

IEEE Applied Imagery Pattern Recognition Workshop

October 19, 2016

The Cosmos Club, Washington, DC

TITLE: Exploiting the Underlying Cepstral Coefficients for Large Scale and Fine-Tuned ECG Time-Imagery Analysis, including R-R, P-R, R-T, and, R-PVC interval imaging.

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Three parts:

Part 1 – Brush up on Fourier and Cepstrum and example using voice

Part 2 – Application and extension of Cepstrum to Physionet MITDB signal showing framing technique in preparation for recurrence plots

Part 3 – Recurrence plots based exclusively on framing in a Cepstral component neighborhood, examples using MITDB and College Student

Part 1

Arthur Winfree

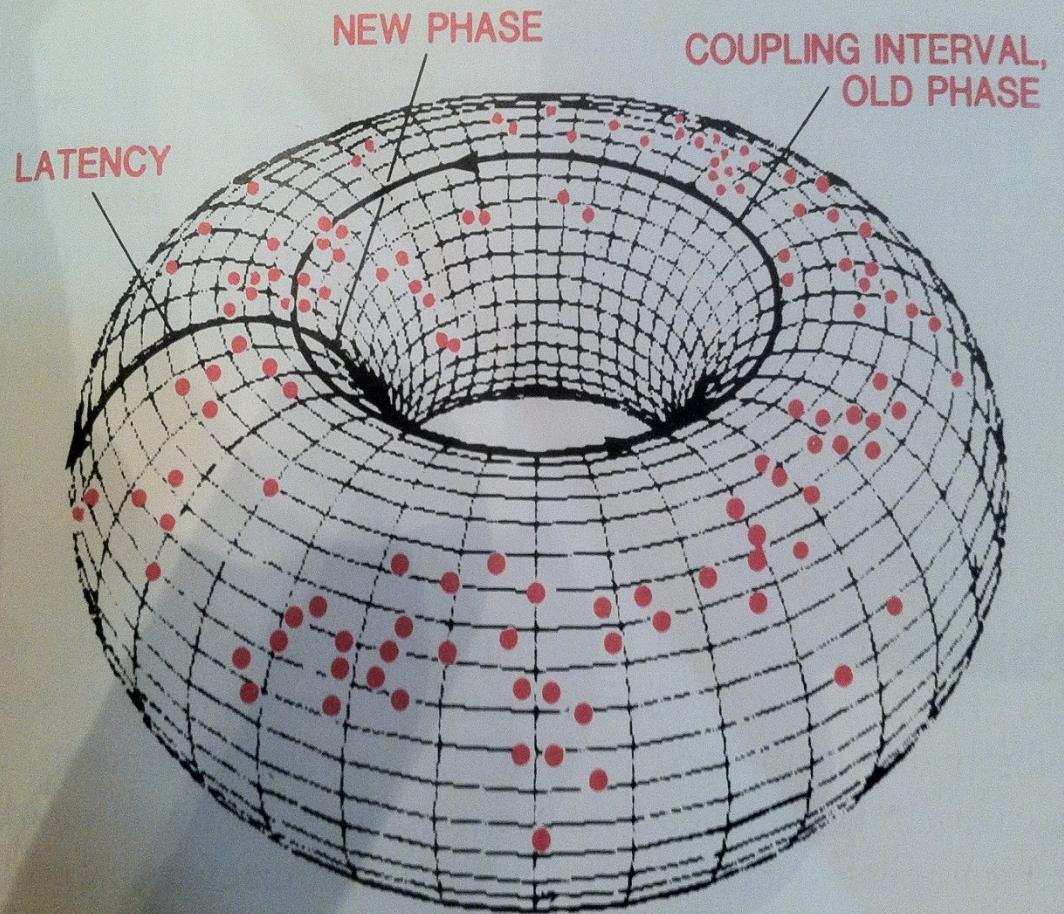
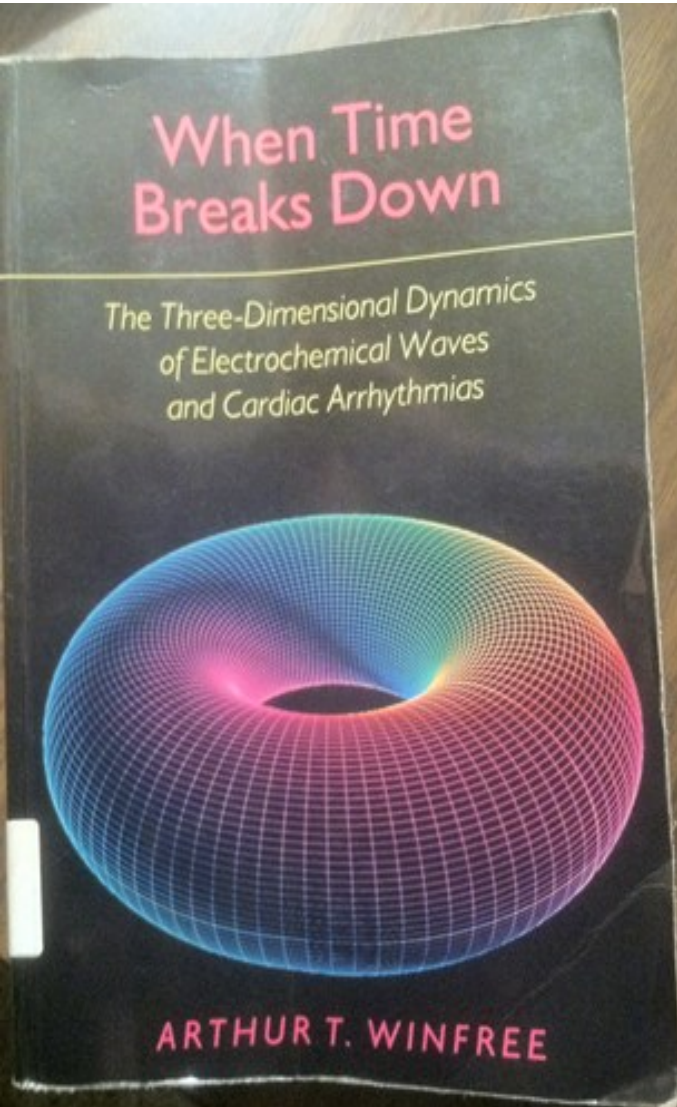


Figure 3.5: The data of Figures 3.2 and 3.4 are replotted on toroidal coordinates to emphasize their peculiar topological connectivity. A time-spatial time is taken as 0 in both coordinates from

B. P. Bogert, M. J. R. Healy, and J. W. Tukey: "The Quefrency Alanysis of Time Series for Echoes: Cepstrum, Pseudo Autocovariance, Cross-Cepstrum and Saphe Cracking". Proceedings of the Symposium on Time Series Analysis (M. Rosenblatt, Ed) Chapter 15, 209-243. New York: Wiley, 1963.

Complex Cepstrum-based Decomposition of Speech for **Glottal Source Estimation**

Thomas Drugman, Baris Bozkurt, Thierry Dutoit,
TCTS Lab, Polytechnique de Mons, Belgium,
Izmir Institute of Technology, Turkey

$$X(\omega) = \sum_{n=-\infty}^{\infty} x(n)e^{-j\omega n}$$
$$\log[X(\omega)] = \log(|X(\omega)|) + j\angle X(\omega)$$
$$\hat{x}(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \log[X(\omega)]e^{j\omega n} d\omega$$

Oppenheim: homomorphic system theory

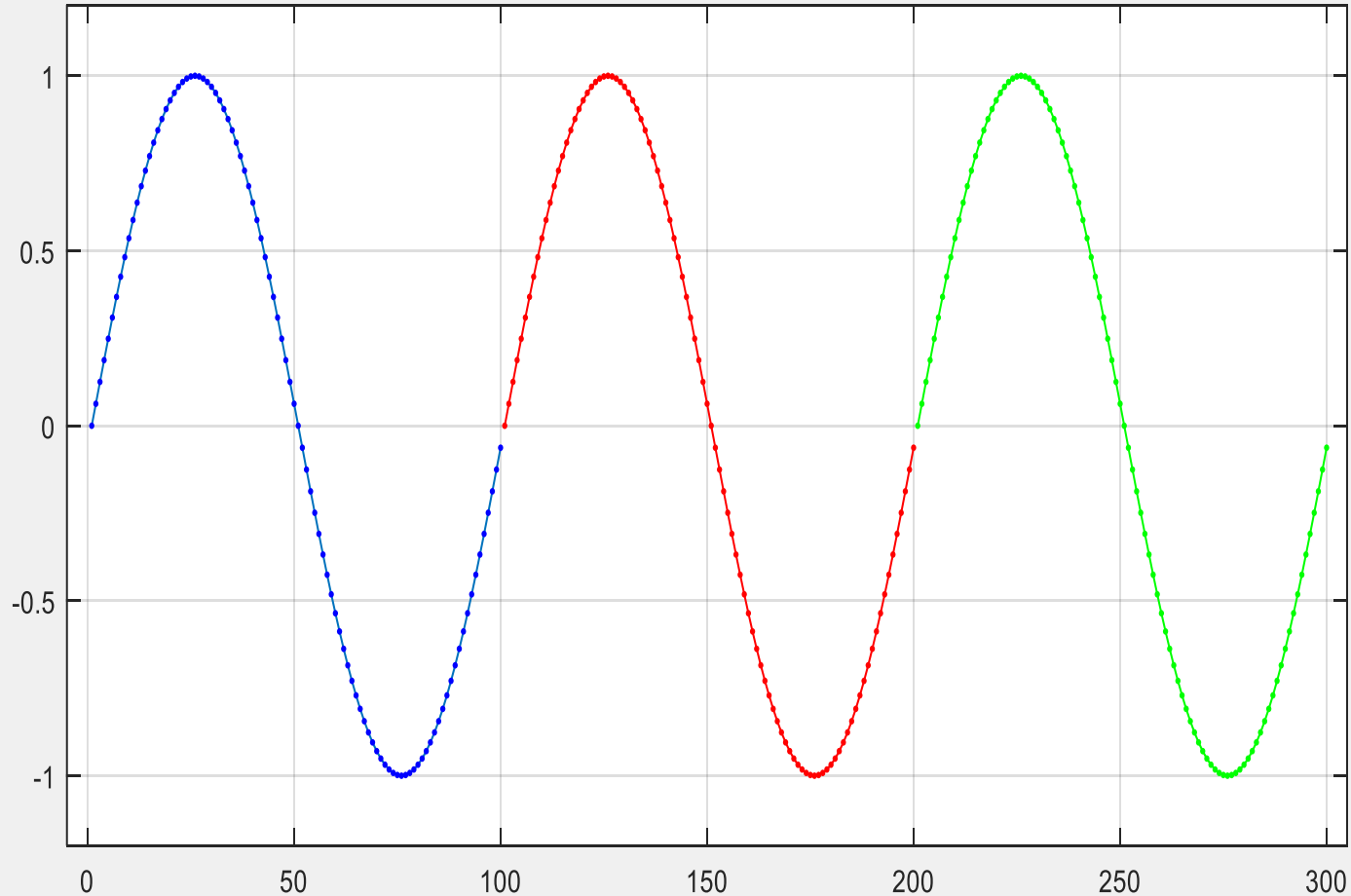
Donald G. Childers, David P. Skinner and Robert C. Kemerait, "The Cepstrum: A Guide to Processing", *The IEEE*, Vol. 65, No. 10, October 1977.

Cepstrum of the signal is defined as the "Inverse Fourier transforms (IFT) of the logarithm of the magnitude of the Fourier transform (FT) of the data sequence"[1] [4].



Akay: Cepstrum analysis is concerned with the deconvolution of two signal types: the fundamental (basic) wavelet and a train of impulses (excitation function)

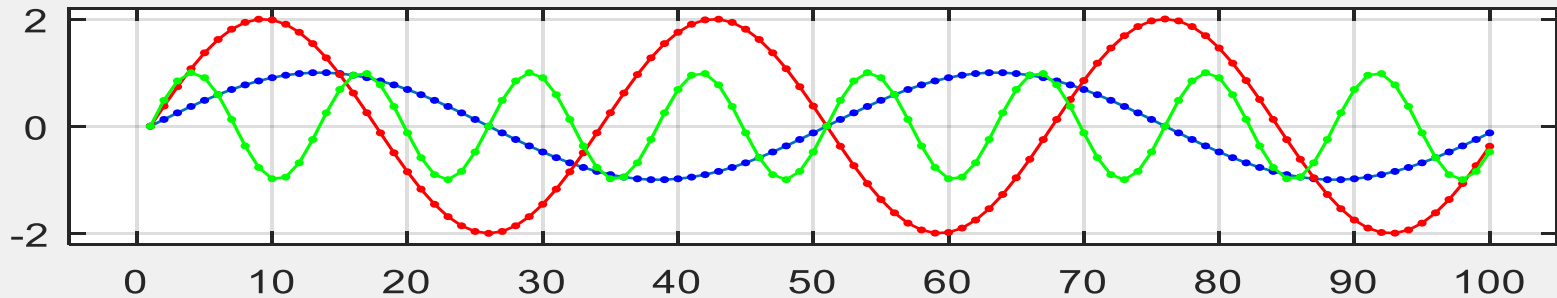
We have periodicity in sinusoids, and we show three such.
And, in particular, we work with applications which means they are discrete, bounded, and of finite duration, which means, we have three sets of start/stops



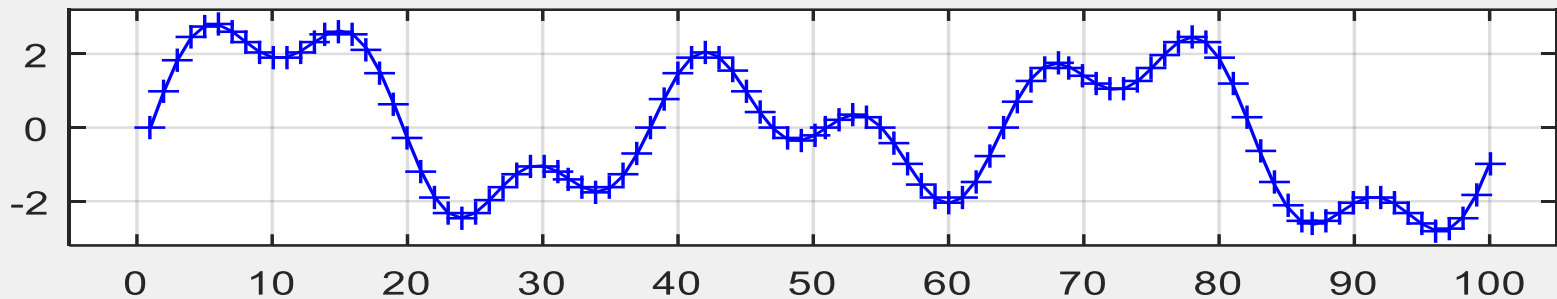
Fourier example showing orthogonal ***ON THE PERIOD***

1. Overlap
2. Add them
3. Correlate against the bank of frequencies showing series of ON/OFF switches

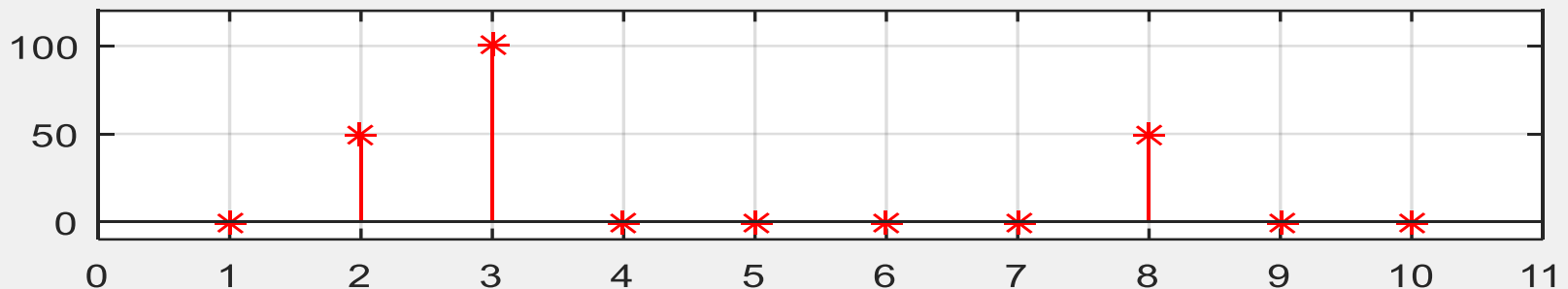
1



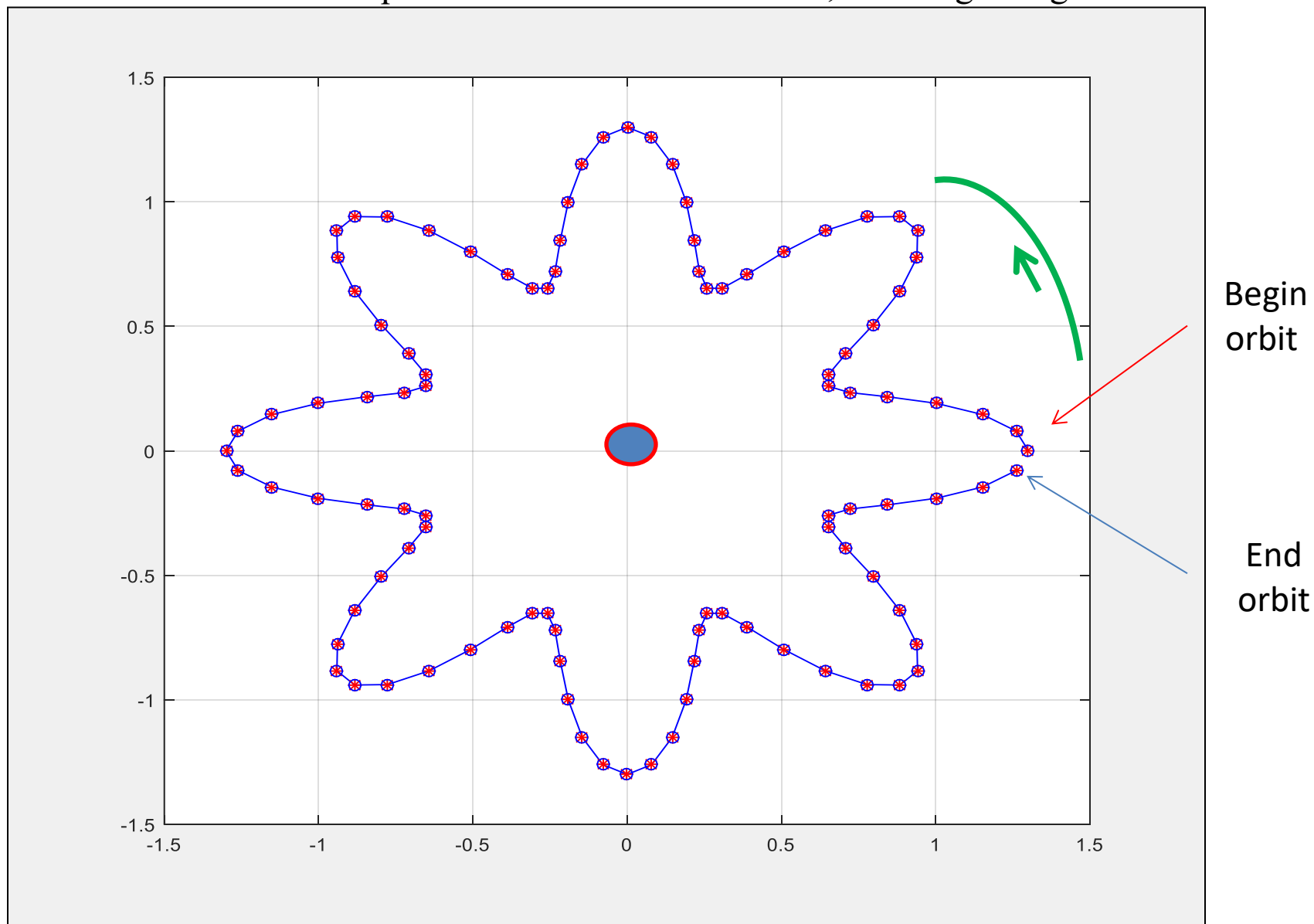
2



3



Fun example from Bohr, de Broglie, Bohm, and Schrödinger:
Possible and so 'Probable' quantum-sized molecular orbit, with beginning and return

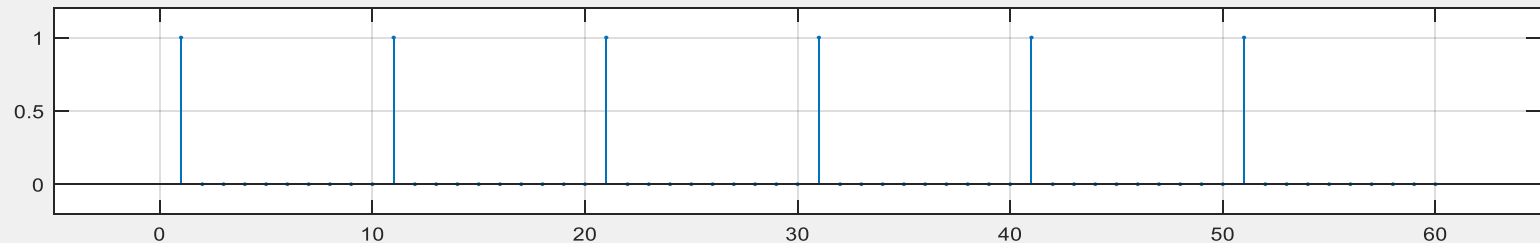


Drew this in Matlab after reading Molecular Orbital Theory by Arno Liberles

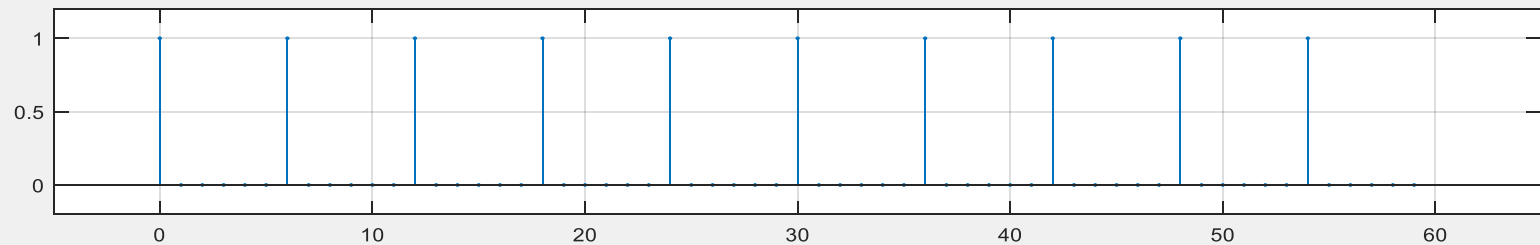
Example 1: The basics of Cepstrum, but with a fabricated signal, NOT a physical signal. Signal is called Sampling function, Shah, Function, or Comb function.

1. Comb in time
2. Comb in Fourier
3. Comb in Cepstrum, which, reflects back to time, by theorem.

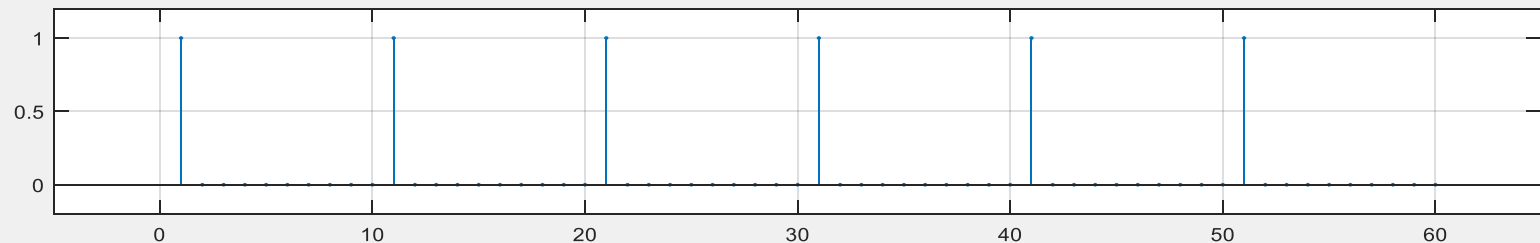
1.



2.

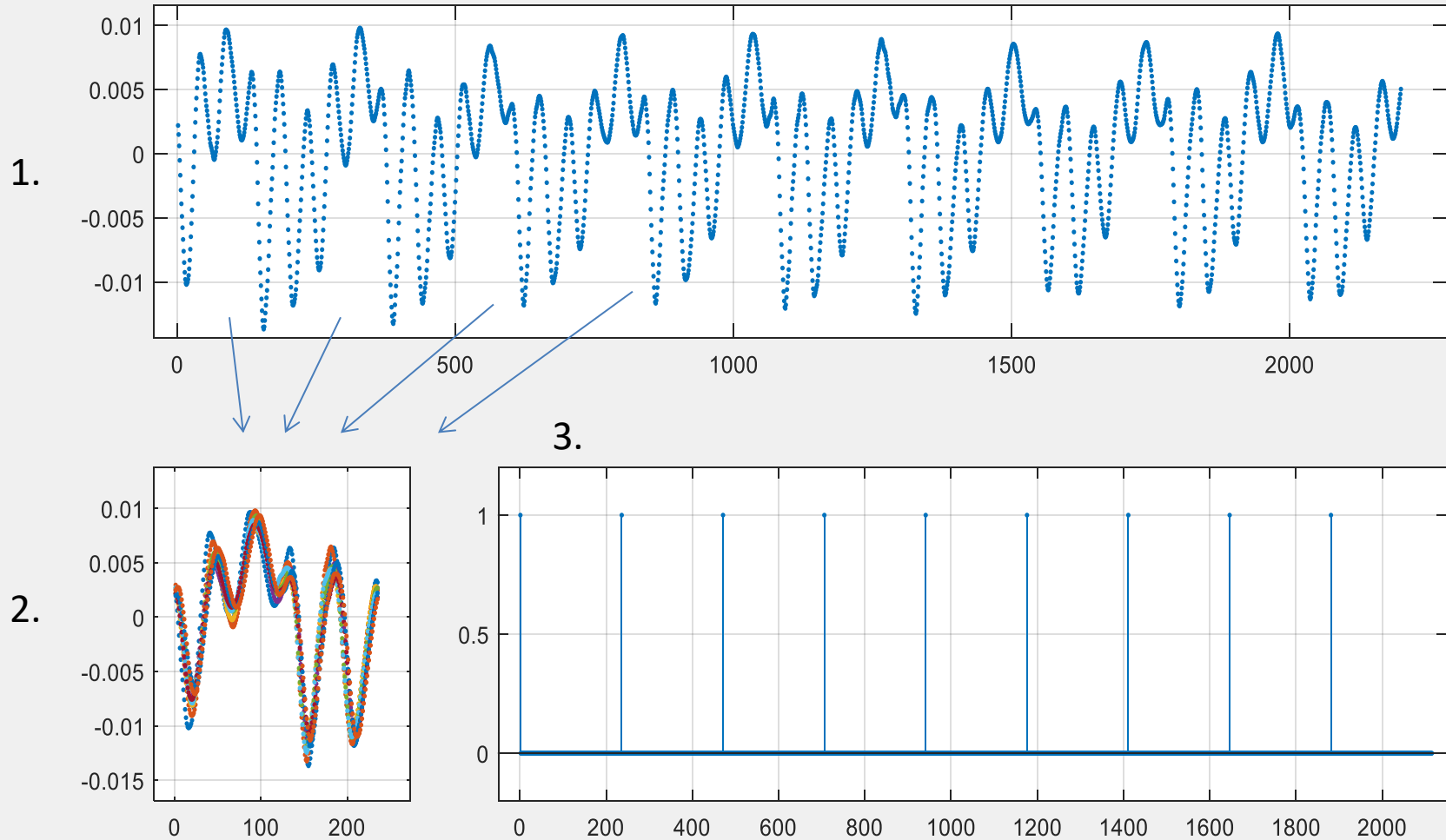


3.



Tying Examples 1 and 2 together, using an author's solfege of 'Do', we have (Akay's) wavelet and train of impulses.

Figure 1

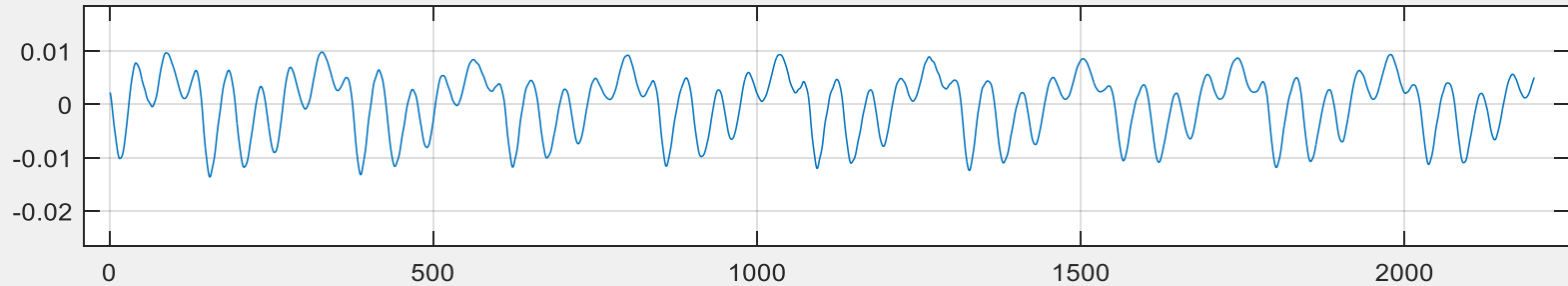


Akay: Cepstrum analysis is concerned with the deconvolution of two signal types: the fundamental (basic) wavelet and a train of impulses (excitation function)

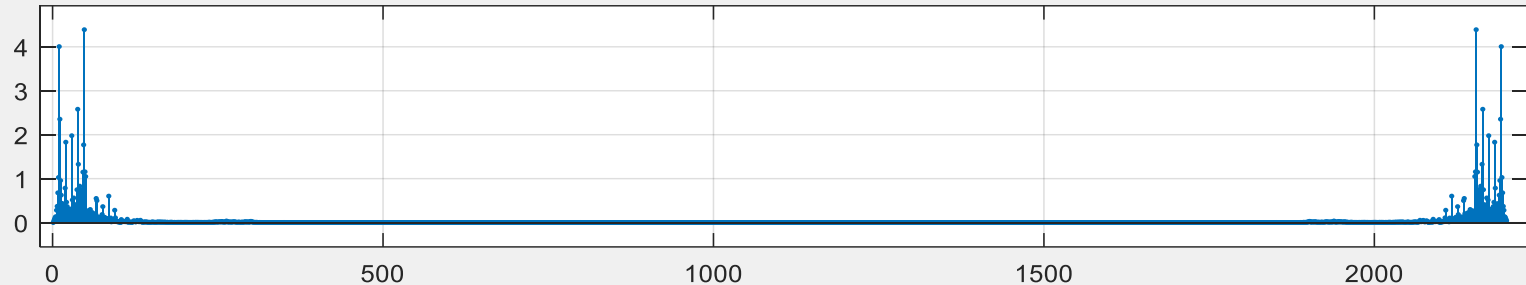
Transformations of 'Do'

1. The time domain waveform with 2350 points sampled.
2. The Fourier Transform of (1)
3. The Cepstrum domain of (1) or the Fourier Transform of (2).

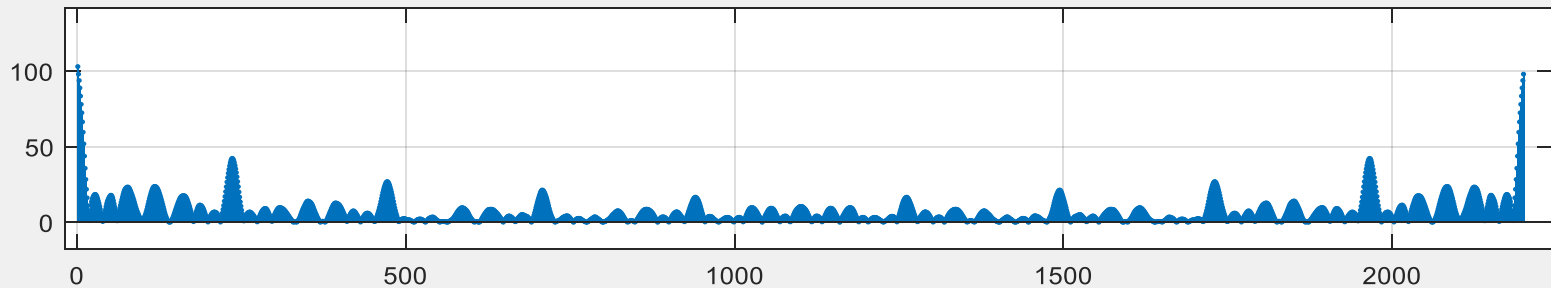
1.



2.

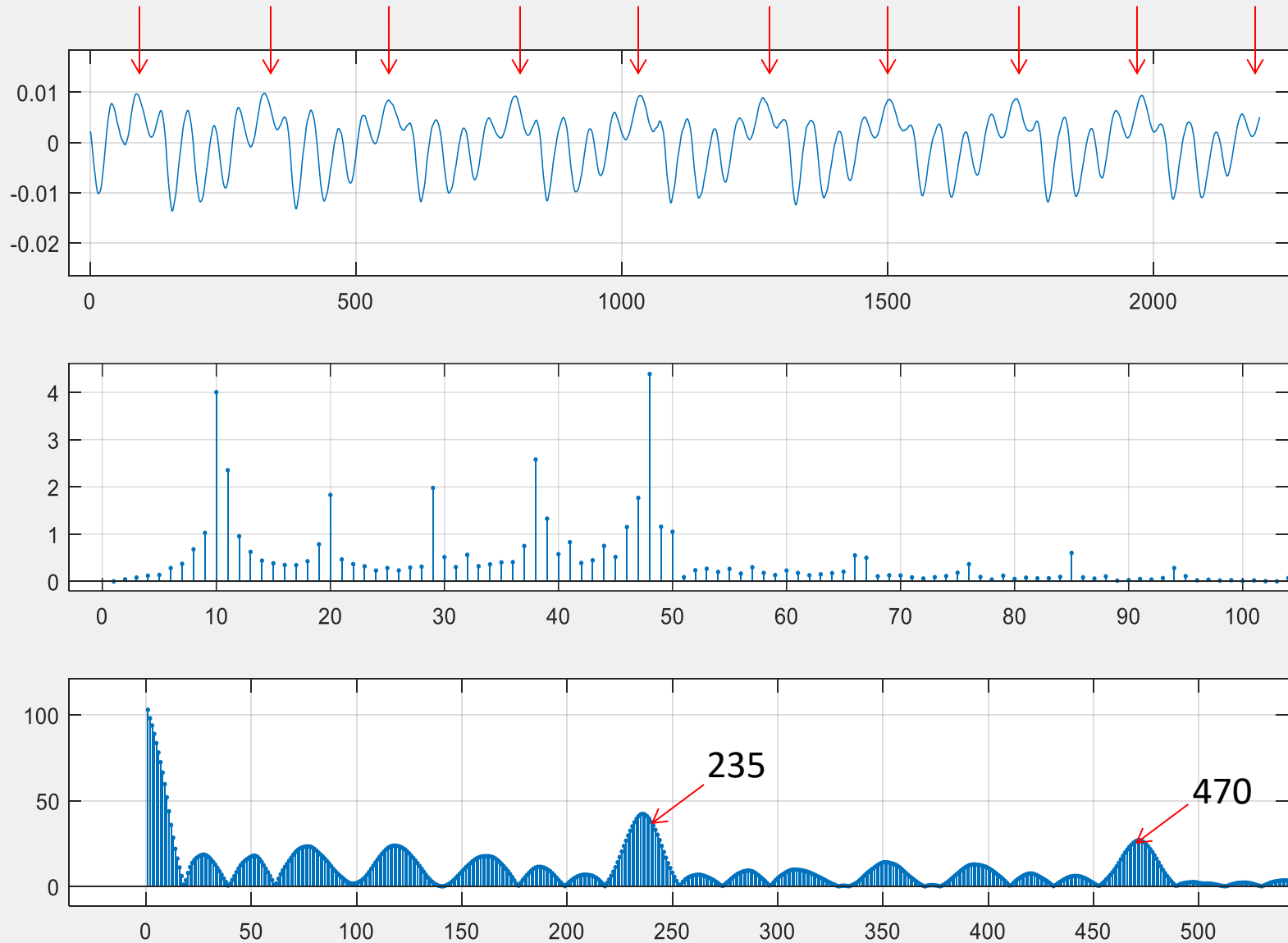


3.



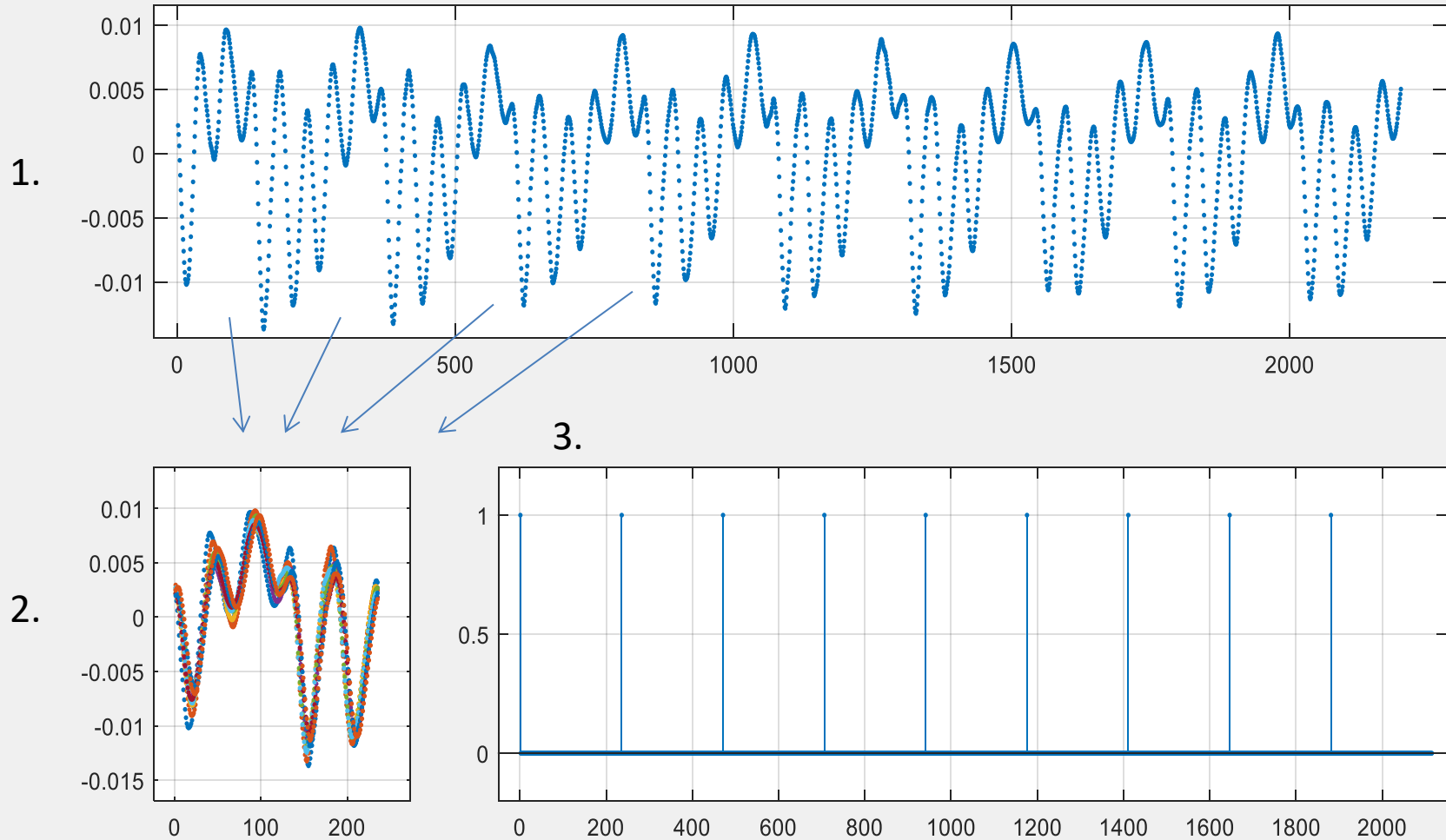
Zoom in

Figure 2



Tying Examples 1 and 2 together, using an author's solfege of 'Do', we have (Akay's) wavelet and train of impulses.

Figure 1



Akay: Cepstrum analysis is concerned with the deconvolution of two signal types: the fundamental (basic) wavelet and a train of impulses (excitation function)

Part 2

Example of Extended CEPSTRAL Approach using Physionet Data

Record 105 (MLII, V1; female, age 73)

Rhythm	Rate	Episodes	Duration
Normal sinus rhythm	78-102	1	30:06

Signal quality	Episodes	Duration
Both clean	31	22:18
Upper noisy	3	0:10
Lower noisy	28	3:27
Both noisy	23	4:06
Unreadable	4	0:04

Points of interest:

[22:02](#) Noise [5:27](#) Artifact
[26:45](#) PVC [7:57](#) PVC
[27:27](#) Noise [15:16](#) Normal sinus rhythm
[28:08](#) Noise [17:52](#) Artifacts
[29:07](#) Noise

Notes:

The PVCs are uniform.
The predominant feature of this tape is high-grade noise and artifact.

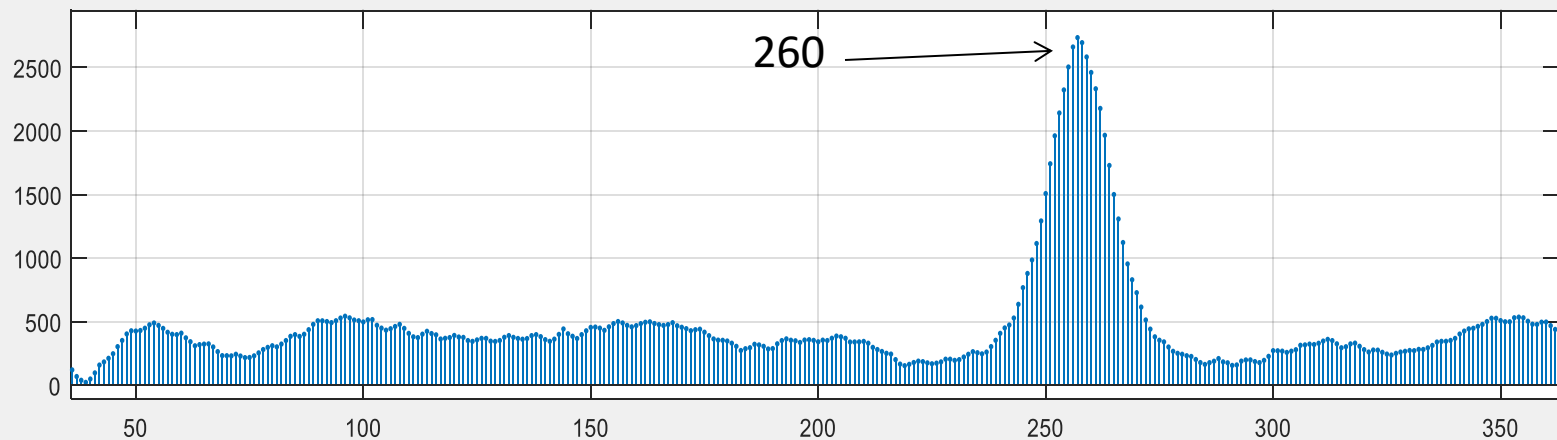
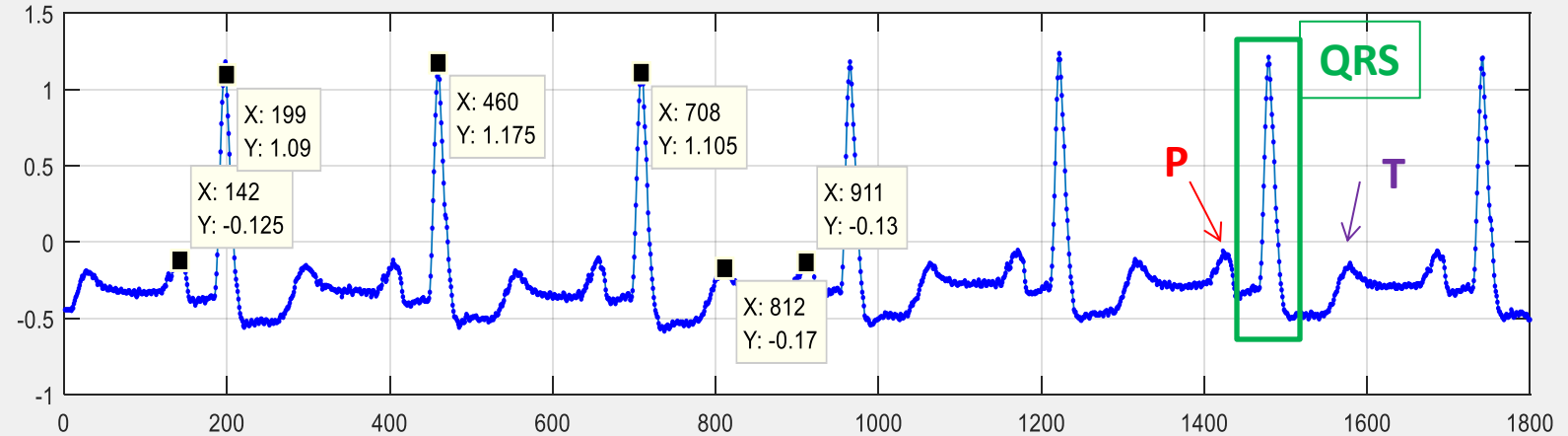
<https://physionet.org/cgi-bin/atm/ATM>
MIT-BIH Arrhythmia Data Base (mitdb)

MITDB 105 first 1800 samples

Top: Time domain with labeled P, R, and T peaks.

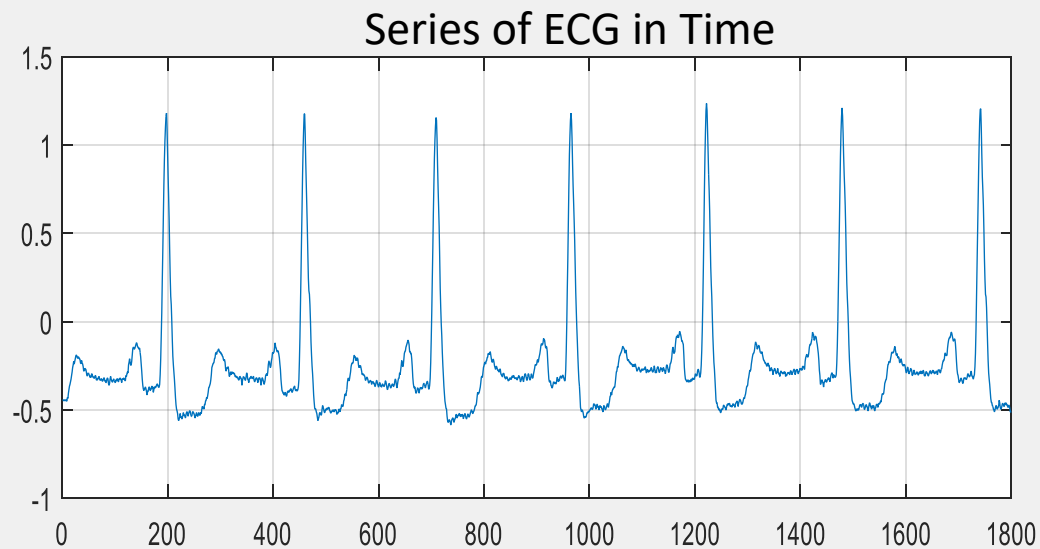
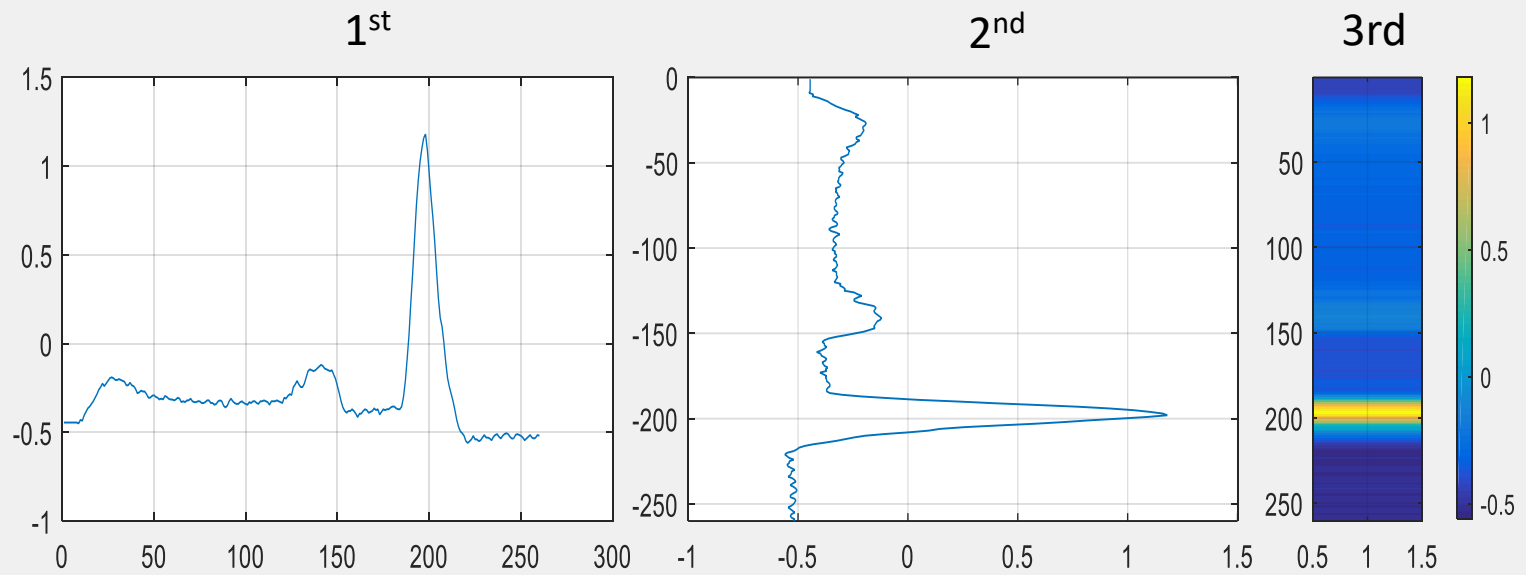
Bottom: Typical cepstral component output (this is known)

Peak at 260 refers to R-R which at 360sample/sec yields an 83 BPM Heart Rate

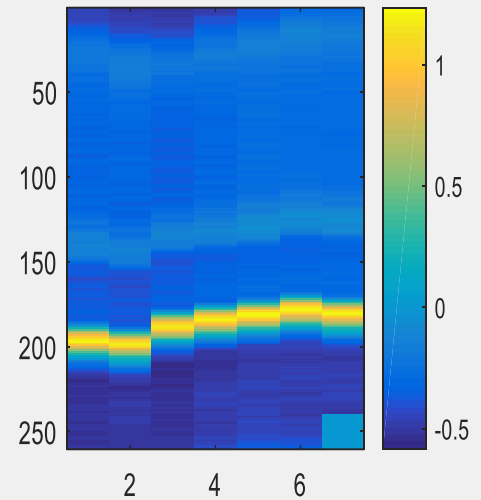


Three steps from time domain to frame domain

Figure 4

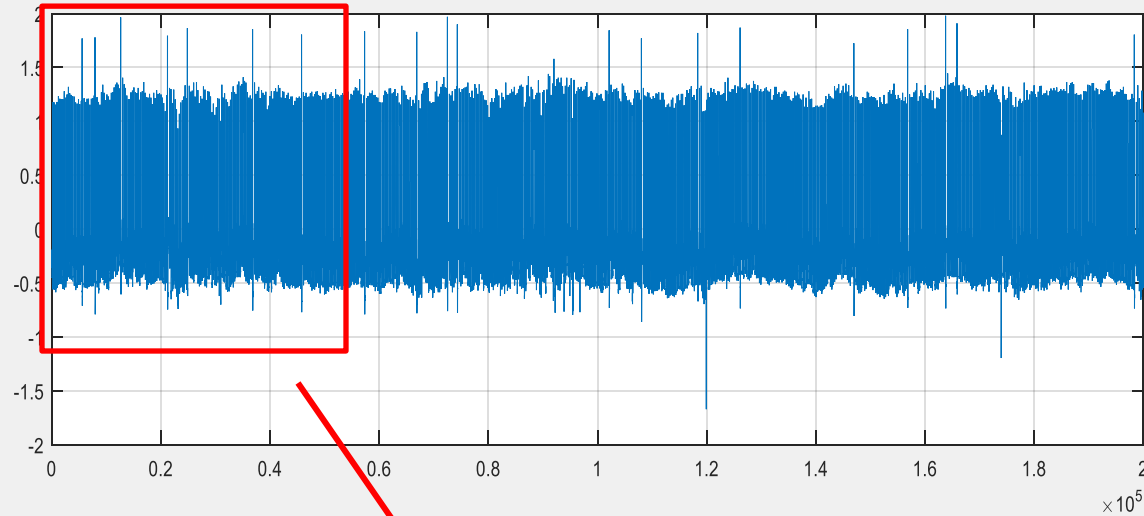


Series of ECG in Frame

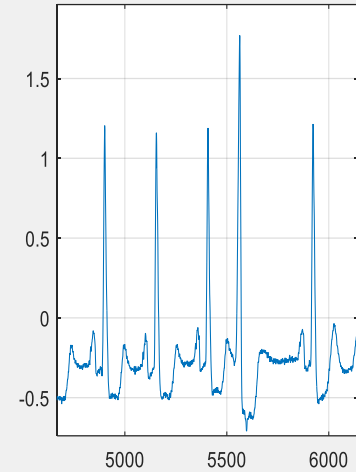


The advantage of Frame over time based on Cepstrum

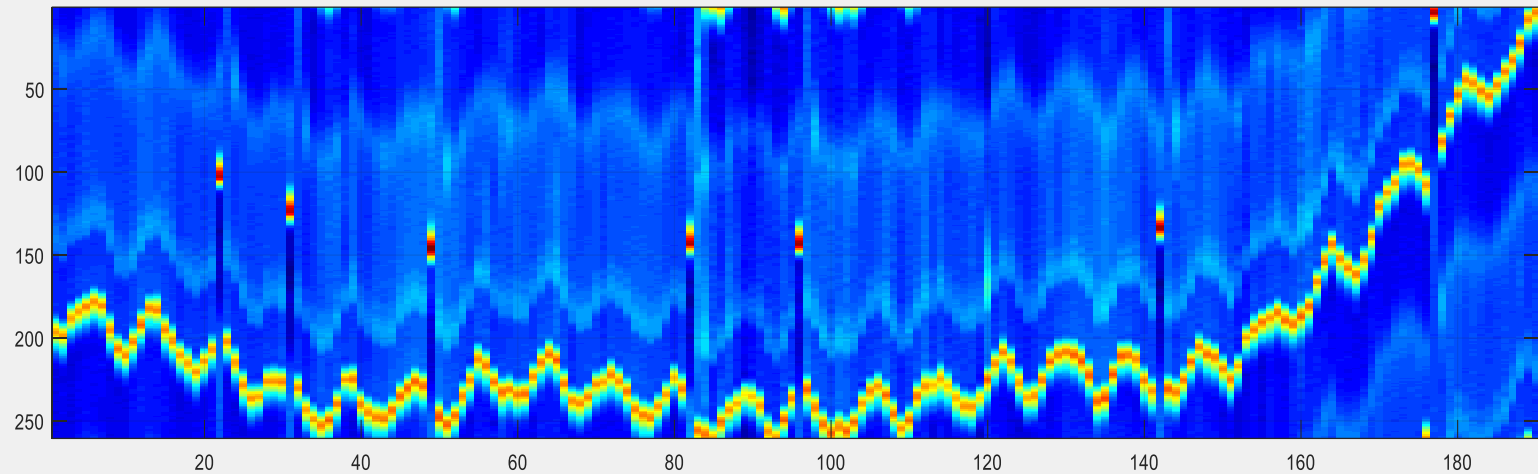
1. Dense plot of 1000 ECGs in time



ECGs with a PVC

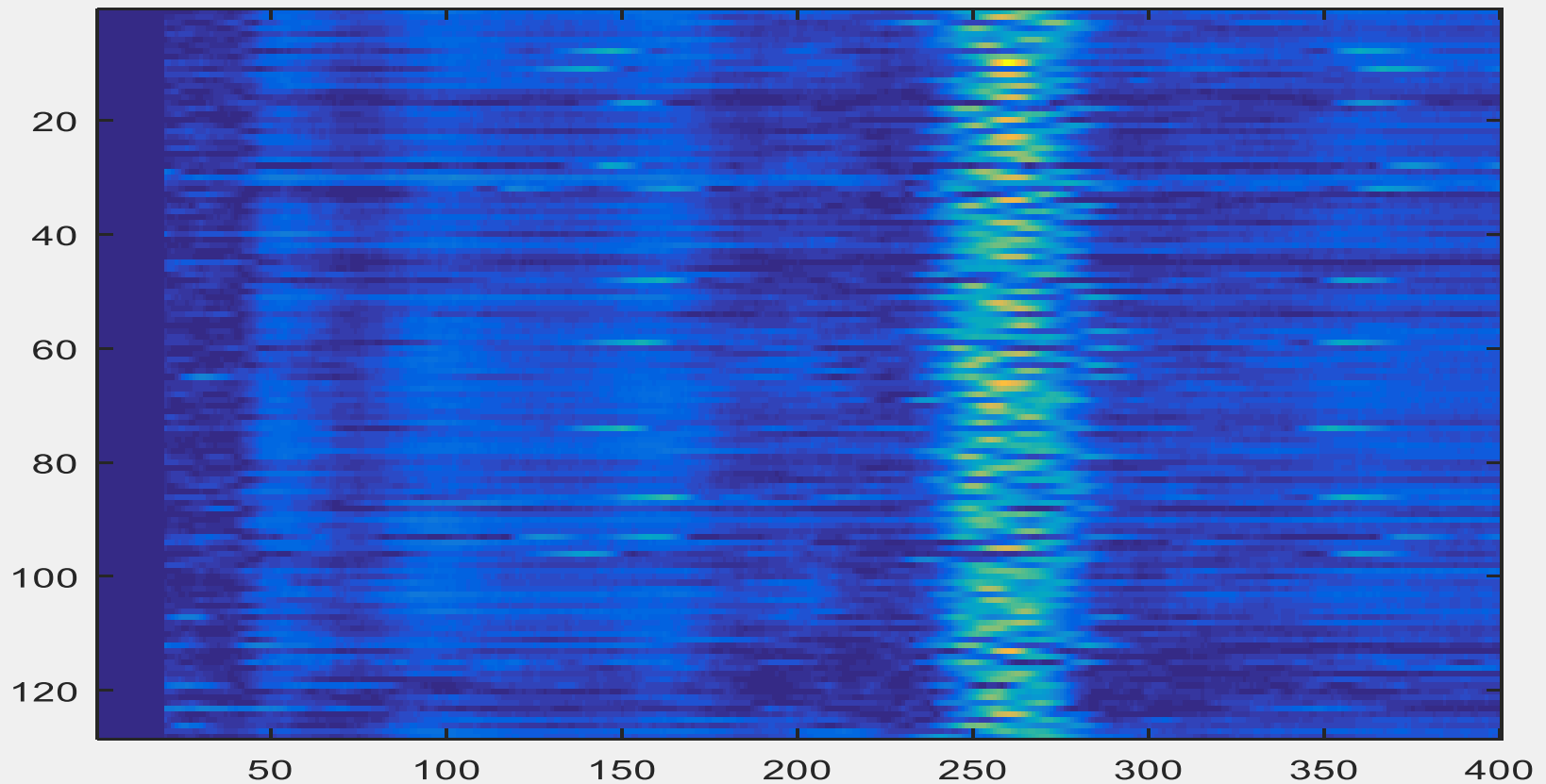
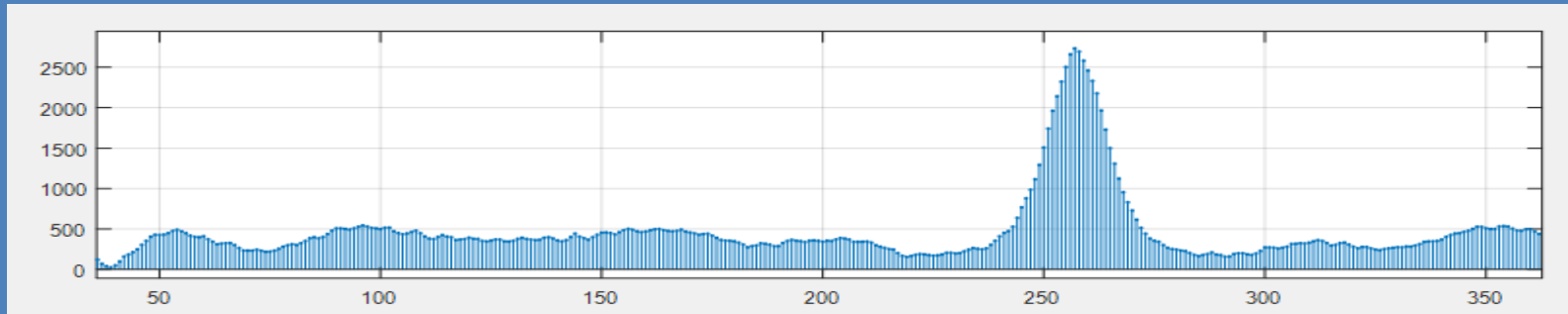


Frame domain of 200 ECGs in Red Box above



A series of STCT (short time cepstral transforms)
In matrix form, 120 sets (rows) of STCTs

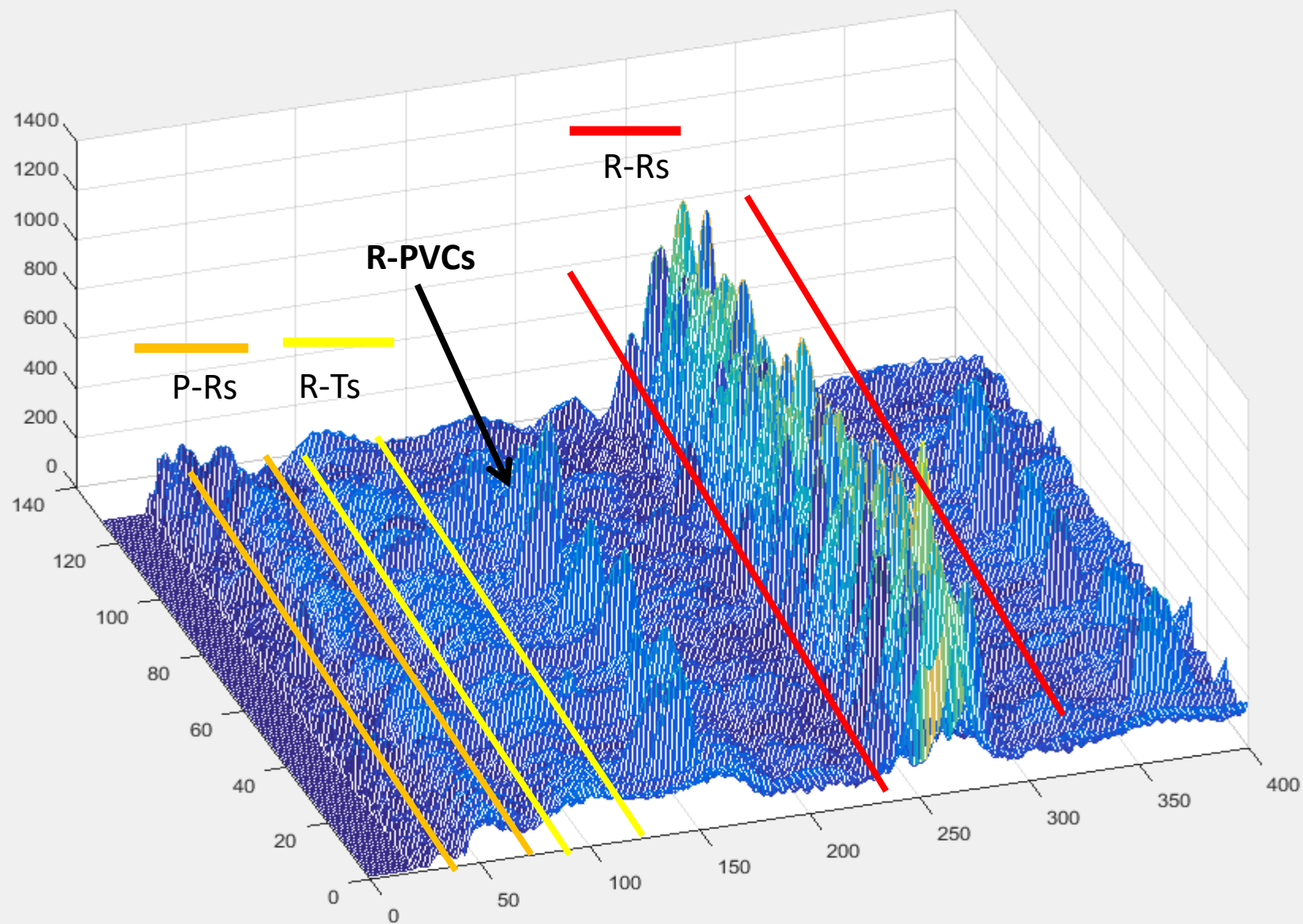
Figure 6A



Proprietary to Jadco Signals

Looking at Figure 6A, but in terms of this EKGs cepstral terrain

Figure 6B



Part 3

Recurrence plots for:
MITDB 105
(compare to)
Clemson student

Usual recurrence plot format

Given a scalar time series $x(1), x(2), x(3), \dots$

form subsequences $x(n), x(n+L), x(n+2*L), x(n+3*L), \dots x(n+M*L)$ where L is the time expanse between samples and M is the number of delays taken in with respect to $x(n)$.

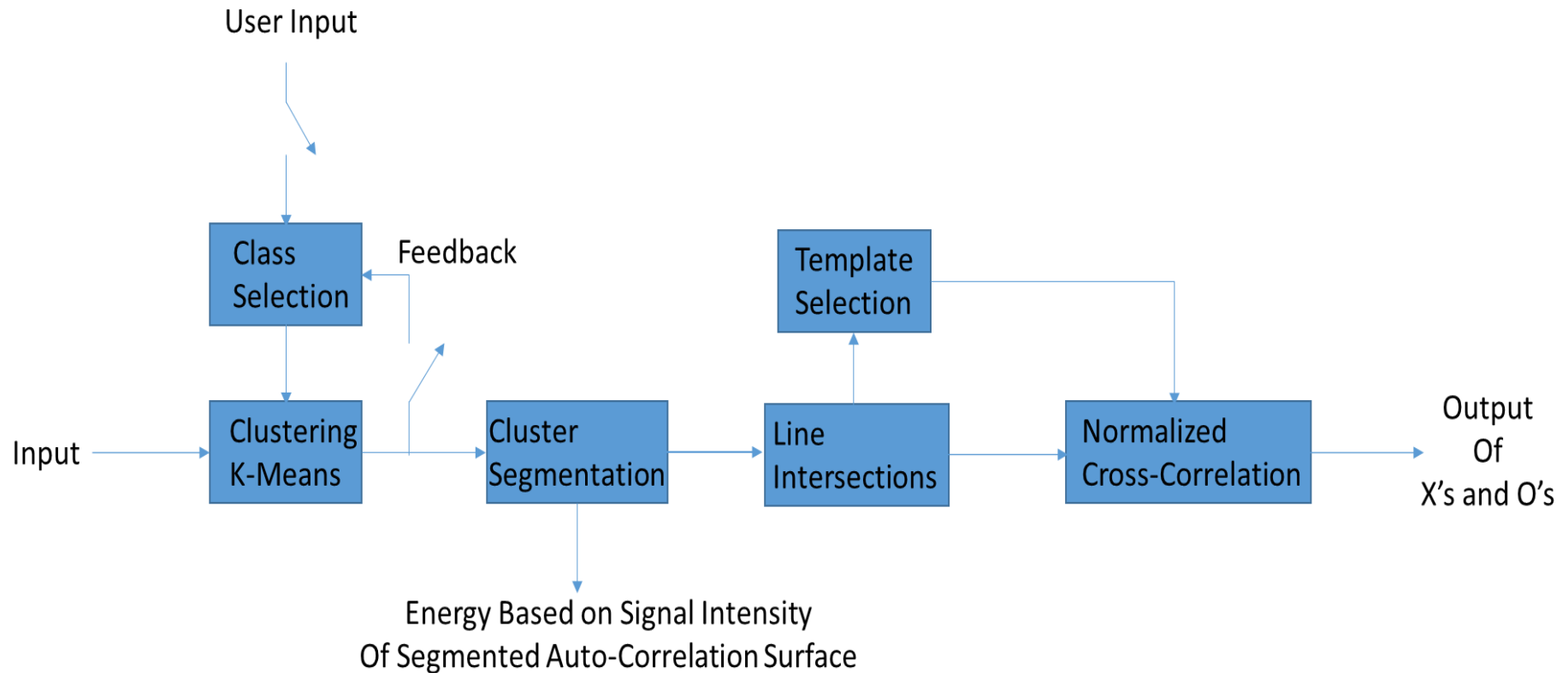
Then, by shifting n to the right, up to $L-1$ times, $L-1$ more subsequences could be formed. A recurrence plot show how any two subsequences correlate.

Ex: correlate with $L=5$,
 $\{x(1) x(6) x(11), \dots x(21)\}$ to
 $\{x(2) x(7) x(12), \dots x(22)\}$

In contrast, our recurrence plot is based on the contiguous columns in the Frame domain, correlating them all at once, and repeating for neighborhood of Framing dimensions, which I think, in what Winfree was showing.

In effect, our recurrence plots are a series of autocorrelation surfaces of a cepstral neighborhood based framing technique, i.e., a relativistic series of ECG cepstral based framings

Originally, we picked up **our measure of Recurrence** along the diagonal of the autocorrelation surface, but then we started looking off diagonal And are now thinking of CNNs (convolutional neural networks with special Gabors).



Input:

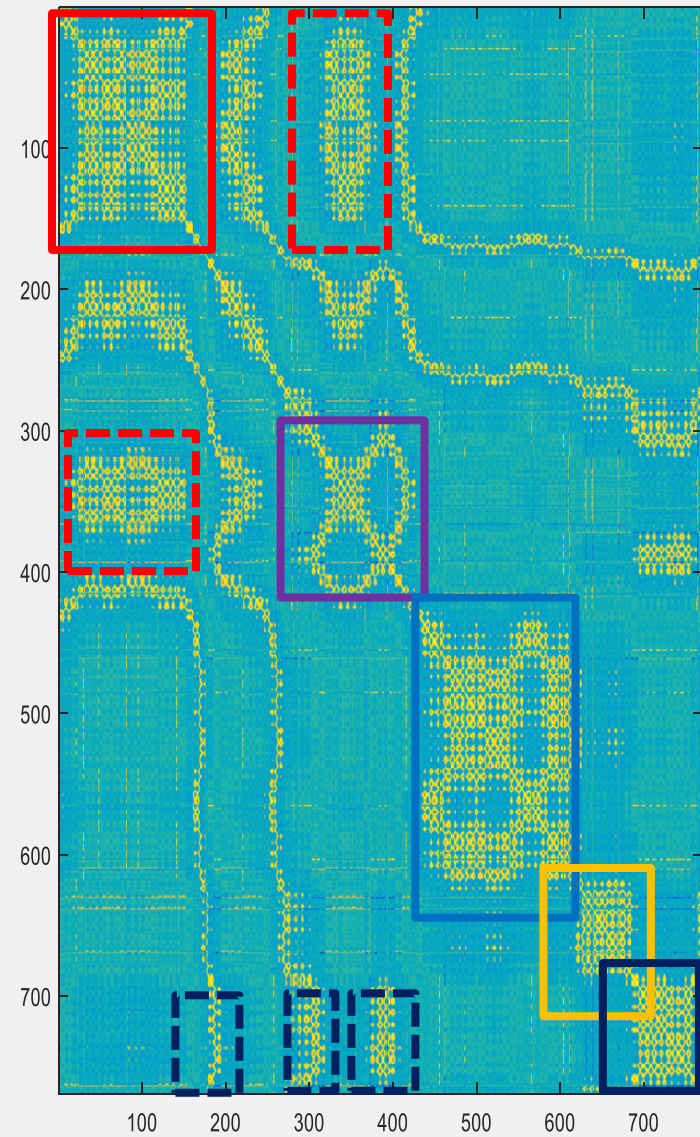
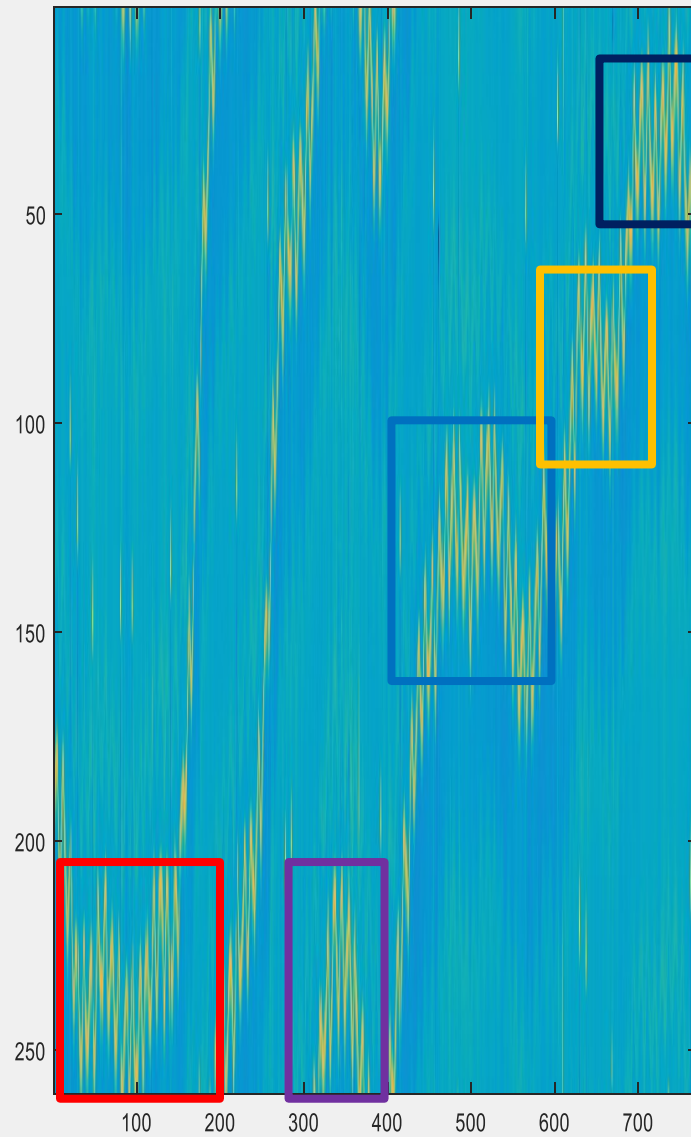
- Auto-Correlation Surface

Output:

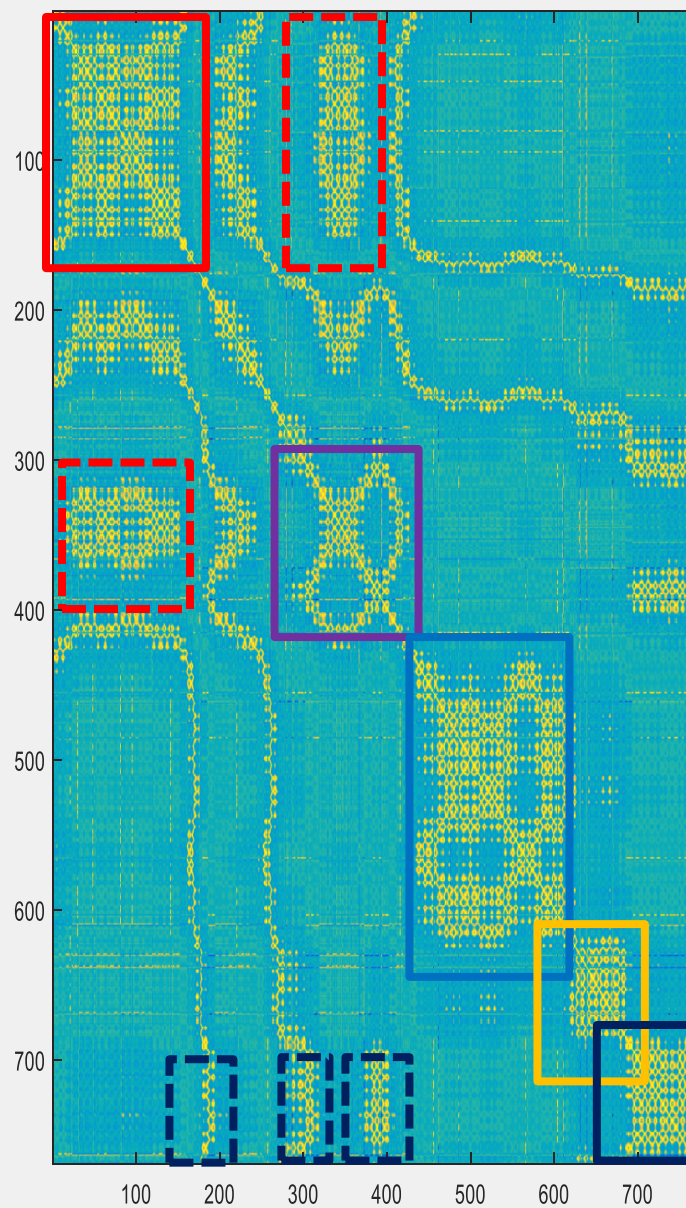
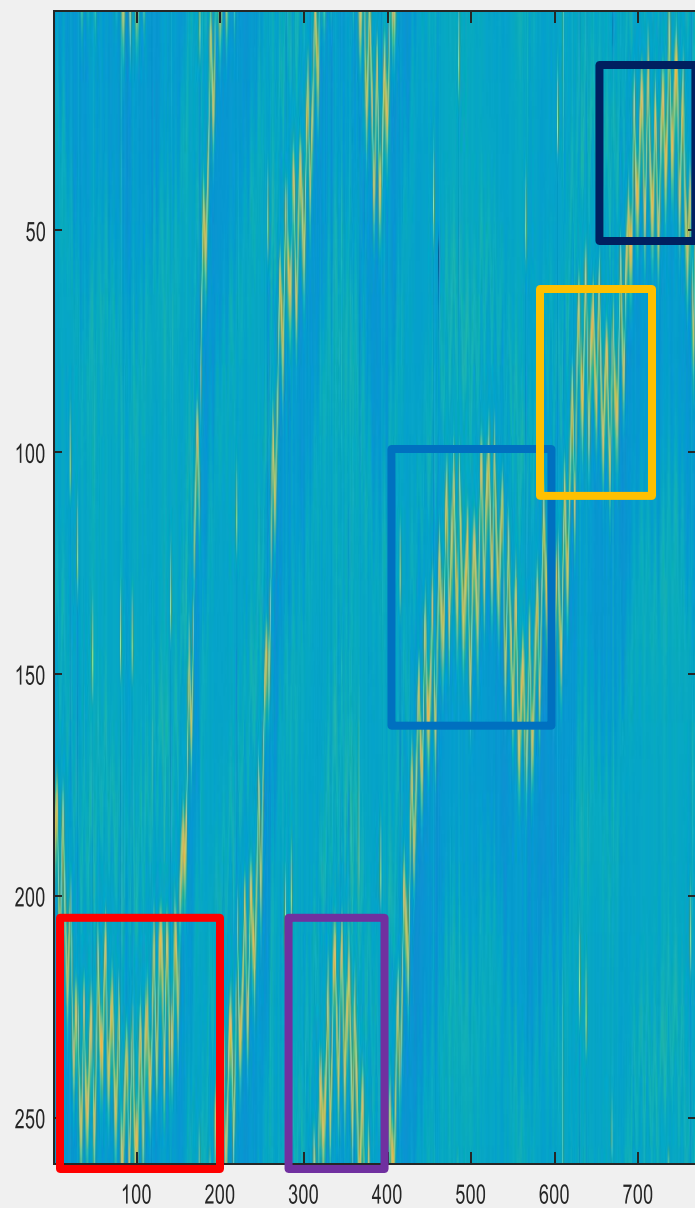
- Line Intersections
- X-Shaped Crossings in Auto-Correlation Surface

MITDB105 Heart rate= $fs * \text{Framesize} * 60 = 360/260 * 60 = 83 \text{ BPM}$

Figure 7



MITDB105 Heart rate= $fs \cdot \text{Framesize} / 60 = 360 / 260 \cdot 60 = 83 \text{ BPM}$

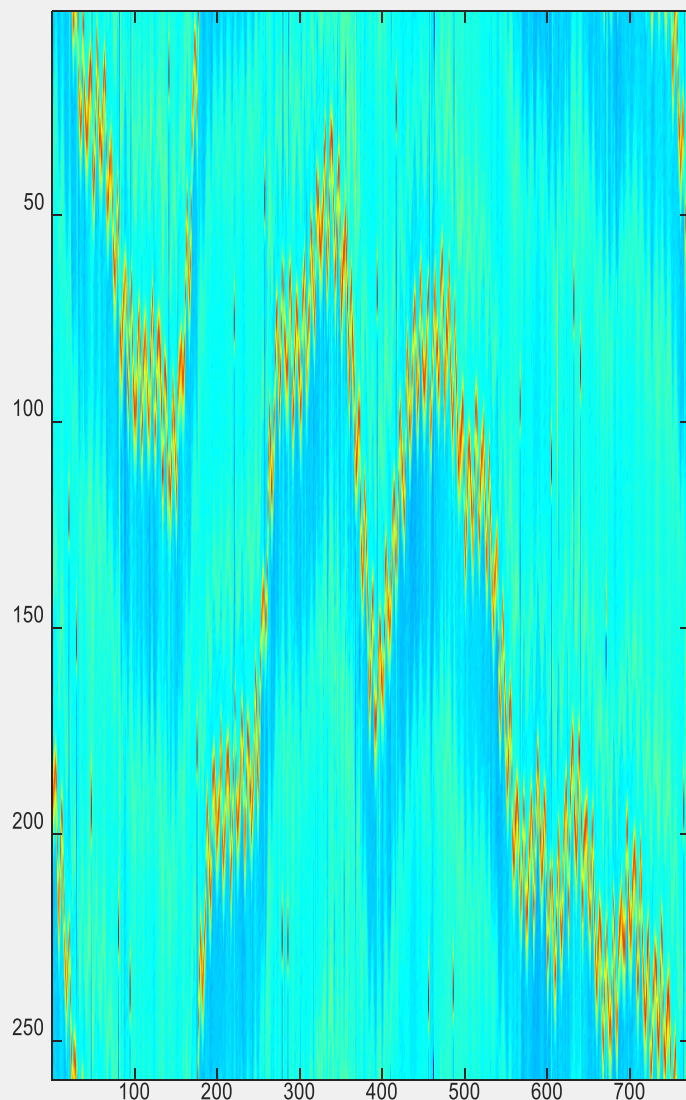


MITDB105 Heart rate= $fs * Framesize * 60 = 360 / 259 * 60 = 83.3$ BPM

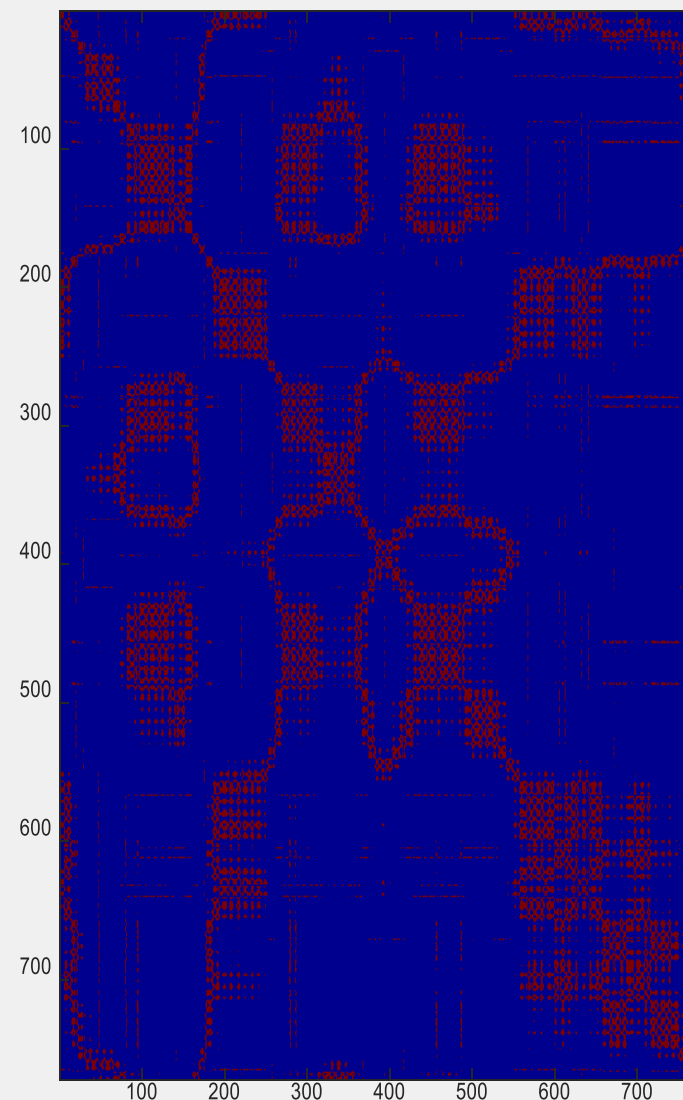
Figure 8

Whack-a-mole
slider

Framing at 83.3 beats per minute



Cross Frame Correlation



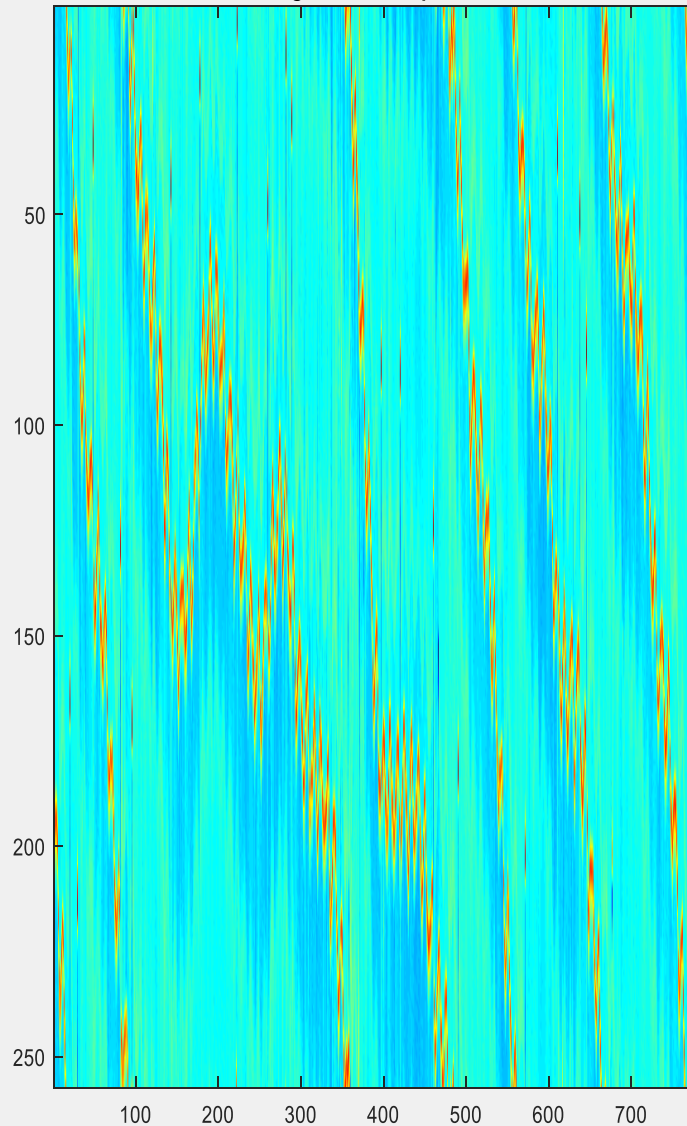
MITDB105 Heart rate= $fs * Framesize * 60 = 360 / 256 * 60 = 84$ BPM

Whack-a-mole

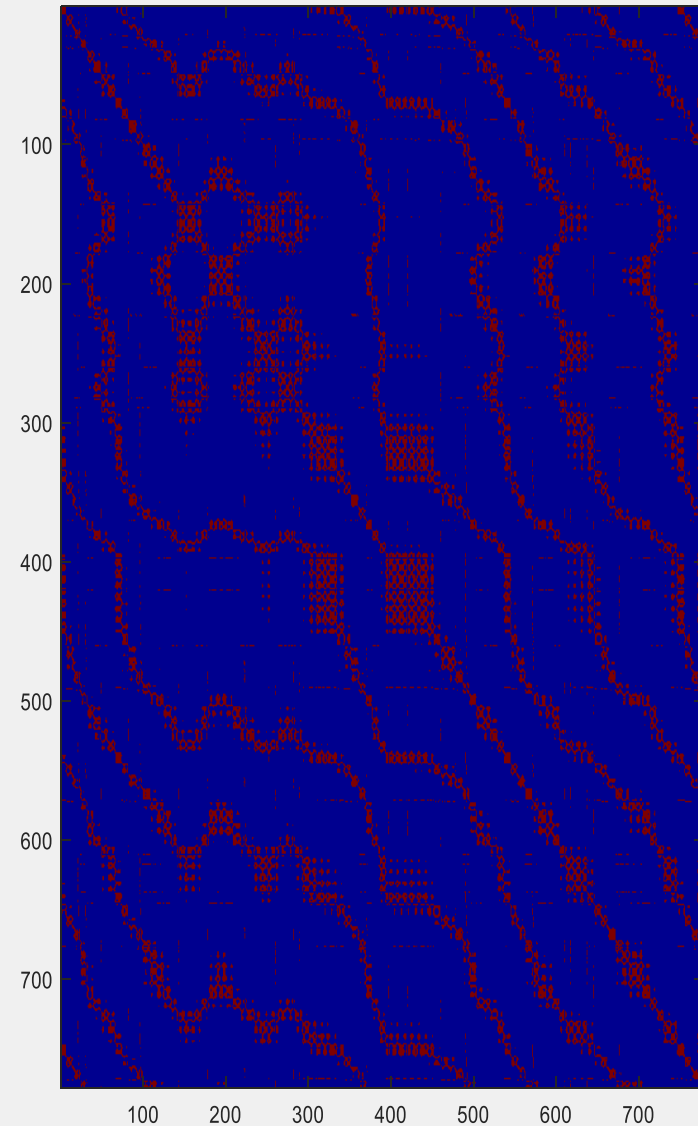
Figure 9

slider

Framing at 84 beats per minute

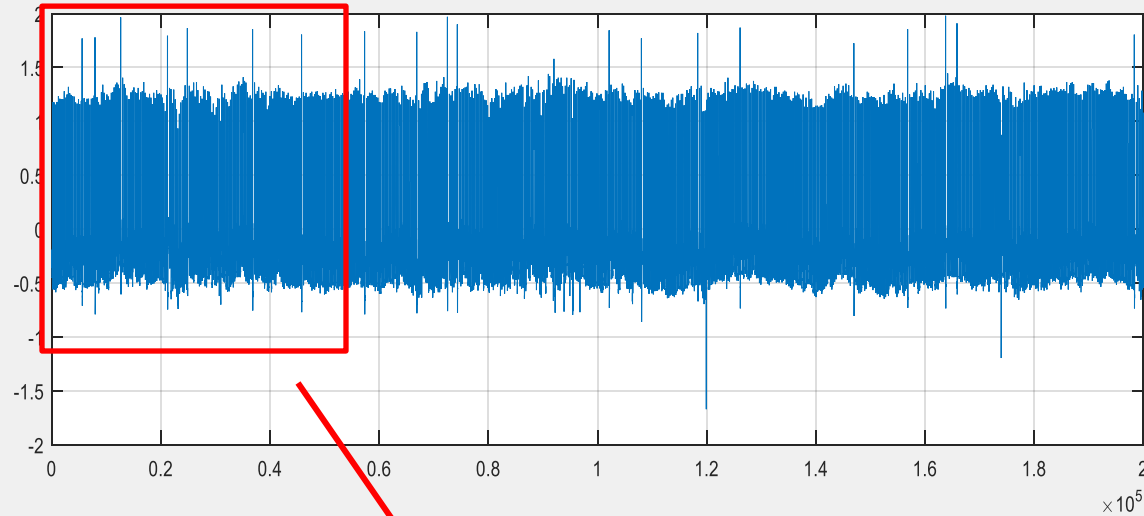


Cross Frame Correlation

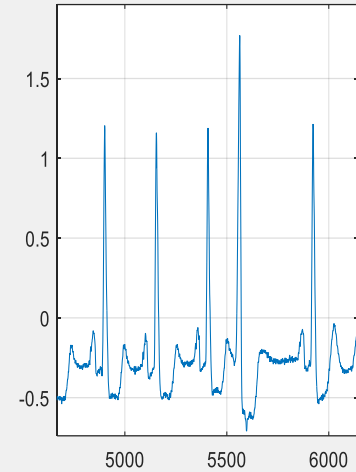


We started with this....

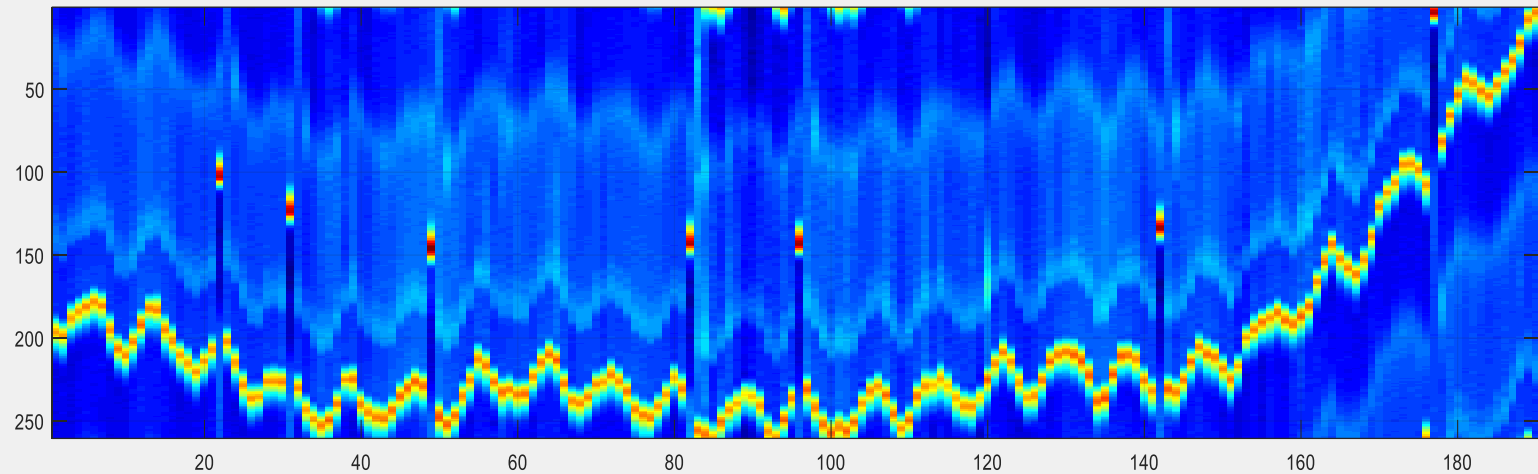
1. Dense plot of 200 ECG in time



ECGs with a PVC



Frame domain of above





Clemson student

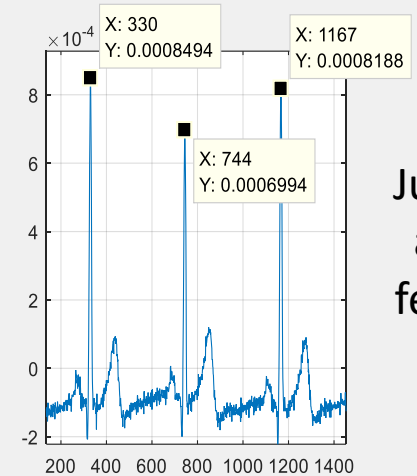
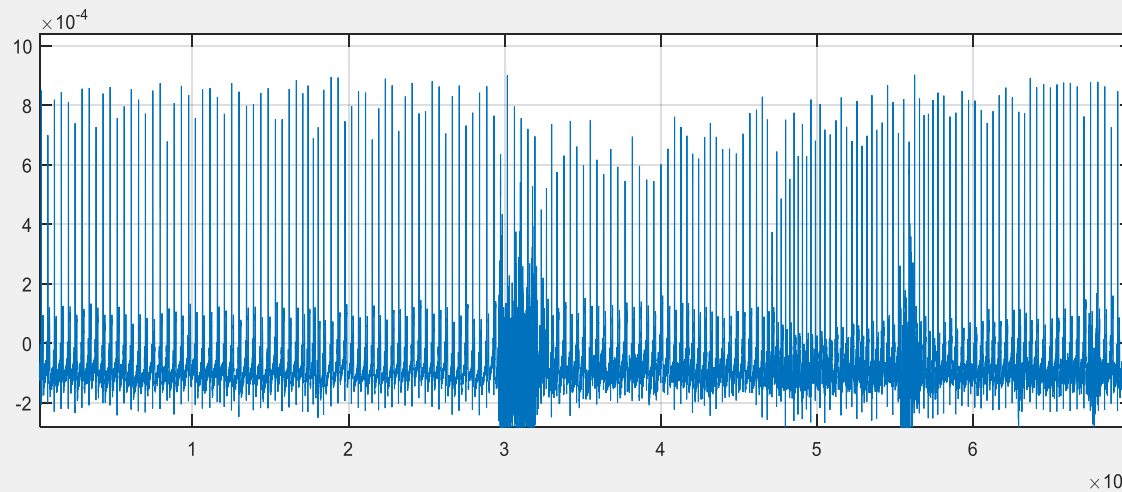
ADInstruments, PowerLab 26T, Model ML856

22 year old BioMed student, *my prodigal son*

3 minutes of ECG recorded at 400 samples/second

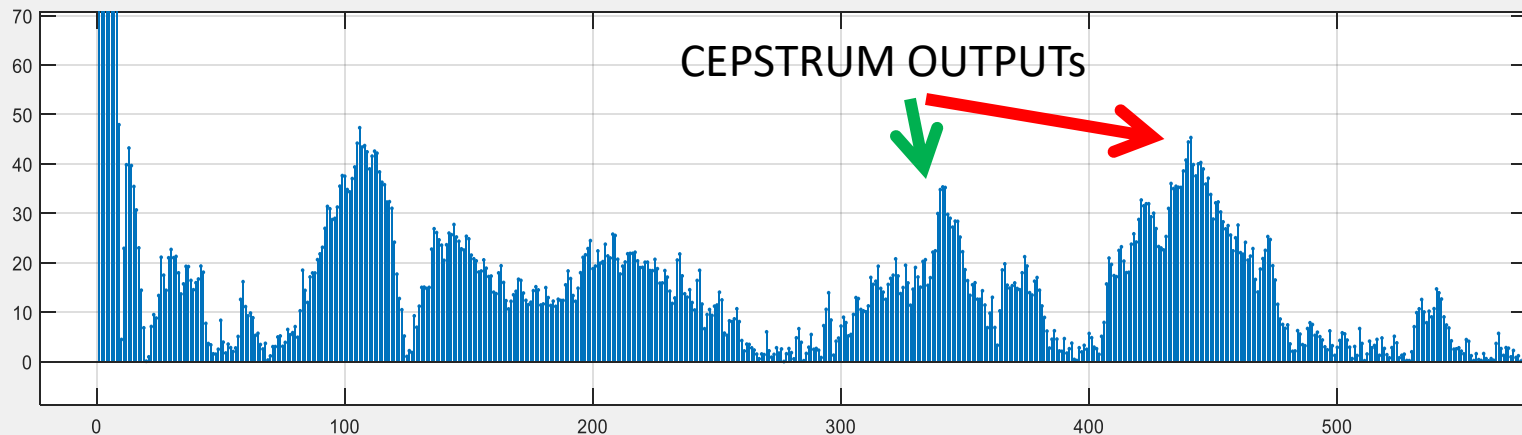
Relaxed state at beginning, fast breathing at end.

Series
of
ECG



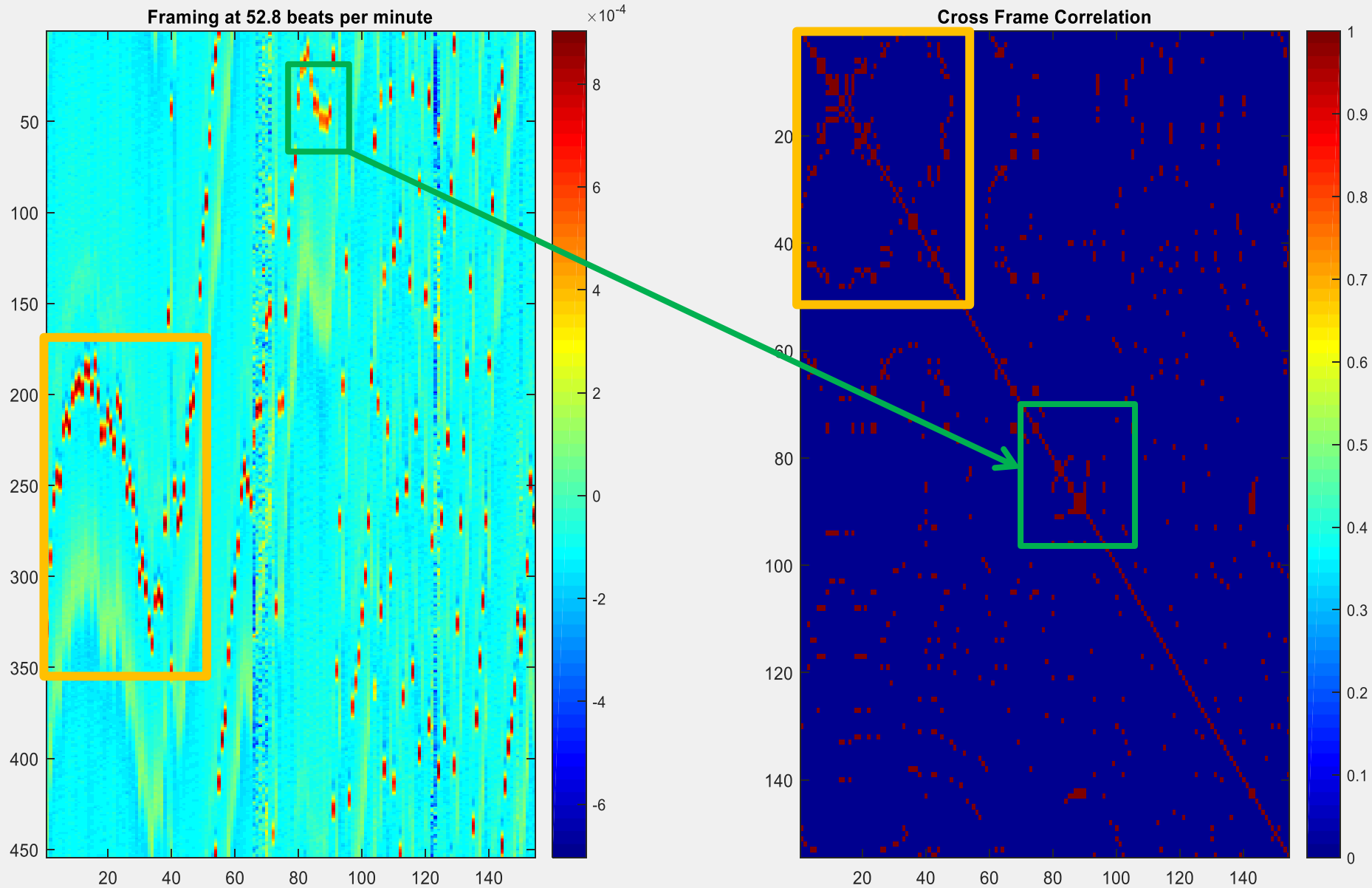
Just
a
few

Figure 10



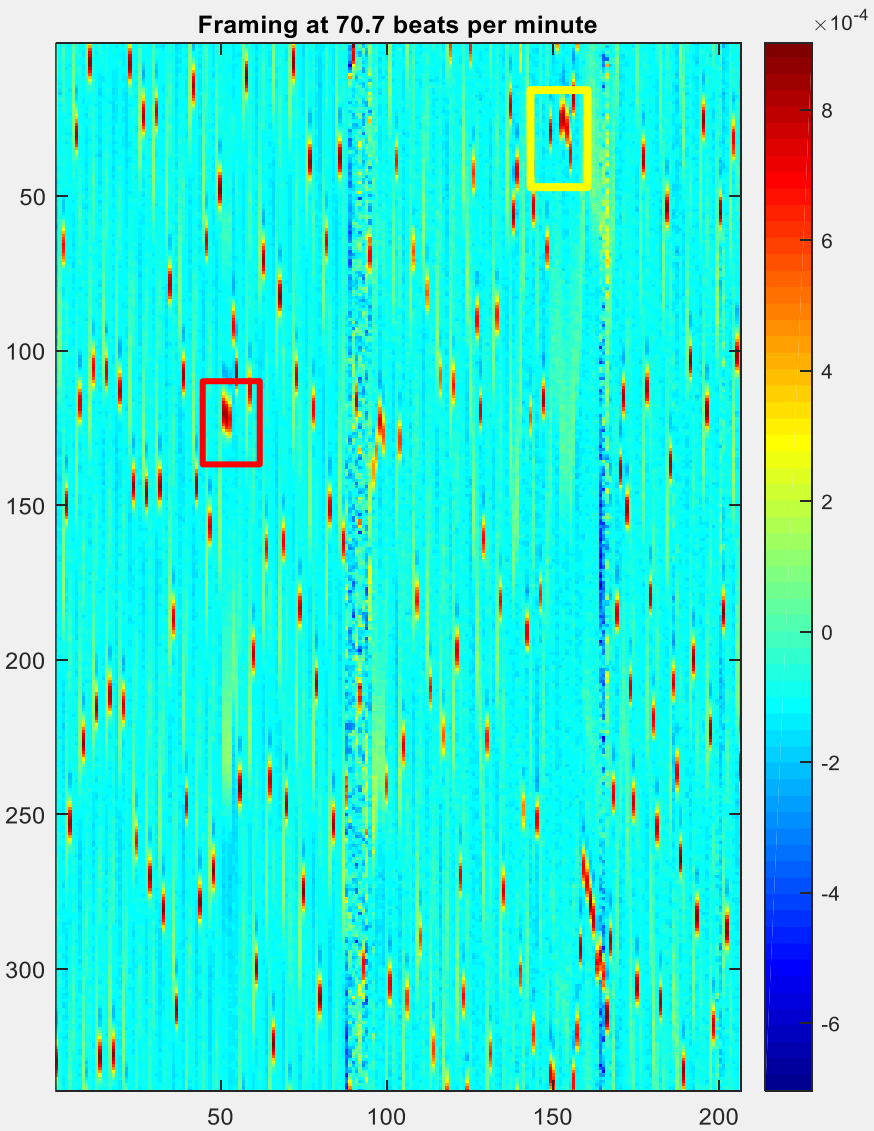
Slow rate *at beginning* shows cubic polynomial shape
With little stationary piece in *Green* later on

Figure 11



Couplets

Framing at 70.7 beats per minute



Cross Frame Correlation

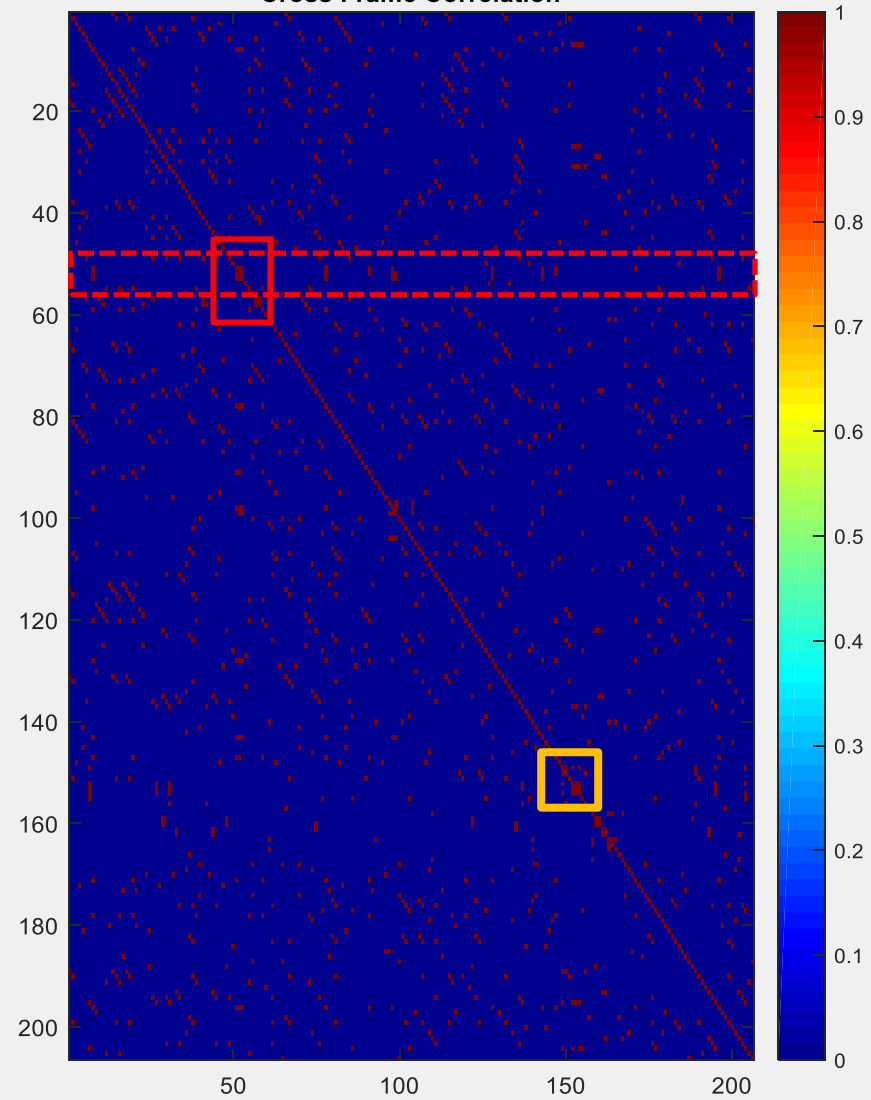
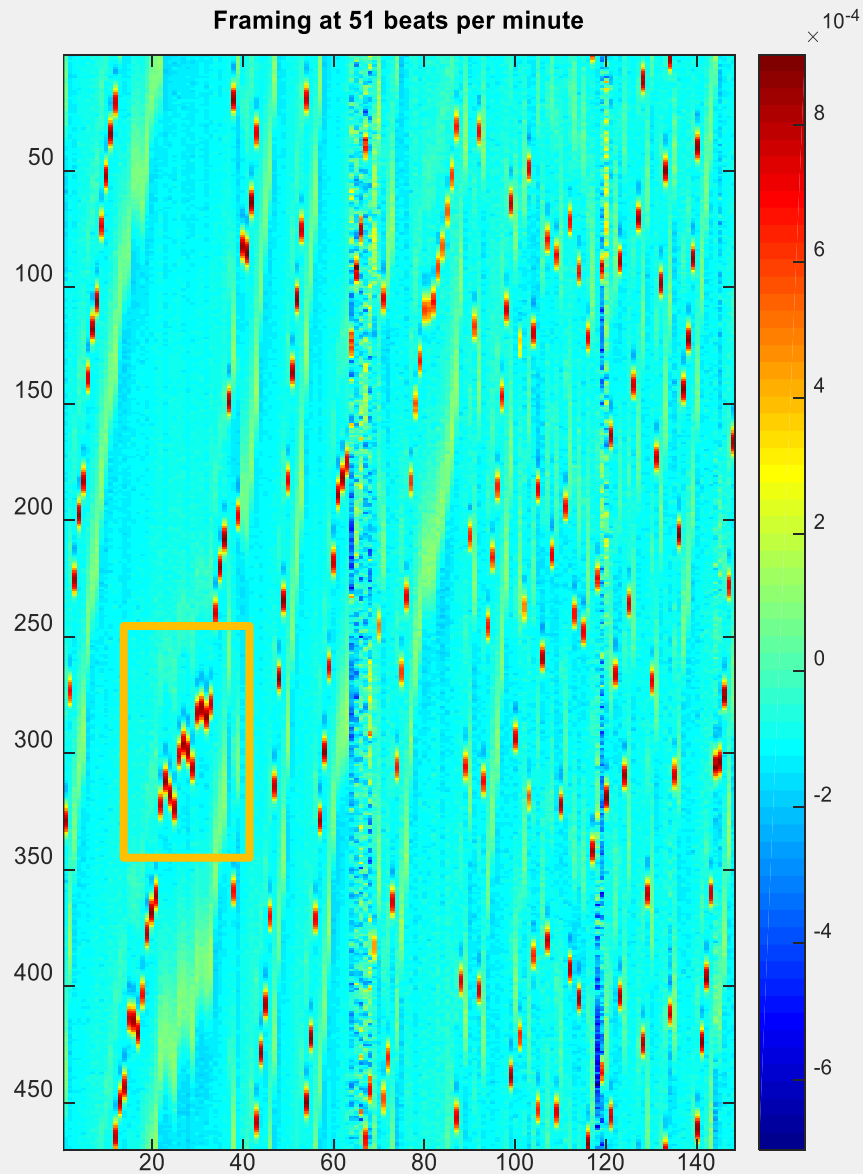
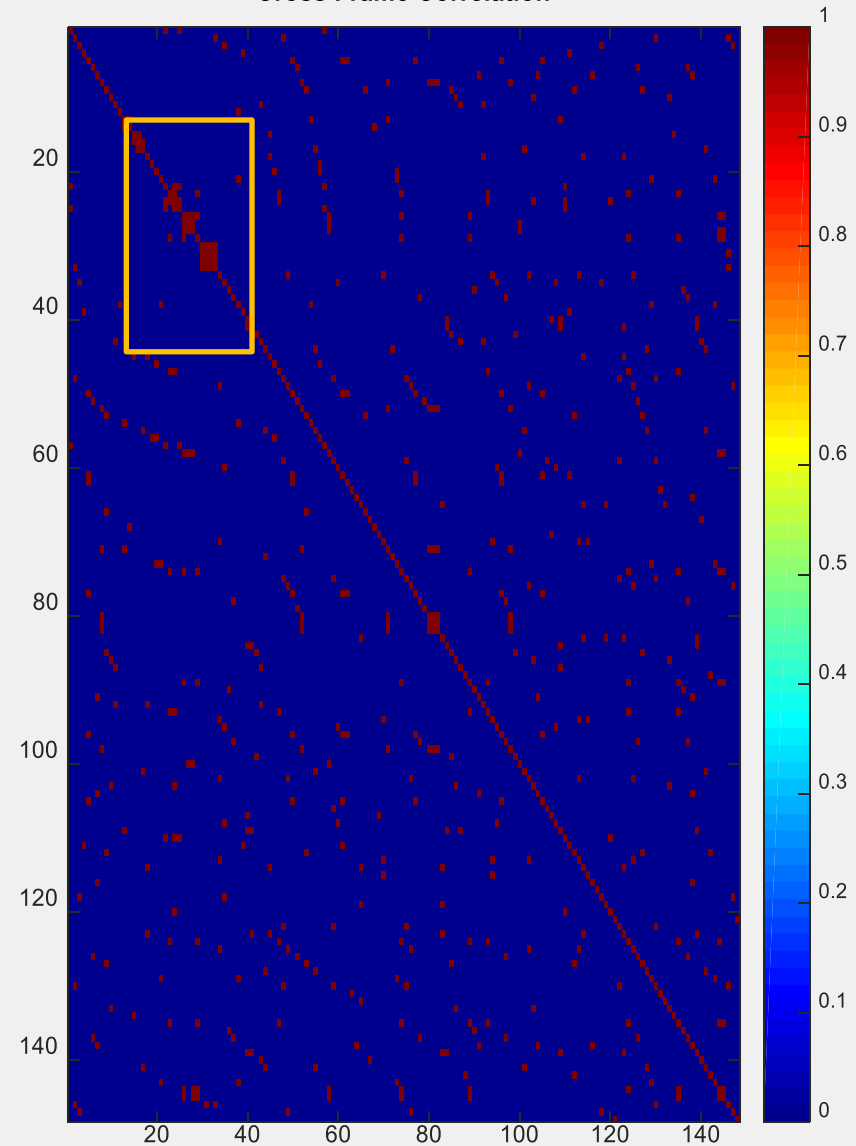


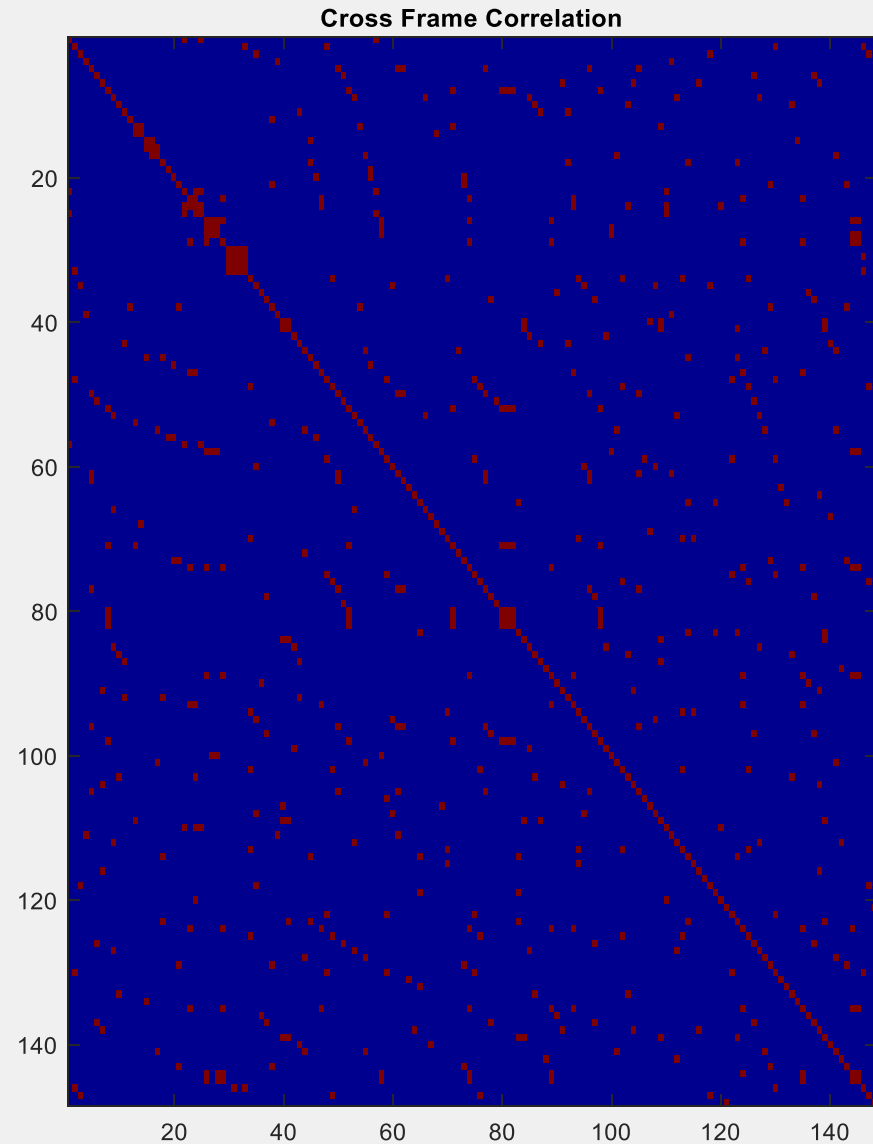
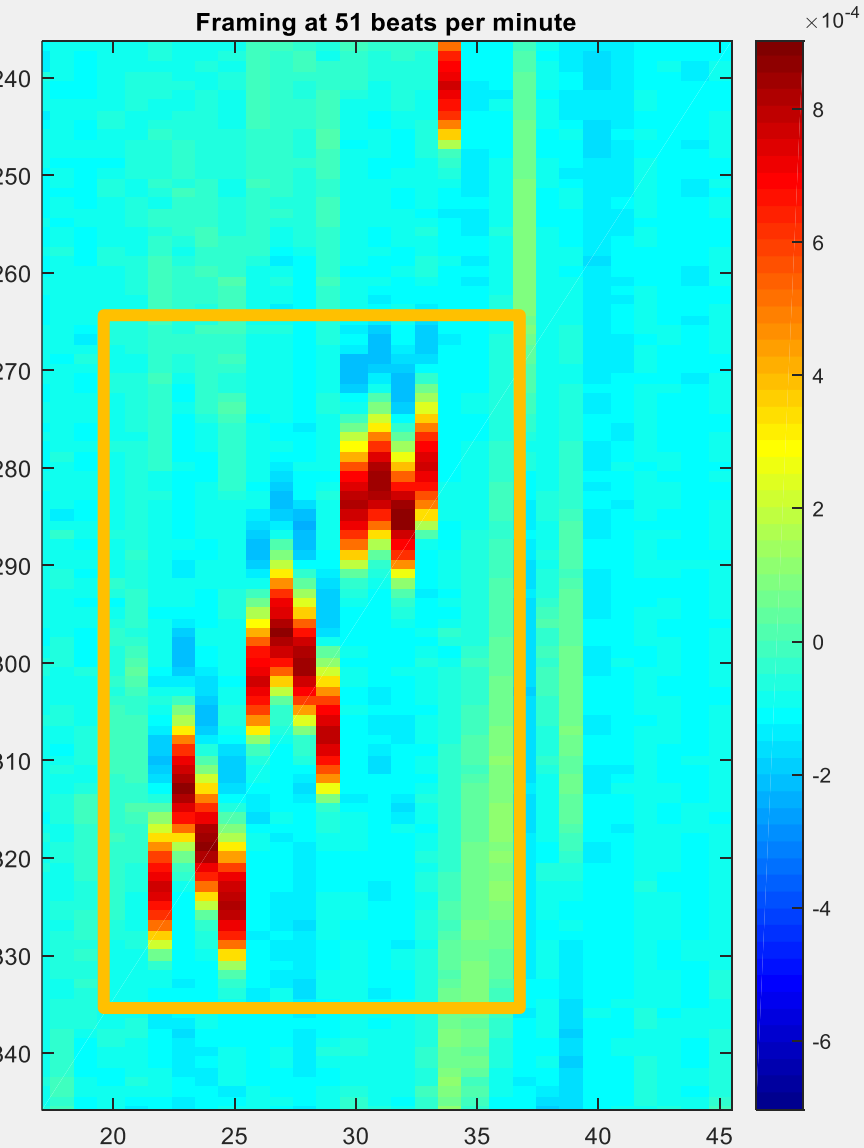
Figure 12

Sets of quazi-stationary ecgs at 51 BPM

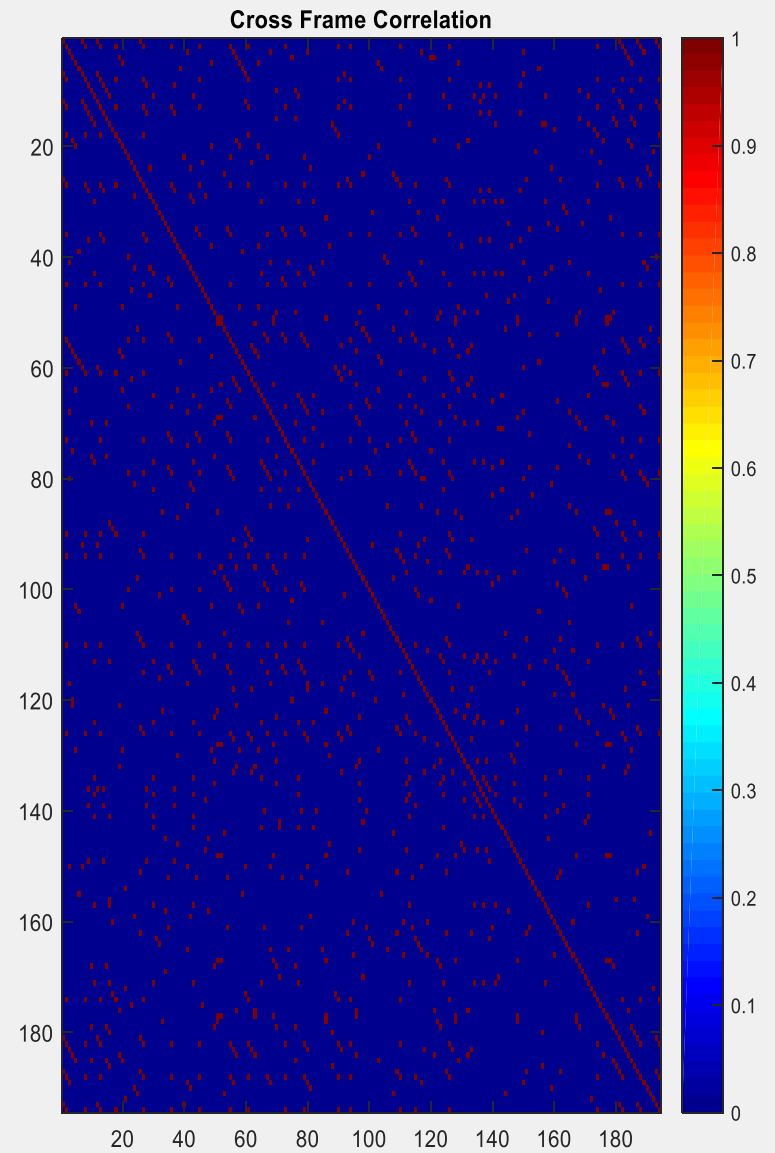
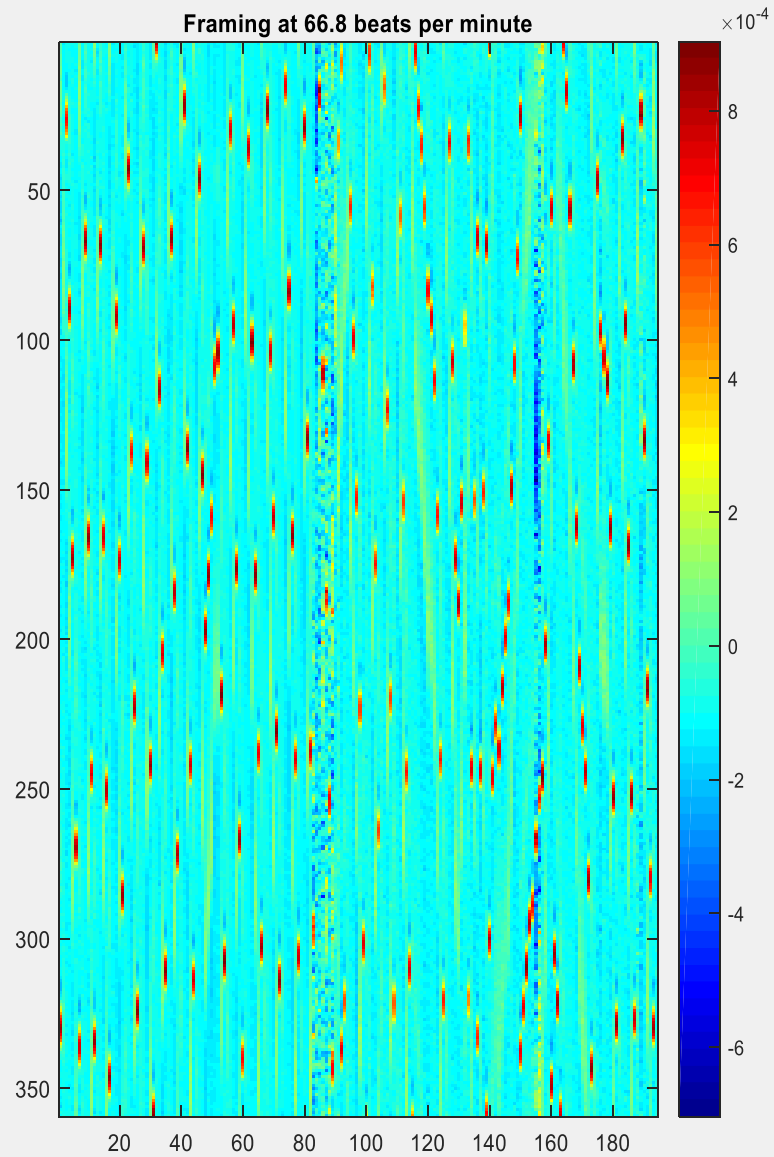
Framing at 51 beats per minute**Cross Frame Correlation**

Zoom in to find three sets of quadruplets

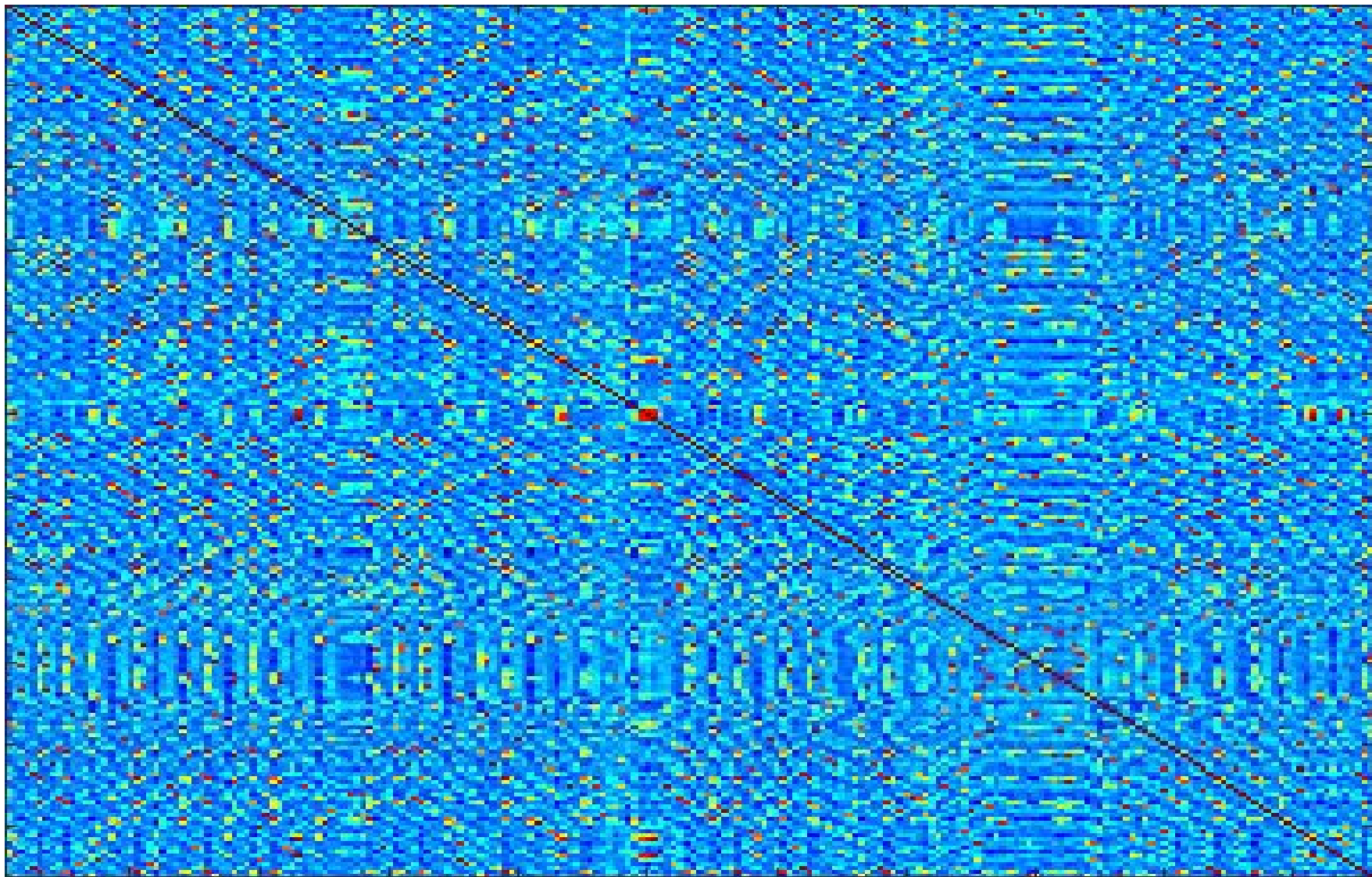
Figure 13



No pattern at this frame rate



Movie: Clemson Cepstral Series of Autocorrelation Surfaces



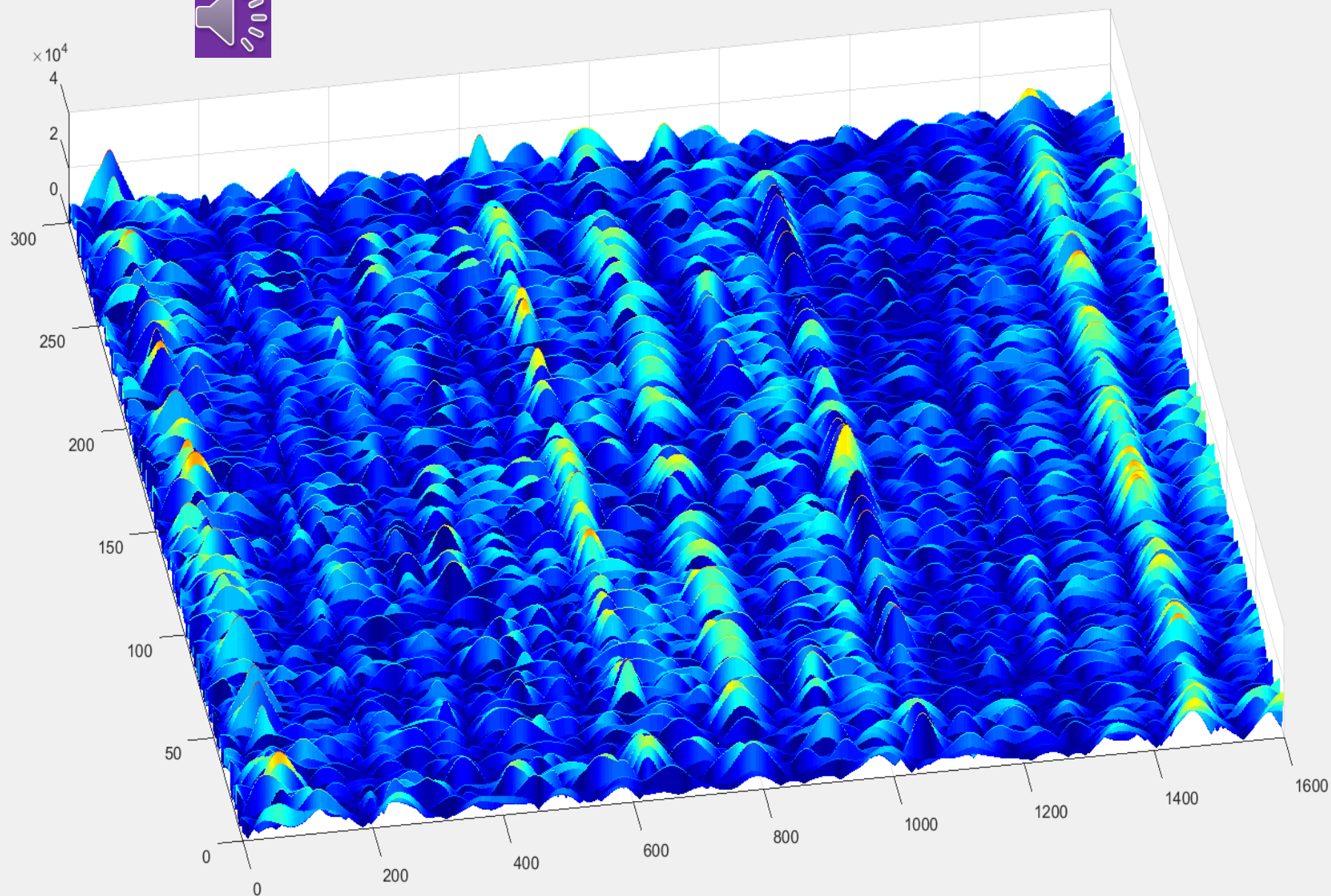
Wrap-Up

Imaging the evolution of ECG
may be done through cepstral-period based
autocorrelation recurrence matrices,

Outlook

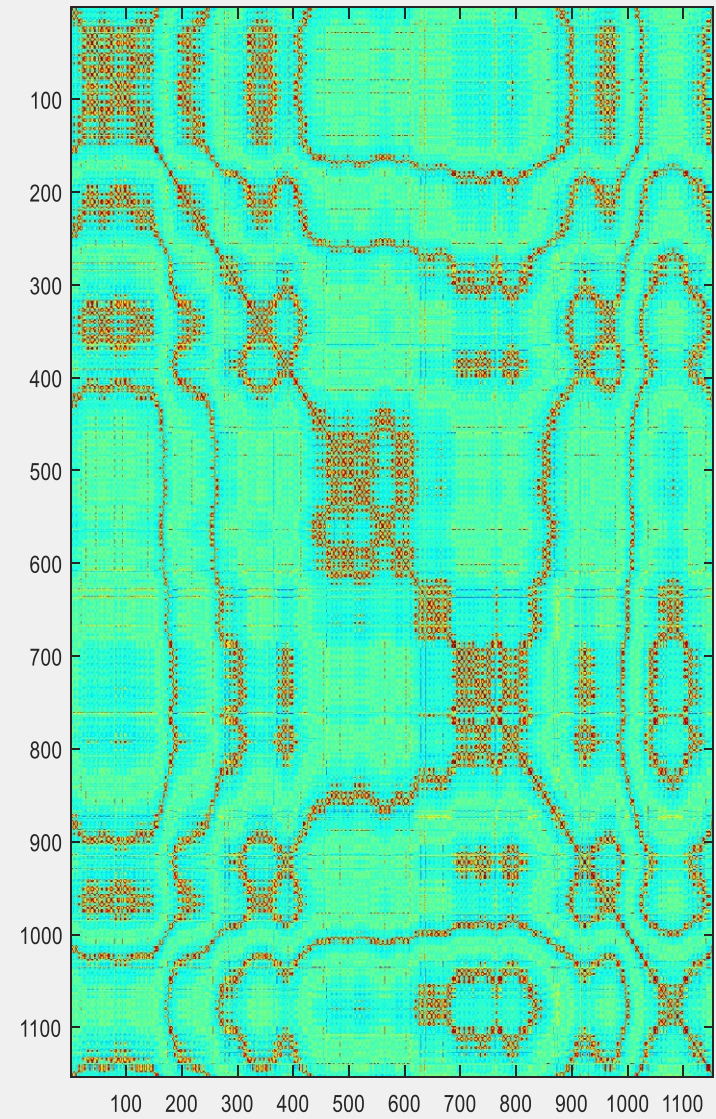
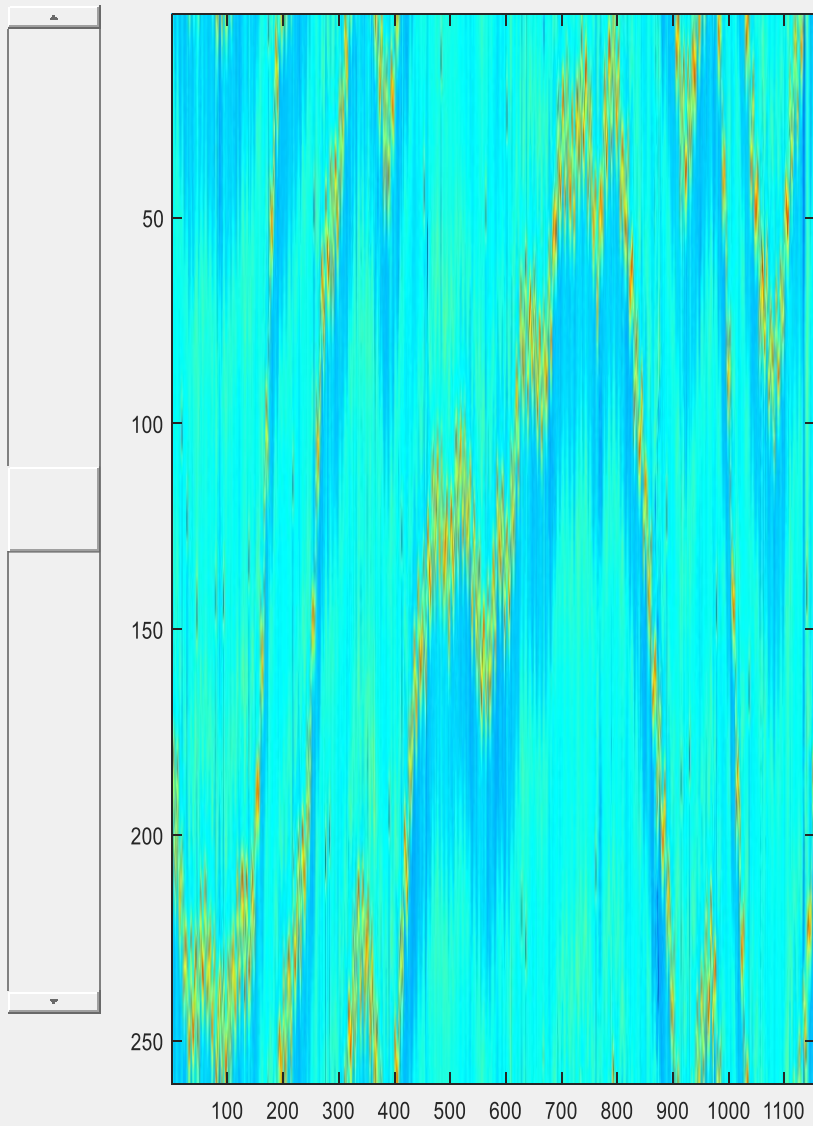
Connect ECG, EEG, and DNA through
Associative Memory streamlining of CNNs
(in preparation for realizing
Cyber-centered HCI)

Cepstral Terrain for Meditation Music



A little Lagniappe

The Dad of Prodigal Son



A Honey Bee Recurrence, before entering the Hive

