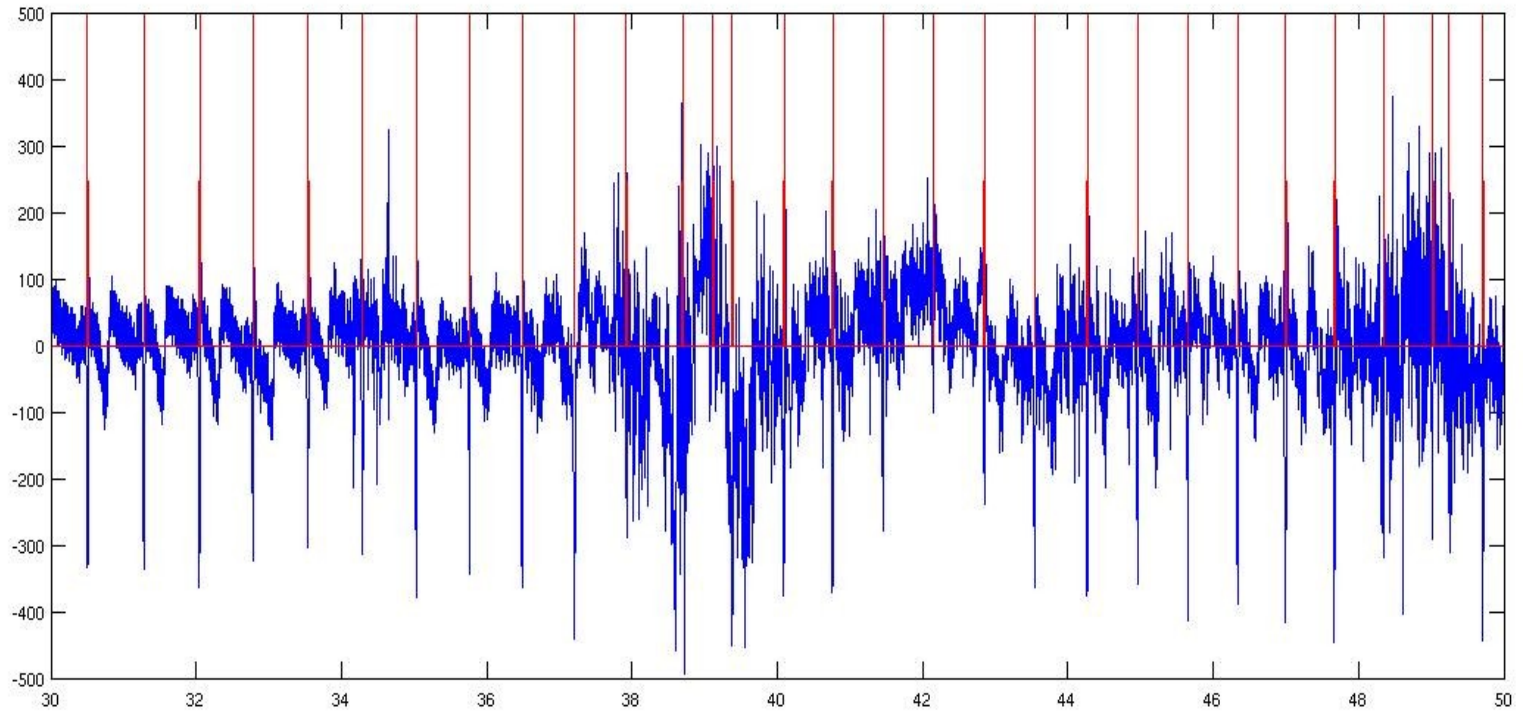
*WaveletPower (nolog), fmin=1.7739, fmax=31.5774*





# RESULTS

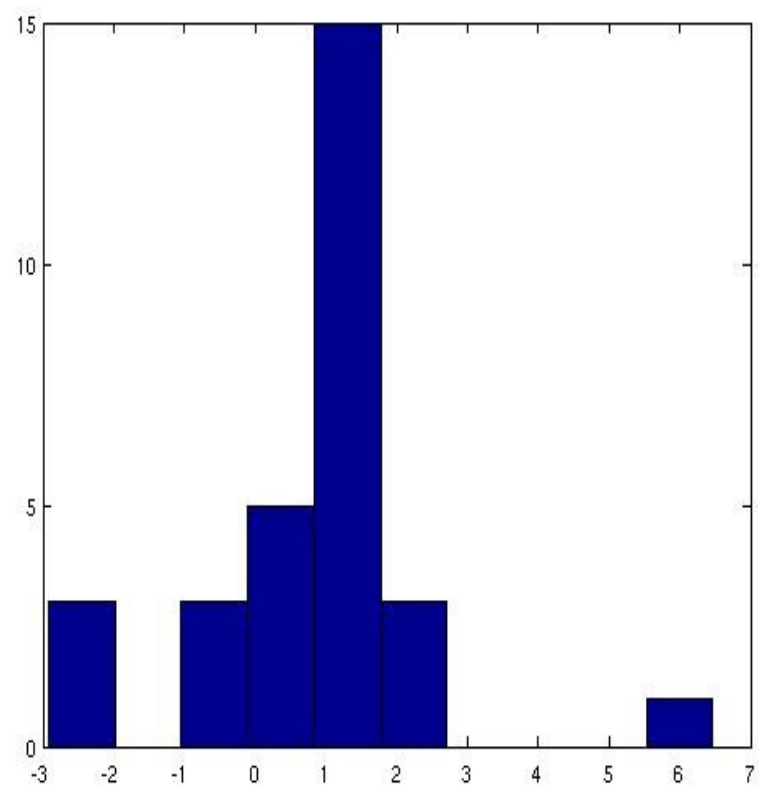
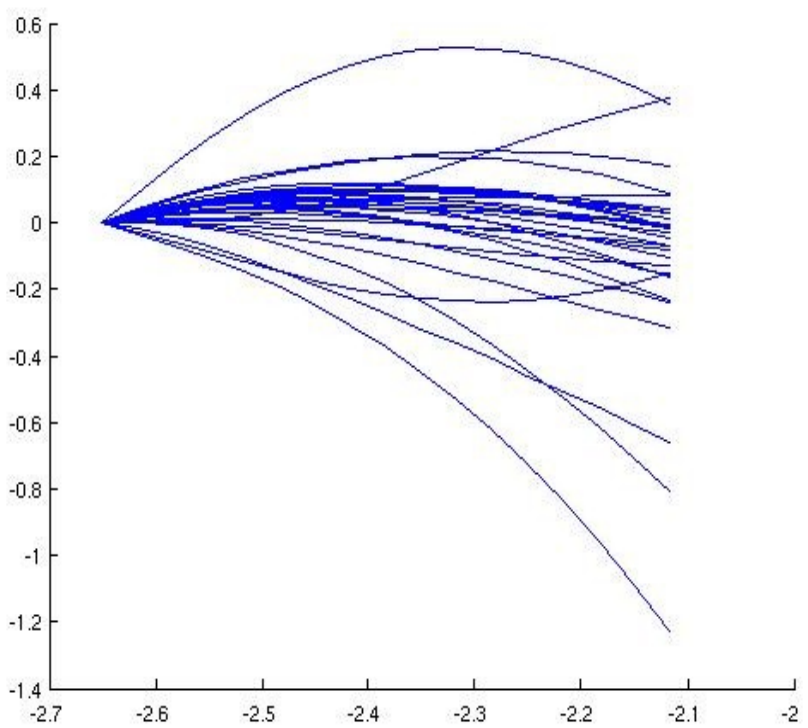
Noisy signal:

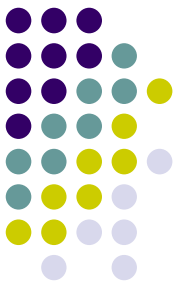




# RESULTS

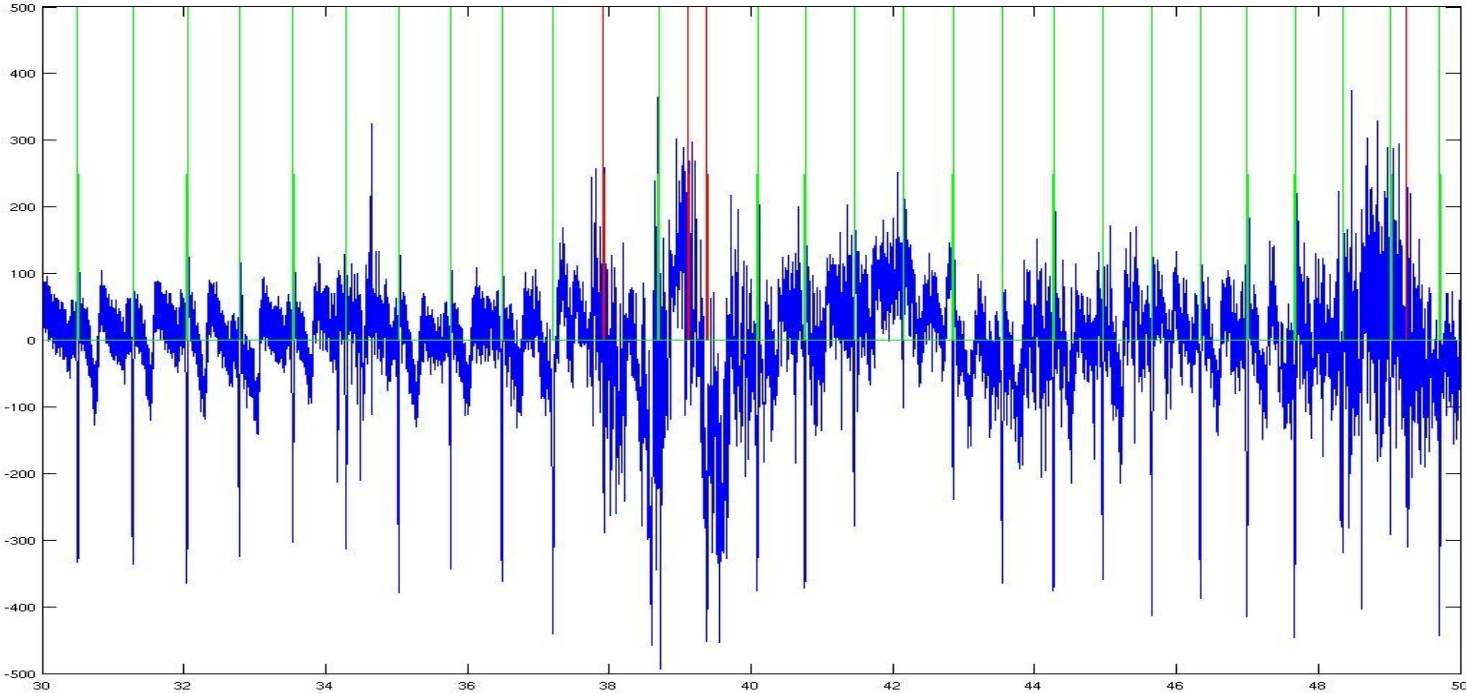
Noisy signal:





# RESULTS

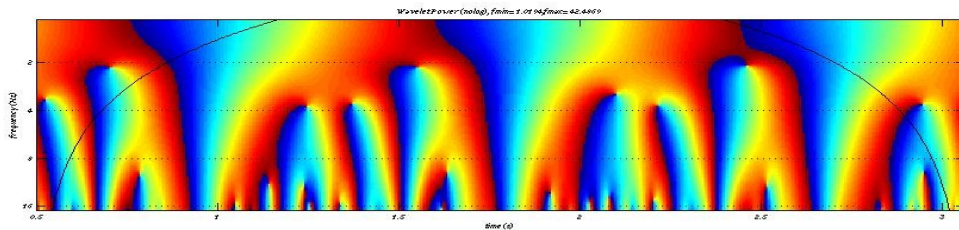
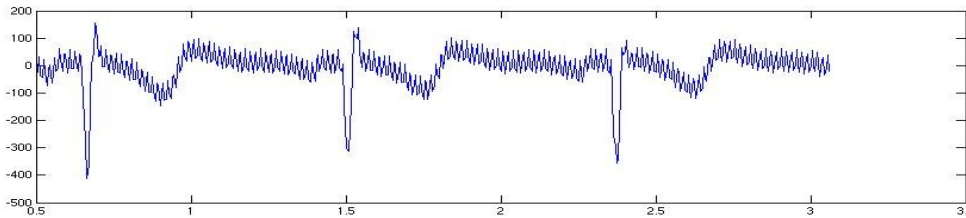
Noisy signal:



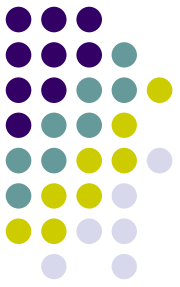
# Validation of QRS complex localization



- Rate of coefficient change with respect to frequency signature
- Phase spectrum signature of the signal
- Robustness to detection parameter variation

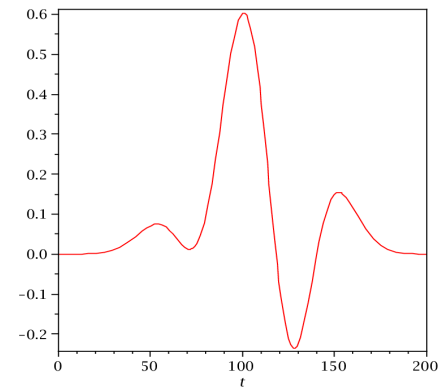


# A constructed Wavelet



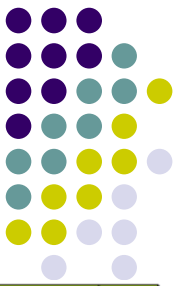
- We can define a projection into a subspace of functions that have desired characteristics.
- There are models to describe the heart beat
- Using the frequency function obtained by one of this simulations we define a wavelet
- Then we see how well this function match the data collected

$$\phi_{a,b} =$$

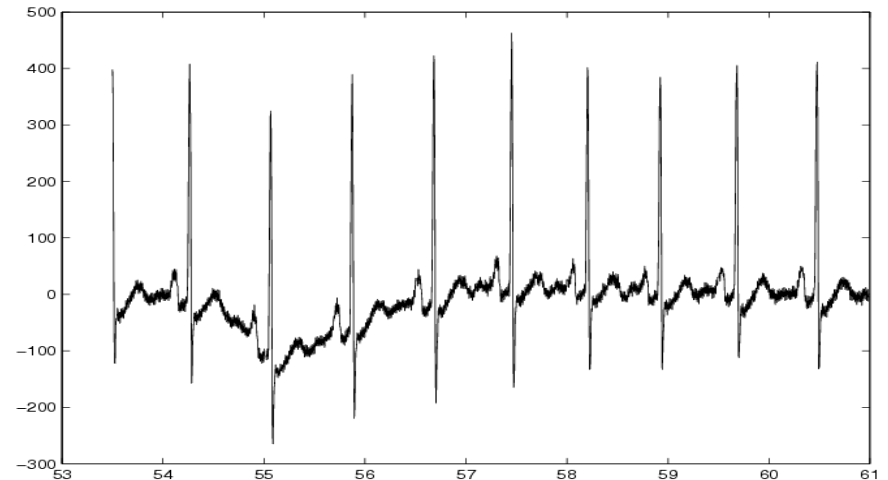
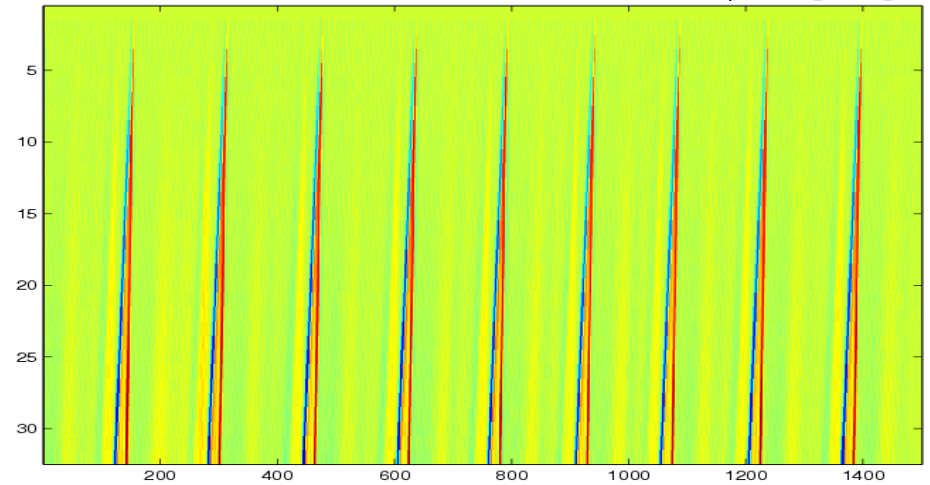


$$\langle f, \phi \rangle_{a,b} = f * \phi = \int f(s) \overline{\phi_{a,b}(s)} ds$$

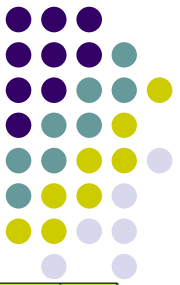
# Clean signals



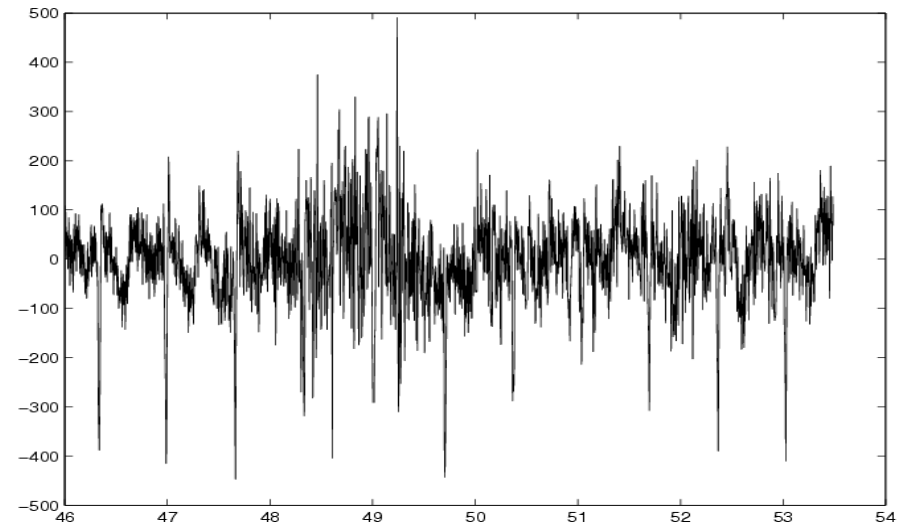
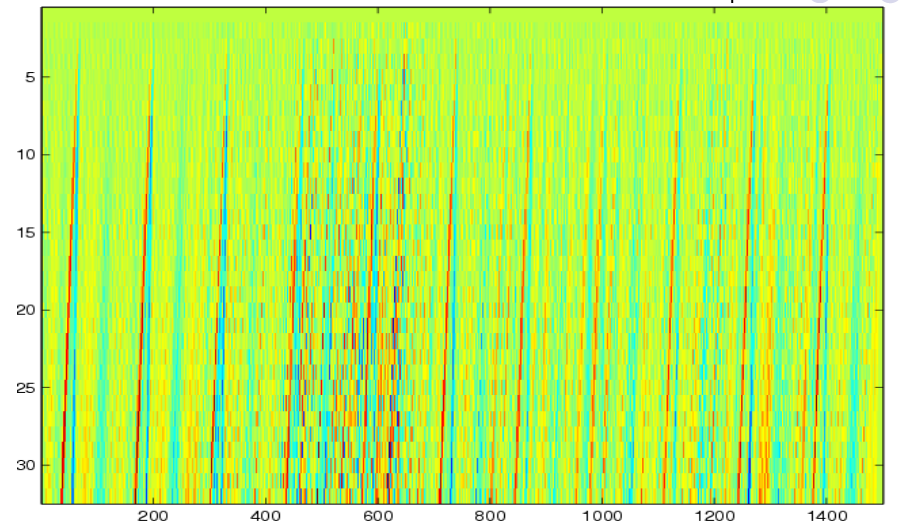
- Here we compare the wavelet coefficients vs. time
- The red lines indicate a high correlation of the signal collected
- Low amplitude noise will vary the color of the back



# Some Noise

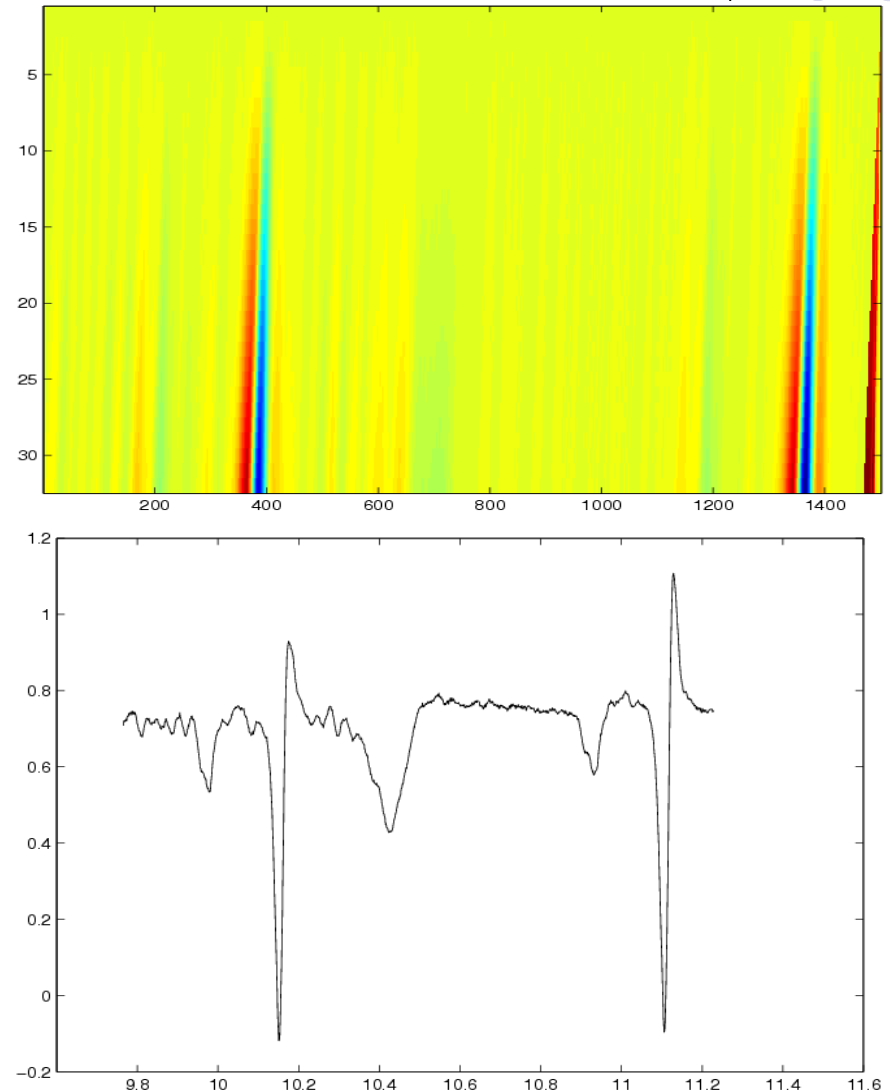


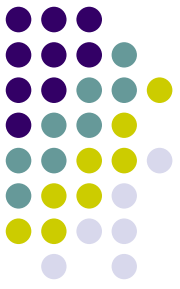
- This method is good cleaning noise that has a similar frequency and amplitude.



# A weakness

- The signal has a jump, this method is not effective very effective.
- Whoever, there are better methods, to eliminate this kind of noise.



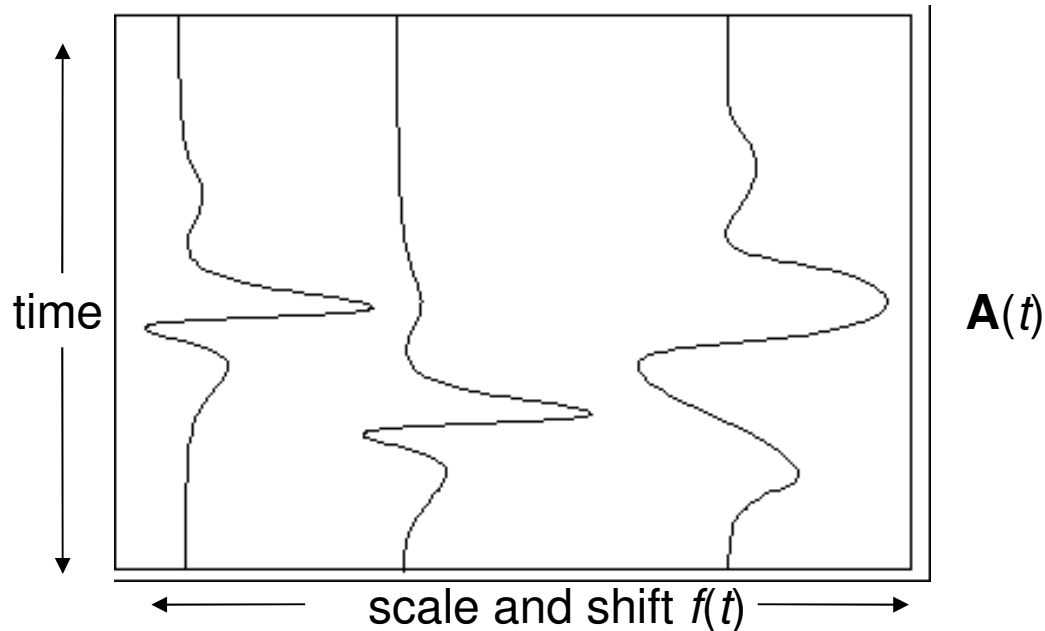


# A 'Dictionary' Method

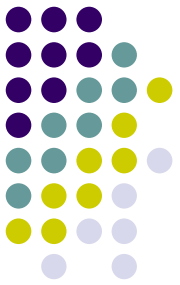
- Suppose we can write the signal as

$$s(t) = \mathbf{A}(t) \mathbf{c} + \text{residuals}$$

where  $\mathbf{A}(t)$  is a “dictionary” of functions and  $\mathbf{c}$  is a vector of coefficients



- Functions  $f(t)$  are analytical models of QRS Complex



# Optimization Problem

- What coefficient vector,  $\mathbf{c}$ , gives the least residual?
- Convert to least squares optimization problem

$$\min_{\mathbf{c}} \|s(t) - \mathbf{A}(t)\mathbf{c}\|^2$$

- This problem alone does not have a unique solution
- Add the condition

$$\|\mathbf{c}\|_1 = |c_1| + |c_2| + \dots \leq \gamma$$

with  $\gamma$  as small as possible for reasonable solutions

- This allows minimal number of coefficients

# Results

