



Clinical neuroscience

A novel method for device-related electroencephalography artifact suppression to explore cochlear implant-related cortical changes in single-sided deafness



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HIGHLIGHTS

- Cortical activity localization in CI users via qEEG is confounded by device artifacts.
- We observed significant characteristic peaks in frequency domain from CI users' EEG.
- CI artifacts in EEG data could be effectively removed with band-limited ICA.
- By applying band-limited ICA, CI users' cortical activity can be evaluated effectively.

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ABSTRACT

Background: Quantitative electroencephalography (qEEG) is effective when used to analyze ongoing cortical oscillations in cochlear implant (CI) users. However, localization of cortical activity in such users via qEEG is confounded by the presence of artifacts produced by the device itself. Typically, independent component analysis (ICA) is used to remove CI artifacts in auditory evoked EEG signals collected upon brief stimulation and it is effective for auditory evoked potentials (AEPs). However, AEPs do not reflect the daily environments of patients, and thus, continuous EEG data that are closer to such environments are desirable. In this case, device-related artifacts in EEG data are difficult to remove selectively via ICA due to over-completion of EEG data removal in the absence of preprocessing.

New methods: EEGs were recorded for a long time under conditions of continuous auditory stimulation. To obviate the over-completion problem, we limited the frequency of CI artifacts to a significant characteristic peak and apply ICA artifact removal.

Results: Topographic brain mapping results analyzed via band-limited (BL)-ICA exhibited a better energy distribution, matched to the CI location, than data obtained using conventional ICA. Also, source localization data verified that BL-ICA effectively removed CI artifacts.

Comparison with existing method: The proposed method selectively removes CI artifacts from continuous EEG recordings, while ICA removal method shows residual peak and removes important brain activity signals.

Conclusion: CI artifacts in EEG data obtained during continuous passive listening can be effectively removed with the aid of BL-ICA, opening up new EEG research possibilities in subjects with CIs.

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1. Introduction

More than 200,000 patients with profound hearing loss have been rehabilitated using cochlear implants (CIs) (Kral and O'Donoghue, 2010), devices that bypass a nonfunctional inner ear and directly stimulate the auditory nerve. Also, cochlear implantation has recently emerged as a possible surgical treatment option

for rehabilitation in subjects having single-sided deafness (SSD) with tinnitus (Arndt et al., 2011; Song et al., 2013b; Vermeire and Van de Heyning, 2009). From a neuroscientific viewpoint, cochlear implantation affords a unique opportunity to study cortical plastic changes associated with unilateral or bilateral profound hearing loss and auditory sensory restoration (Lee et al., 2007; Song et al., 2015a; Song et al., 2014b; Song et al., 2015c; Song et al., 2015d). To explore such plastic changes related to cochlear implantation, neuroimaging modalities such as positron emission tomography (PET), functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), and quantitative electroencephalography (qEEG) have been employed.

Of these various methods, fMRI or MEG cannot be easily performed on subjects with metal implants, and repetitive PET examinations should be minimized to avoid overexposure to radiation, whereas qEEG can be performed repeatedly, without any associated hazard following cochlear implantation. In this regard, qEEG is the most effective method used to analyze ongoing cortical oscillations in CI users. However, localization of the cortical resting state or auditory evoked potentials (AEPs) in CI users via qEEG is confounded by the presence of a stimulus artifact produced by the device per se. Hence, development of a reliable method of suppression of device-associated artifacts from the EEG stream is a prerequisite if qEEG is to be employed as a neuroimaging tool in subjects with CIs.

To suppress CI-induced noise, the use of AEP-based EEG measurements of very short duration, triggered by extremely brief sound stimuli, has been suggested (Viola et al., 2012). An AEP-based EEG measurement method typically evaluates repeat signals triggered by identical stimulations and averages the data to reduce noise. Such preprocessing, or averaging of repeat signals, affords an appropriate environment for artifact removal. CI-related artifact signaling is correlated with the AEP because such signaling is in fact the source of the AEP per se. Hence, the pattern of CI artifacts can be observed and separated from the AEPs and background brain activities via independent component analysis (ICA) (Gilley et al., 2006; Viola et al., 2012). This approach, however, does not reflect the daily environments of patients; the AEP-based approach uses a very short, particular sound, such as a click.

In this context, EEG measurements taken during passive listening to a continuous sound stimulus (such as music) over several minutes may afford more natural brain activation upon sound stimulation than the AEP approach. However, removing CI-related artifacts from EEG data obtained during continuous passive listening is difficult, unlike the case with AEP data, because preprocessing the signals is not possible as no repeat signals exist to be averaged. Therefore, the data are very noisy and may contain numerous signals from many brain activities not associated with auditory stimuli. As ICA thus cannot be used to separate independent sources, thereby identifying artifactual signals, the artifact-independent source is admixed with other brain activities. Unfortunately, the auditory brainstem response (ABR) is one signal admixed with the CI artifact. Therefore, rejection of CI artifact-independent sources via ICA may remove important brain information as well as the CI artifact.

The main objective of the present study was to develop a novel method of suppressing EEG stream energy from a CI. To

selectively control only the artifactual signal, we applied an ICA artifact removal method described in previous studies. As applying ICA artifact removal methods to continuous EEG data obtained while passively listening to continuous auditory stimuli is difficult, we tested modified ICA methods including sub-band decomposition ICA (SD-ICA) (Tanaka and Cichocki, 2004) and band-selective ICA (BS-ICA) (Zhang and Chan, 2006) in an attempt to solve the problem of ICA failure. As spectral analysis includes examining the characteristics of the CI artifact spectrum, limitation of the frequency band to focus on CI artifact characteristics in the frequency domain may effectively discard many irrelevant sources and facilitate ICA-mediated artifact removal. In the current study, we describe CI artifact removal from specific bands in the EEG streams of four patients with CIs using band-limited (BL)-ICA. Source localization and comparison of spectra are performed to confirm suppression of CI artifacts with preservation of brain activities associated with cortical auditory evoked responses.

2. Materials and methods

2.1. Subjects and EEG recordings

Four patients with unilateral acquired SSD and ipsilateral tinnitus underwent cochlear implantation using Med-EL devices (see Table 1 for further information). The duration of deafness ranged from 9 months to 10 years (median, 4.5 years), and all patients had left SSD (Table 1).

EEGs were recorded under two conditions: condition 1, CI switch-on with a continuous music stimulus at most comfortable loudness (MCL) level of each patient monaurally to the implant using a cable; condition 2, CI switch-off with no auditory stimulus. Under both conditions, EEGs were recorded for 5 min using WinEEG software version 2.84.44 (Mitsar, St. Petersburg, Russia; <http://www.mitsar-medical.com>) in a fully lit room shielded against sound and stray electric fields, with the eyes closed and all patients sitting upright. The EEG streams were sampled using 19 electrodes of the standard 10–20 International placement, referenced to linked ears. The impedances of all electrodes were maintained below 5 k Ω throughout the EEG recordings. Data were recorded at a sampling rate of 1024 Hz using a 0.15-Hz high-pass filter and a 200-Hz low-pass filter. After recording, all data were processed off-line by resampling to 128 Hz and band-pass filtering (employing a fast Fourier transform filter with application of a Hanning window) at 2–44 Hz and next imported into Eureka! software (Sherlin and Congedo, 2005). Antwerp University Hospital Ethics Committee reviewed and approved the study and all applicable documents prior to study initiation. All patients signed an approved informed consent in order to be enrolled into the study.

All participants abstained from alcohol for 24 h prior to EEG recording and from caffeinated beverages on the day of the recording to avoid alcohol- or caffeine-induced changes in EEG power (Logan et al., 2002; Siepmann and Kirch, 2002; Volkow et al., 2000). The vigilance of all participants was checked by monitoring of EEG streams to prevent drowsiness-induced changes such as slowing of the alpha rhythm or the appearance of spindles (Moazami-Goudarzi et al., 2010); no participant exhibited any drowsiness-related EEG change.

Table 1
Demographic characteristics of the included subjects.

Subject number	Duration of deafness	Psychoacoustic characteristics of tinnitus	Name of the implanted device (in detail, please)	Side of the cochlear implant
1	4 years	Pure tone	MED-EL Sonata ti 100 FLEX Soft electrode	Left
2	5 years	Pure tone	MEDEL Sonata ti 100 FLEX Soft electrode	Left
3	9 months	Pure tone	MED-EL Sonata ti 100 FLEX 24 electrode	Left
4	10 years	Narrow band noise	MED-EL Pulsar ci 100 Standard electrode	Left

2.2. ICA artifact removal

AEP-based EEG measurement methods record short-duration EEG signals when very brief sound stimuli are repeatedly given. When a short repetitive signal is used to collect AEPs, preprocessing that averages trial data reduces noise because noise is independently distributed. In addition, background brain activities that are not related to auditory function can be reduced because they are not present in every trial. Taking advantage of this AEP approach, several studies have removed CI artifacts with the aid of ICA (Gilley et al., 2006; Viola et al., 2012), which can identify independent sources in multichannel EEG signals. In even a single channel, an EEG signal contains multiple brain activities with different weights based on their locations. A multichannel EEG signal can be represented as

$$\mathbf{x} = \mathbf{A}\mathbf{s} + \mathbf{v}, \quad (1)$$

where $\mathbf{x} = [x_1(t), x_2(t), \dots, x_i(t)]^T$, x_i is the i th channel EEG signal, $\mathbf{A}$ is a mixing matrix, $\mathbf{s} = [s_1(t), s_2(t), \dots, s_j(t)]^T$, s_j is the j th source signal, and is $\mathbf{v}$ noise. Given $\mathbf{x}$, the independent components (ICs) are represented by

$$\hat{\mathbf{s}} = \mathbf{W}\mathbf{x}, \quad (2)$$

where $\mathbf{W}$ is the unmixing matrix and $\mathbf{W} \approx \mathbf{A}^{-1}$. Therefore, a well-estimated $\mathbf{W}$ affords approximately independent sources, $\hat{\mathbf{s}}$. Several algorithms can successfully estimate $\mathbf{W}$ based on these assumptions using an information theory approach termed the infomax algorithm (Bell and Sejnowski, 1995) and second-order statistics termed second-order blind identification (SOBI) (Belouchrani et al., 1997). The CI artifact signal can be represented as an estimated source signal $\hat{\mathbf{s}}_{\text{CI}}$. Subtraction of $\hat{\mathbf{s}}_{\text{CI}}$ from $\hat{\mathbf{s}}$ generates an artifact-free vector $\tilde{\mathbf{s}}$, and reconstruction then proceeds as follows:

$$\tilde{\mathbf{x}} = \mathbf{W}^{-1}\tilde{\mathbf{s}} \quad (3)$$

The reconstructed signal $\tilde{\mathbf{x}}$ does not include the artifact signal. As such ICA-mediated artifact rejection selectively removes the artifact signal only, brain activity signals can be preserved, although they may be weak.

CI rejection studies on AEP-based EEG measurements (Gilley et al., 2006; Viola et al., 2012) used this CI component rejection method, which successfully separated and removed artifact signals from measured AEP data. However, ICA is of limited utility when the signal is noisy or the number of unknown sources is greater than the number of channels (Sanei and Chambers, 2008). Although AEP-based EEG measurements may be repeated using simple brief stimuli, and the signal-to-noise power ratio (SNR) can be enhanced by averaging trial data, continuous EEG signals obtained under conditions of continuous auditory stimulation cannot be subjected to any preprocessing (such as averaging) to enhance the SNR since the signals do not have a repetitive pattern and thus cannot be easily analyzed to reduce background signals that are not auditory in nature. Hence, existing ICA artifact removal methods for EEG streams obtained under conditions of continuous auditory stimulation cannot perfectly separate or remove CI source signals.

2.3. BL-ICA

To separate more sources than the number that can be efficiently measured, SD-ICA (Tanaka and Cichocki, 2004) utilizes a filter bank to separate independent sources into sub-bands. The method assumes that unknown wideband source signals can be interdependent, whereas some narrowband subcomponents are independent. The method calculates the unmixing matrix $\mathbf{W}$ for each sub-band and estimates independent source numbers by analyzing the multiple unmixing matrices of sub-band signals.

However, SD-ICA cannot adjust the bandwidth, which affects the performance. BS-ICA adaptively adjusts the band size to avoid performance degradation (Zhang and Chan, 2006). Both methods use a sub-band approach to improve ICA performance when many noisy unknown sources are present, the number of which is larger than the number of channels.

SD-ICA and BS-ICA assume that the filter is unknown. Therefore, they search all sub-bands and adjust the bandwidth to find ICs. In the present study, however, we assumed that the filter was known, and that the CI artifact power was large over only a narrow band. If CI artifact power is dominant in a band, the SNR_{CI} (the CI artifact power divided by other signal power) in that band will be much larger than the entire band SNR_{CI} for the whole band. Therefore, even if EEG data are collected for a long time under conditions of continuous auditory stimulation, ICA can separate the sources and selectively reject only CI artifacts, if the two assumptions presented above are valid.

To remove CI artifacts with the preservation of natural EEG signals, we recorded continuous EEG data under conditions of continuous auditory stimulation suitable for application of ICA to separate artifacts from brain activity sources in the chosen frequency band. As the filter is known, and has a narrow band, a simple narrow band-pass filter can be used. If we limit the band using a filter focusing on the CI artifact, the relative power of that artifact is enhanced. In addition, if the band is narrow, it will likely contain fewer source signals. Therefore, in such a limited band, we can create an EEG stream under continuous auditory stimulation that is suitable for application of ICA. The BL approach can be represented as

$$\hat{\mathbf{s}}_b = \hat{\mathbf{W}}\mathbf{x}_b = \hat{\mathbf{W}} \begin{bmatrix} h_b(t) \otimes x_1(t) \\ \vdots \\ h_b(t) \otimes x_n(t) \end{bmatrix}, \quad (4)$$

where $\hat{\mathbf{s}}_b$, $\mathbf{x}_b$, $h_b(t)$, $\otimes$, and $\hat{\mathbf{W}}$ are the estimated independent source in the limited band, the BL signal, the known band-pass filter, the convolution operation, and the unmixing matrix for the band, respectively. If $\mathbf{x}_b$ has a smaller number of independent sources than the number of channels and enhances artifact power, ICA can successfully separate artifacts from brain activity sources.

2.4. Narrowband artifact component rejection

In order to apply BL-ICA, frequency detection is required to specify sub-bands that have dominant CI artifact signal. For the frequency detection, we manually search for unnatural frequency responses such as significant characteristic peaks in the frequency domain in the entire EEG recording channels. Since the subjects were listening to music while measuring EEGs, characteristic peaks can hardly exist in the frequency domain. In addition, by checking whether the characteristic peak power is higher in channels near the CI device than that in the other channels, we choose the band that contains a characteristic peak as a sub-band of BL-ICA for the design of the narrow band pass filter $h_b(t)$.

Based on the sub-bands obtained by manual frequency detection, BL-ICA generates ICs in the sub-bands. Among the ICs, $\hat{\mathbf{s}}_{\text{CI}}$ can be chosen by examining both a significant characteristic peak in the frequency domain and locations of ICs in the scalp map which is plotted by $\hat{\mathbf{W}}$. That is, if the ICs contain the peak in frequency domain and are related to locations near the CI device components such as RF transmitter, ground electrode, and stimulation electrodes, we choose them as CI artifact components in the sub-band.

To remove narrowband CI artifact signals via SD-ICA, a filter bank approach is required to assemble all the sub-bands into an entire band. In the present study, however, we consider only a

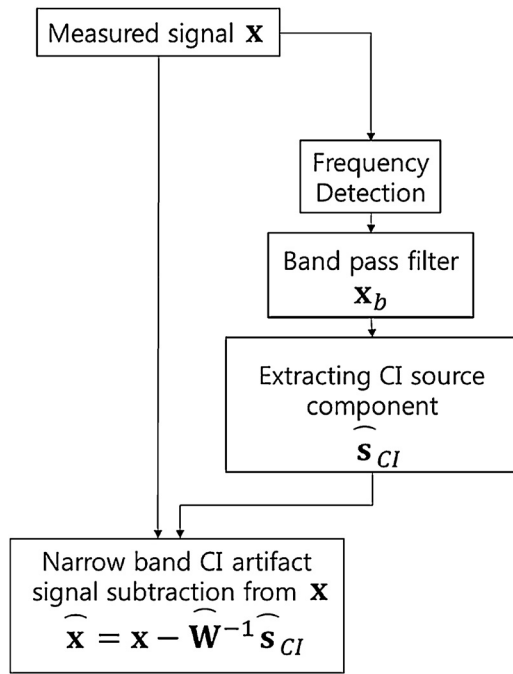


Fig. 1. Block diagram of band limited independent component analysis for suppressing device-related artifact.

single narrow band, thus reducing the computational burden. Without the assembly of sub-bands, simple CI artifact rejection via $\hat{S}_{CI}$, utilizing subtraction is accomplished as follows:

$$\hat{\mathbf{x}} = \mathbf{x} - \hat{\mathbf{W}}^{-1} \hat{\mathbf{S}}_{CI} \quad (5)$$

where $\hat{\mathbf{x}}$ denotes artifact data rejected using BL-ICA. Hence, we have successfully removed CI artifacts from mixed data in the band. Although the band is narrow, if the CI artifact signal is dominant in the band, we suppress most of the CI artifact signal in the entire band. Fig. 1 shows the complete process of CI artifact removal using BL-ICA. In this process, MATLAB version R2012a (MathWorks, Natick, MA, USA) and EEGLAB toolbox version 12.0.6.2b (Delorme and Makeig, 2004) are used for filtering, frequency detection, and infor-max ICA.

2.5. Source localization

Standardized low-resolution brain electromagnetic tomography (sLORETA, <http://www.unizh.ch/keyinst/NewLORETA/LORETA01.htm>), a functional imaging toolbox yielding standardized current densities (Pascual-Marqui, 2002), was used to compare conditions 1 (CI switch-on) and 2 (switch-off) and thus to explore the numbers of relatively activated cortical regions when the CI was on using both ICA and BL-ICA EEG data. sLORETA estimates the numbers of intracerebral sources generating scalp-recorded electrical activities within each of the following eight frequency bands: delta (2–3.5 Hz), theta (4–7.5 Hz), alpha 1 (8–10 Hz), alpha 2 (10–12 Hz), beta 1 (13–18 Hz), beta 2 (18.5–21 Hz), beta 3 (21.5–30 Hz), and gamma (30.5–44 Hz) (Song et al., 2013a; Song et al., 2014a; Song et al., 2013b; Song et al., 2015b; Vanneste et al., 2013). The solution spaces of the current study are those implemented in LORETA-Key software (available at <http://www.uzh.ch/keyinst/loreta.htm>). This software uses realistic electrode coordinates (Jurcak et al., 2007) and the lead field produced earlier (Fuchs et al., 2002) by implementing the boundary element method of MNI-152 (Montreal Neurological Institute, Canada). The sLORETA solution space consists of 6239 voxels

Table 2

Information on characteristic peaks due to CI artifact for each subject.

Subject	Center frequency (Hz)	Amplitude (dB)
1	22.5, 32.3	8.151, 5.72
2	22.5	12.166
3	48.25	6.689
4	38.5	7.032

5 × 5 × 5 mm in dimensions. Anatomical labeling of significant clusters was achieved using a toolbox built into sLORETA.

Statistical analysis of sLORETA-based source localization features nonparametric mapping (SnPM) via permutation testing of labels, affording comparisons. SnPM deals with the multiple comparisons problem implicit in standard voxel-by-voxel hypothesis testing and yields results similar to those obtained via a comparable statistical parametric mapping approach using a general linear model in which multiple comparison corrections are derived using random field theory (Nichols and Holmes, 2002). As the method is nonparametric in nature, the validity of the SnPM does not rely on any assumption of a Gaussian character (Nichols and Holmes, 2002). The threshold of significance for all tests was derived using a permutation test featuring 5000 permutations.

3. Results

3.1. Frequency detection

We observed significant characteristic peaks in the frequency domains of the subjects with CIs. Based on characteristic peak information, we could apply a narrow band-pass filter 2 Hz in width. Table 2 shows the characteristic peak information for each patient. The center frequency represents the peak frequency and the differences between the peak and bottom amplitudes are shown. The characteristic peaks were located primarily in the beta 3 and gamma frequency bands. No alpha frequency band peak was detected in any study subject.

3.2. Scalp map analysis

The independent sources and energy distributions of the characteristic peaks detected by both ICA and BL-ICA are illustrated on the scalp maps in Fig. 2. The graphic representations of the ICA-derived scalp maps of subjects 1, 2, and 4 fail to reveal the location of the implanted device, which is the temporoparietal region. However, BL-ICA affords a better graphic representation of CI locations in subjects 2 and 4. Subject 1 has two peaks at 22.5 Hz and 32.3 Hz in the frequency domain, and the ICs for the 32.3 Hz peak show the energy distributions of the stimulation electrodes, ground electrodes, and RF transmitter when either ICA or BL-ICA was used. BL-ICA retains less energy from the occipital and frontal regions than ICA. For subject 2, the BL-ICA result differed greatly from the ICA finding. ICA revealed only the energy from the left temporal region, whereas BL-ICA displayed a much clearer energy distribution from the CI in which the locations of both the stimulation electrodes, ground electrode, and RF transmitter were apparent. In addition, the BL-ICA data from subject 4 clearly show energy from the CI, whereas the ICA data do not. In addition, when only ICA was used, the independent sources were mixed with other brain activities. The ICA data in Fig. 2 show the ICs containing the most significant peaks of energy. Most ICs shown by ICA exhibit peak energies, meaning that ICA cannot clearly separate ICs associated with the significant characteristic peak. However, the BL-ICA results of Fig. 2 show ICs that contain only significant characteristic peaks, indicating that BL-ICA near-perfectly separates and identifies the ICs with such peaks. Furthermore, unlike what was noted using

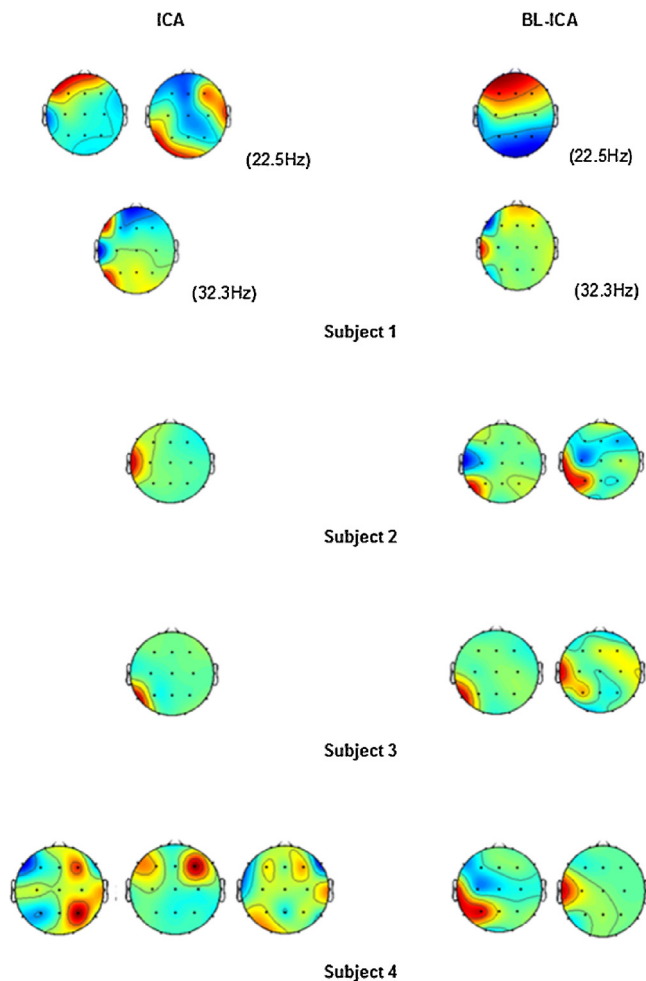


Fig. 2. Comparison of electroencephalography scalp maps using independent component analysis (ICA) and band limited ICA in all four subjects.

ICA, only one or two independent component sources included all characteristic peak energies so that the other components were free from the characteristic peak of the CI artifact. In other words, BL-ICA-independent sources were less-mixed with other signals, and thus, selective removal of a signal solely attributable to the CI was possible using BL-ICA.

3.3. Spectrum analysis

We next evaluated the accuracy of BL-ICA by comparing the artifact-removed spectrum derived using BL-ICA with that obtained employing ICA. Fig. 3 shows EEG spectra measured both under CI-on and CI-off states, and spectra obtained after artifact removal using both ICA and BL-ICA for each subject. The BL-ICA spectra overlapped notably with the CI-on spectra except for several narrow peak bands, and the presumed CI-related peaks could be easily removed using those bands. However, the ICA artifact removal spectra lost a great deal of energy over the entire frequency band compared to BL-ICA artifact removal. In subject 2, the ICA artifact removal spectrum was similar to the CI-off spectrum because the former spectrum lost a significant amount of energy (Fig. 3b). In addition, residual characteristic peaks were evident after ICA artifact removal, although we rejected several independent source components. As CI energy in the characteristic peaks was not separated successfully, being admixed with other ICs associated with hearing function after ICA artifact removal, rejection of only a few components was not adequate to erase all peak energy.

3.4. Source localization

When artifact removal was performed using ICA, all patients showed significantly increased activities in the right primary and secondary auditory cortices (A1 and A2; the beta 1 and 2 frequency bands) and in the left A1 and A2 cortical regions (the beta 3 and gamma bands) when the intragroup contrast 'CI-on-CI-off' was performed (Fig. 4a). However, for the same contrast, all patients showed significantly decreased activities in the bilateral middle and inferior frontal cortices (MFC and IFC) of the delta frequency band, and in the pregenual anterior cingulate cortex (pgACC) and parahippocampus (PHC) (both the delta and gamma bands) (Fig. 4b).

4. Discussion

In the current study, we sought to develop a novel method of selectively suppressing CI-related artifacts in EEG streams obtained under conditions of continuous auditory stimulation. We first attempted ICA-mediated artifact removal, as in previous studies, and also tested BL-ICA-mediated artifact rejection methods including SD-ICA and BS-ICA. Comparisons of spectra and source-localized activities using sLORETA revealed stark differences between the ICA- and BL-ICA-based artifact rejection methods.

4.1. Artifact suppression

The principal goal of the present study was to remove only CI artifact signals from EEG data collected under conditions of continuous auditory stimulation. Such artifacts cannot be separated and selectively removed employing existing ICA methods, although such methods work for AEP-based EEG data. We consider that this problem is caused by the over-completeness of ICA. As EEG data obtained under continuous auditory stimulation feature many sources of brain activity, including irrelevant sources, signals measured from 19 electrodes are not adequate to separate the many sources. BL-ICA successfully solves this problem by applying a narrow band-pass filter, which limits the number of sources and enhances SNR_{CI}, thus allowing CI artifacts to be clearly detected and separated from other brain sources. We found that the existing ICA method creates residual peaks because the CI artifact signal is not successfully separated. However, BL-ICA yields no residuals and rejects only one or two ICs.

BL-ICA removes CI artifact signals in a very narrow band, which is so narrow that it is impossible to claim that the CI artifact signal has been successfully removed from the entire band. However, significant energy is removed, and most of the CI artifact signal effect is suppressed. In addition, such band narrowness preserves not only brain signals within the band, but also signals in other bands. Hence, BL-ICA can be used to suppress CI artifact signals with the preservation of brain signals. As the results show, such CI artifact suppression renders EEG analysis possible even when EEG data are collected under conditions of continuous auditory stimulation.

4.2. Comparison between ICA and BL-ICA in terms of source-localized activity

When artifact removal was performed using ICA, all patients exhibited significantly increased activities in the right A1 and A2 beta 1 and 2 frequency bands, and the left A1 and A2 beta 3 and gamma bands, in the intragroup contrast 'CI-on-CI-off' (Fig. 4a). All patients showed significantly decreased activities in the bilateral MFC and IFC (the delta frequency band) and the pgACC and PHC (the delta and gamma bands) (Fig. 4b) for the same contrast

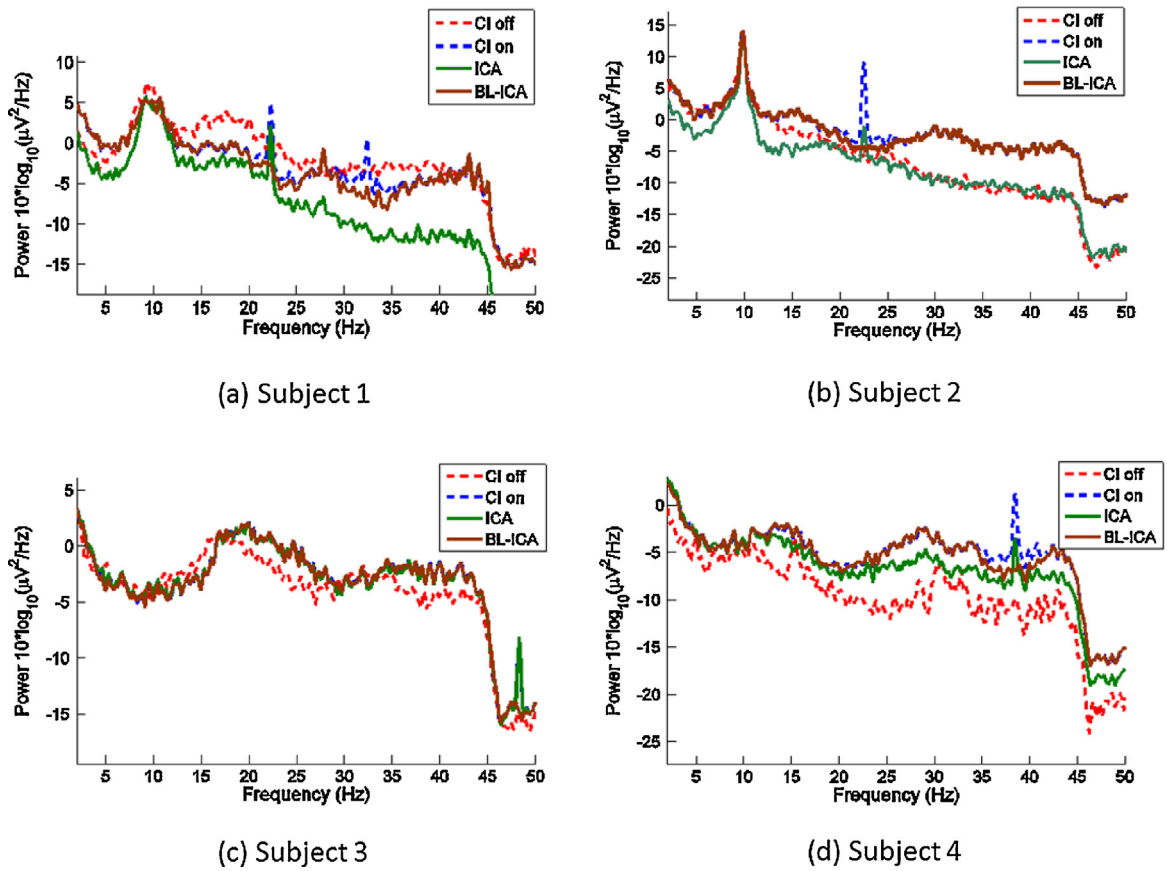


Fig. 3. Spectrum results of all four patients using independent component analysis (ICA) and band limited ICA rejections.

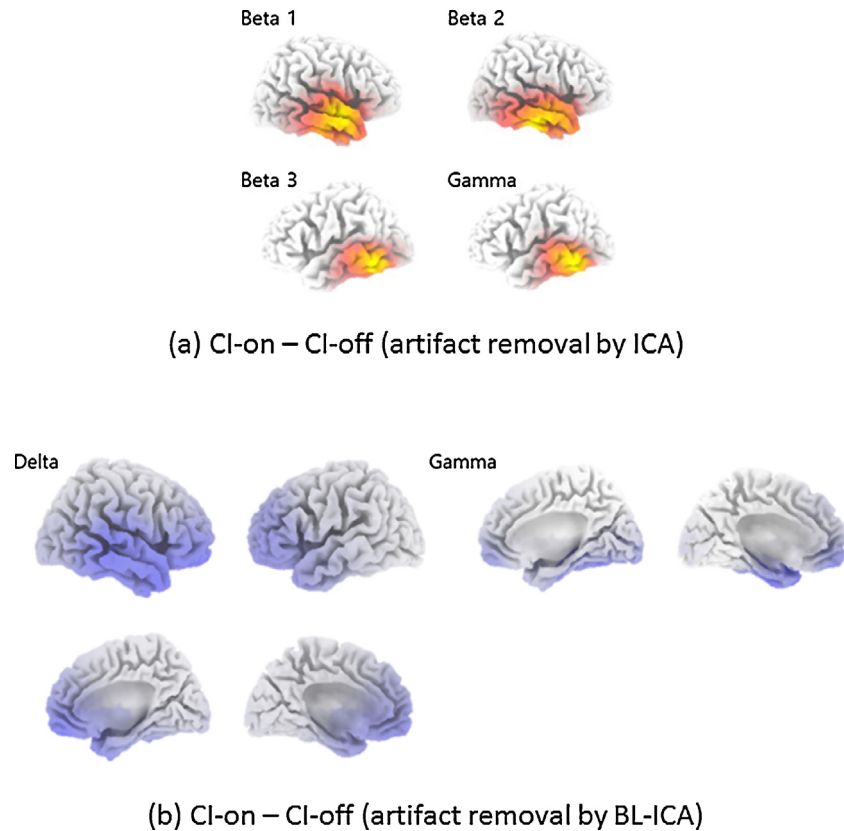


Fig. 4. Comparison of sLORETA contrast analysis results between post-cochlear implant (CI) datasets and pre-CI datasets with artifact removal using independent component analysis (ICA) (a) and band limited ICA (b).

('CI-on–CI-off') when artifact removal was performed with the aid of BL-ICA.

As debilitating tinnitus improved in the four patients after CI, but only when the devices were switched on, the source localization results exhibiting only bilateral auditory cortical hyperactivity do not adequately explain the observed symptomatic improvements. Earlier neuroimaging studies found that the activity of the auditory cortex in patients with tinnitus was greater than that of normal controls (without tinnitus) (Chang et al., 2012; Weisz et al., 2005). In contrast, the decreased activities of the bilateral MFC and IFC (the delta frequency band) and the pgACC and PHC (both the delta and gamma bands) explain the observed reductions in tinnitus intensities and tinnitus-related distress because these areas have been frequently reported to be activated in subjects with tinnitus (De Ridder et al., 2011; De Ridder et al., 2013; Golm et al., 2013; Langguth et al., 2013; Song et al., 2012; Vanneste et al., 2010). Our findings reconfirm that BL-ICA-based artifact rejection is more accurate than ICA-based rejection when the EEG streams of patients with CIs are analyzed.

5. Conclusions

We observed characteristic peaks in the frequency domain of the qEEG stream and confirmed that the peaks were CI artifacts by analyzing frequency domain characteristics and scalp maps. To reduce the CI artifact effect on qEEG, we utilized BL-ICA, in which ICA is applied to a limited band, and successfully separated CI artifacts from natural EEG signals. Also, the BL-ICA spectra and the sLORETA data show that our proposed method selectively removes CI artifacts from continuous EEG recordings. The method permits effective analysis of cortical oscillations in patients with CIs and may facilitate future research on cortical activity changes in such subjects.

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