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Improving electrocorticograms of awake and anaesthetized mice using wavelet denoising

Abstract: The quality of bioelectrical signals is essential for functional evaluation of cellular circuits. The electrical activity recorded from the cortical brain surface represents the average of many individual synaptic processes. By downsizing micro-electrode arrays, the spatial resolution of electrocortico-grams (ECoGs) can be increased. But, upon increasing electrode impedance, recorded noise from the electrode–tissue interface and the surroundings will become more prominent. Frequently, signal interpretation is improved by post-processing using filtering or pattern recognition. For a variety of applications, wavelet denoising has become an accepted tool. Here, we present how wavelet denoising affects the signal-to-noise ratio of ECoGs. The recording qualities from awake and anesthetized mice was artificially reduced by adding two noise models prior to filtering. Raw and filtered signals were compared by calculating the linear correlation coefficient.

Keywords: Electrocorticograms, noise models, denoising, correlation coefficient, mouse model.

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1 Introduction

For animal studies, the recording of the electrocorticogram (ECoG) is becoming increasingly popular because it provides a good compromise between invasiveness and spatial resolution. Various electrode arrays on different miniaturization levels have already been developed that are capable of detecting individual action potentials from the cortical surface [1]. However, with decreasing electrode size and enhanced tissue integration, the electrode impedance can dramatically increase [2]. Thereby, higher noise levels could affect the recordings. Standard ECoG signals in mice are in an amplitude range of less than ± 2 mV and in a frequency range of less than 100 Hz. However, in recordings of evoked potentials, higher frequencies can occur due to enhanced synchronous activation of the neurons and synapses.

To improve ECoG recordings, electrodes could be modified, for example, by electroplating processes to decrease the electrode tissue impedance [3]. The quality of recordings could also be improved by using signal post-processing such as filtering or pattern recognition. Besides standard filtering (e.g. bandpass or bandstop filtering), wavelet denoising is an accepted tool to improve signal quality in different applications [4–6]. Here, we analyzed the applicability of wavelet denoising to improve ECoG recordings obtained from awake and anesthetized mice with an artificially reduced signal-to-noise ratio (see Figure 1).

Figure 1: Examples of recorded electrocorticograms (thick line) from an awake mouse (left) and an anaesthetized mouse (right). In A) the signal with white noise is shown (thick line plus shadow) and in B) the resulting signal with Gaussian noise is shown.

2 Materials and Methods

2.1 Recording of ECoGs and noisy signal generation

The ECoGs were recorded using a self-developed electrode array (16 channels, Ø 150 µm, platinum, electrode impedance
at 10 Hz \(|Z(f=10Hz)| \approx 65 \text{k}\Omega\) placed directly over the cortex of the right hemisphere after a craniotomy. A screw electrode (M1x2) used as the reference electrode was implanted through the skull over the left hemisphere. The signal acquisition was done in a Faraday cage with a previously described recording system [7] at a sampling rate of 1.2 kS/s, and with broadband bandpass filtering of 0.5 Hz–500 Hz and a notch filter of 50 Hz. The ECoG was post-processed by applying notch filters at interference frequencies of 150 Hz, 200 Hz, 250 Hz, and 300 Hz resulting from the power supply, which could not be eliminated by the Faraday cage.

The signal-to-noise ratios (SNR) of the recorded signal were artificially reduced by adding white or Gaussian noise. The MATLAB functions `rand()` and `randn()` were used for noise generation and the resulting SNR was calculated in accordance with Eq. 1, where the root-mean-square values from the recordings and the noises are compared. The noise amplitudes were selected to generate SNRs down to −5dB. Therefore, the noise amplitudes were raised up to ± 300 µV for white noise and approximately ± 500 µV amplitudes for Gaussian noise, because of their non-uniform distribution. The frequency band of the noise was chosen within the range of >0 Hz to 600 Hz, which was the theoretical bandwidth for the used sampling rate.

\[
\text{SNR (dB)} = 10\log\left(\frac{w_{\text{signal}}}{w_{\text{noise}}}ight)
\]  

\(\text{(1)}\)

### 2.2 Wavelet denoising

The wavelet denoising process of the ECoGs includes three steps (see Figure 2). First, the discrete wavelet transform was used to determine the detail and approximation coefficients for different decomposition levels. This was achieved by highpass and lowpass filtering (and downsampling) with the chosen wavelets. In this serial calculation, the approximation coefficients of one level are the input signal for the following level; thereby, the signal segmentation is higher with an increasing decomposition level. In this study, a decomposition level of 5 was used when no other parameter was pointed out, because it provided a good compromise between denoising and preserving the original signal. After decomposition, a soft threshold was applied to the calculated coefficients. Coefficients under a threshold value were set to zero and values over this threshold (\(\tau\)) were weighted with a linear function from zero to one. To find the threshold value, an estimation (Donoho’s) method was used (see Eq. 2, where \(n\) is the number of samples, \(\sigma\) is the standard derivation of the signal, and \(K\) is a user-dependent scale factor). After this denoising step, the inverse discrete wavelet transformation generated the filtered signal from the modified coefficients.

\[
\tau = K \cdot \sigma \cdot \sqrt{2 \cdot \log (n)}
\]

(Fehler! Textmarke nicht definiert.)

Three different wavelets (db4, db8, sym24) were compared for the denoising approach because these were proposed for use with recordings of electroencephalograms (EEG) [4]. To determine the impact of the wavelet denoising, the signals prior to and after signal procession were compared by calculating the Pearson’s correlation coefficients between them (use of MATLAB `corr()`-function). First, the filtering with three different wavelets was applied to the recorded signals for different threshold levels by varying the K-factor in Eq. 2 from 0 to 1.2. Second, the denoising algorithm with a K-value of 0.6 was used on the noisy signals because this was the preferred value from the literature for EEG and we did not see any significant difference in our application for values ranging from 0.3 to 1.2.

![Figure 2](image-url)

**Figure 2:** Upper part: Principle of wavelet denoising by calculation of approximation (A) and detail coefficients (D), applying a soft threshold and back calculation. The lower part shows the wavelets used in the denoising algorithm (left: db4; middle: db8; and right: sym24).

### 3 Results and Discussion

#### 3.1 No impact on the original ECoG

The calculation of Pearson’s correlation coefficient shows no significant impact of the wavelet denoising on the recorded ECoGs without noise (Figure 3A). For the three wavelets
and tested thresholds (by variation of the K-value from 0 to 1.2), the coefficients were always over 0.995. The calculation of the significance level resulted in zero, which showed the strongest possible significance due to the large number of single numbers. In Figure 3B, the wavelet transform of the ECoG for the awake and anesthetized mice is shown. As visible in the time signal and as described in the literature [8], the neurons appear to work more synchronously in the anesthetized condition.

3.2 Improving the signal-to-noise ratio

In Figure 4, the results of the correlation calculation for the ECoG recordings with a length of 30 s prior to and after denoising with all the three wavelets are shown. With a decreasing signal-to-noise ratio the correlation coefficient decreases dramatically upon comparing the noisy signal with the recorded signal, independently from the noise model or mouse constitution (awake, anesthetized). In contrast, the correlation results of the denoised signals with the raw signal show a much higher correlation, which means that the original ECoG can be restored well. The denoising has more of an effect on the signal from the anesthetized mouse than that from the awake mouse. This results from continuously high neuronal activity in the recording of the awake mouse, whereas in the anesthetized mouse periods of less and sparse activity is visible. No differences are visible between the different wavelets, and only a small difference is visible between the noise models, with a slightly better result for the Gaussian noise model.

The comparison of different filtering techniques (see Figure 5) shows that wavelet denoising has an advantage over standard lowpass filtering (100 Hz cut-off frequency, filter order 20) and a moving average filter (10 ms time window). The wavelet denoising was carried out using the dB4 wavelet at two different decomposition levels (lighter trace: level 5; darker trace: level 9) and shows the least noise of all time traces. With an increasing decomposition level, the high-frequency parts of the signal will be increasingly attenuated due to the threshold of the detail coefficients after a discrete wavelet transform. The better denoising properties using the wavelet method are also visible in the calculation of the linear correlation coefficient (see Figure 5E and Figure 5J), where the results for lowpass filtering and moving average filtering are close to zero. The calculations are performed for signal sections of 10 s. Upon comparing the different decomposition levels, only a small difference in the results is visible mainly in the signal section without (strong and synchronized) neuronal activity, where the correlation result is anyway lower than in the other sections.

4 Conclusion

We show that wavelet denoising algorithms have only minimal effects on the recorded ECoGs of mice, but a high effect on the artificially applied signal noise. Compared with other standard filtering methods, the strong advantage to restore the ECoG signal of the wavelet approach is shown. In addition, we tested three different wavelets (dB4, dB8, sym24). They demonstrated a similar performance but the sym24 wavelet required substantially more computer time than the dB4 and dB8 wavelets. (denoising of the 120 s signal of Figure 5 needed approximately 15 s rather than <1 s).
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References

Figure 5: Comparison of different filtering methods for a two-minute recording of an anesthetized mouse (A-E) and awake mouse (F-J). A, F) Recorded ECoG. B, G) ECoG after denoising with lowpass filtering (cut-off frequency: 100 Hz; filter order: 20). C, H) ECoG after denoising by calculating the moving average value of the signal (time constant: 10 ms). D, I) ECoG after wavelet denoising with dB4 wavelet with two different decomposition levels (5 and 9). E, J) Results of correlation calculation (crosses: wavelet denoising; squares: lowpass filtering; diamonds: moving average filter).