Algorithms for processing accelerator sensor data

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1. Use of acceleration sensor data

Modern mobile phones are often equipped with acceleration sensors. Automatic landscape -portrait change – pretty much a standard feature in high-end smart phones – can be implemented with an acceleration sensor in the most cost-efficient way. The sensor can be used for other purposes, however. If the user actually carries the mobile phone, the sensor's data can be used to extract information with regards to the user's environmental condition or the user's activity.

The following classification is proposed with regards to the acceleration sensor measurements.

- Static. This means that we measure some property that does not change quickly, e.g. the device's orientation in the Earth's coordinate system. The built-in landscape-portrait screen adaptation is a static measurement.
- Dynamic. This means that we measure the effect of some movement. For example we try to figure out the user's movements. Shake detection – also a standard feature in many applications – falls into this category.

In case of static measurements, the purpose of signal processing may be to eliminate distortion. For example if the user sits in an accelerating aircraft, that acceleration is added to Earth's acceleration, distorting the orientation measurement. In case of dynamic measurements the purpose may be more diverse. Any information may be useful that can be extracted from the sensor data and reveals anything about the user's environment and actions.

2. Extracting motion pattern information

One particularly interesting dynamic measurement is the motion pattern recognition. In this case, the user carries the mobile phone which samples the acceleration sensor in the background. The samples are analysed and context data is extracted regarding the motion the user is doing. For example the result of such an analysis may be that the user is walking. Other result may be the count of the steps he made from a certain initial point.

Some parts of this processing is quite simple. Shake detection may be performed by simply calculating the maximum acceleration. If the acceleration is higher than 2.5-3 g, there is a high chance that the device is being shaken. Distinguishing other movements is a harder task. For example running (Illustration 1) generates almost as high acceleration as shaking (Illustration 2). Clearly, the difference is in the temporal behaviour. Even without detailed analysis in the frequency domain it is clear that the spike-like signal of shaking has a different frequency spectrum than the sinusoid-like signal of running. Reliably distinguishing these signals requires frequency-domain analysis.

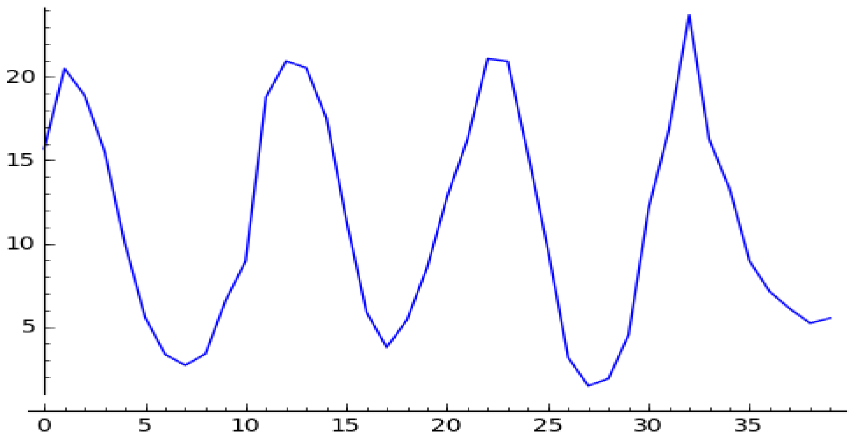

Illustration 1: Waveform of running

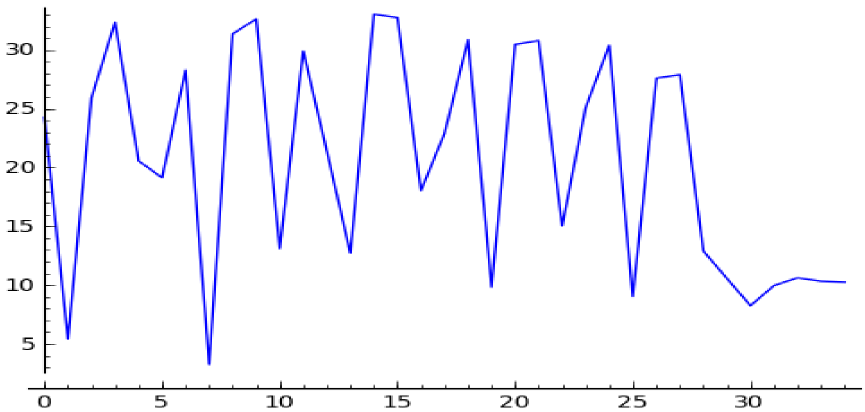

Illustration 2: Waveform of shaking

There is an extensive literature of acceleration signal processing, mostly in medical journals. Their goal is much similar to ours, they want to extract movement information from acceleration sensor signals. There are significant differences too, however.

- Medical sensor researchers have the advantage that they can position and fix the sensors with great care [5]. This condition cannot be guaranteed with mobile phones. The phone is not guaranteed to be fixed to the user's body (e.g. it may be in the user's bag whose movement is related to the user's movement but is not guaranteed to be the same) and the user may even leave the device behind (e.g. leaves the phone on the desk and goes for a walk).
- Medical sensor researchers try to extract very exact information e.g. about a certain medical condition [4]. Our ambitions must be much lower, partly because such exact information is not needed, partly because it is not even possible because the sensor's position with regards to the user's body is rather accidental (depending where the user holds the phone, etc.)
- In medical research, it is often acceptable to record acceleration data and process them off-line. If we want to extract context data from acceleration data, the delay between acquisition and availability of context data must be short. Algorithms with

high computational complexity like Matching Pursuit [4] are less suitable for context data processing.

The prior research focused on the frequency analysis of accelerator signals too. Their conclusions are the following.

- Different versions of Fourier-transform were found less accurate than wavelet-based classification methods [2]. This is due to the flexibility of wavelet method when it comes to optimization of the time-frequency parameters. Fourier-transform's frequency resolution depends on the length of its sampling window. The longer the window, the more exact is the spectral analysis. This causes problems, e.g. n case walking signals, the long window may contain both “walk” and “no walk” sections.
- There are no magic bullets. There is no algorithm that is able to classify all the practically relevant movement types. Instead, the movement classifier should employ a toolbox of algorithms, e.g. peak detectors, signal power calculation, frequency-domain analysis, etc. [3].

3. Wavelet-based frequency-domain analysis

Due to the problems with versions of Fourier-transform, wavelet transformation has been proposed for the analysis of acceleration sensor signals. Wavelet is time-limited signal that interferes with components of the signal to be analysed. The wavelet and its window function (that makes the wavelet time-limited) is carefully designed to interfere with components of interest in the measured signal. Convolution is performed between the wavelet and the signal. The result of the convolution indicates, how strongly the components represented by the wavelet were present in the measured signal. The advantage of the wavelet transformation is that the time-frequency behaviour of the transformation can be tuned with the parameters of the wavelet therefore compromises can be made between the quick detection of the signal components of interest and the frequency resolution.

Many wavelet functions have been designed since the introduction of the wavelet transformation. We will use the Morlet wavelet [6] in this report. The Morlet wavelet is a sine wave modulated by the Gaussian window function.

In the complex number space:

$$f(t)=c_\sigma \mathrm{e}^{\frac{-1}{2}t^2}(\mathrm{e}^{j\sigma t}-k_\sigma)$$

Or in the space of the real numbers:

$$f(t)=c_\sigma \mathrm{e}^{\frac{-1}{2}t^2}(\cos(\sigma t)-k_\sigma)$$

where

$$c_\sigma=\pi^{\frac{-1}{4}}(1+\mathrm{e}^{-\sigma^2}+2\mathrm{e}^{\frac{-3}{4}\sigma^2})^{\frac{-1}{2}}$$

$$k_\sigma=\mathrm{e}^{\frac{-1}{2}\sigma^2}$$

The time-frequency resolution can be tuned with the σ parameter. Lower the σ parameter is, the better temporal resolution the Morlet wavelet has, at the expense of frequency resolution. $\sigma>5$ is often proposed.

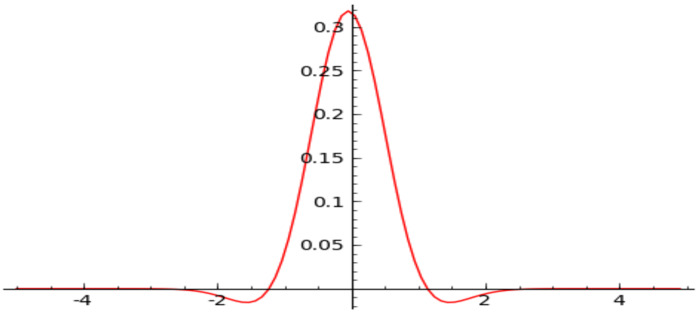

Illustration 3: Morlet wavelet, sigma=1

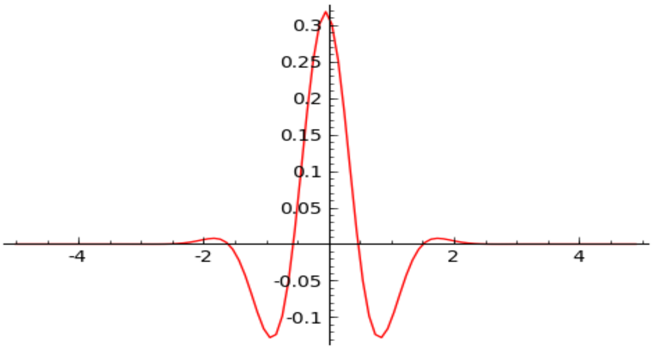

Illustration 4: Morlet wavelet, sigma=3

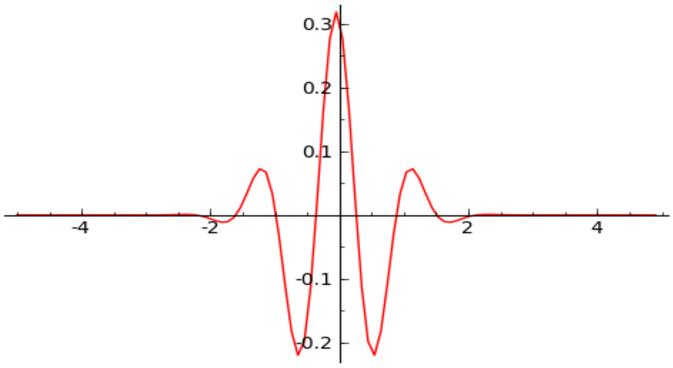

Illustration 5: Morlet wavelet, sigma=5

The output of the wavelet transformation is the convolution of the wavelet with the input signal.

$$w(t)=\int_{-\infty}^{\infty} x(\tau)f(t-\tau)d\tau$$

or in the discrete domain:

$$w[n]=\sum_{m=-\infty}^{\infty} x[m]f[n-m]$$

In order to specify the frequency band the wavelet transformation extracts, the wavelet function is rescaled along the *t* axis.

$$f_a(t)=\frac{1}{\sqrt{(a)}}f(\frac{t}{a})$$

Rescaled versions of the wavelet function form a filterbank. As we know the wavelet function, elements of the filterbank can be generated by just sampling the wavelet function with different sampling rates.

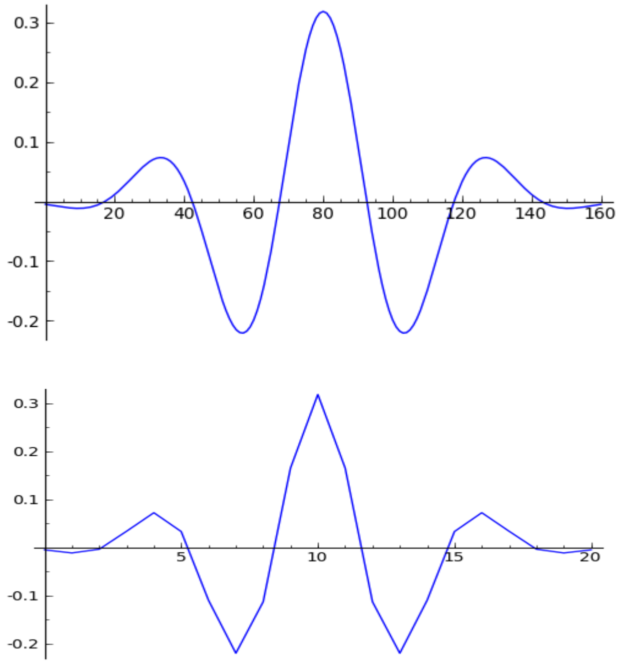

Illustration 6: Scaled Morlet wavelet - x axis represents sample count

Illustration 6 presents the effect of such scaling. Note that x axis represents sample count. The same slice of wavelet function (-2,2 range, σ=5) takes about 160 samples in the upper figure and only about 20 in the lower figure. If the two wavelets are applied to the same input sample, the center frequency of the lower wavelet's center frequency is 8 times higher than the upper wavelet's center frequency. The exact frequency can be obtained only if we know the real sampling frequency of the input signal. Also note that if we apply the two wavelets to the last N samples of the input signal (N=160 in case of the upper wavelet, N=20 in case of the lower wavelet), there will be a time shift between the output signals. They will be about 70 samples off from each other (observe the position of the peak of the two wavelets in terms of sample count).

4. Using wavelets for analysing accelerator signals

Now let's see, how can we use the wavelets for analysing accelerator signals. Let's try to differentiate the running and shaking signals presented in Ilustrations 1 and 2. We know that their maximum amplitude is about the same, simple threshold check will not help. We use a wavelet filter bank to analyse these signals in the frequency domain.

The signals were measured with about 25 Hz sampling frequency. Android's sampler is not that exact, the frequency fluctuates between about 22-26 Hz, therefore all the frequency data that follows are inexact. The wavelet filter bank is composed of 7 filters where the Morlet wavelet was sampled from -2 and 2 with the following step samples.

Wavelet ID	Step sample
w0	0.0125
w1	0.0250
w2	0.0500
w3	0.1000
w4	0.2000
w5	0.4000
w6	0.5000

The appropriate scaled Morlet wavelet is calculated for each filter bank and is applied to the input signal as described in section 3. $w_n[k]$ denotes the output of the nth wavelet filter bank.

The power of the output of the nth wavelet filter bank is calculated as follows.

$$p_n[k]=\frac{1}{N}\sqrt{\sum_{k-N+1}^{k} w_n[k]^2}$$

where N is the averaging factor. In our measurements, N=20 was used.

Let's start with simple walking. Illustrations 7, 8 and 9 present the power in all bands, in the band with the highest output and the output signal in the band with the highest output. The output of w3 is by far the highest. The output of the wavelet transformation provides the sine wave of the base frequency of the walking which is about 1 Hz. I walked about 1 step per second.

Running is quite similar. Illustrations 10, 11 and 12 present the powers in bands and the output of the w3/w4 bands. Two differences can be observed compared to walking: the power of the top bands are higher than walking and there frequency distribution moved toward the higher-frequency w4 band. The output of w3 and w4 can both be used to determine that I made about 2.5 steps per second.

Shake has peculiar characteristics. Illustrations 13, 14 and 15 present the powers in bands and the output of w4/w5 bands. It is very clear that the power is now in the highest frequency bands. Also, the power of the two highest bands (w5 and w6) is even higher we experienced in case of running. If we observe the output of w5/w6 bands, we can even count how many times I shook the device.

5. Conclusions

There is no single perfect algorithm when analysing acceleration signals. The analysis framework should provide a toolbox of different algorithms, some working in the time-domain, some operating in the frequency domain. The decision engine that classifies the movements may use a number of algorithms, a characteristic set for each movement type.

It has been concluded in the medical research community that wavelet transformation is the most optimal algorithm for frequency-domain analysis of acceleration signals. This report presented concrete cases, how wavelet transformation can be used to classify three common movements: walking, running and shake. In addition, the wavelet transformation provided data series that can be used to extract other interesting information, e.g. step count.

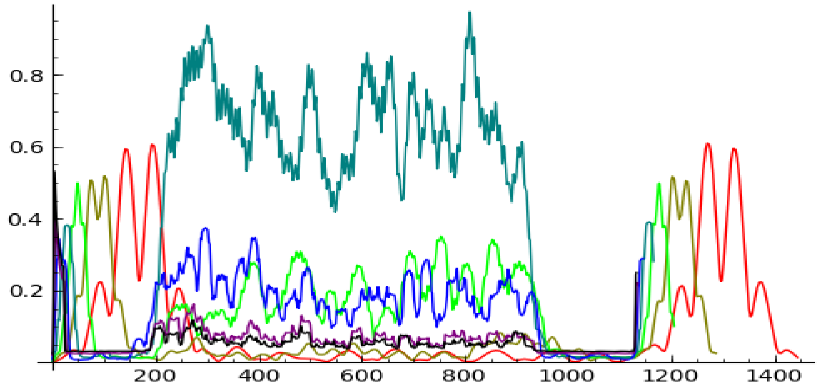

Illustration 7: Walking: power density in the 7 frequency bands

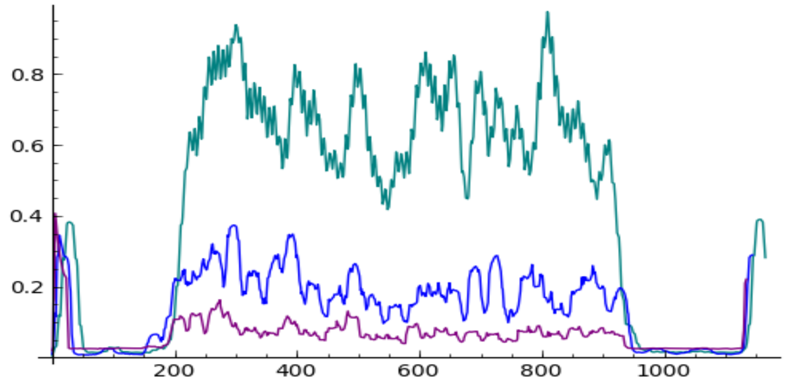

Illustration 8: Walking: power density in bands 3 (turquoise), 4 (blue), 5 (purple)

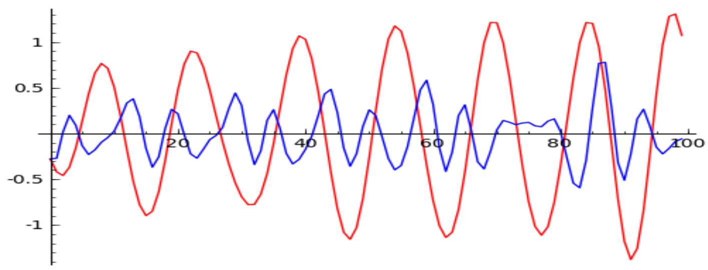

Illustration 9: Walking: output of w3 (red) and w4 (blue)

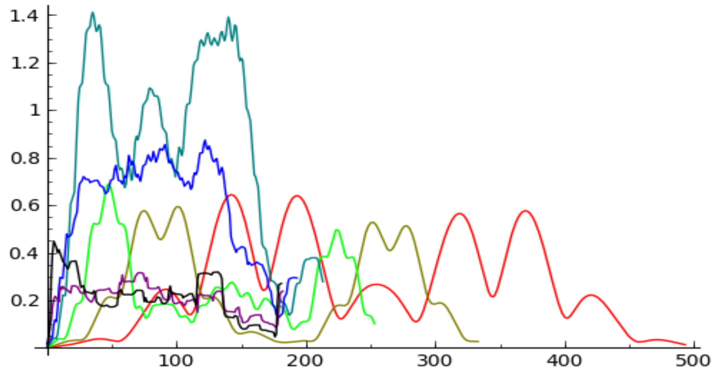

Illustration 10: Running: power density in the 7 frequency bands

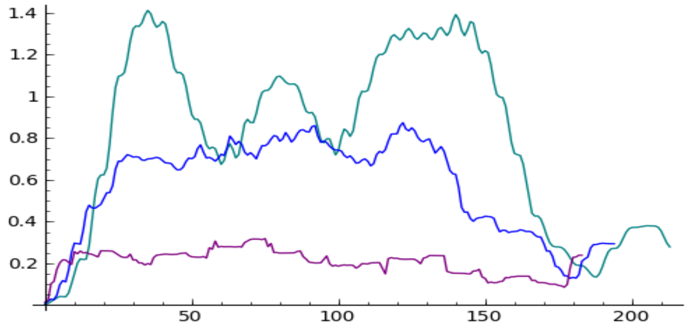

Illustration 11: Running: power density in bands 3 (turquoise), 4 (blue), 5 (purple)

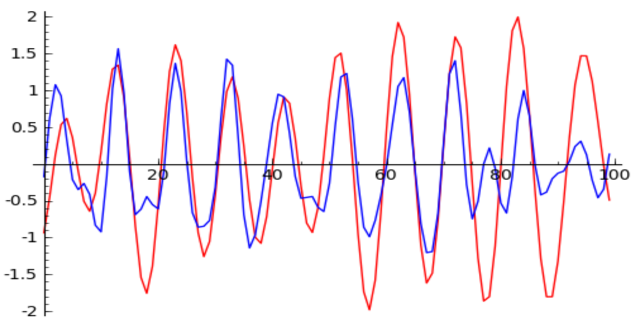

Illustration 12: Running: output of w3 (red) and w4 (blue)

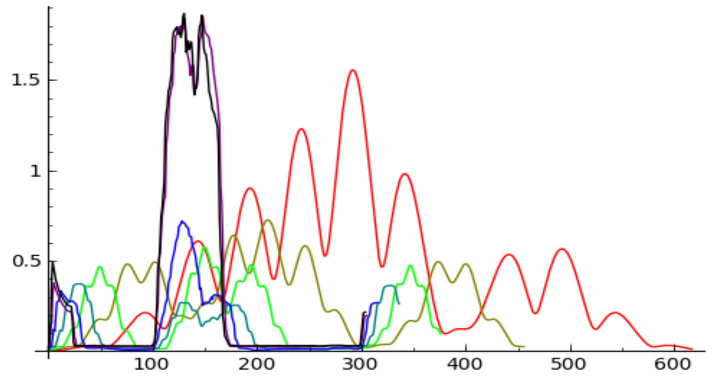

Illustration 13: Shake: power density in the 7 frequency bands

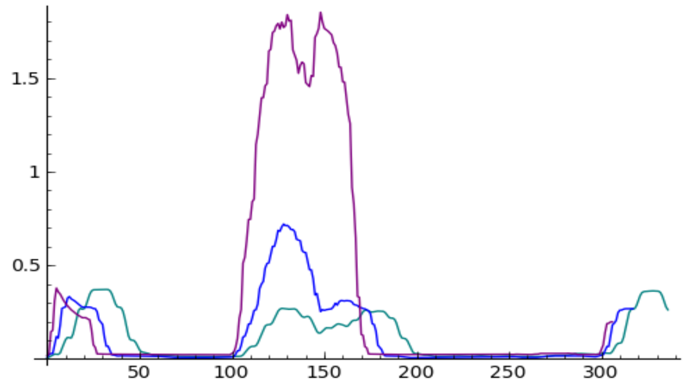

Illustration 14: Shake: power density in bands 3 (turquoise), 4 (blue), 5 (purple)

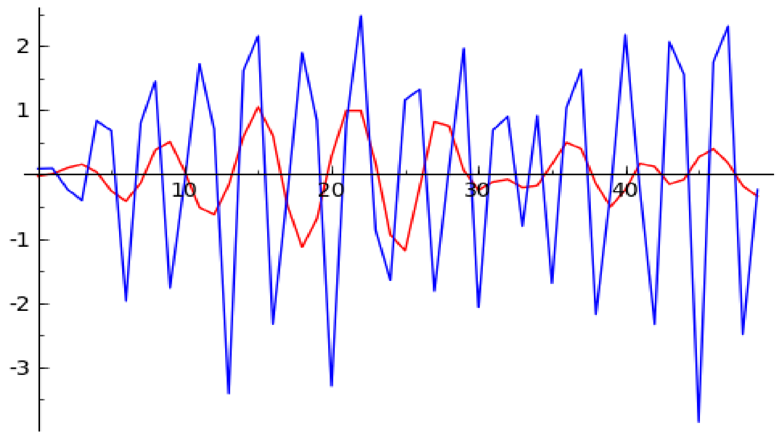

Illustration 15: Shake: output of w3 (red) and w4 (blue)

6. References

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