Practicalities of analysing biosignals

August 24, 2015

In [1]:
```
import IPython.display as display
import numpy as np
import matplotlib.pyplot as plt
import matplotlib as mpl
%matplotlib inline
```

1 Practicalities of analysing biosignals

1.1 Dr. Emlyn Clay Head of Software Development Viditeck AG, Director of OpenVivo ltd.

2 Who am I?

- Undergraduate Pharmacology (~2009) and doctorate of Pharamcology (2015)
- Writing software since I was 18, professionally since 22
- Web stuff (PHP), then VBscript, then MATLAB, then Python, then C ... etc
- I spend most of my time programming and distributing biomedical equipment.

In [8]:
```
display.Image(filename='images/emlyn.jpg')
```

Out[8]:

3 Committee member of PyData London!

- Monthly meetup for data science peoples using Python.
- ~1800 members, regular 200 people meetups.
- Yearly conference.
- Advocate the Python community.

In [9]:
```
display.Image(filename='images/pydata_logo.png')
```

Out[9]:

4 Emlyn said . . .

```
To: dgorissen@gmail.com
CC: "london@pydata.org" <london@pydata.org>
Subject: PyData London Call for Proposal - mind circulating?

Hello Dirk,

Do you mind forwarding the following call for proposal, below, for our PyData London Conference 2015 on

Thanks Dirk,

Emlyn

------

Hello Big Omegas,

...
```

5 Dirk said . . .

```
Date: Fri, 8 May 2015 22:00:53 +0100
```

```
Subject: Re: PyData London Call for Proposal - mind circulating?
To: Emlyn Clay <eclay101@gmail.com>

On the condition you come do a talk ;) I have a slot week of 17 August :)
-----------------------------------------
Dr. Dirk Gorissen
Research - Tech4Good - Flying Robots
Skype: dirk.gorissen
Mob: +44-7763-806-809
Twitter  : https://twitter.com/dirkgor
LinkedIn: http://www.linkedin.com/in/dirkgorissen
```

Bribery!

6 Biosignals

Definitvely -

> A biosignal is any signal in living organisms that can be measured and monitored, contiually or intermittently. Some are bioelectrical, but it may refer to both electrical and non-electrical signals.

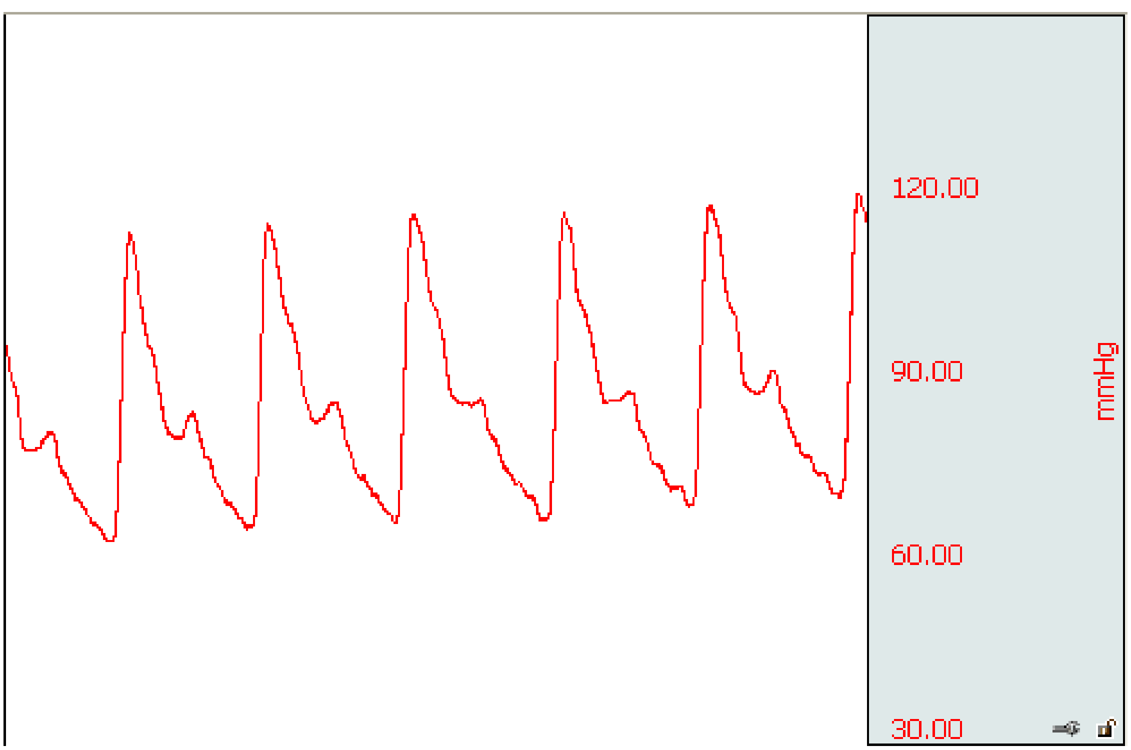
Analysing them can be used to assess:

- Healthy "normative" states
- Disease states
- Fundamental understanding

6.1 Blood pressure

```
In [10]: display.Image(filename='images/signal_blood-pressure.png')
```

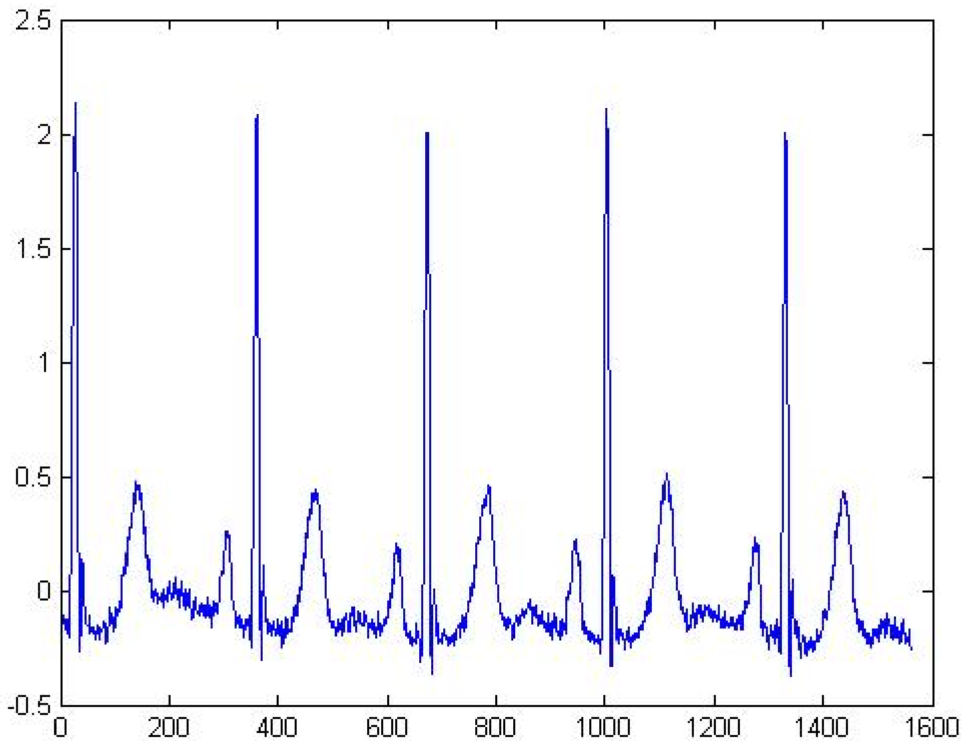
Out[10]:



6.2 ECG

```
In [12]: display.Image(filename='images/signal_ECG.jpeg')
```

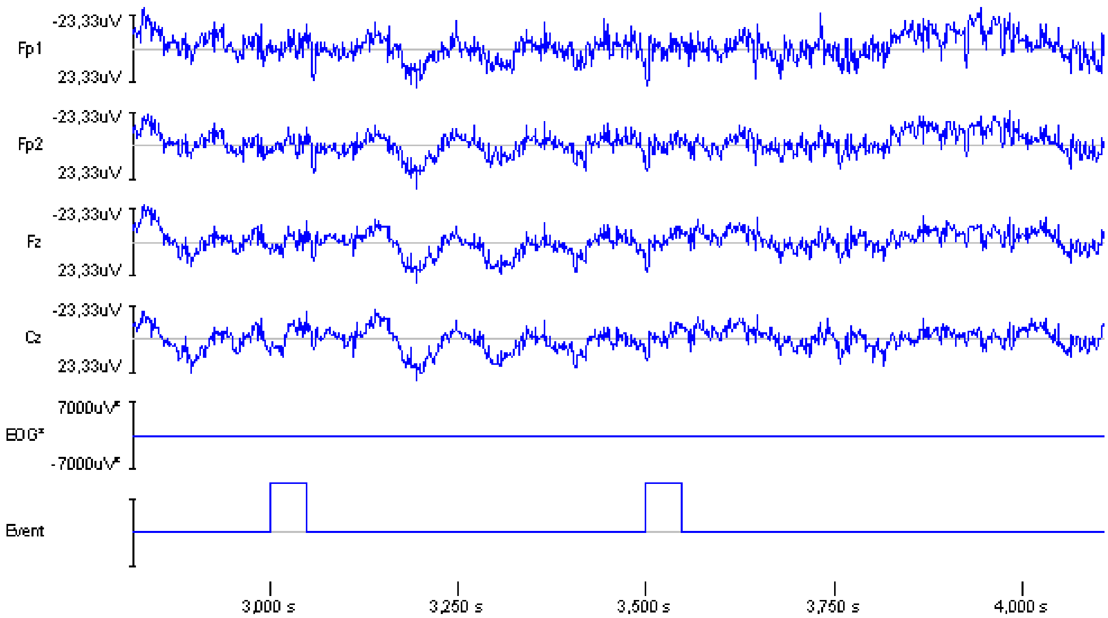
Out[12]:



6.3 EEG

```
In [13]: display.Image(filename='images/signal_EEG.png')
```

Out[13]:



7 What are we looking at today?

Practicalities.

- Record biosignals
- Storing them
- Process them
- Analyse them

8 Recording biosignals

Things you are going to need -

- Sensor
- Amplifier
- Analogue to Digital Convertor
- Storage media

8.1 Sensors

- A thing that attaches to the person,
- Possibly a box that is powering and conditioning the signal
- Something that connects to your amplifier

In [18]:
```
display.Image(filename="images/sensors.png")
```

Out[18]:

8.2 Amplifier and data acquisition

Often they are in the same box.

```
In [19]: display.Image(filename="images/gusbamp.png")
```

Out[19]:

8.3 Storage media

Often it's a laptop or sometimes some embedded storage like a flash disk

In [20]:
```python
display.Image(filename="images/digital_storage.jpg")
```

Out[20]:

9 Salient points on equipment

Sensors + Calibrated + Sensitive, but not noisy

Amplifier/DAQ + Certified for use (CE, FDA) — not strictly necessary for hobbyist use, + *Don't connect hobby tech to mains! Use a battery.* + High raw sampling rate — oversampling. + Low noise, high input impedance.

Storage + Make sure it can handle your bandwidth + Get lots of it - one minute of ECG uncompressed, ~120Mb (2 x 1024 x 60)

10 Storing Biosignals

Large vectors of doubles, some metadata about what we've recorded and feature markers for features we've spotted.

11 HDF5!

12 HDF5

- Portable
- Bindings to everything (C, Fortran, Python, Matlab, Java . . .)

- Supports contiguous or chunked datasets
- Performant.
- Good features for storing metadata

13 HDF5 in Python

```
In [2]: import h5py
        import numpy as np

        f = h5py.File("ecg.h5", "w")
        dset = f.create_dataset("ECG", (1024,), dtype='f')
```

14 HDF5 datasets

Store the raw signal in one dataset, store a processed signal in another.

```
In [3]: raw_ECG = f.create_dataset("raw_ECG", (65772,), dtype='f')
        normal_ECG = f.create_dataset("normal_ECG", (65772,), dtype='f')
        smoothed_ECG = f.create_dataset("smoothed_ECG", (65772,), dtype='f')
```

15 HDF5 groups

Useful for grouping results by subject

```
In [ ]: emlyn = f.create_group("subject_emlyn")
```

16 HDF5 attributes

You can store metadata right next to the data it describes! Yay!

```
In [8]: normal_ECG.attrs['species'] = 'human'
        normal_ECG.attrs['subject'] = 'emlyn'
        normal_ECG.attrs['date'] = '12/06/2007'
        normal_ECG.attrs['sex'] = 'Yes please'
```

17 Processing biosignals

Essentially it's digital signal processing — same rules apply. Biosignals tends to be continuous, periodic and complex waveforms.

17.1 Basic a.ka. cleaning the signal

- Filtering noise
- Correct the baseline
- Smoothing

17.2 Advanced a.k.a feature detection

- Peak detection
- Wavelet transformations
- Morphology analysis

18 Basic processing

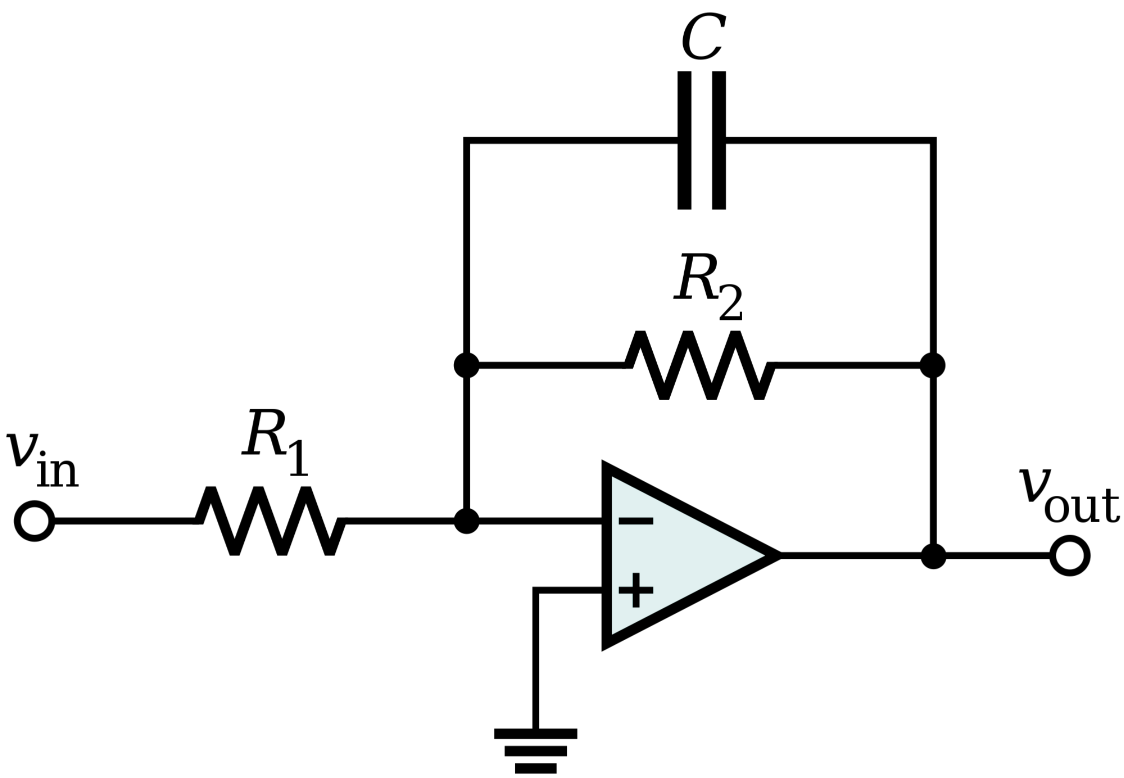
19 Filtering noise

The signal you are looking for is usually between a specific wavelength so you can apply bandpass filters to just focus on the region of interest.

... you can do this with analogue electronics

```
In [18]: display.Image(filename='images/lowpass_filter.png', width='400px')
```

Out[18]:



... but, then you have to worry about all sorts of compromises due to frequency responses and cut-off definition.

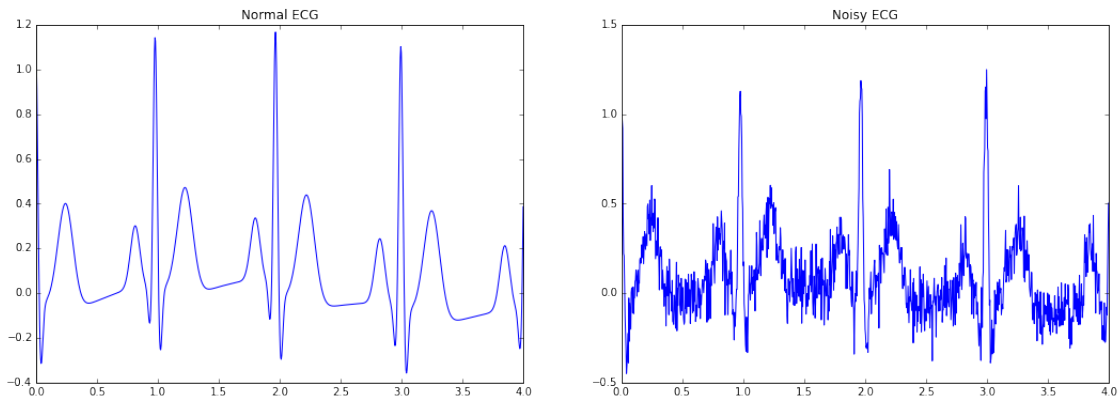
Filtering noise with the FFT

The grand conceit of Fourier's work was that all sinusoids can be described as a series of sinusoids superimposed on one another.

```
In [3]: # Load an ECG
        samples = 1024
        time = np.loadtxt('data/ecgsyn.dat', usecols=(0,))
        ecg = np.loadtxt('data/ecgsyn.dat', usecols=(1,))
        noise = np.random.normal(0,0.1,samples)

        figure = plt.figure(figsize=(18, 6))
        ax1 = figure.add_subplot(121)
        ax2 = figure.add_subplot(122)
```

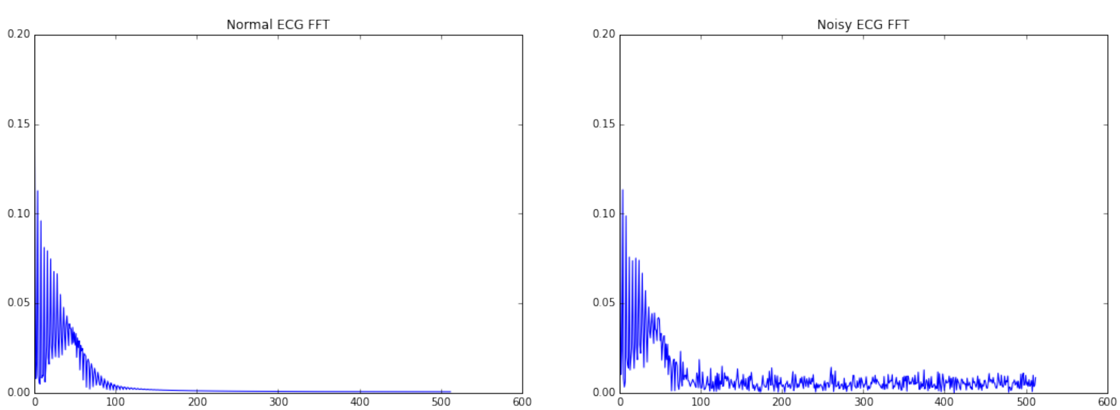
```
        ax1.set_title('Normal ECG')
        ax1.plot(time[:samples], ecg[:samples])

        # Add some noise
        ax2.set_title('Noisy ECG')
        ax2.plot(time[:samples], ecg[:samples]+noise)
```

Out[3]: [<matplotlib.lines.Line2D at 0x109359690>]




```
In [4]: normal_ecg_fft = np.fft.fft(ecg[:samples])
        noisy_ecg_fft = np.fft.fft(ecg[:samples]+noise)

        figure = plt.figure(figsize=(18, 6))
        ax1 = figure.add_subplot(121)
        ax2 = figure.add_subplot(122)

        freqs = np.linspace(0.0, 1.0/(2.0*(1/samples)), samples/2)

        ax1.set_title('Normal ECG FFT')
        ax1.plot(freqs, 2.0/samples * np.abs(normal_ecg_fft[0:samples/2]))

        ax2.set_title('Noisy ECG FFT')
        ax2.plot(freqs, 2.0/samples * np.abs(noisy_ecg_fft[0:samples/2]))
```

Out[4]: [<matplotlib.lines.Line2D at 0x10a1a3a90>]



... zero the numbers of the frequencies you don't want and you filter them from the signal.

20 Correct a baseline

20.1 ... for quiet signals (ECG)

- Substract the modal value away from the signal
- FFT and filter lower frequency components

20.2 ... for noisy signals (EEG)

- Substract the mean away from the signal
- Substract a window mean also.

20.3 ... or it's a trivial point

- The segment behind the P-wave is the baseline for the ECG
- The trough of diastole is the baseline for blood pressure

21 Smoothing

Noise is often random so a moving-average moving-exponential window are good, but there are caveats. There is a tradeoff between:

- How smooth the signal is
- How precise the peaks (and troughs) are

... I often use the Savitzky-Golay smooth with biosignals because it favours maintaining the shape of the signal.

21.1 Introduction to Signal Processing — Smoothing University of Maryland

```
In [51]: display.IFrame('http://terpconnect.umd.edu/~toh/spectrum/Smoothing.html', width="100%", height
```

```
Out[51]: <IPython.lib.display.IFrame at 0x10b9ce590>
```

22 Advanced processing

22.1 Peak detection

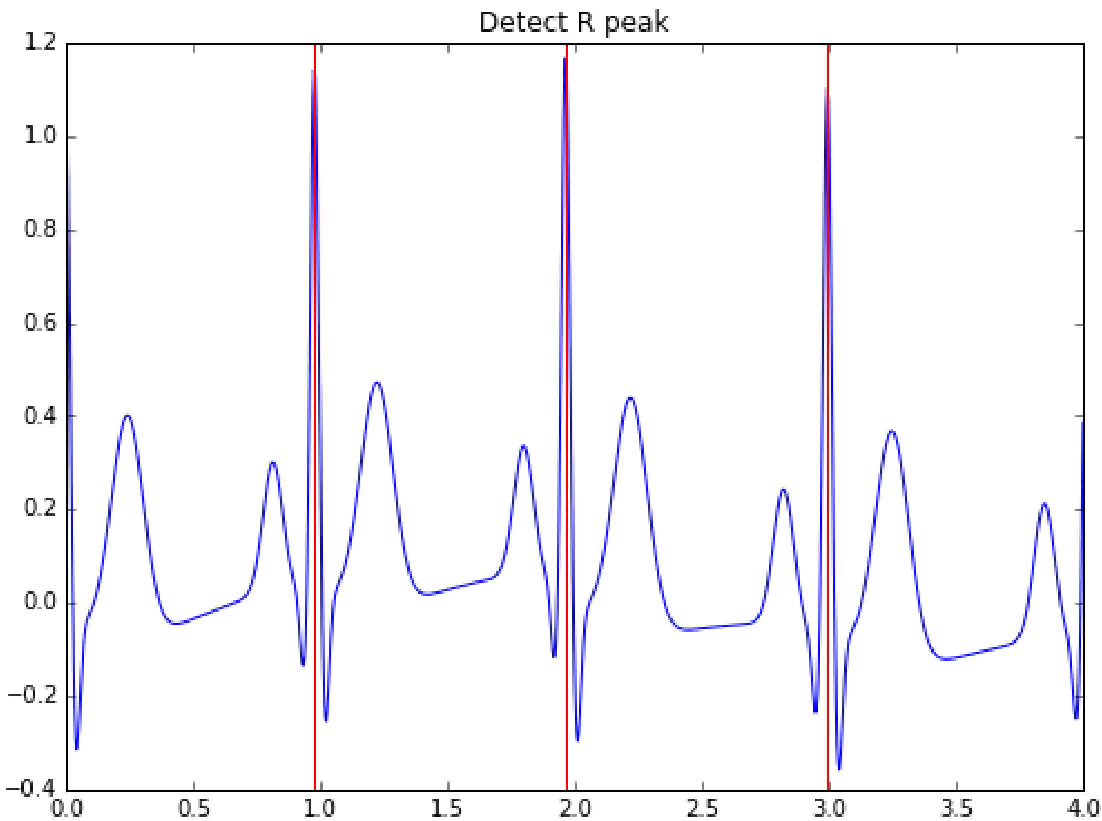
Signals have a variety of peaks that often relate to an event.

The strategy is to: 1. Smooth the signal to reduce local maxima influence 2. Set a treshold height and width 3. Use a moving-window regression to locate peaks

23 R-peak detection

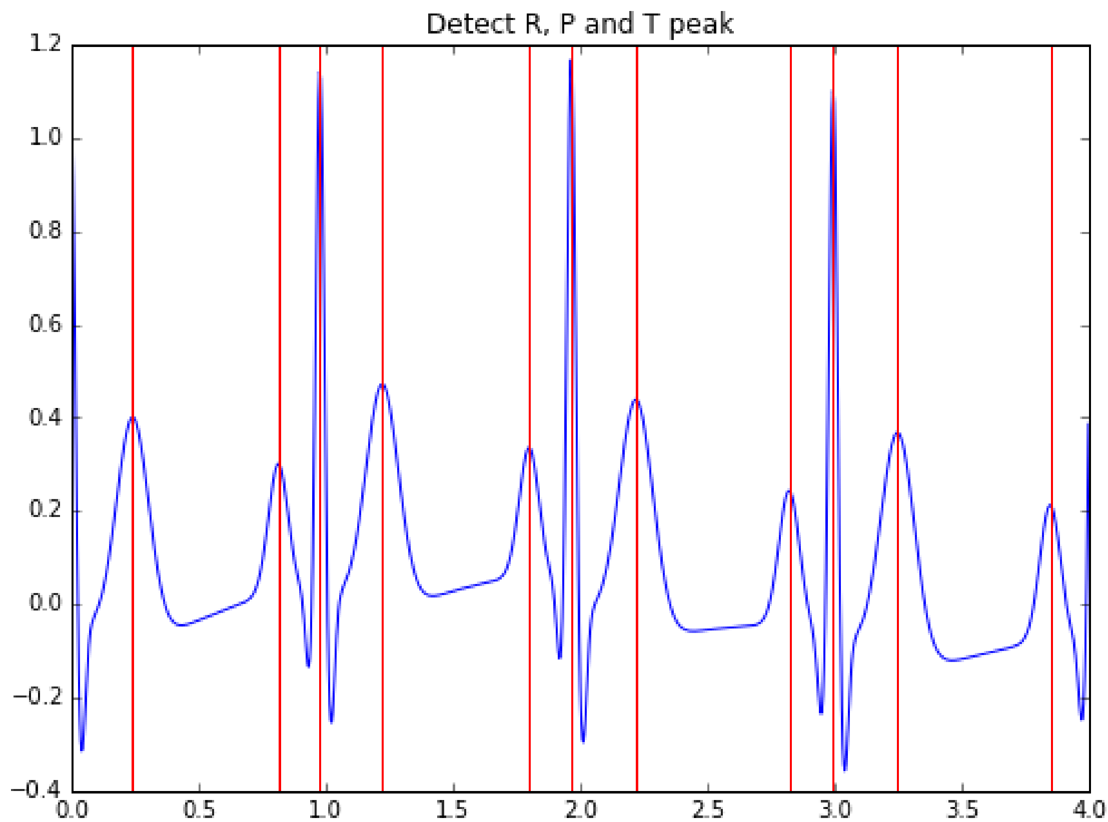
```
In [22]: import peakutils # arg! this should be in scipy.signal

         peak_index = peakutils.indexes(ecg[:samples], thres=0.4, min_dist=0.1)

         figure = plt.figure(figsize=(18, 6))
```

```
ax1 = figure.add_subplot(121)

ax1.set_title('Detect R peak')
ax1.plot(time[:samples], ecg[:samples])

for peak in peak_index:
    ax1.axvline(x=time[peak], color='r')
```



24 R-peak, P-wave and T-wave detection

```
In [25]: import peakutils

         peak_index = peakutils.indexes(ecg[:samples], thres=0.1, min_dist=0.1)

         figure = plt.figure(figsize=(18, 6))
         ax1 = figure.add_subplot(121)

         ax1.set_title('Detect R, P and T peak')
         ax1.plot(time[:samples], ecg[:samples])

         for peak in peak_index:
             ax1.axvline(x=time[peak], color='r')
```



24.1 Wavelet transformations

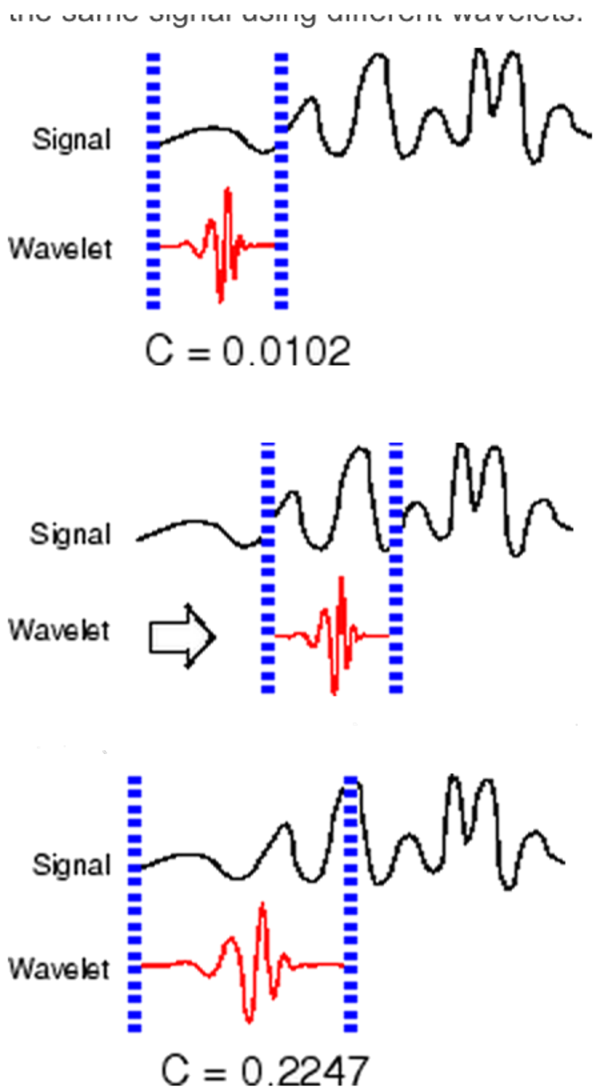
FFT is great, but it isn't very good for telling us about the time-frequency relationship at a given point in time.

24.1.1 Continuous wavelet

> Continues wavelet transform (CWT) [are] defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function Ψ Gautum & Kaur, Apr. 2012, Vol. 2(4) pp: 632-635

In [39]:
```
display.Image(filename="images/cwt.png")
```

Out[39]:



Useful article on Continuous Wavelet Transforms: http://uk.mathworks.com/help/wavelet/gs/continuous-wavelet-transform.html

Relevance to the ECG

- They have a much better detection rate of P-waves and T-waves — reduce the need to have a clear cut-off

24.2 Morphology analysis

The shape and size of particular features can be important.

- Slope steepness - peak to trough
- Area under the curve

25 Analysing Biosignals

The most involved part of the process by far.

Usually you are looking at changes in the detected features, the information in a biosignal is hardly ever just in the time domain.

Broadly,

- Trends — i.e. does heart rate increase or decrease over time.
- Dose response - i.e. when you eat a doughnut does your blood sugar level go up
- Periodic effects — i.e. does the frequency of coughing increase in the night

26 ECG

Normal characteristics:

Metric	Utility
Heart Rate Variability	Sign of aging, fitness
Base heart rate	Healthy individuals tend to have a lower heart rate

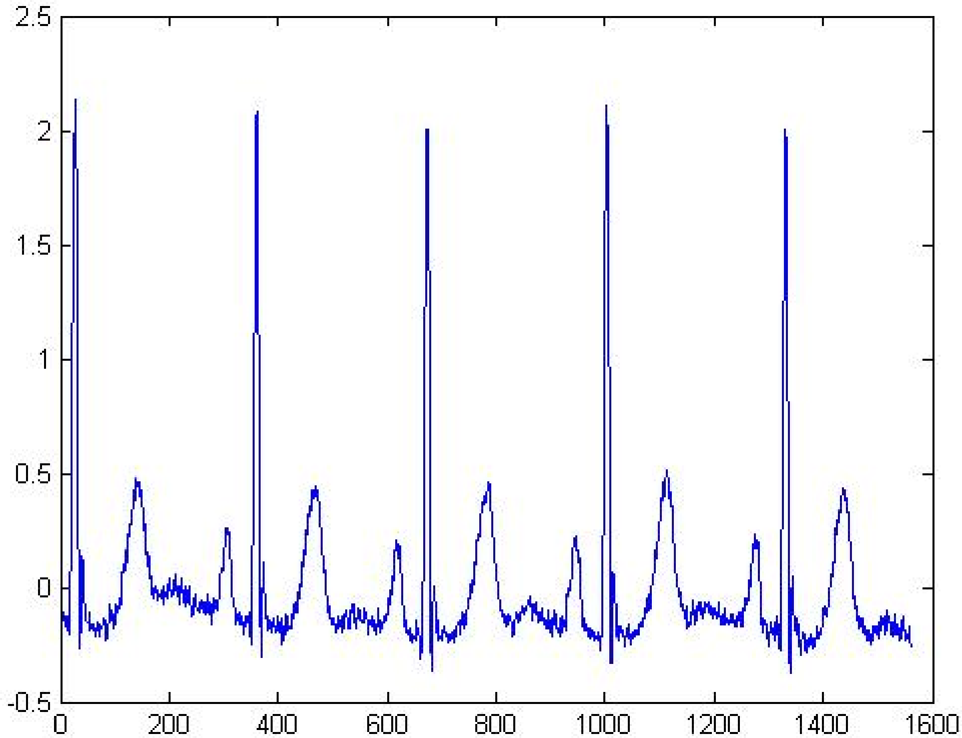
Characteristics associated with disease:

Name of abnormality	Characteristic features
Dextrocardia	P-wave Inverted
Tachycardia	R-R interval < 0.6 s
Bradycardia	R-R interval > 1 s
Hyperkalemia	Tall T-wave and absence of P-wave
Myocardial ischaemia	Inverted T-wave
Hypercalcaemia	QRS interval < 0.1 s
Sinoatrial block	Complete drop out of a cardiac cycle
Sudden cardiac death	Irregular ECG

Citation: ECG Detection Using a Convolution Wavelet Algorithm for Denoising of Surface EMG, Yeom et al. (2012)

```
In [11]: display.Image(filename="images/signal_ecg.jpeg")
```

Out[11]:

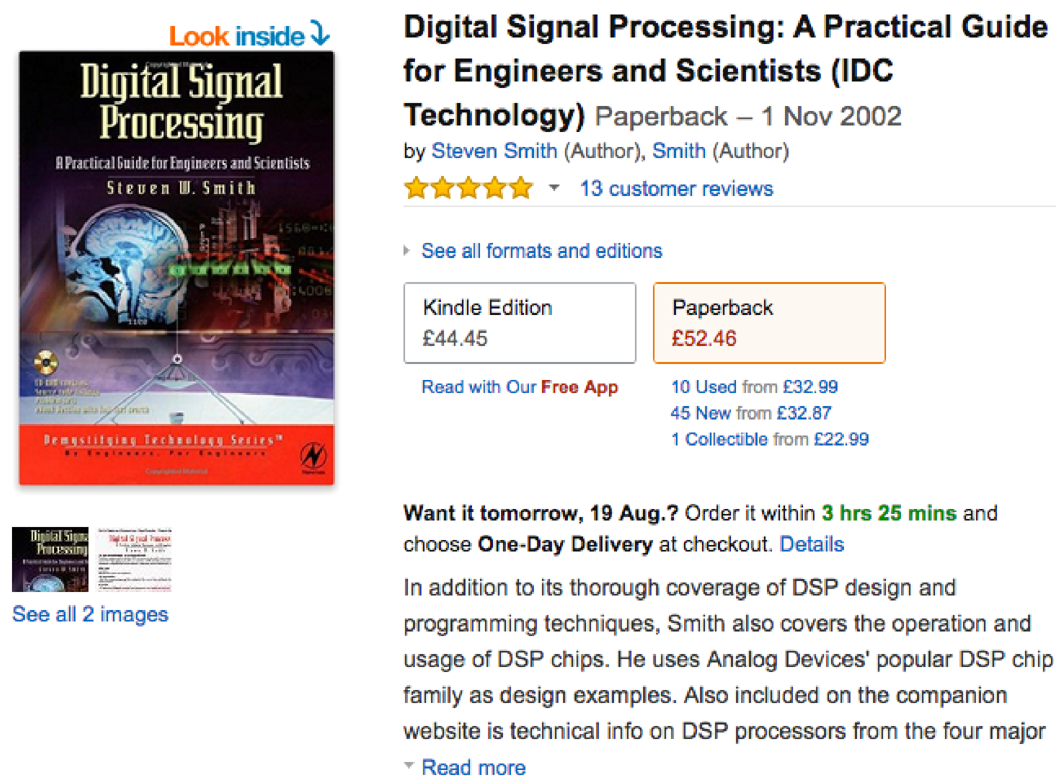


27 Conclusions

- Use equipment that's certified for use, or if you can't please don't connect it to mains power.
- Understanding digital signal processing is key to analysing biosignals
- Analysing biosignals requires a strong knowledge of physiology

```
In [26]: display.Image(filename="images/dsp_book.png")
```

```
Out[26]:
```



Also available for *free* as a webpage - http://www.dspguide.com/

28 Questions?

- Twitter: @emlynclay
- Email: eclay101@gmail.com