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Research Article

Filtering noise for synchronised activity in multi-trial electrophysiology data using Wiener and Kalman filters

Yang Zhan[a,*], Shuixia Guo[c], Keith M. Kendrick[a], Jianfeng Feng[b]

[a] Laboratory of Cognitive and Behavioural Neuroscience, The Babraham Institute, Cambridge CB22 3AT, UK
[b] Department of Computer Science and Mathematics, University of Warwick, Coventry CV4 7AL, UK
[c] Department of Mathematics, Hunan Normal University, Changsha, China

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ABSTRACT

Novel approaches to effectively reduce noise in data recorded from multi-trial physiology experiments have been investigated using two-dimensional filtering methods, adaptive Wiener filtering and reduced update Kalman filtering. Test data based on signal and noise model consisting of different conditions of signal components mixed with noise have been considered with filtering effects evaluated using analysis of frequency coherence and of time-dependent coherence. Various situations that may affect the filtering results have been explored and reveal that Wiener and Kalman filtering can considerably improve the coherence values between two channels of multi-trial data and suppress uncorrelated components. We have extended our approach to experimental data: multi-electrode array (MEA) local field potential (LFPs) recordings from the inferotemporal cortex of sheep and LFP vs. electromyogram (LFP-EMG) recording data during resting tremor in Parkinson's disease patients. Finally general procedures for implementation of these filtering techniques are described.

1. Introduction

When dealing with electrophysiological recordings from the brain, we are always faced with the problem of reducing noise in order to better discriminate electrical signals. Noise can come from external electrical or mechanical interference or can be intrinsic to the recording apparatus or the brain itself. Therefore, after brain recordings have been made, the first problem with the captured data is how to selectively filter out the noise components reliably so that the neural signals can be analysed. Fortunately, similar problems are inherent to many signal processing and engineering tasks and so many efficient filtering methods have been developed. Two of the best known methods are Wiener and Kalman filtering (Haykin, 2001). Both methods are optimal under a wide range of conditions and there are many software packages utilising them that are available in the public domain. Here we hoped initially that by employing such filtering manipulations we could reduce the influence of noise and improve subsequent analysis of different types of electrophysiological recording signals. Wiener filtering has been used to extract the evoked potential features from multiple sweeps of scalp EEG recordings (Paul et al., 2001). Kalman filtering approach has been applied to estimate and track the the dynamics of EEG spectrum (Tarvainen et al., 2004).

In our recording experiments a main objective is to explore correlated or synchronised information from simultaneously recorded LFPs in vivo using multi-electrode array (MEA). These, as with most typical conscious recording experiments, involve sessions where each task that is required to be performed is repeated a number of different times. Since data is therefore acquired over a number of trial repetitions we can use the number of trials and the time within each trial as indices for a two-dimensional representation of the captured data. Thus the multi-trial electrophysiological data can be shaped into an image format which implies an application of 2D filtering algorithms.

Coherence analysis is widespread in analysing coupled relationships of two electrophysiological recordings such as EEG-EMG, MEG-EMG or different units between multiple EEG and local field potential (LFP) channels. Coherence detects common correlated signal components in the two channels of recordings and its values are presented as a function of frequency. If at certain frequency bands there appears high coherence values we can conclude that the two signals are synchronised at that frequency band. In real applications estimation of coherence values can vary with the specific techniques such as the number of segments and the amount of overlap between them (Terry and Griffin, 2008). Small level of synchrony within the data and short trial duration can lead to small coherence incidence and failure of detection (Terry and Griffin, 2008). This makes it difficult to distinguish real correlated spectral components at different frequency range. The main reason of such small coherence is that strong background noise prevails at

* Corresponding author.
E-mail address: yang.zhan@bbsrc.ac.uk (Y. Zhan).

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all levels of electrophysiology data. Besides the same measure of repeated experiment design tends to have stochastic factors within it. We hope through coherence analysis of the filtered data we could demonstrate the effectiveness of the 2D filters.

Our aim in this report is therefore to investigate whether such two-dimensional "image" -based representation can suppress the noise in raw electrophysiological recording data while retaining the underlying oscillatory signals so that synchronised activity can be readily and reliably detected with analysis of coherence.

2. Filtering Methods and Assessing Their Effectiveness

We have evaluated our filtering results using analysis of classic coherence in frequency domain and time-dependent coherence in joint time–frequency domain. Coherence is defined as the square of the cross spectrum normalised by the individual autospectra. For noisy electrophysiological data with low signal-to-noise ratio (SNR), we anticipate that the improvement brought by our filtering methods will be demonstrated by increased coherence values as an indication of synchronised oscillations.

Performance of both 2D filters (Wiener and Kalman) in both the frequency (via coherence) and time–frequency domains (via time-dependent coherence) will first be assessed using a computer simulation to generate two channels of multi-trial white noise processes that contain within each trial a number of sinusoidal signals that are mixed into the white noise with a low SNR. The aim of this process is to evaluate the extent to which noise is reduced while maintaining the spectral integrity of the sinusoidal signals. The evaluation of the filtering results is via both frequency domain coherence and time-dependent coherence, which uses short-time Fourier transform (STFT) in the frequency domain and continuous wavelet transform (CWT) in time–frequency domain. We model the signal and noise under a series of low SNRs and evaluate the coherence results as an indicator of SNR.

In the next step we will further modify our simulated data so that sine waves are not regularly inserted in all the trials. Two situations are considered. The first one is to produce unmatched sine waves so that in certain trials sine waves are absent in both channels. The second case is to introduce jittering across the trials so that sine waves can jitter around certain fixed time point with variable latencies. When the 2D data format is formed, data from each trial are always stacked up by certain stimulus cues to common starting point one can refer to ensure correct alignment. The jittering of sine waves can also come from the misalignment of the data with certain bias in each trial. These tests aim to examine the filtering results in a broader sense because real data collected during an experiment can be biased for various reasons; for example inconsistent performance of the subjects or external interference.

We will further explore the possibility of applying our filtering approach repeatedly. As is seen with single time filtering we will assess whether our method can considerably improve coherence values at correlated frequencies. The idea of such a repeated manoeuvre is to test if a maximal filtering result can be achieved and to what extent the filtering can no longer improve the coherence estimation.

Lastly the filtering algorithms will be applied to real electrophysiological recordings of multi-unit LFPs recorded from the sheep inferotemporal cortex (IT) and simultaneous LFP-EMG recordings made from humans.

2.1. Adaptive Wiener Filtering

The first filter we use is adaptive Wiener filter. Wiener filtering is regarded as an optimal filtering as it minimises the mean square error (MSE) of the observed and the output signal of the filter. The Wiener filter assumes that the signal $s(m,n)$ at position $(m,n)\in\mathbb{Z}^2$ in a local region is stationary, and within the local region the signal is represented by Lim (1990)

$$s(m,n)=\mu_s+\sigma_s^2 w(m,n) \tag{1}$$

where μ_s and σ_s are the local mean and standard deviation of $s(m,n)$, and $w(m,n)$ is zero mean white noise with unit variance. It is also assumed that the additive white noise $v(m,n)$ has zero mean and variance of σ_v^2 and the received signal is $r(m,n)=s(m,n)+v(m,n)$. In the application of image processing, a two dimensional adaptive Wiener filter finds the local mean and variance around a given pixel within its neighbourhood and the filtered value at each pixel is given by the following formula (Lim, 1990)

$$b(m,n)=\mu_s(m,n)+\frac{\sigma_s^2(m,n)}{\sigma_s^2(m,n)+\sigma_v^2}(r(m,n)-\mu_s(m,n)) \tag{2}$$

where $b(m,n)$ is the filtered signal, $\mu_s(m,n)$ is the local mean, $\sigma_s^2(m,n)$ is the local variance, and $r(m,n)$ is the received signal. The use of the estimation of the local variance instead of estimating for the entire image results in a space-variant Wiener filter. The filter performs filtering pixel-wise in the local neighbourhood around that pixel, and if the original data differs greatly from the local mean the filter will adjust the filtered result adaptively, yielding a higher or lower signal intensity depending on the difference (Lim, 1990).

The estimation of the local mean μ_s and variance σ_v^2 can be done in the local region R of size $M\times N$ following the equations below:

$$\hat{\mu}_s(m,n)=\frac{1}{MN}\sum_{k,l\in R} r(k,l) \tag{3}$$

$$\hat{\sigma}_s^2(m,n)=\begin{cases}\hat{\sigma}_r^2(m,n)-\sigma_v^2 & \hat{\sigma}_r^2(m,n)>\sigma_v^2\\ 0 & \text{elsewhere}\end{cases} \tag{4}$$

where

$$\hat{\sigma}_r^2(m,n)=\frac{1}{MN}\sum_{k,l\in R}(r(k,l)-\hat{\mu}_s(m,n))^2 \tag{5}$$

2.2. Image Kalman Filtering

Kalman filter is another frequently used optimal filter. Since its introduction in 1960, Kalman filtering has been applied in many fields and has been the subject of extensive investigation. The Kalman filter is often formulated in the form of a state-space model. The application of a Kalman filter in image processing requires a proper 2D model to be established before the recursive estimation procedure can be applied. This approach is potentially different from the Wiener type filter which is derived from the image power spectrum and the chosen model can impact greatly on the filtering results. In general, an autoregressive (AR) model can be viewed as a candidate and the AR coefficients can be identified by the Kalman filtering algorithm. There have been a number of previous attempts to apply Kalman filtering to image processing and in which update and estimate of the parameters can be made in blocks (Jo et al., 1998) and pixels (Bouzouba and Radouane, 2000; Boutalis et al., 1990). One of the established methods is the reduced update Kalman filter (RUKF) (Kaufman et al., 1983; Woods and Radewan, 1977). The image model of this method has its coefficients support region in nonsymmetric half-plane (shown in Fig. 1) (Ekstrom and Woods, 1976). Consider an image data with the density $s(m,n)$ of the pixel with horizontal coordinate m and vertical coordinate n, it can be represented by Kaufman et al. (1983).

$$s(m,n)=\sum_{(m-k,n-l)\in R_M} c(k,l)s(m-k,n-l)+w(m,n) \tag{6}$$