Supplemental Information

Hearing an illusory vowel in noise: Suppression of auditory cortical activity

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Supplemental Materials and Methods

Application of ICA in EEG data analysis allows the removal of repetitive artifacts without the need to reject entire data epochs (e.g., Jung et al., 2000b; Jung et al., 2000a; Delorme et al., 2007a). It further allows the extraction of cortical activities of interest that are little contaminated by the mixing of different source activities through volume conduction (Jung et al., 2001; Makeig et al., 2002; Contreras-Vidal and Kerick, 2004; Makeig et al., 2004; Debener et al., 2005a; Debener et al., 2005b; Onton et al., 2005; Onton et al., 2006; Delorme et al., 2007b; Huang et al., 2008).

Our first goal of using ICA was to remove artifacts while preserving a reasonably large number of epochs. EEG channel data were decomposed into maximally temporally ICs using the extended Infomax ICA algorithm (Bell and Sejnowski, 1995; Makeig et al., 1997; Lee et al., 2000). ICs resembling artifacts were identified by assessing visually the goodness-of-fit of the scalp topography, power spectrum, and event-related waveform of each IC to templates of artifacts described elsewhere (see Figures 2B, 3B, 6A in Jung et al., 2000b; Figures 1B, 2A, 2B in Jung et al., 2000a; Figure 1 in Delorme et al., 2007; and section I.9.4 in the EEGLAB manual, see Delorme and Makeig, 2004). To reduce the degree of subjectivity, the assessment was repeated. For participants P1–P5, this was done by a different experimenter. The assessments yielded similar numbers of artifactual ICs, differing by 1 ± 3 ICs (mean ± s.d. across participants); consequently the larger set of artifactual ICs was removed from the data. As illustrated by Fig. S1 (right column), these artifactual ICs revealed scalp topographies that were mostly inconsistent with dipolar sources, being far-frontally distributed (which, together with a power peak at 1–3 Hz, was indicative of an eye-related artifact), strongly lateralized to temporal channels (which, together with a power peak at 20–50 Hz, was indicative of a temporal muscle artifact), or confined to single channels (indicative of temporary channel dropouts). On average, these putative artifactual ICs showed substantially weaker auditory-evoked activity than the ICs deemed as brain activity (Fig. S1C, compare column 3 with columns 1 and 2).

Our second goal of using ICA was to extract auditory cortical activities that were little contaminated by mixing with other source activities. Moreover, extraction of these activities enabled group analyses including the direct comparison with previous work that used the same methods (Riecke et al., 2009). To that end, the 318 ICs deemed as brain activity (see Fig. S1, left and middle columns) were clustered based on similarities in their scalp topographies, event-related activity waveforms, and power spectra. To reduce their dimensionality, these three measures were first decomposed into six, two, and two principal components (respectively); this was done automatically for each IC using principal component analysis. The three measures were standardized (matched for variance) by dividing each principal component by the variance of the first principal component, separately for each measure. Similarity among ICs was estimated from the distance of their principal components in the 10-dimensional Euclidean space that was defined jointly by the dimension-reduced
measures. The summed squared distance was then minimized between the principal components of each IC and those of the estimated mean IC clusters, which was done automatically using the $k$-means algorithm (Matlab Signal Processing Toolbox). The arbitrary polarity of each IC was adjusted so that IC topography correlated positively with the respective cluster topography. Finally, the clustering was refined to improve uniformity among the clustered ICs in terms of auditory event-locking. This was done by assessing visually the goodness-of-fit of the event-related activity of each IC to the event-related activity of the cluster revealing the strongest auditory event-locking (Fig. S1C, left column) and affected the cluster membership of $1 \pm 1$ ICs (mean ± s.d. across participants; see asterisks in Figs. S1B and S1C).

Similar applications of ICA have been demonstrated by several research groups investigating visuomotor tasks (Contreras-Vidal and Kerick, 2004; Makeig et al., 2004; Delorme et al., 2007b; Huang et al., 2008), visual attention (Makeig et al., 2002), working memory (Onton et al., 2005), auditory novelty (Debener et al., 2005a), and performance monitoring (Debener et al., 2005b). In the present study, we used the ICA-based approach to identify and extract brain activities that were most indicative of auditory cortical activities, based on a reasonably large number of artifact-reduced epochs. To further reduce potential influences due to the partial subjectivity of the IC-pruning procedure, we conducted additional analyses based on non-clustered artifact-reduced data (Fig. S1, left and middle columns). These distributed source analyses revealed effects in AC (see manuscript, Fig. 6) that were consistent with the effects obtained from the ICs presumed to resemble AC activity (Fig. S1, left column), thereby supporting our initial presumption.

**Figure S1.** IC-based artifact rejection and IC clustering (see next page).

The EEG channel data were decomposed into maximally temporally ICs. The upper plot in panel A shows the average scalp topography of these ICs, which were then separated into artifacts (see bottom, right) and non-artifacts (see bottom, left and middle). The non-artifacts were further separated based on their functional-anatomical properties (i.e., their scalp topographies, event-related activity waveforms, and power spectra). ICs that were strongly time-locked to auditory events (see bottom, left) were selected for further analyses testing for specific experimental effects. Panels B and C show the same as the bottom of panel A, but separately for each participant and each IC (panel B), and for event-related activity waveform (panel C, top) and power spectrum (panel C, bottom). The insert (panel C, left) shows the event-related activity waveform of ICs whose cluster membership was refined based on visual inspection (marked by asterisks in panel B).
Supplemental Results

To explore vowel restoration-related effects on auditory cortical activity across a wide frequency range, we compared average EEG power in the Restoration and No-restoration conditions, separately for several common frequency bands (delta: 1–2 Hz, theta: 3–7 Hz, alpha: 8–12 Hz, beta: 13–27 Hz, gamma: 28–50 Hz). The time-frequency analysis involved one cycle per wavelet (for frequencies from 1 to 2 Hz) or 3–25 cycles per wavelet (increased linearly for frequencies from 3 to 50 Hz). The outcomes are described in Figure S2. No significant effect of vowel restoration on auditory cortical activity was observed beyond the 3–4 Hz range (see also Fig. 7B).

Figure S2. Effects of vowel restoration on EEG power in typical frequency bands.

The figure shows EEG power in the Restoration condition (gray) and No-restoration condition (black) relative to baseline as a function of time, separately for the frequency bands denoted above the time series. The plots indicate that all bands contained on average less power during the interval of the vowel interruption (delineated by the vertical lines) when the vowel was restored than when the vowel was not restored. However, the differences between the conditions did not reach significance at any time point or in any band ($P < 0.05$; FDR-corrected).
Supplemental References


