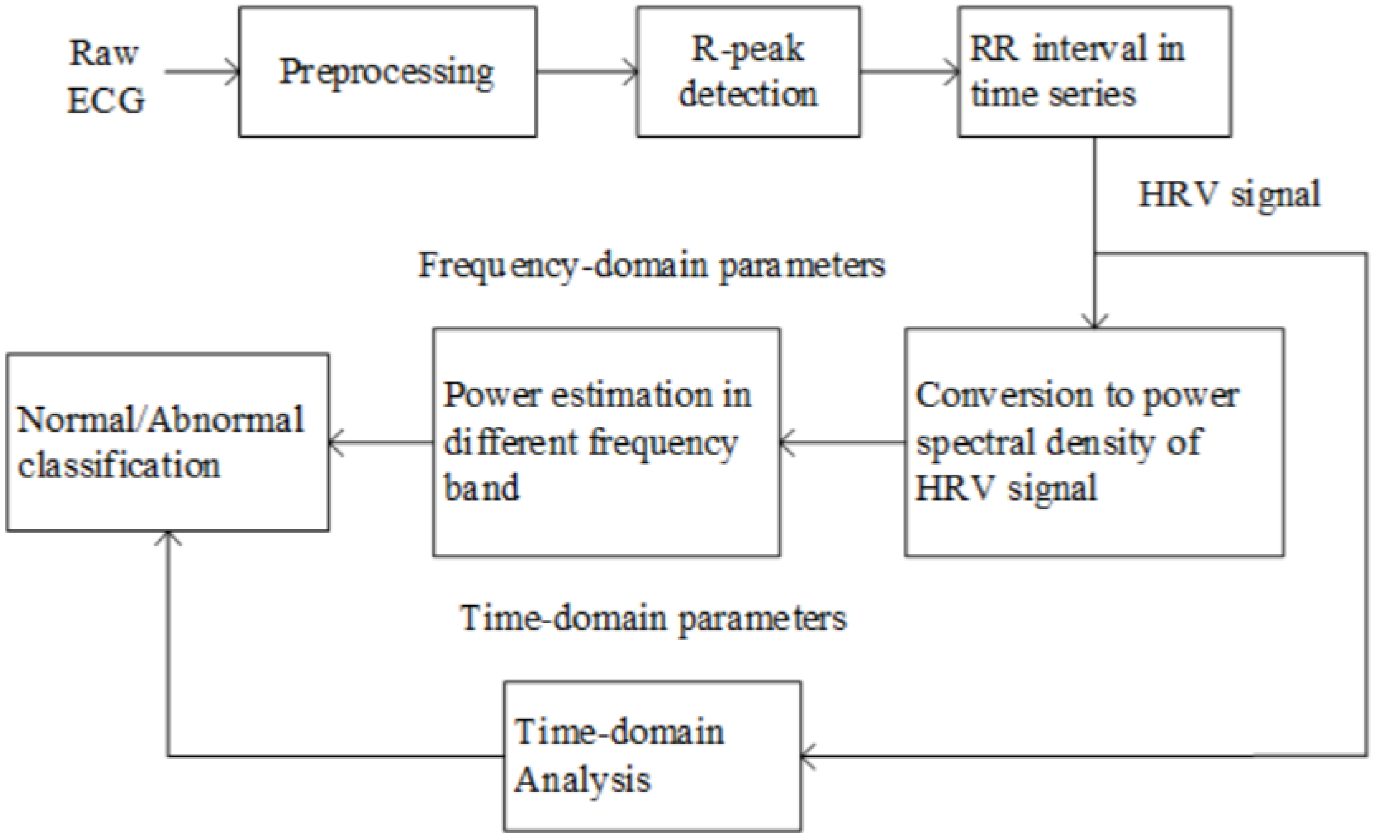
HRV Extraction and Analysis Methods

Group 31

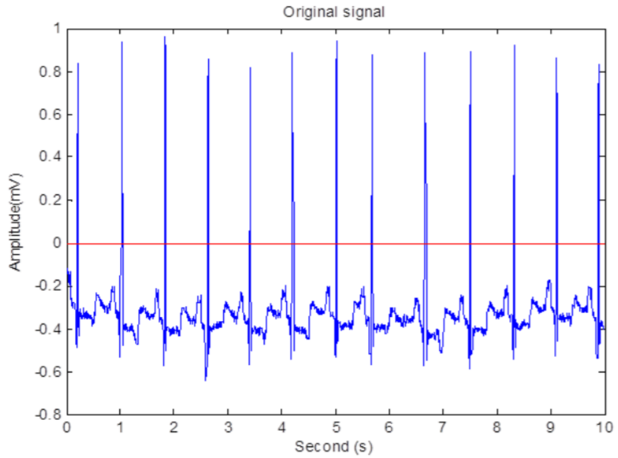
Overview of the process to extract HRV from ECG



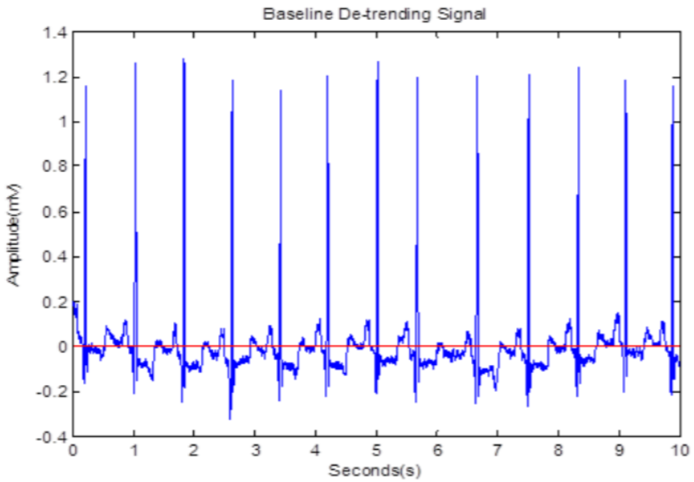
Tun et al. : http://medcraveonline.com/MOJPB/MOJPB-07-00223.pdf

Procedure for ECG signal detrending - DWT

- Wander baseline drift is a major source of noise ~ 1Hz
- Normal filters not effective in removing noise because ECG is non-stationary
- Wavelet based approach is more efficient



Before detrending



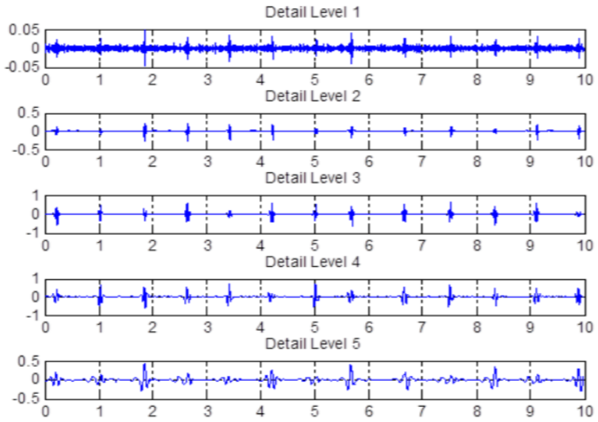
After detrending

Tun et al. : http://medcraveonline.com/MOJPB/MOJPB-07-00223.pdf

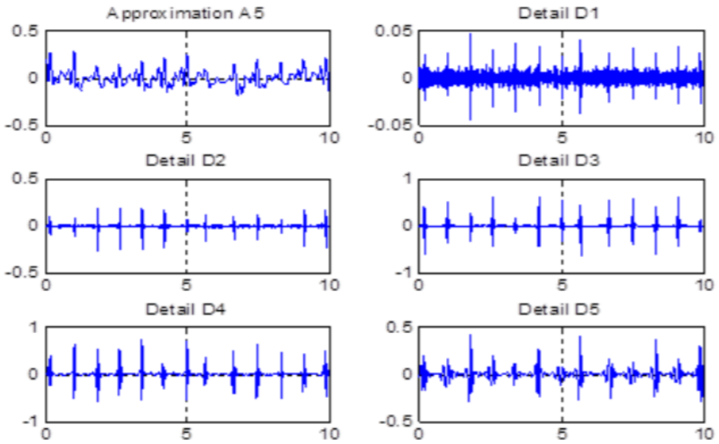
Procedure for ECG signal denoising - DWT

3 important steps:

1. Decomposition of detail levels
2. Thresholding detail coefficients
3. Reconstruction of approximation and detail levels



Decomposition



Reconstruction

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Procedure for ECG signal denoising - DWT

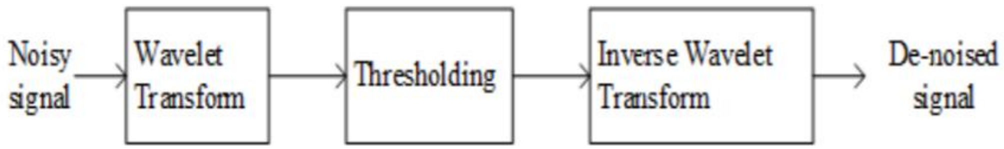


Figure 2 Block Diagram for ECG Signal De-noising.

The DWT of a signal x(t) is given by:

$$X_{DWT_K} = \int_{-\infty}^{\infty} x(t)\, 2^{m/2} \psi\left(2^m t - k\right) dt \qquad (1)$$

where $\psi_{m,k}$ is the wavelet function.

The approximation and details coefficients are respectively defined by the following Equations 4.2 and 4.3.

$$cA_{j+1}(k) = \sum_{n=-\infty}^{\infty} h(n-2k)\, cA_j(k) \qquad (2)$$

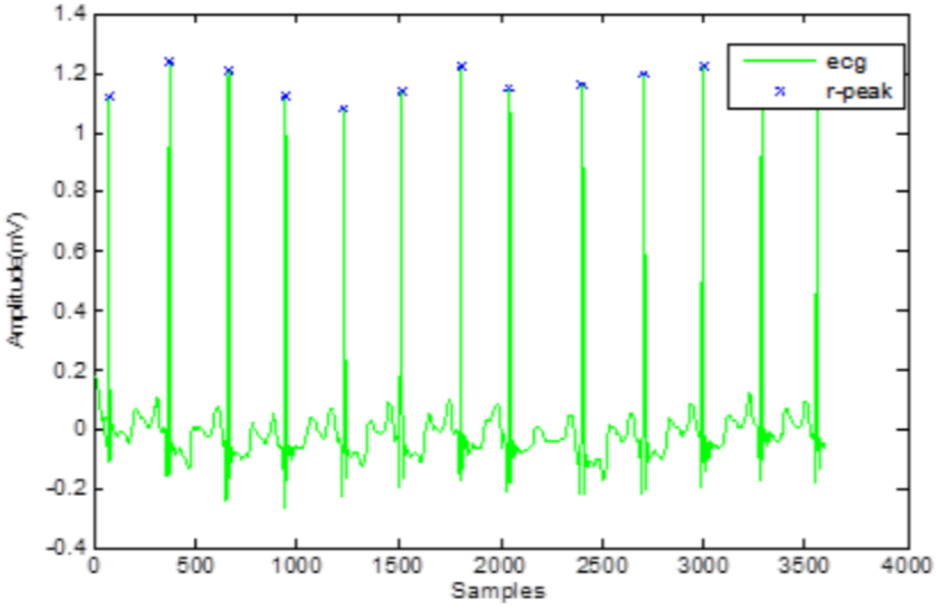
$$cD_{j+1}(k) = \sum_{n=-\infty}^{\infty} g(n-2k)\, cA_j(k) \qquad (3)$$

$$X_{IDWT}(t) = \int_{-\infty}^{\infty} \sum_{m=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} X_k^m 2^{m/2} \Psi(t-k)\, dt \qquad (4)$$

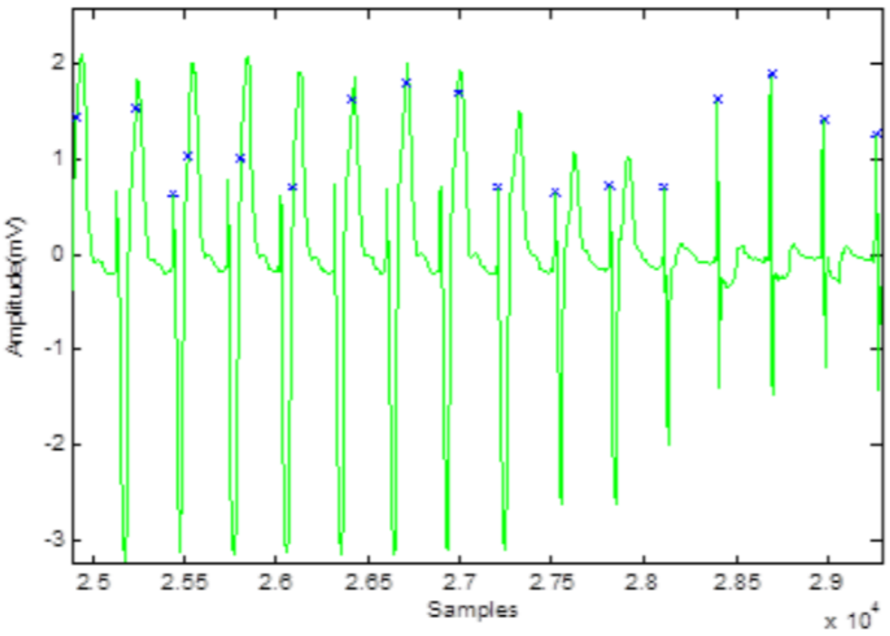
Tun et al. : http://medcraveonline.com/MOJPB/MOJPB-07-00223.pdf

Procedure for R peak detection – Wavelet filtering by DWT again

- Advantage: Efficient and accurate in computing R peak positions without changing position or shape of original signal



99% accuracy (most patients)



73% accuracy

Tun et al. : http://medcraveonline.com/MOJPB/MOJPB-07-00223.pdf

Procedure for R peak detection

3 important steps:

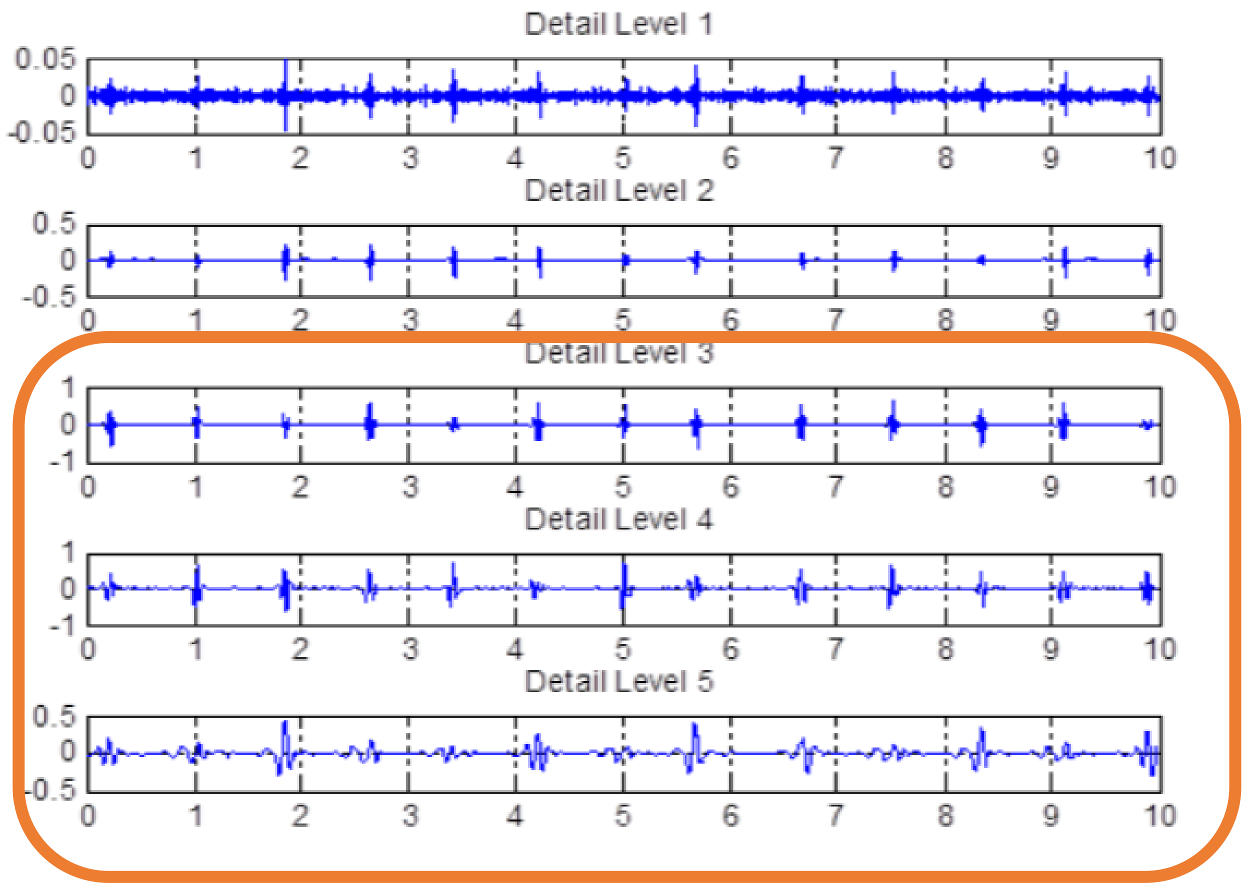
1. Decomposition into 8 detail levels using Db6 wavelet – closely matches the shape of ECG QRS complex

2. Thresholding of wavelet coefficients

3. Reconstruction – addition of 3rd, 4th, and 5th detail levels (because most energy is concentrated in these coefficients)

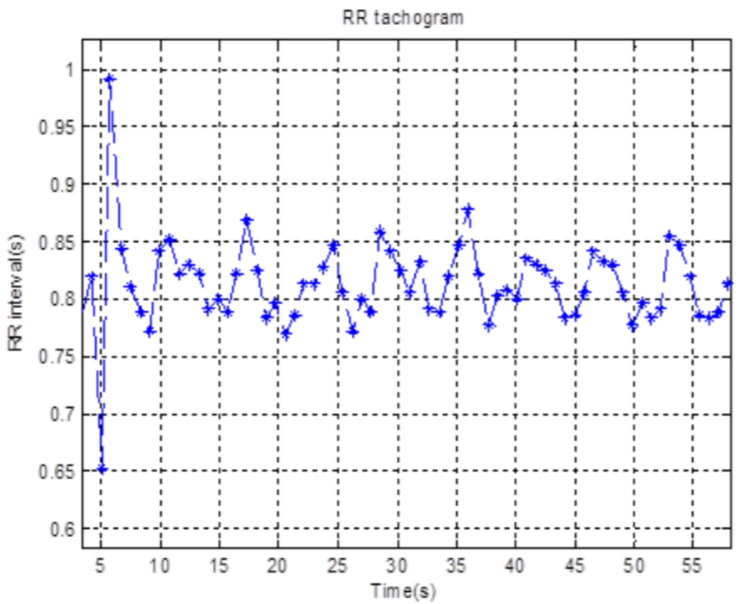
Tun et al. : http://medcraveonline.com/MOJPB/MOJPB-07-00223.pdf

Addition of detail levels for reconstruction to detect R peaks



Tun et al. : http://medcraveonline.com/MOJPB/MOJPB-07-00223.pdf

HRV Analysis – Linear Methods



RR Tachogram – plot of RR interval against time interval for each heartbeat

Time Domain Analysis

- Mean NN interval
- Mean heart rate
- Difference between longest and shortest NN interval
- RMSSD

Frequency Domain Analysis

- PSD estimate obtained using Lomb-Scargleperiodogram
- Advantage: avoid the need for resampling because ECG is non-stationary and spaced unevenly

Tun et al. : http://medcraveonline.com/MOJPB/MOJPB-07-00223.pdf

Derivative-based approach: method

- Detect QRS region
  - Squared double differences e(n) → difference array d(j)
  - Windowing
- Detect R peaks
  - Maximum relative magnitude and its position
- Process RR intervals
  - Comparisons with average intervals for successive peaks

$$d1(i) = e(i+1) - e(i),\ i = 1,2\ldots\ n-1$$
$$d2(j) = d1(j+1) - d1(j),\ j = 1,2..\ n-2$$
$$d(j) = [d2(j)]^2$$

Derivative-based approach: analysis

- Good performance – overall detection sensitivity of 99.8%
- No need to eliminate baseline noise – insensitive to low-frequency noise

- Relies on many assumptions/pre-determined threshold values
- Elimination if criteria not met - loss of information?

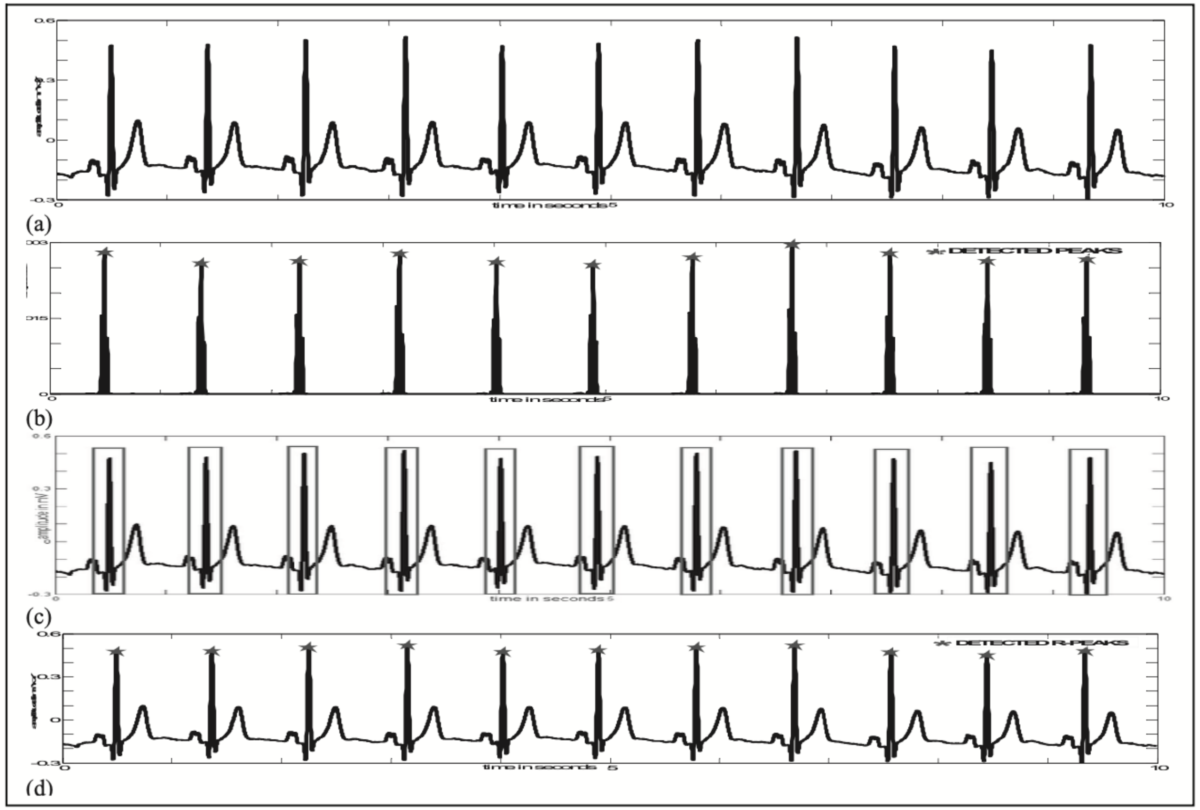
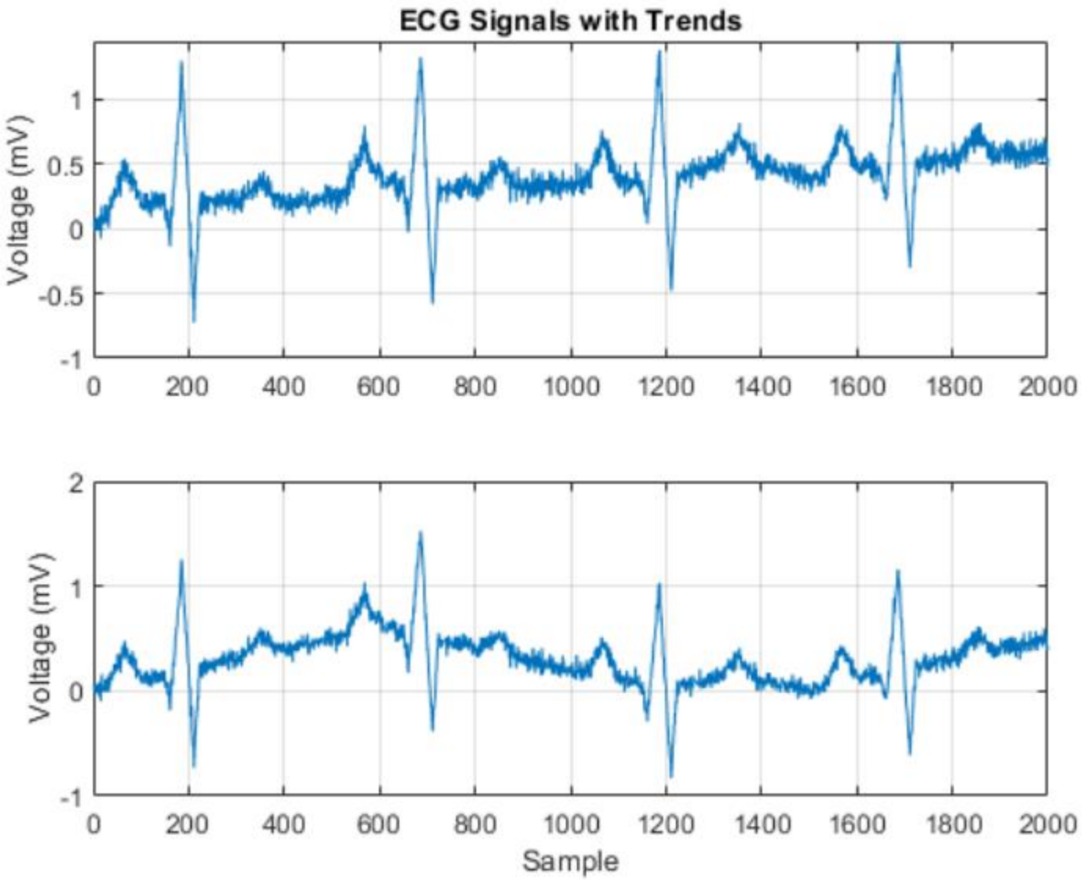


Fig 2. Processing steps for R-peak detection (a) Filtered ECG data; (b) Selection of the double difference signal peaks (marked with '*') (c) detected QRS windows (d) final detected R peaks (marked with '*').

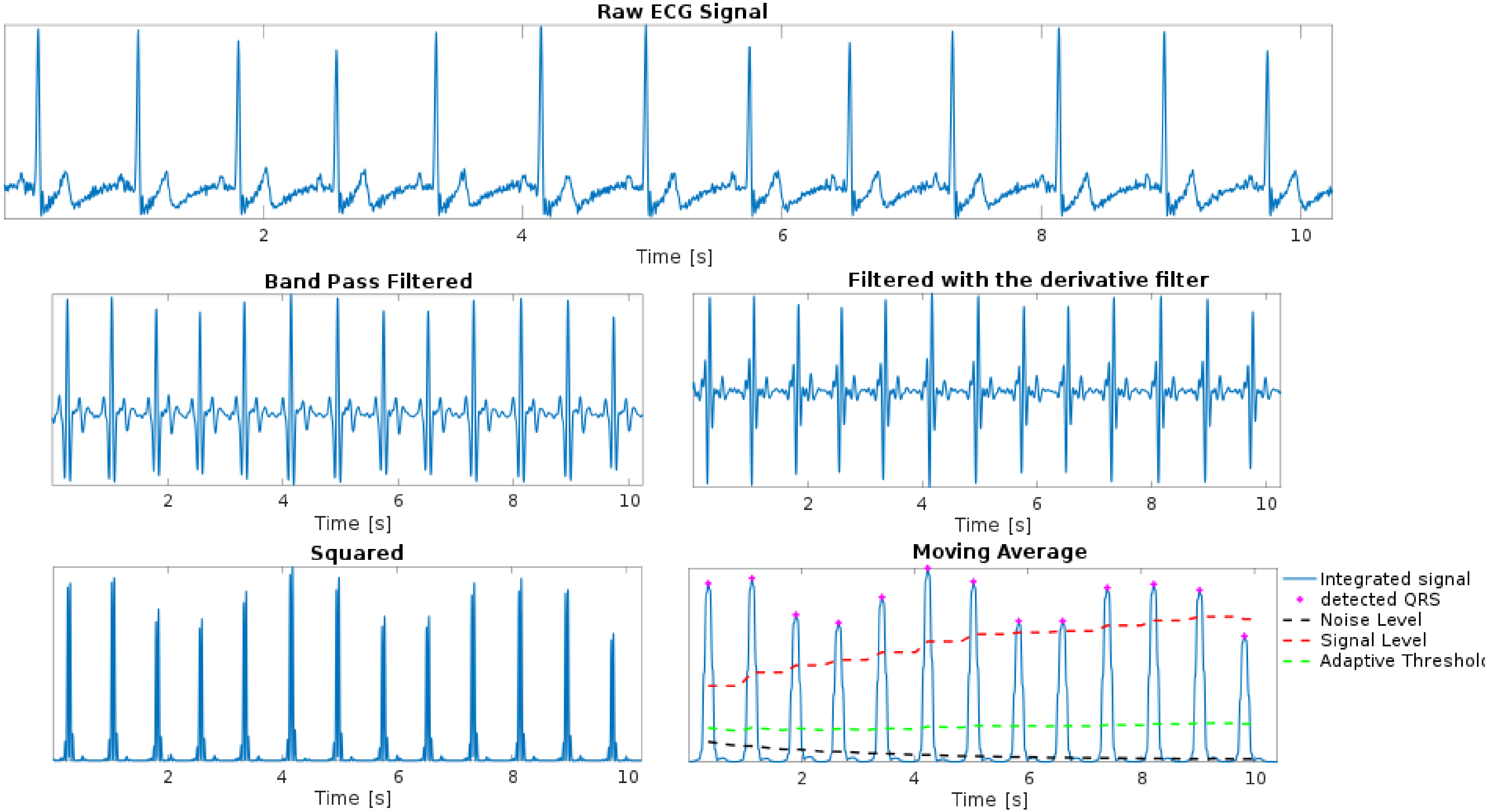
Processing before Identification and Correction of Doubtful Points

- ECG Signal was pre-processed using a 50Hz notch filter (this is to remove mains noise).
- A low-order polynomial is applied to eliminate non-linearity in the signal.
- Signal then resampled at 1kHz (some processing algorithms require the signal to have a certain frequency in order to work).
- A Modified version of the Pan-Tompkins algorithm was used to detect R peaks
- DC component and linear trend eliminated to get to a series of time intervals



https://uk.mathworks.com/help/signal/ug/remove-trends-from-data.html

Steps for Pan-Tompkins



Sedghamiz, Hooman. "Complete Pan Tompkins Implementation ECG QRS detector - File Exchange - MATLAB Central". ww2.mathworks.cn

Identification and Correction of Doubtful Points

Identification of Artifacts and Ectopic Beats	Correction of these Doubtful Points
SD Method (Standard Deviation) – beat is normal if the RR interval is within 4 standard deviations of the mean of all RR intervals	DEL Method – deletes the detected artifacts from the signal. Simple method, with no interpolation
IRF Method (Impulse Rejection Filter) – nonlinear filter, more appropriate for artifact removal in biomedical signals since it only gives a signal to alter the signal where the artefact is detected	RMV Method – replaces each anomalous beat with the median of the previous five and following five Superior to DEL since it does have interpolation of degree 0, therefore decreasing the error due to these doubtful beats.

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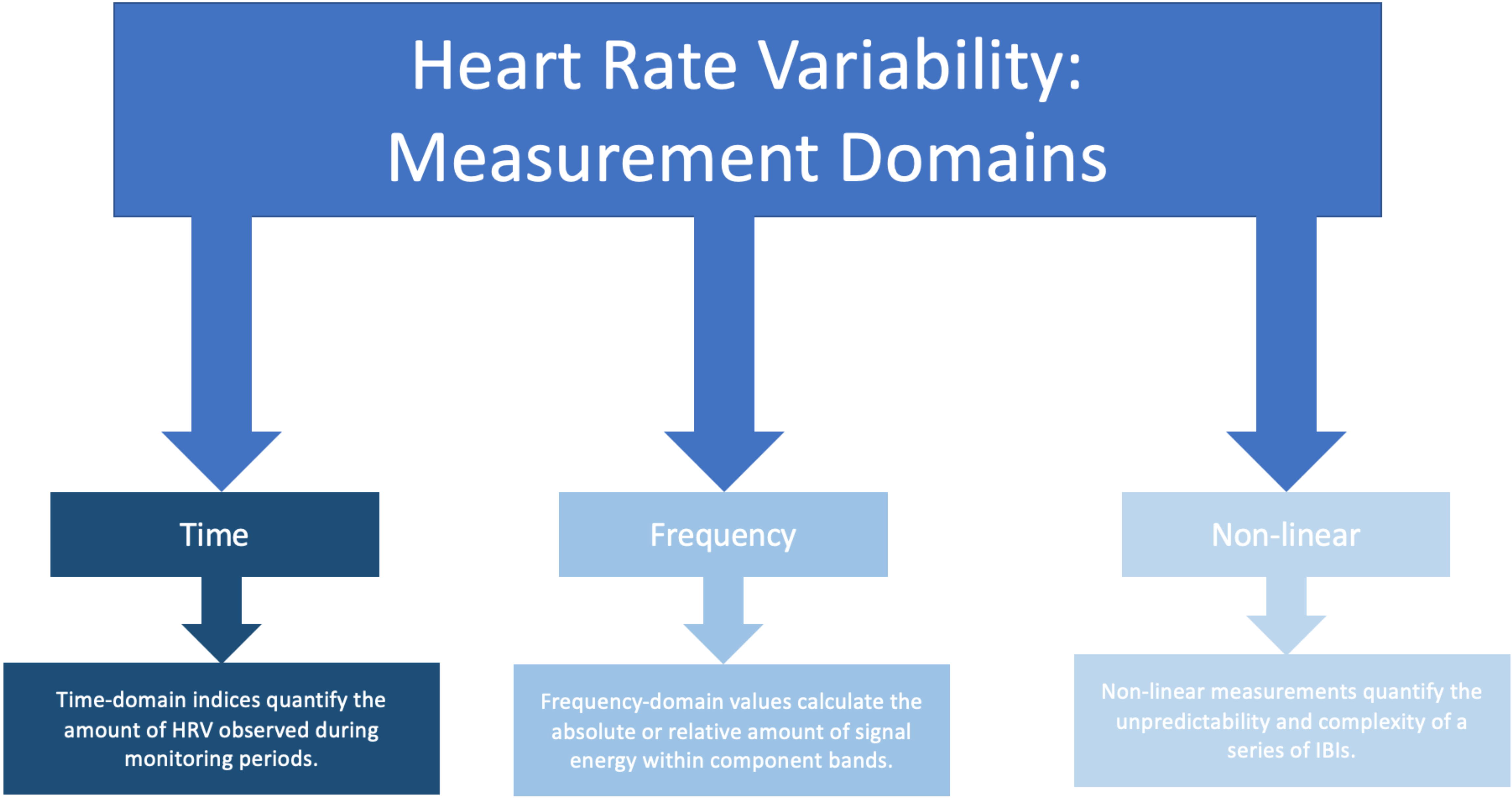
An Overview of Heart Rate Variability Metrics and Norms

Fred Shaffer[1,*] and J. P. Ginsberg[2]



*Text and descriptions extracted directly from paper available at doi: 10.3389/fpubh.2017.00258

Domain Measures Compared – Problematic?

Table 1

HRV time-domain measures.

Parameter	Unit	Description
SDNN	ms	Standard deviation of NN intervals
SDRR	ms	Standard deviation of RR intervals
SDANN	ms	Standard deviation of the average NN intervals for each 5 min segment of a 24 h HRV recording
SDNN index (SDNNI)	ms	Mean of the standard deviations of all the NN intervals for each 5 min segment of a 24 h HRV recording
pNN50	%	Percentage of successive RR intervals that differ by more than 50 ms
HR Max – HR Min	bpm	Average difference between the highest and lowest heart rates during each respiratory cycle
RMSSD	ms	Root mean square of successive RR interval differences
HRV triangular index		Integral of the density of the RR interval histogram divided by its height
TINN	ms	Baseline width of the RR interval histogram

Interbeat interval, time interval between successive heartbeats; NN intervals, interbeat intervals from which artifacts have been removed; RR intervals, interbeat intervals between all successive heartbeats.

Table 2

HRV frequency-domain measures.

Parameter	Unit	Description
ULF power	ms^2	Absolute power of the ultra-low-frequency band (≤0.003 Hz)
VLF power	ms^2	Absolute power of the very-low-frequency band (0.0033–0.04 Hz)
LF peak	Hz	Peak frequency of the low-frequency band (0.04–0.15 Hz)
LF power	ms^2	Absolute power of the low-frequency band (0.04–0.15 Hz)
LF power	nu	Relative power of the low-frequency band (0.04–0.15 Hz) in normal units
LF power	%	Relative power of the low-frequency band (0.04–0.15 Hz)
HF peak	Hz	Peak frequency of the high-frequency band (0.15–0.4 Hz)
HF power	ms^2	Absolute power of the high-frequency band (0.15–0.4 Hz)
HF power	nu	Relative power of the high-frequency band (0.15–0.4 Hz) in normal units
HF power	%	Relative power of the high-frequency band (0.15–0.4 Hz)
LF/HF	%	Ratio of LF-to-HF power

Table 3

HRV non-linear measures.

Parameter	Unit	Description
S	ms	Area of the ellipse which represents total HRV
SD1	ms	Poincaré plot standard deviation perpendicular the line of identity
SD2	ms	Poincaré plot standard deviation along the line of identity
SD1/SD2	%	Ratio of SD1-to-SD2
ApEn		Approximate entropy, which measures the regularity and complexity of a time series
SampEn		Sample entropy, which measures the regularity and complexity of a time series
DFA α1		Detrended fluctuation analysis, which describes short-term fluctuations
DFA α2		Detrended fluctuation analysis, which describes long-term fluctuations
D_2		Correlation dimension, which estimates the minimum number of variables required to construct a model of system dynamics

Time Domain Analysis

Variables

- NN interval
- mean HR
- difference between longest and shortest NN interval, difference between night and day HR
- variations in HR due to respiration, tilt, Valsalva maneuver or phenylephrine infusion

Statistical Measures

- SDNN
  - equal to total power of spectral analysis
- SDANN
- RMSSD
- NN50
- pNN50

Geometrical Methods

- Lorenz plot of NN/RR intervals
- HRV triangular index
- Advantage:

  Insensitivity to quality of the series of NN intervals
- Disadvantage:

  Need a reasonable number of NN intervals

Comparison of Frequency Domain Analyses

Methods	Advantages	Disadvantages
FFT	• Simple and widely available • High processing speed • Good reproducibility • Low Computational Cost	• Requires interpolation -> bias • Needs stationary data • Needs an adequate amount of data
Autoregressive models	• Smoother spectral components • Easy postprocessing of spectrum • No interpolation and shorter data needed	• Needs stationary data • Complex so less reliable
MTRS	• No interpolation • Can be applied in non-stationary conditions • Can work with data as short as 20-30s	• Less widely available

Time Windows

	Short Time Window (a few minutes)	Long time window (hours)
Functions	Estimate autonomic status, track dynamic changes	Assess autonomic function, describe changes over longer timespans and predict prognosis
Advantage	1. Less or no error 2. Easy to perform 3. Factors like body position can be easily controlled 4. Least time for data processing	1. More stable 2. Estimate longer fluctuations including the ULF power
Disadvantage	Not stable due to fluctuating parameters	1. More expensive and time consuming 2. More noise due to ectopic beats, artifacts, and events 3. Varying environmental factors throughout the day

Summary

Steps	Methods	Advantages	Limitations
Pre-processing/R peak detection	Discrete Wavelet Transform (DWT)	Wavelet based approach is more efficient/accurate/perform better at high noise levels	Requires suitability of mother wavelet and scale values
	Derivative-based	High efficiency/accuracy Simple to implement No need to consider noise	Relies on many assumptions Potential loss of information
	Pan-Tompkins	High Detection Accuracy of Peaks	Larger error in terms of time value compared to Hilbert
HRV Analysis	Time domain	Easier to perform	Cannot compare recordings of different durations
	Frequency domain	Provides more information	Requires experience and theoretical knowledge
	Lomb-Scargleperiodogram	Doesn't require resampling of data	

Next steps

- All methods researched are highly effective
- Other approaches
  - Digital filter based (frequencies)
  - Template matching techniques (cross-correlation)
  - Non-linear Hilbert transform
  - Other wavelet based techniques