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Comparative power spectral analysis of simultaneous elecroencephalographic and magnetoencephalographic recordings in humans suggests non-resistive extracellular media

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Supplementary material

Supplementary methods

We give details below to some of the methods and quantities used in the Results.

SNR

Two of the used methods for noise-correction are based on band-specific signal-to-noise ratio (SNR) in order to cancel the effects of background colored-noise in the spectra of interest. In each subject, average PSD was used to calculate signal-to-noise ratio (SNR). For SNR calculation, few frequency bands were defined based on the categorization in Buzsaki & Draguhn (2004): 0-10 Hz (Slow, Delta and Theta), 11-30 Hz (Beta), 30-80 Hz (Gamma), 80-200 Hz (Fast oscillation), 200-500 Hz (Ultra-fast oscillation). SNR was calculated as:

$$SNR_{bi} = \frac{\sum 10 * log10(\frac{PSDsignal_{bi}}{PSDnoise_{bi}})}{n} \quad (1)$$

for a given band "b" and sensor "i", "n" is the frequency resolution of that band. This method was applied on individual average PSD as well as shape preserving spline of each average PSD where each PSD was fist smoothed in log10 scale using a shape preserving spline, i.e, Piecewise Cubic Hermite Interpolating Polynomial (PCHIP).

Multiband spectral subtraction

Assuming the additive noise to be stationary and uncorrelated with the clean signal, nearly most spectral subtraction methods can be formulated using a parametric equation:

$$|\widehat{S(k)}|^{\alpha} = a_k |Y(k)|^{\alpha} - b_k |\widehat{D(k)}|^{\alpha} \quad (2)$$

where $|\widehat{S}_k|$, $|Y_k|$ and $|\widehat{D}_k|$ refer to enhanced magnitude spectrum estimate (corrected signal), the noisy magnitude spectrum (original signal) and noise magnitude spectrum estimate ("noise"), respectively. k is the frequency index, while a_k and b_k are

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linear coefficient parameters of the summation. Spectral subtraction methods fall into three main categories (Sim et al., 1998). The simplest of all, a linear method where a_k = b_k = 1, α=2, following Boll (1979) was used here. This linear multiband spectral subtraction (LMSS) method is well-established for noise subtraction (see Loizou, 2007 for a comparative study of noise subtraction methods).

An improved method, with a_k = 1 and b_k = v, where "v" is the oversubtraction factor. This method uses oversubtraction and introduces a spectral flooring to minimize residual noise and musical noise (Berouti et al., 1979). A second category of spectral subtraction is based on a_k = b_k = *f(k)*. Third and the most robust methods are based on a non-linear multiband subtraction (NMSS) where a_k = 1 and b_k = *v(k)*; i.e., the oversubtraction factor is adjusted based on a specfic band's SNR. These methods proposed by (Kamath and Loizou, 2002; Loizou, 2007) are suitable for dealing with colored noise (Boubakir et al., 2007; Sim et al., 1998), a case similar to MEG recordings. The spectrum is divided into N non-overlapping bands, and spectral subtraction is performed independently in each band. The Eqs. 2 is simply reduced to:

$$|\widehat{S_i(k)}|^2 = |Y_i(k)|^2 - \alpha_i \delta_i |\widehat{D_i(k)}|^2, b_i \leq k \leq e_i \tag{3}$$

where b_i and e_i are the beginning and ending frequency bins of the ith frequency band, α_i is the overall oversubtraction factor of the ith band and δ_i is a tweaking factor. The band specific oversubtraction factor α_i is a function of the segmental SNR_i of the ith frequency band. After calculating bandspecific SNR (Eqs. 1), we used the product of lower 10 percent of crosssubject average SNR and standard deviation of SNR_i to estimate the α_i δ_i subtraction coefficient. Next, simply by multiplying the noise PSD by this coefficient and subtracting it from the measured PSD, the enhanced PSD was achieved.

Wiener filter (WF) spectral enhancement

The principle of the Wiener filter is to obtain an estimate of the clean signal from that of the noisy measurement through minimizing the Mean Square Error (MSE) between the desired and the measured signal (Lim and Oppenheim, 1979; Abd El-Fattah et al., 2008). In the frequency domain, this relation is formulated as filtering transfer function:

$$WF(k) = \frac{P_s(k)}{P_s(k) + P_n(k)} \tag{4}$$

where, as before, $P_s(k)$ and $P_n(k)$ refer to enhanced power spectrum estimate and noise power spectrum estimate respectively for a signal frame and k is the frequency index. Based on the definition of SNR as, the ratio of these two elements, one can formulate the WF as:

$$WF_K = [1 + \frac{1}{SNR_k}]^{-1} \tag{5}$$

After calculation of bandspecific WF, the noisy signal is simply muliplied by the WF to obtain the enhanced signal.

Partial least square (PLS) approximation of non-noisy spectrum

Partial least squares (PLS) regression, combines "Principal component analysis" (PCA) and "Multiple linear regression" (Abdi, 2010; Abdi and Williams, 2010). While PCA finds hyperplanes of maximum variance between the response and independent variables, PLS projects the predicted variables and the observable variables to a new space. Then from this new space, it finds a linear regression model for the projected data. Next, using this model, PLS finds the multidimensional direction in the X space that explains the maximum multidimensional variance direction in the Y space (Abdi, 2010; Garthwaite, 1994). If X is the PSD of noise measurement and Y is the PSD of the measured signal contaminated with background noise, one can use PLS to "clean" one matrix (Y) by predicting Y from X and then using the residual of the prediction of Y by X as the estimate of pure PSD. The patterns of the awake spectrum that statistically resembles the patterns of emptyroom spectral noise are those that should be removed. As during the PLS algorithm used here, the data is mean subtracted and z-normalized, the predection of Y from X is an approximate of the zscored PSD. Therefore, the reseidual Y, which is taken as the spectral features that can not be predicted by noise, also has zscored values. It has too be emphasized that this approach of denoising only works in the spectral but not the time domain.

Supplementary table

A. Mean and standard deviation

	EEG	MEG (awake)	MEG(empty)	LMSS
All	-1.33 $\pm$ 0.19	-1.24 $\pm$ 0.26	-1.04 $\pm$ 0.13	-1.24 $\pm$ 0.28
FR ROI	-1.36 $\pm$ 0.25	-0.97 $\pm$ 0.10	-0.97 $\pm$ 0.06	-0.96 $\pm$ 0.11
VX ROI	-1.21 $\pm$ 0.13	-1.36 $\pm$ 0.10	-1.10 $\pm$ 0.09	-1.36 $\pm$ 0.10
PT ROI	-1.36 $\pm$ 0.12	-1.30 $\pm$ 0.29	-1.08 $\pm$ 0.15	-1.31 $\pm$ 0.32

	NMSS	WF	PLS	ES
All	-1.06 $\pm$ 0.29	-1.05 $\pm$ 0.27	-0.50 $\pm$ 0.11	-0.20 $\pm$ 0.23
FR ROI	-0.76 $\pm$ 0.09	-0.76 $\pm$ 0.08	-0.40 $\pm$ 0.05	-0.00 $\pm$ 0.09
VX ROI	-1.14 $\pm$ 0.11	-1.12 $\pm$ 0.11	-0.50 $\pm$ 0.04	-0.26 $\pm$ 0.08
PT ROI	-1.16 $\pm$ 0.32	-1.14 $\pm$ 0.30	-0.54 $\pm$ 0.11	-0.22 $\pm$ 0.26

B. Pearson correlation of EEG vs.

	MEG	LMSS	NMSS	WF	PLS	ES
All	0.29	0.29	0.32	0.33	0.37	0.35
FR ROI	0.41	0.39	0.32	0.37	0.01	0.17
VX ROI	-0.17	-0.10	-0.15	-0.13	0.01	-0.28
PT ROI	0.35	0.34	0.38	0.39	0.46	0.41

C. Kendall Rank Corr of EEG vs.

	MEG	LMSS	NMSS	WF	PLS	ES
All	0.21	0.21	0.24	0.25	0.29	0.23
FR ROI	0.29	0.23	0.21	0.27	-0.06	0.12
VX ROI	-0.03	0.04	-0.04	-0.03	0.07	-0.09
PT ROI	0.23	0.23	0.26	0.26	0.30	0.27

Table 1 ROI statistical comparison for different noise correction methods. A. mean and std of frequency scale exponent for all regions and individual ROI. B. numerical values of linear Pearson correlation. C. rank-based Kendall correlation.

Supplementary figures

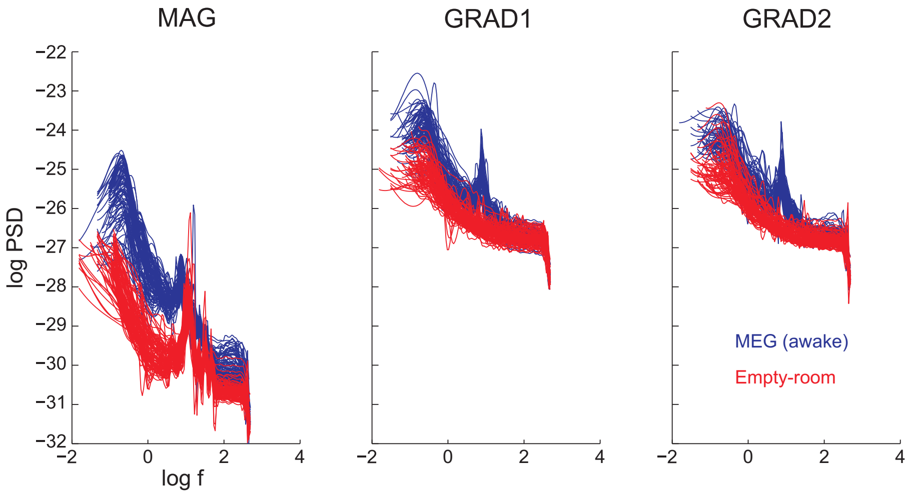

Figure S1: Frequency spectra of magnetometers and gradiometers. Comparison of awake (blue) vs empty-room (red) recordings between Magnetometers (MAG) and Gradiometers (GRAD1, GRAD2) in a sample subject. As for the EEG, the MEG signal is characterized by a peak at around 10 Hz, which is presumably due to residual alpha rhythm (although the subject had eyes open). This is also visible from the MEG signals (Fig. 1) as well as from their PSD (Fig. 3 and MAG panel here). The power spectrum from the empty-room signals also show a peak at around 10 Hz, but this peak disappears from the gradiometer empty-room signals, while the 10 Hz peak of MEG still persists for gradiometers awake recordings. This suggests that these two 10 Hz peaks are different oscillation phenomena. All other subjects showed a similar pattern.

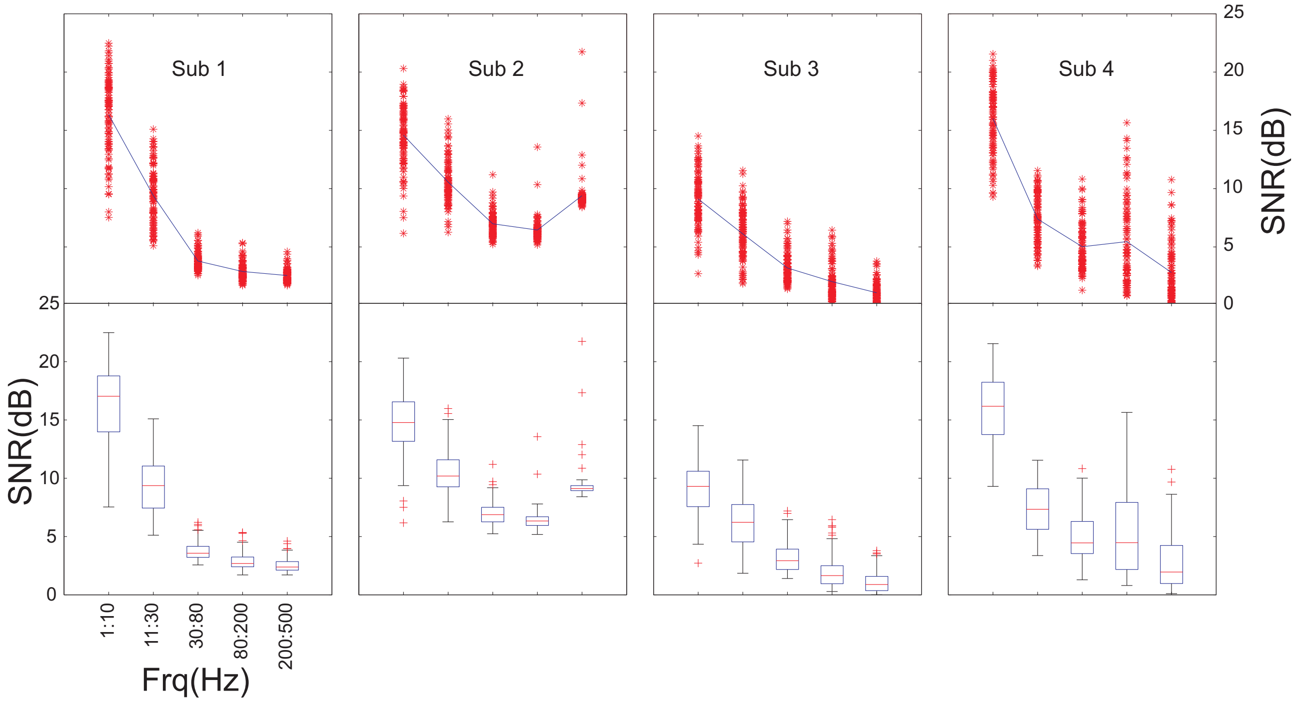

Figure S2: Signal-to-noise ratio (SNR) of Magnetometers (MAG) for multiple frequency bands: 0-10 Hz (Slow, Delta and Theta), 11-30 Hz (Beta), 30-80 Hz (Gamma), 80-200 Hz (Fast oscillation), 200-500 Hz (Ultra-fast oscillation). In the scatterplots, red astrisks relate to individual sensors and the blue line is the band-specific mean across the sensors. In boxplots, the box has lines at the lower quartile, median (red), and upper quartile values. Smallest and biggest non-outlier observations (1.5 times the interquartile range IRQ) are shown as whiskers. Outliers are data with values beyond the ends of the whiskers and are displayed with a red + sign. In all subjects, the SNR shows a band-specific trend and has the highest value for lower frequencies and gradually drops down as band frequency goes up. As the frequency drops, the variability of SNR (among sensors) rises; therefore, the SNR of the lowest band (1-10 Hz) shows the highest sensors-to-sensor variability and the highest SNR in comparison to other frequency bands.

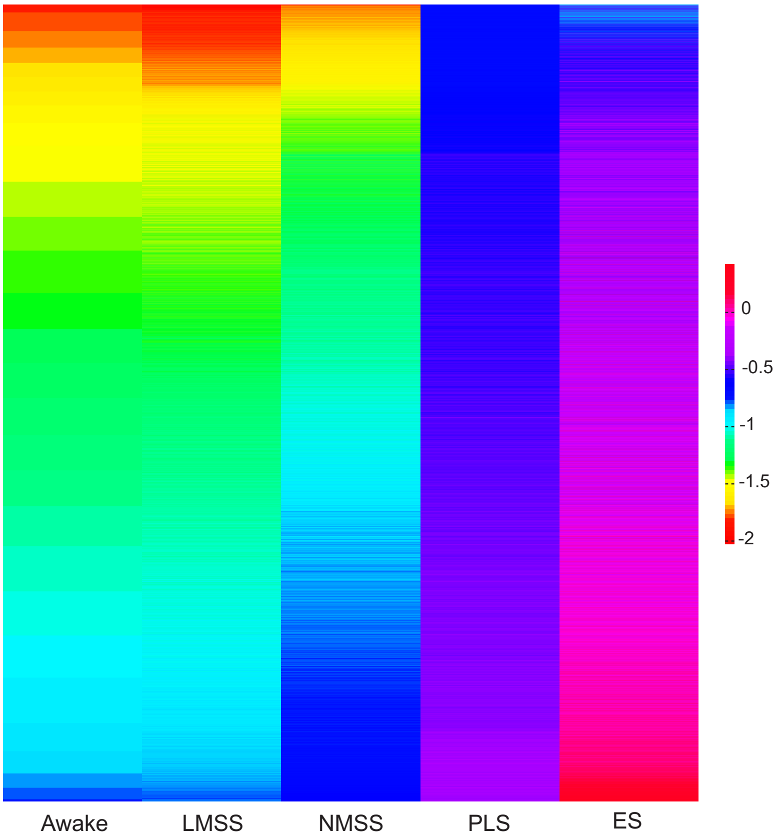

Figure S3: Noise correction comparison. Every horizontal line showes a voxel of the topographical maps shown in Fig. 4 sorted based on the scaling exponent values of awake MEG (left stripe). Using a continuous color spectrum, these stripes show that minimal correction is achived by LMSS. As indicated in the text, the performance of this method is not reliable due to the nonlinear nature of SNR (see Suppl. Fig. S2). NMSS yields higher degree of correction. WF performs almost identical to NMSS (not shown here). Exponent subtraction almost abolishes the sacling all together (far right stripe). PLS results in values between NMSS and ”Exponent subtraction”. For details of each of these correction procedures, see Methods. LMSS, NMSS and WF rely on additive uncorrelated nature of noise. “Exponent subtraction” assumes that the noise is intrinsic to SQUID. PLS ascertains the characteristics of noise to the collective obeserved pattern of spectral domain across all frequencies. See text for more details.

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