Realtime bioelectrical data acquisition and processing from 128 channels utilizing the Wavelet-Transformation

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Abstract

We propose a versatile signal processing and analysis framework for bioelectrical data, and in particular for neural recordings and EEG. Within this framework the signal is decomposed into subbands using fast wavelet transform algorithms, executed in real-time on a current DSP hardware platform. The decomposition is used to perform various processing and analysis tasks. Besides fast implementation of high, band, low pass filters, the decomposition is used for denoising and lossy, as well as lossless compression. Furthermore specific electrophysiologic analysis tasks like spike detection and sorting are perfomed within this decomposition scheme.

Within the project VSAMUEL we developed successfully a versatile data acquisition system based on DSP boards [4]. The system is used for continous neural data acquisiton in vivo or in vitro with a high channel count (up to 128 channels) at sampling rate $F = 50$ kHz with a precision of 16 bits per sample (12.6 MB/sec). Data processing tasks include filtering and spike detection and classification, but also compression, transmission and storage. We propose a signal processing framework within which these tasks can be performed in an elegant way. The signal is decomposed into N+1 subbands by a N-level wavelet transform (WT), called $d_j, j = 1, \ldots, N$ and a_N. The subbands d_j represent the frequency band $[F/2^{j+1}, F/2^{j+2}]$ and a_N represents $[0, F/2^{N+1}]$. The wavelet transform is implemented using the lifting scheme which is faster than the standard implementation, it is done in-place, and with a small modification it implements a WT that maps integers onto integers $[1, 2]$ while preserving the possibility of perfect reconstruction.

The decomposition allows a simple implementation of filters with different high pass, band pass, or low pass characteristics. Consider e.g. a neural recording sampled at $F = 50$ kHz which contains both field potentials and action potential. If it is decomposed by a 6-level WT into 7 subbands, then the field potentials are found in subband a_6. Setting the coefficients of a_6 to zero, eliminates the field potentials and corresponds to a high pass filter (Figure 1). Possible cut-off frequencies when using the WT are determined by the sampling rate and the number of levels. Arbitrary filters can be implemented when a Wavelet Packet Transform (WPT, see [8]) is utilized. The computation of the WPT transform involves more operations than the WT. Because the number of operations has to be as low as possible to allow real-time computation on our DSP, we restrict ourselfs to the WT.

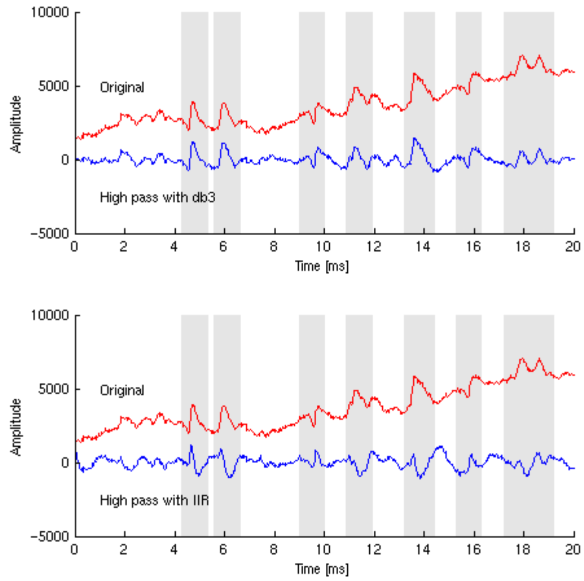

Figure 1: High pass filtering using IIR versus elimination of wavelet approximation coefficients. The original neural recording has been decomposed with a 6 level WT using the Daubechies 3 wavelet. The coefficients of a_6 have been set to zero, corresponding to a high pass filtering with cut-off at 390.62 Hz. In a second approach the signal has been filtered by a 4-pole IIR filter with cut-off at frequency 400 Hz, which was designed using the Butterworth method. Spike shapes in the IIR filtered result show significant distortions, while the spike shapes are apparently not distorted by the wavelet based high pass. Field potentials are eliminate well by both filters.

One important property of the WT is that it decorrelates the signal, i.e. the main information about the signal is collected in a few large coefficients, while the details are collected in many small coefficients. Thus the entropy of the decomposition is smaller than entropy of the raw signal. The entropy of a neural recording from a rat was quantified in [7] to be about 13.9 bits per sample and it is about 8.5 bits per coefficient for the decompositon. Therefore, the possible optimal compression rate achievable with Huffman coding can be improved from 0.86 for the raw data down to 0.53 for the decomposition.

Another important task is the denoising of neural recordings. The typical background noise of neural recordings is mainly found in first few levels $d_1, \ldots, d_3$ of the decomposition. Under the reasonable assumption that the background noise has a Gaussian distribution [6], a universal threshold can be found as $\delta = \sqrt{2\sigma^2 \log(n)}$ where σ^2 is the variance of the Gaussian noise and n is the length of the sequence [3]. Since the true variance σ^2 is usually unknown, it is estimated from the coefficients in d_1 which are dominated by the noise. In our case the standard deviation estimator *median absolute deviation* (MAD) is well suited, because it is robust against large coefficients representing the signal that might occur in d_1.

Compression and denoising are closely related. The thresholded decomposition which represents the denoised signal has a much lower entropy than the original decomposition and thus can be compressed with a better rate. Depending on the chosen thresholds, the compression rate can reach values below 0.1 without losing a significant part of the signal. With the universal threshold for instance we obtain a compression rate of about 0.06 for neural recordings from a rat (Figure 2). Lossy compression which does not distort the signal significantly is particularly usefull for longterm recordings.

The decomposition is used to analyse neural recordings. Spikes, for instance, are represented by a few large coefficients in subbands $d_2, \ldots, d_6$. A spike detection method which is well suited for low signal-to-noise ratio conditions based on this property is proposed in [5] and will be implemented in our system soon.

Altogether, we can state, that our DAQ system is able to record from a high number of channels, while still performing processing of incoming electrophysiological data in realtime.

References

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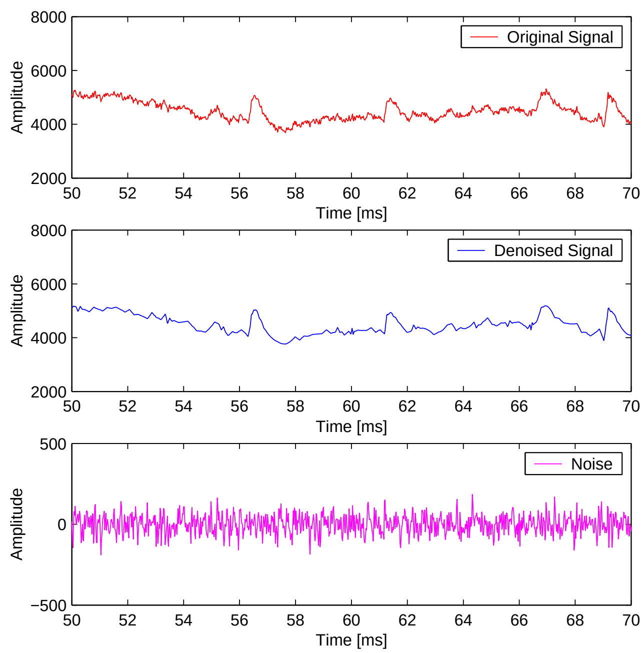

Figure 2: Compression and Denoising. The comparison of the orginal neural signal at the top and the denoised signal in the middle reveals no apparent distortion of the signal. This is confirmed by the difference of signal and denoised signal, i.e. the removed noise, which is shown at the bottom. The entropy of the decomposition drops from 8.34 bits per value down to 1.04 bits per coefficient. In other words the compression rate can be improved by a factor of 8.

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