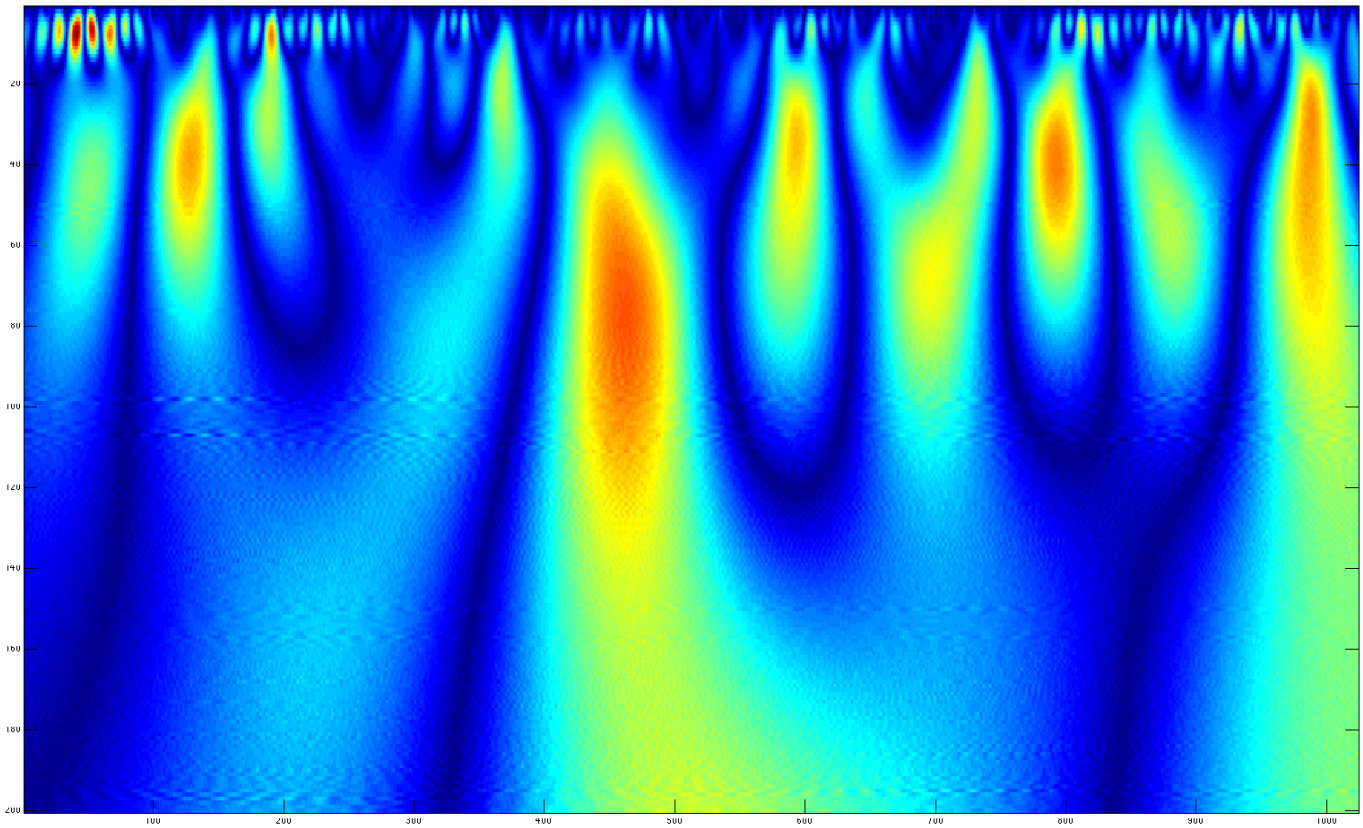
Lecture 3

Introduction to Applications

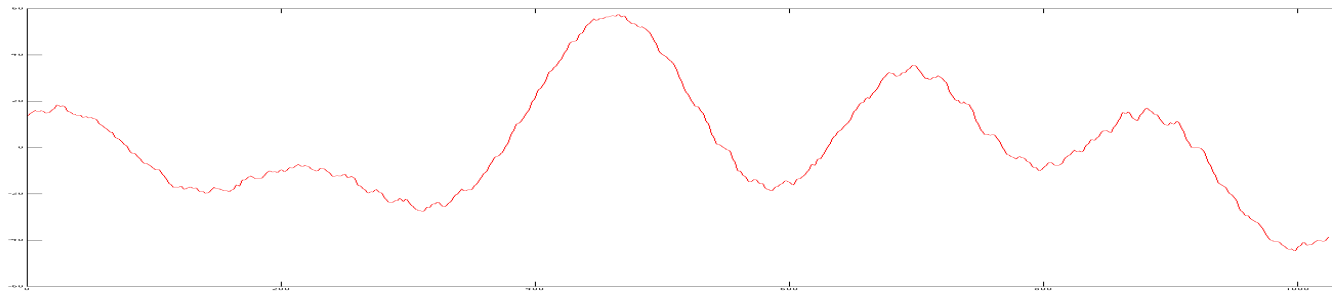
The CWT is an excellet tool, giving time-frequency information on all scales. It gives a lot of information; for example, let's load the eeg file and do a CWT:

```
>> load eeg
>> y2=eeg(2,:);
>> ecwt=cwt(y2, [1:1:512], 'gaus1');
imagesc([1:1024],[1:512],abs(ecwt)), colormap(jet)
```



Notice the high-power surge between levels 60-120, at time 400-500. If that surge is all we care about, we've too much information. This allows us to focus:

```
> plot(ecwt(100, :))
```



The CWT over-computes in situations like these, where all we want, say, is to detect power at one scale.

Similarly, with the CWT we have immense freedom of choice. A Gaussian can detect function size, the first derivative can detect slope; the second can detect discontinuities in slope, etc. Again, very powerful. But if we have only one well-defined problem to solve, that's more than we need.

Here's the kind of thing we have in mind. The Armed Forces would like to monitor the health of their troops on the ground, in real-time. Part of the reason is the "golden hour" effect, a short period of time during which treated injuries can save a life. We'd like to know as soon as a soldier (military terminology is "warfighter") is injured.

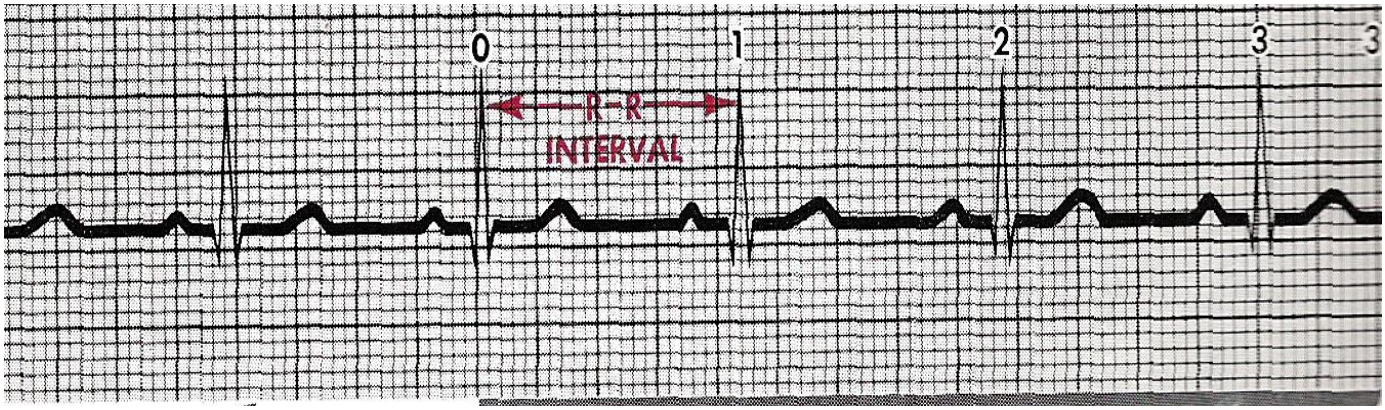
To accomplish this, the military envisages an iPod-like device worn by the warfighter, which monitors health information and sends that information to central command. Because the heart participates in so many bodily activities, it makes sense to monitor the heart rate.

The technical problem is that detecting a heartbeat under combat conditions is difficult. The heart pumps blood when the muscles in it contract. Much like a car with timing issues, if the muscles do not contract in the correct sequence, the system will not work. For hearts, this is called fibrillation; it can lead to death in minutes.

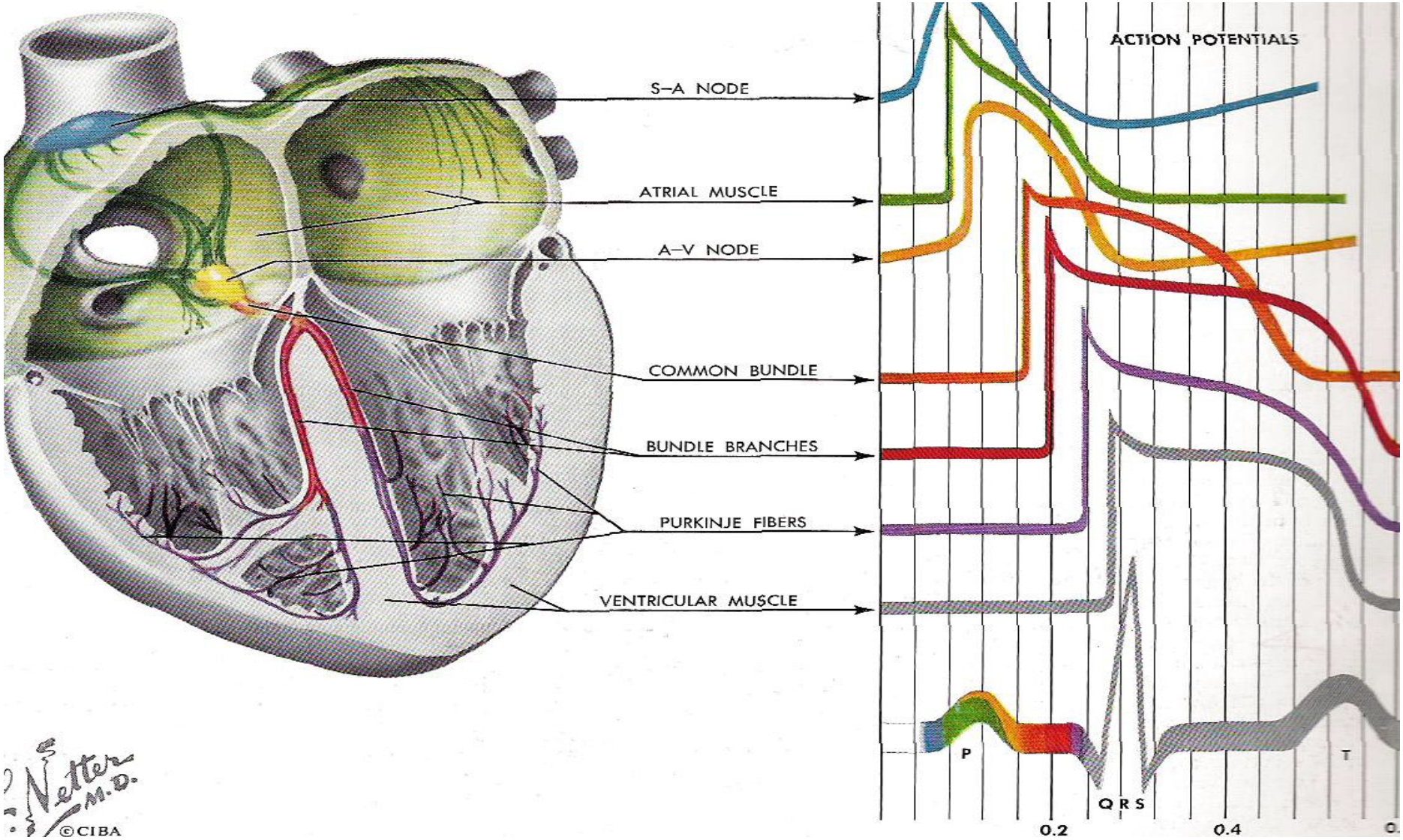
Unfortunately for us, the heart evolved rather than being designed, which means it regulates muscular firing by the spread of one electrical signal throughout the muscle. A blockage in parts of the muscle can affect the spread of the firing signal, causing irregularities.

The picture on the next page shows a schematized heart, and the electrical peaks caused by signals as they pass through the various regions of the heart. The larger muscles cause larger peaks. As the main pumping is accomplished by the contraction of the ventricles, these contribute the greatest peak.

The entire complex of peaks, corresponding to one beat, is called the PQRST wave. However, if you are measuring heart electrical activity on the surface of the body (the electrocardiogram, EKG), the easiest signal to detect is the R peak, when the ventricles contract. This is the fiducal point for most measurement of heartbeat, though the real beat is the entire PQRST complex. The time between R waves is called the RR interval, and 1/RR is a measure of the number of beats/min of the heart, called the heart rate. Immediately below, a typical EKG taken from a person lying down, resting, in a hospital. This is the optimal kind of EKG recording, and the R-waves are clearly defined, as indeed are the P and T waves.



Hospital Quality ECG


S–A NODE
ATRIAL MUSCLE
A–V NODE
COMMON BUNDLE
BUNDLE BRANCHES
PURKINJE FIBERS
VENTRICULAR MUSCLE
ACTION POTENTIALS
P
Q R S
T
0.2
0.4
Netter M.D.
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PQRST Waves

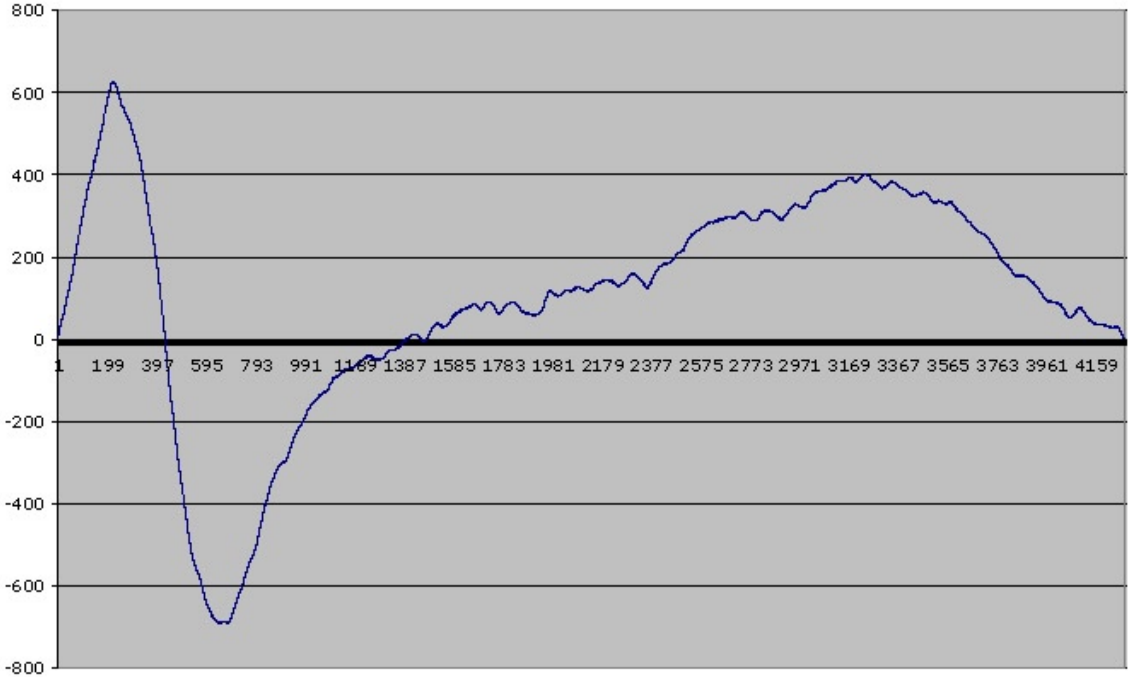
Below, in contrast, are the EKG's of subject who are not resting; both of them are undergoing some kind of exercise. The exercise requires muscular contractions, which again leads to electrical signals on the surface of the body, which again shows up as peaks in the EKG.

Abscercize

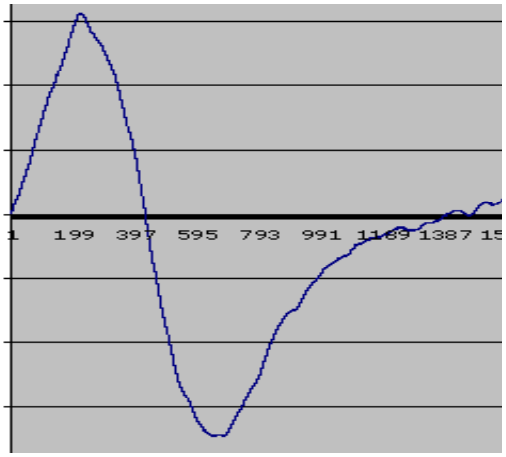
Taebo

These are the kind of real heart signals that our warPod would have to scan for beats. How can it possibly pick out the EKG beat from the muscle noise? Or even, for that matter, the P-wave from the R-wave?

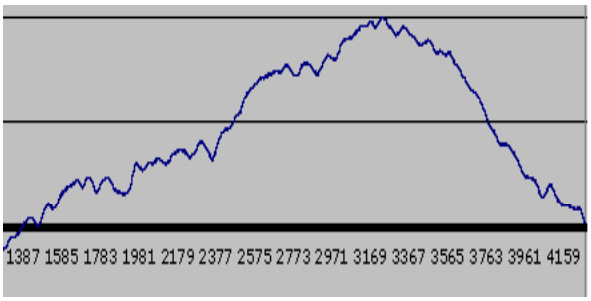
The short answer is, wavelets. Here's the original consultant's work for the warPod group. We'll give a quick summary. The critical property of wavelets is that they can resolve signals in time and frequency, simultaneously. So, the first question is, what frequencies do the P, Q, R, S and T waves contain?



Very nice QRST wave, sampled at 20,000Hz for high resolution

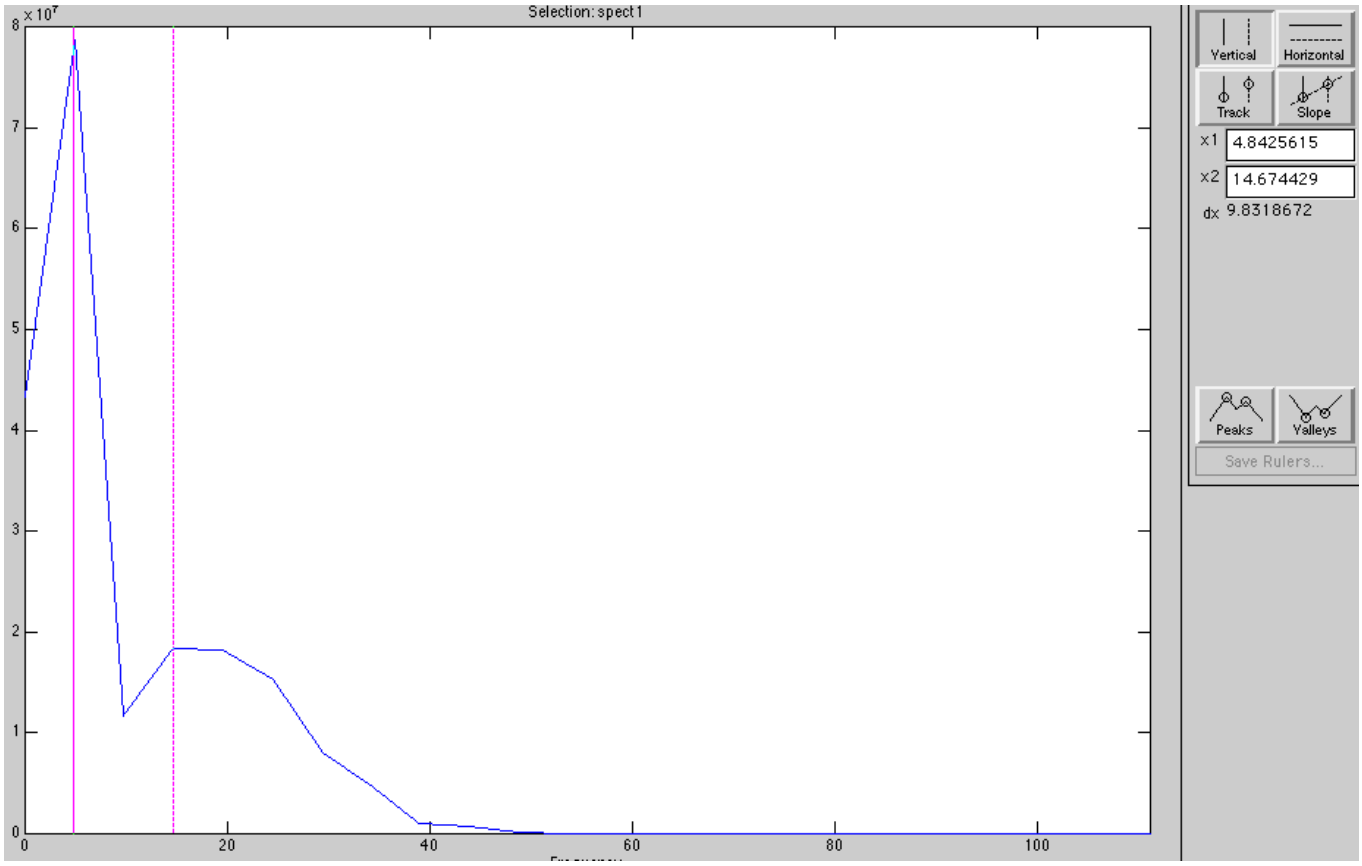


To compute frequencies, start with the QRS-complex. Pretend it's a sine wave. It lasts 1400 points; at 20,000 points per second that's .07 seconds for a full cycle, or 14.3 cycles per second. So, the QRS complex contributes a frequency of about 14Hz.



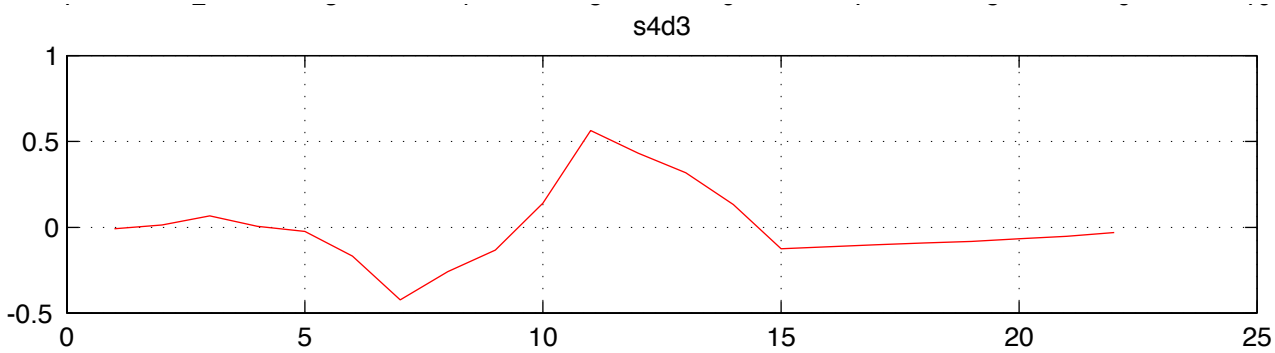
Here's the T-wave. Obviously there's a good deal of energy there. It takes 2877 points for a half-cycle, giving a 3.47 Hz contribution.

And here's the official Matlab spectrum. There are two main peaks -- at 4.84hz and 14.67 hz. Not bad.

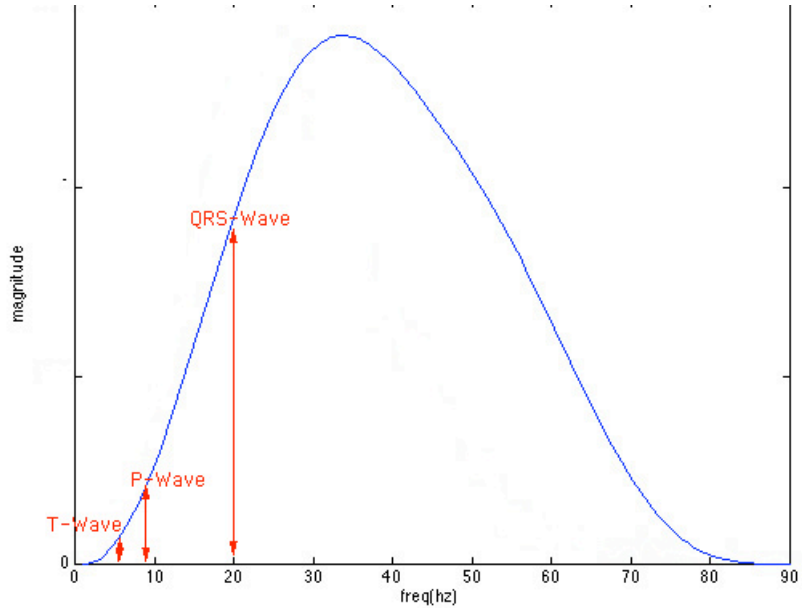


What we need, then, is a wavelet that can separate out a 4Hz from a 14Hz signal, as well as from myographic (muscular) noise. Unfortunately, the muscle noise can be of pretty much any frequency; filtering by frequency alone won't help. Fortunately, the firing of a single muscle, or even a complex of muscles, is nothing like as complicated as the firing of the PQRST complex:

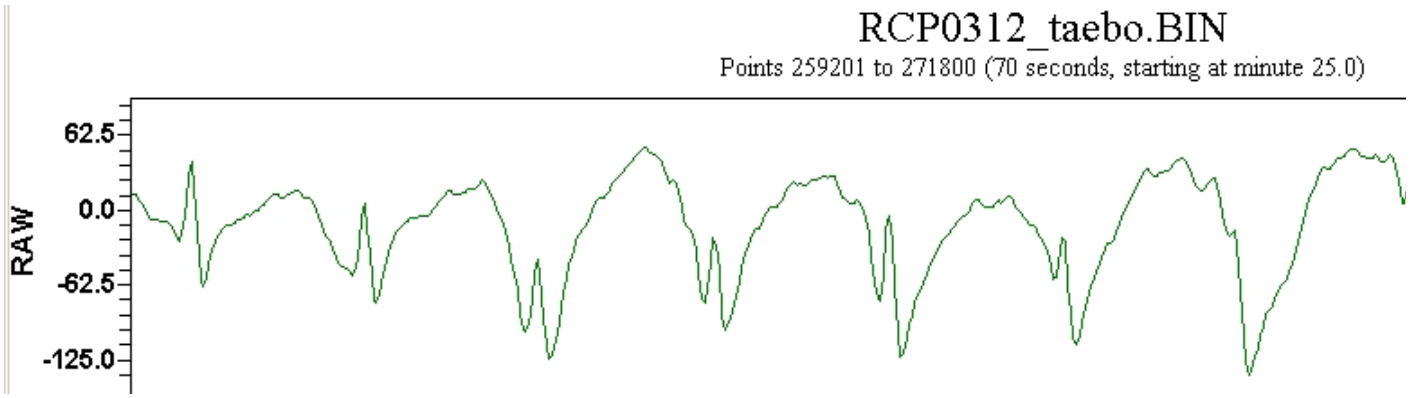
That's where the *time* part of time-frequency resolution comes in. We take a wavelet that looks more like a QRS wave than like a muscle contraction. Then filtering the EKG with the wavelet computes how similar the EKG is to the QRS complex. In parts generated by muscle or noise, the lack of similarity will make the filtered signal small. So, here it is: the Daubechies s4d3 wavelet:



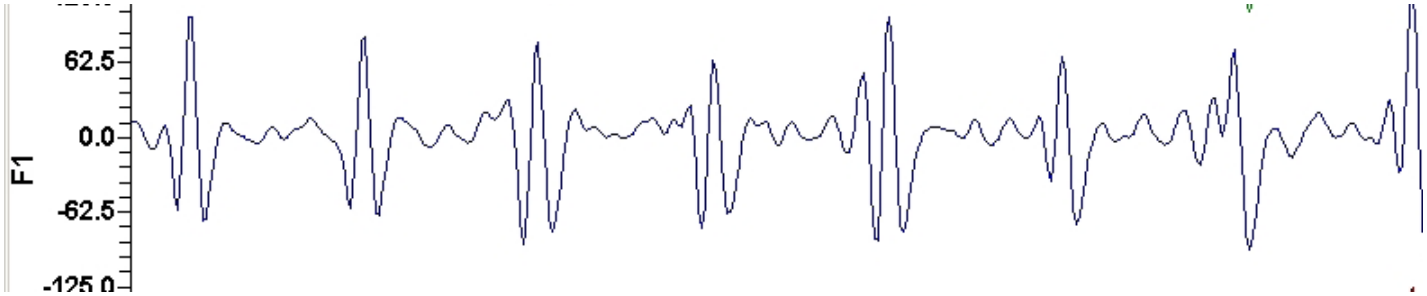
Looks a bit like a QRS complex; how's the frequency response?



Ah, excellent! It surpresses the P and T waves, while emphasizing the QRS complex. Just what we need for filtering out noise and picking out the R-wave.

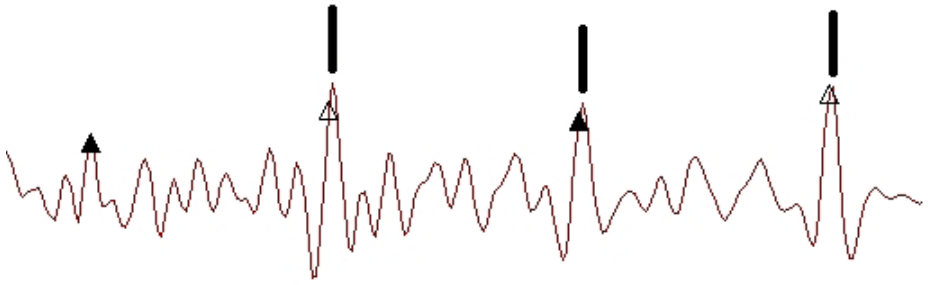


Healthy subject doing taebo: raw EKG



Above signal, wavelet-filtered with s4d3

Healthy subject doing abs exercises: raw



Above signal, wavelet-filtered with s4d3.
Thick bars indicate automatic detection of
R-wave.

Once the EKG is filtered, we apply standard R-wave peak detectors to it. In the case of the abs exercises, the detection without wavelet filtering had a 75% error rate. With wavelet filtering, the error rate was zero. To compute error rates over a collection of exercises, one typically measures false positives, FP, and False Negatives, FN. The accuracy of the detection method is measured by two ratios:

> The performance of R-wave detection techniques is evaluated not through percentage of peaks detected, but rather by two indices: sensitivity and predictability. These indices take into account not only the number of true peaks (TP) correctly identified, but also the number of spurious peaks produced (false positives: FP) as well as the number of peaks which were missed (false negatives, FN). These are computed as proportions:
>
> $$S_e = \frac{TP}{TP + FN}; \qquad S_p = \frac{TP}{TP + FP}$$
>
> The results are shown in Figure 9; we applied the s4d3 detection scheme outlined above to six exercise files, ranging from upper body to abdominal exercises, to lower body, and to mixed exercise files. It is not surprising that the best results are for lower body exercises; muscle noise in this case was well away from the EKG leads. It is also not surprising that the worst performance was on taebo exercises. .....
>
> What is surprising is that the sensitivity and specificity in all cases exceeded 99%. This is comparable to or better than best performance of other techniques on clinical databases, where typically much less noise is present.

s4D3	TP	# FP	# FN	SE	SP
abdadd	791.00	0.00	1.00	99.87	100.00
abs	993.00	6.00	4.00	99.60	99.40
ellip	2342.00	4.00	1.00	99.96	99.83
gauntlet	778.00	0.00	1.00	99.87	100.00
stair	3402.00	0.00	1.00	99.97	100.00
taebo	7146.00	44.00	32.00	99.55	99.39

A Novel Application of Wavelets to Real-Time Detection of R-waves

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