Artifact reduction for EEG/fMRI recording part 1: nonlinear reduction of ballistocardiogram artifact

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Abstract:

**Objective:** We present a new method to effectively remove ballistocardiogram artifacts (BAs) of electroencephalography (EEG), recorded inside a 1.5 T static magnetic field scanner, and conserve the time and frequency features of EEG activity.

**Methods:** The BAs are approximated as deterministically chaotic dynamics. A wavelet-based nonlinear noise reduction (WNNR) method consisting of wavelet transform, nonlinear noise reduction and spatial average subtraction, is developed to effectively reduce the BAs to be smaller than the EEG activity.

**Results:** The effectiveness of the WNNR method to conserve the temporal EEG signals is evaluated by simulations and real human experiments inside a 1.5 T static magnetic field, both visual evoked EEG dynamics and alpha waves during subject's eyes closed.

**Significance:** The current method has ability to conserve the time-frequency features of EEG activity, specifically event-related EEG dynamics. Moreover, it might effectively work in the higher field strength as well.
Key Words: ballistocardiogram artifact; nonlinear noise reduction; wavelet transform; EEG; MRI; visual evoked potentials (VEP); fMRI; alpha waves.

Introduction

The concurrent combination of electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) is increasingly an important technique used to obtain higher spatiotemporal resolutions of the human brain neural activity. This technique has been extensively applied in visual (Kruggel et al., 2001) and auditory evoked potentials (Liebenthal et al., 2003), epilepsy (Warach et al., 1996; Krakow et al., 1999), as well as sleep (Huang-Hellinger et al., 1995). However, the merits of the combination are compromised by the mutual interferences between EEG and fMRI systems. Although it is possible to obtain artifact free functional MR images, acquisition of clean EEG data is not trivial. The EEG system is sensitive to magnetic field interferences. Two kinds of artifacts are induced during fMRI scanning, namely imaging artifacts (Allen et al, 2000, Wan et al, submitted) and ballistocardiogram artifacts (BA) (Allen et al, 1998, Ellingson et al. 2004). In this paper the latter artifact is concerned. The BA, ubiquitously existing in the condition of inside MRI scanners, even without fMRI scanning, is probably caused by the subject's cardiac pulsation in the static $B_0$.
field (Ellingson et al. 2004). For example, Inside a 1.5 T static magnetic field, the BA amplitude is often at the level of 100 µV, considerably higher than scalp EEG signals. Hence, the BA severely obscures our ability to directly analyze and interpret EEG signals.

Due to similarity of BAs in epochs of each channel, a simple way is subtracting an average artifact template calculated from a specific number of previous consecutive epochs in each channel (Allen et al. 1998). However, as both the durations and amplitudes of BAs stochastically vary so much from epoch to epoch, considerable residual artifacts might remain in the filtered data by the average subtraction approach (Kim et al., 2004). To ameliorate this method to be more adaptive to the BA variability, an extensive modification had been made by using the median in place of the average of a specific number of previous consecutive artifacts, and also allowing for the width and amplitude scale of the template flexible to fit the data of each epoch (Ellingson et al. 2004). However, the residual artifacts are yet apparently observed in the corrected data (see Results). Recently, a wavelet-based denoising method has also been reported (Kim et al., 2004) to adaptively reduce the residual artifacts after average subtraction (Allen et al., 1998) However, in their method selectively suppressing
the wavelet coefficients in the range of 2~7 Hz might lost the ongoing EEG activity of the theta and delta bands. The same effect might also be elicited to the event-related EEG dynamics. Using a piezoelectric motion sensor on the subject’s temporal artery, both motion artifacts and BAs of EEG recordings correlated with the detected motion were able to be reduced by an adaptive Kalman filter (Bonmassar et al., 2002). Their technique assumes that the detected motion has a linear relationship with the BAs in the other locations across the scalp. On the other hand, as the stochastic BAs of all channels are synchronized with electrocardiogram (ECG), Kruggel et al. (2000) employed a spatial averaging filter to reduce BAs. However, our preliminary comparison of the BAs of all EEG channels indicated that the artifact waveforms are not exactly synchronized, and the waveform shapes are not consistent even after normalization. These facts suggest a straightforward spatial averaging filter is unsatisfactory.

The currently increasing interests of simultaneous EEG/fMRI recording require more stringent technique to retrieve temporal EEG signals, not only the average event-related potentials (ERPs) or average powers, which had been primarily used to evaluate effectiveness of the previous methods (Allen et al, 1998,
Ellingson et al. 2004, Bonmassar et al., 2002). This requirement entails a potential technique to remove BAs as far as possible in each epoch of BA-contaminated EEG data, but not distort the underlying EEG activity. Unfortunately, Because of highly non-stationary and nonlinear dynamics of BAs, linear methods might have limited ability of tracking the BA fluctuation to recover temporal EEG signals in all epochs. In this paper, we develop and demonstrate a novel nonlinear method, namely, wavelet-based nonlinear noise reduction (WNNR), to retrieve temporal EEG signals from the BA contaminated data, especially, the event-related EEG dynamics. The basic idea of this method is that the variable BAs might be taken as deterministically chaotic dynamics. If the strengths of EEG signals are much smaller than the BAs, the EEG signals can be interpreted as perturbation to the BA dynamics. Hence, removal of the BAs from the data is technically equivalent to reconstruction of the BAs, using the nonlinear noise reduction technique based on the phase (state) space embedding raised by the theory of deterministically chaotic dynamics (Grassberger et al., 1993; Kanz et al., 1997). This technique makes use of the fact that the deterministically chaotic dynamics takes place on the attractors which are smooth sub-manifolds of the available embedding space. This implies
that it is appropriate to use locally linear method to restore the low-dimensional structure of BAs. The nonlinear noise reduction had been used to reduce the ECG (Schreiber et al., 1996a&b) and ERP (Effern et al., 2000) noises. Here, the wavelet decomposing is used to divide the original data into multiple bands to be capable of finely detecting the fast and slow structures of the BAs.

In this paper, using the WNNR method (state space processing), our purpose is to retrieve EEG signals from the BA contaminated data with aim to conserve the temporal and frequency EEG features. The effectiveness of the proposed method is demonstrated by the simulations and the experimental data, both event-related visual experiments and alpha waves with continuous eye closed. The restored EEG signals are compared with those processed by the average waveform subtraction (AWS), as well as those outside the scanner under the same paradigms.

**Materials and Methods**

The alpha waves and visual evoked potentials (VEP) recordings were carried out to evaluate the performances of our method. The results of this method were compared with those outside the scanner, as well as those using the AWS.
method (Ellingson et al. 2004), in which the same parameters as they selected were used as previous 10 consecutive epochs to average, 90% width of the template and adaptive fitting amplitude scale of the template. Before applying the current method to the real experimental data, simulations were carried out to estimate its effectiveness.

Subject information

Four healthy subjects (3 male and 1 female, age 22~35) participated in our experiments. Informed consent was obtained from each subject prior to the experiments. The experiments had the approval of the local ethical committee of Tohoku University.

EEG recording

The EEG was recorded inside the scanner with a commercially available MR-compatible 32-channel BrainAmp system (Brain Products GmbH, Munich, Germany). The battery-powered amplifier located in the scanner tunnel was connected via a 15m fiber optic link to a standard PC in the MR console room. The data were acquired by Brain Record 1.4 software (Brain Products GmbH, Munich, Germany). The stimulus triggers were received from the stimulus PC. The helium pump of the scanner was switched off during EEG recording to
reduce the background noise, i.e., gantry vibrations. The electrodes were set up according to the international 10/20 system, with additional 4 channels dedicated for EOG, 2 channels for EMG and 1 channel for ECG. The reference electrode ($A_1$) and the electrode $A_2$ were attached to the subjects’ left and right earlobes, respectively. The ECG electrode was placed on the subjects’ backs to avoid any movement artifacts associated with respiration. The impedances of all channels were maintained below 5kΩ. The resolution and dynamic range of the amplifier were 0.5 µV and ±3.2mV, respectively. The EEG was recorded with a sampling rate of 5000 samples/s. Prior to the main amplification a band pass filter from 0.5 to 250 Hz was applied to the amplified data by a small gain using the same strategy of EEG recording system as in Allen et al. (2000). Finally the recording data were filtered with a phase shift-free Butterworth 125 Hz LPF.

**Visual Stimulation**

In a block, the visual stimuli consisted of 30 seconds of a black and white pattern reversing checkerboard of $16 \times 12$ patches (full field visual angle 11.5 degrees, 42 arc min per pattern), followed by 30 seconds of a uniformly gray field. The pattern was inverted at a mean interval of 2 seconds (*a trial*) with random variables ($\text{ISI}=2.0\pm0.5$ s) to compensate for the subjects’ habituation.
The experiment consisted of 5 blocks. In all conditions a central fixation spot was provided. This experiment was realized using Cogent 2000 developed by the Cogent 2000 team at the FIL and the ICN (http://www.vislab.ucl.ac.uk). The stimulation pattern was projected onto a screen in the scanner tunnel from an LCD projector (NEC, LT-260SJ, Tokyo, Japan) located outside the scanner room.

### Alpha wave recording

The alpha waves were recorded by repeated eye closed. The subjects were instructed to lie quietly in the scanner by opening and closing their eyes successively for one minute in each segment. This paradigm lasted for 10 minutes. Spectrograms of the alpha-wave data (256 points at the sampling rate of 256, with 128 point overlap, using Hanning window on each 256-point segment) were computed to compare the spectral powers. The power spectral density (PSD) was estimated using Welch’s method (Welch et al., 1967).

The same paradigms were carried out outside the MRI scanner for VEP and alpha waves experiments. However, the stimuli for VEP outside the scanner were presented by an LCD monitor, and the subjects were seated before the screen with the same visual angle as inside the scanner.
BA artifact reduction algorithm

The proposed WNNR method to reduce the BAs is schemed in Fig. 1. Basically, there are two stages in performing the method. Firstly, the EEG data of each channel are separated into multi-bands by wavelet transform. Subsequently, state space embedding of the wavelet coefficients is built on each band, respectively. Consequently, nonlinear noise reduction of BAs is manipulated on the space embedding by the local projective method, and then the data after noise reduction are inversely transformed into the time domain. Secondly, as the residual artifacts are usually observable in the corrected data, spatial average subtraction is used to reduce the common artifacts in all EEG channels. Prior to these procedures, the QRS peaks of ECG are identified as the markers of BA epochs in all EEG channels.

QRS detection: Although the strengths of the QRS complexes are smaller than those of the T waves in ECG recorded inside the scanner due to BA contamination, the waveforms of QRS complexes are considerably sharper and briefer than the T waves. Based on this fact we could correctly detect most of the QRS complexes, with exception of those obscured by irregular noises, i.e., head
movements. In one fragment of 12 second consecutive data, a low-pass filter (LPF) with a cutoff frequency of 30 Hz is used to smooth the original ECG. After the ECG signals are filtered, the first-order difference is calculated by a 50-point lag across the data (the sampling rate is 5000 Hz, so that a 50 point lag corresponds to a 10 ms time delay). On the QRS complexes, the symmetrically brief QRS complexes are differentiated into a bipolar transient waveform. The true QRS complexes are detected and the R peaks are identified by the following criteria: (1) the peaks cross over half of the maximum; (2) The bipolar transient waveform constitutes a positive polarity immediately followed by a negative polarity; (3) The distance between the pair peaks of polarities is below 30 ms; (4) The median points of the pair peaks satisfying the previous criteria are marked as the R peaks. (4) The R peak with its distance from the previous identified R peak outside the range between 0.6 s and 1.5 s is deleted.

Insert Figure 2. around here

Wavelet transform: Firstly, down-sampling is performed to restrain the data point in each epoch close to but not more than 256 points (the wavelet transformation is based on a 256-point window) and zero-padding is applied to those epochs with data points smaller than 256. The multi-resolution
decomposition of wavelet transform separates the data into details at different scales and conserves the local time-frequency features. Here, the original data were decomposed into 3 scales using the Quadratic bi-orthogonal B-spline (Cohen et al., 1992; Quiroga et al., 2003) basis functions due to being similar to the BAs. Therefore, there are 3 scales of details and one final approximation (Fig. 2). Since the power of the BAs primarily rests on the low frequency bands (Allen et al. 1998), the nonlinear noise reduction was carried out only in the three lowest frequency bands.

Space embedding: Space embedding of the wavelet coefficients is built using the time delay method. Vectors in the embedding space, were formed from the consecutive time delayed values of the wavelet coefficients \( X_n = (x_{n-(m-1)\tau}, x_{n-(m-2)\tau}, \ldots, x_n) \). The number \( m \) of elements is called embedding dimension, and \( \tau \) refers to the time delay or lag. Takens’s embedding theorem (Takens, 1981; Sauer et al., 1991) states that if \( m \) is large enough, the dynamics of deterministically chaotic system recovered by time delay embedding are the same as the dynamics of the original system. The local projective noise reduction algorithm is used to reconstruct the chaotic BA (see Appendix). This technique had been discussed in detail in the case of nonlinear noise reduction
of deterministically chaotic dynamics contaminated by small measurement noise (Grassberger et al., 1993). Technically, in the space embedding of dimension m, the mean and covariance matrix is calculated through a specific number of neighbors around the point of interest. If the BAs lie on a smooth sub-manifold having a lower dimension $d >> m$, and the variances of the BAs are larger than those of EEG signals, then the eigenvectors associated with the largest $d$ eigenvalues of the covariance matrix are spanned by the BAs and the other eigenvectors associated with smaller eigenvalues are spanned by the EEG signals. Therefore, the BAs and the underlying EEG signals can be separated in the embedding state space.

Parameter selection

There are three important parameters in the method to determine how to separate the BAs and EEG: (1) The length of embedding window ($m \times \tau$); (2) the neighborhood size ($K_n$) used to form the linear approximation and (3) the BA manifold dimension ($d$). Unfortunately, it is very difficult to directly determine these parameters from the chaos theory. Here, trial-and-test was employed to determine these parameters. In the case of VEP experiments, our tests show that the results are not sensitive to the length of embedding window and
neighborhood size in reasonable ranges of these values, but not the BA manifold
dimension (Fig. 3). With change of the length of embedding window, m=16, 24
and 32 (τ =1 unit in the wavelet domain), and the neighborhood size, \( K_n \) =15, 20,
25, these average VEP differences (subject KI) are not significant (Wilcoxon
signed rank test, \( P > 0.40 \) and \( P > 0.55 \) for the length of embedding window and
the neighborhood size, respectively). However, with change of the BA manifold
dimension, \( d = 0, 2, 3, 5 \), these average VEPs are apparently different. The BA
manifold dimension was set to zero means all variations within the neighborhood
were ascribed to the EEG signals. Evidently it was under-filtering. In contrast, in
the case of the dimension selected to be 3 or 5, it appeared to be over-filtering
(the strengths of VEPs significantly decrease with the BA dimension increase).
From these results, the parameters of the local projective noise reduction
algorithm used in this paper are listed as follows: For the VEP experiments, the
embedding dimension m was 32, the neighborhood size was 20 and the BA
manifold dimension was 2. In contrast, in the case of alpha waves experiments,
the strengths of alpha rhythm are usually much higher than the visual
stimulus-related EEG. Hence, the neighborhood size and the BA manifold
dimension were adapted to tolerate larger variations of EEG activity. Specifically,
the neighborhood size was 50 and the BA manifold dimension was 0.

Insert Figure 3. around here

Spatial average: Indeed, it is very difficult to entirely separate the BAs and EEG signals. So as to not distort the EEG signals, the tradeoff of selecting the BA manifold dimension as 2 did not completely remove the BA. There were relatively small but manifest residual artifacts in the corrected data of all EEG channels. To further reduce these residual artifacts, the corrected data were post-processed by subtracting the spatial average, which was exactly the same as the conventional EEG process to change the A1 reference into average reference.

Simulated data: the surrogate BAs, reconstructed from the POz channel using the WNNR method to process the original EEG data recorded with Subject XW inside the 1.5 T static magnetic field, was used for the simulations. Three kinds of signals were inserted into the BAs: (1) a generated white noise ($\sigma=10\mu$V); (2) a segment of visual-evoked EEG data outside the scanner; (3) a segment of alpha wave EEG data (continuously closing eyes) outside the scanner. Both of the EEG data were extracted from recordings with the same subject (XW). The signal to noise ratios (SNR) were 0.44, 0.20 and 0.33 in the cases of the white
noise, ERP and alpha waves, respectively.

**Results**

**Simulations**

The results of the simulations are collected in Fig. 4. We found the nonlinear noise reduction method used in this paper to be effective to separate the signals and artifacts. The trains of the restored data are very consistent with the original data. Morphologically, the retrieved data are closer to the original signals in the white noise case than in the ERP and alpha waves cases, whereas the retrieved alpha waves have larger errors than the ERP. The power spectral densities (PSD) illustrated in the right part of Fig. 4, were estimated using Welch’s method. The PSD differences between the corrected data and the original data obviously appear at the low frequency band (<20 Hz), where the BA powers are concentrated. Even so, the differences are trivial with respect to the original powers. It appeared that the average ERP of the retrieved data was the same as the original ERP (Fig. 4d, 30 trials in the dataset). In the case of alpha waves, the recovered data have similar PSD of the original alpha waves, with exception of the alpha power being reduced by about 10 µV² (alpha band: 8~13 Hz). The spectrograms show the retrieved data conserve the time-frequency features very
well throughout the course when the subject has his eyes closed (Fig. 4e and Fig. 4f).

Insert Figure 4. around here

VEP

Shown in Figure 5, the BAs of original data recorded inside the 1.5 T static magnetic field considerably vary from epoch to epoch. Although the AWS method enormously reduced the BAs, the residual artifacts are clearly discerned in the retrieved data. In contrast, the residual artifacts of retrieved data processed by the WNNR method are significantly smaller. Interestingly, the spatial average process by removing the common artifacts considerably reduced the residual artifacts which exist in the retrieved data processed by the AWS method, although the differences are yet obvious compared with the results of WNNR method. These results show that the AWS method usually under-filters the BAs, so that a lot of residual artifacts remain in the corrected data. However, conversely, whether does the WNNR method over-filter the BAs and concurrently remove somewhat of the EEG signals? As mentioned above, because the true EEG signals are unknown, here we used an indirect approach to test this issue. Specifically, we compared the average ERPs with the different
processes and that outside the scanner. If somewhat of the EEG signals were removed by the WNNR method, the average ERPs should be reduced as well. Fig. 6 illustrates two examples of ERPs (POz, Subject XW and LT, N=100), after artifact rejection using an amplitude threshold criterion of $\pm 30 \, \mu V$. Our tests show that the ERPs processed by the WNNR method are significantly closer to those outside the scanner, but the ERPs processed by the AWS method are significantly closer to the original ERPs (Wilcoxon signed rank test, $P<0.05$ and $P<0.03$, respectively. The tests include all channels of the four subjects). It is important to note that the original ERPs without reducing the BAs are not as bad as intuitively expected (for example, in Fig. 6b, these ERPs of the original data and the retrieved data are very similar). Conventionally, ERPs are calculated by averaging a number of trials. Hence, in many cases, whenever the strengths of artifacts non-time-locked with the events are large, like BAs, the average ERPs might be similar to the real ERPs. On the other viewpoint, this implies average ERPs may not be a good measurement to assess the effectiveness of the methods reducing BAs, especially, when BAs are only several times of the EEG signals, like in the 1.5 T static magnetic field. We address that another property of the event-related dynamics might be more reasonable and important. That is
the time-frequency features, termed event-related desynchronization (ERD) defined as a localized decrease in oscillatory power, or event-related synchronization (ERS) defined as a localized increase in oscillatory power (Pfurtscheller and Lopes da Silva 1999). Usually the time-frequency powers are calculated by averaging the powers across trials. Hence, the contamination of non-time-locked BAs will be revealed in the time-frequency representations, not like average ERPs, in which the non-time-locked artifacts are cancelled out. The time-frequency powers (POz) by averaging all 4 subjects are illustrated in the right column of Fig. 7. Time-frequency powers were calculated using Morlet wavelet analysis. The wavelets used have a 2-D Gaussian profile, such that the full-width half-maximum (FWHM) of the response in the time and frequency domains are $W_t$ and $W_f$, respectively. We used a wavelet family parameter of 10, which at each frequency, $f$, gives $W_f = 0.235f$ and $W_t = 3.74/f$. Again large residual artifacts can be clearly observed from the 2-D ERP image processed by the AWS method. This leads to the time-frequency features of the event-related dynamics completely vanish in the dominated artifact broad band (Fig. 7A). After removing the common artifacts across all EEG channels by subtracting the spatial average, the residual artifacts are significantly reduced and the
event-related time-frequency features emerge (Fig 7C). However, the contamination at the narrow band around 7 Hz still exists. The appearance of ERS at the narrow band around 10 Hz may also be contamination by the residual artifacts, compared with the time-frequency powers processed by WNNR method (Fig 7B &D).

*Insert Figure 5. around here*

Alpha waves

The strengths of alpha rhythm are usually much higher than the ERPs. This makes it necessary to use different parameters to separate BAs and EEG in the framework of WNNR method. i.e., the neighborhood size was 50 instead of 20 and the BA manifold dimension was 0 instead of 2 using in ERP. These changes would guarantee the underlying EEG signals to be reserved with compromise of artifacts increase. These effects can be evidenced from Fig. 8. After the subject's eyes closed, the strengths of EEG activity radically increase. Both of the methods retrieved temporal alpha rhythm very well (Fig. 8A). This is also clearly shown in the time-frequency powers (Fig. 8C&D). While the residual artifacts in the retrieved data after AWS processing are a little larger than those processed by the WNNR method. The average powers across the subject's eyes
closed session indicate effectiveness of both methods to retrieve the ongoing EEG (Fig. 9). However, our tests show that the powers of alpha rhythm processed by the WN NR method are significantly closer to those outside the scanner and those processed by the AWS method are significantly closer to the original data (Wilcoxon signed rank test, P<0.1 and P<0.05, respectively. The tests include all channels of the four subjects).

Insert Figure 6. around here

Discussion

The WNNR method is elaborated by a set of techniques, wavelet transform, nonlinear noise reduction and spatial average subtraction. All of the efforts are aimed to reduce the BAs to be smaller than the EEG signals from epoch to epoch without distorting the EEG signals, using the temporal and spatial information of the BAs. Although many methods reducing BAs from EEG recording with fMRI had been proposed, to our knowledge, this is the first time to show the possibility of conserving the time-frequency features of EEG activity by reducing BAs.

Insert Figure 7. around here

Although the idea of the WNNR method is originated from the deterministically
chaotic dynamics theory, the techniques used in this paper have more general meaning in terms of state space processing. Using a specific length of time-shifting window to separate the temporal data into a number of states, from the state ensemble finding a specific number of similar states defined by the $K_n$ shortest distances from the state of interest, the template averaging the set of the states represents the BA of interest. If only the average template is subtracted, it corresponds to the case that the manifold dimension in the WNNR method is set to zero. Otherwise, if the variations around the average state within the set of states is accounted for using the principle component analysis (PCA), for instance, remaining the first two PCs, is equivalent to the case that the BA manifold dimension in the WNNR method is set to 2 (the parameter used for processing the VEP data in this paper). From the above discussion, even if the assumption of the deterministically chaotic dynamics of the BAs was not satisfied, it should not affect the effectiveness of the WNNR method to reduce BAs.

*Insert Figure 8. around here*

However, only the nonlinear noise reduction could not absolutely separate the BAs and EEG signals. This necessitates further processing to reduce the
residual artifacts, for example, simply subtracting the spatial average to remove the common residual artifacts across all EEG channels. The spatial average subtraction is also very useful to reduce the residual artifacts in the AWS method.

Moreover, the WNNR method definitely has advantage in the higher $B_0$ field strength. It is clear that the variations of BAs proportionally increase with the filed strength increase. Since the WNNR method has the ability to reduce the variations to be smaller than EEG signals regardless of the BA strengths, the residual artifacts processed by WNNR should be radically smaller than those processed by the AWS method in the higher field strength.

Currently, compared with the AWS method, the disadvantage of the WNNR method is much slow. It takes approximately 2 hours to fully process a data set (10 minutes of EEG data sampled at 256 Hz from 32 channels) on a 2.2-GHz PC Processor running MATLAB 6.0, while the AWS method needs only 4 minutes.

**Conclusion**

In EEG/fMRI studies, the ubiquitous BAs usually preclude us to correctly obtain the underlying temporal EEG signals. We have developed a novel nonlinear
method, WNNR, being capable of reducing these artifacts and conserving the
time-frequency features of EEG activity, especially, the event-related EEG
dynamics. Moreover, the elaborate WNNR method has opportunity effectively
working in the higher field strength as well.

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Appendix: local projective noise reduction

For the embedding vector $x_n$, a small neighborhood $\mathcal{G}_n$ around this point is first
formed by finding the shortest $K_n$ Euclidean distance from the point, where $K_n$ is
the number of points in the neighborhood. From the points $x_k, k \in \mathcal{G}_n$, we
construct the average
\[ \eta_i^n = \frac{1}{K_n} \sum_{k \in \partial_n} x_{k-m+i}, i = 0, 1, \ldots, m-1 \quad (A.1) \]

and the \( m \times m \) covariance matrix

\[ C_{ij}^n = \frac{1}{K_n} \sum_{k \in \partial_n} x_{k+i} x_{k+j} - \eta_i^n \eta_j^n . \quad (A.2) \]

Then a diagonal weight matrix \( R \) is introduced and a transformation of the covariance matrix is performed as follows

\[ \Gamma_{ij}^n = R_{ij} C_{ij}^n R_{ij} . \quad (A.3) \]

In order to penalize the correction of the first and last coordinates in the delay window we set \( R_{00} = R_{mm} = r \) (where \( r \) is large), and the others to 1 on the diagonal of \( R \). The \( Q \) orthonormal eigenvectors of the matrix \( \Gamma \) with the smallest eigenvalues are called \( e_q, q = 1, \ldots, Q \). The vector projected onto the subspace spanned by these vectors is denoted as \( \xi^n \), i.e.,

\[ \xi_{ij}^n = \sum_{q=1}^{Q} e_{q,i} e_{q,j} . \quad (A.4) \]

Therefore, the \( i \)-th component of the correction \( \theta_n \) is given by

\[ \theta_{n,i} = \frac{1}{R_{ij}} \sum_{j=0}^{m-1} \xi_{ij}^n R_{ij} (\eta_j^n - x_{n-m+j}) . \quad (A.5) \]

The penalty matrix \( R \) makes the two largest eigenvalues lie in the subspace spanned by the first and last coordinates of the embedding space, and prevents any components in these directions (In this paper, the parameter of the manifold dimension used did not count these two eigenvalues). Since each element of the
scalar series is involved in \( m \) different embedding vectors, average of these corrections is calculated using the same weighted matrix \( R \).

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**Figure Legends**

**Figure 1.** Schematic diagram of the WNNR algorithm. The original EEG recording is segmented by the R markers of electrocardiogram (ECG). After digital wavelet transformation (DWT), the wavelet coefficients are embedded into state space. The dynamics of BAs are reconstructed in wavelet domain by application of nonlinear noise reduction. Inverse wavelet transformation (IWT) is followed to transform BAs into time domain. The differences between the original data and the reconstructed BAs are the retrieved EEG data. Finally, the spatial average subtraction across the EEG channels reduces the residual artifacts and retrieves the underlying EEG signals.

**Figure 2.** Wavelet transform and nonlinear noise reduction. (A) One epoch of EEG data with BA contamination; (B) Wavelet decomposing EEG data into 4 different scales; the highest frequency band (64~128 Hz) is eliminated without further processing; (C) In the wavelet domain, the remaining 3 bands are embedded into state space by time delay method, respectively; (D) The reconstructed BA structures using nonlinear noise reduction.

**Figure 3.** (A) The average ERPs (POz, Subject KI) with change of the length of embedding window, m =16, 24 and 32 (τ =1 unit in the wavelet domain); (B) The
average ERPs with change of the neighborhood size, $K_n = 15, 20, 25$; (C) The average ERPs with change of the BA manifold dimension, $d = 0, 2, 3, 5$.

**Figure 4.** The results of simulations using the WNNR method (without spatial average subtraction). The black line shows the original trace, and the green line shows the retrieved trace. The upper left shows the EEG time series and the upper right shows the corresponding power spectral density (PSD). (a) White noise ($\sigma = 10 \, \mu V$); (b) Visual evoked EEG; (c) Alpha wave EEG (continuous eye closure). (d) The average VEP waveform; (e) The original alpha wave spectrogram; (f) The retrieved alpha wave spectrogram.

**Figure 5.** (A) EEG recording inside the 1.5 T static magnetic field (Subject XW) under visual stimuli; the large BAs have observable variations in the epochs, segmented by the R markers of ECG; (B) The retrieved EEG data after BA reduction of (A). The red trace is the data processed by the AWS method and the black line is the same data processed by the WNNR method without spatial average subtraction. Obviously, the residual artifacts in the red trace are much larger than those in the black trace; (C) subtraction of the spatial average to reduce the residual artifacts in (B). The black trace is that processed by the WNNR method and the green trace is that processed by the AWS method.
Figure 6. The average VEPs (POz). All VEPs are subtracted by the spatial average.

Figure 7. The time-frequency features of visual evoked EEG activity. The images in the left column are the 2-D VEP plots (Subject XW), in which the abscissa is peristimulus time, and each trial is shown as a horizontal line in the images. The activities (vertically) are smoothed over trials using a moving average (width = 2). The images in the right column are the time-frequency images using continuous Morlet wavelets, averaged across the trials in all 4 subjects. (A) processed by the AWS method; (B) processed by the WNNR method without spatial average; (C) the data of (A) after spatial average subtraction; (D) the data of (B) after spatial average subtraction.

Figure 8. EEG recording of alpha waves during eye closed (Subject UI), by subtracting the spatial average. (A) One segment EEG data before and after eye closed; (B) The spectrogram of original data with BA contamination; (C) The spectrogram of corrected data processed by the AWS method; (D) The spectrogram of corrected data processed by the WNNR method.

Figure 9. The alpha waves power (POz, Subject UI), by subtracting the spatial average.
Figure 1
Figure 3
Figure 4
Figure 6
Figure 8
Figure 9