# A robust multichannel method for estimation of EEG power spectra and coherences

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## Introduction

EEG (electroencephalography) assays cortical electrical activity as recorded through electrodes placed on the scalp. Its advantages include high temporal resolution, low cost, and portability. However, results are greatly affected by noise from sources including muscle movement, eye blinks, and environmental electrical sources.

Because the recorded activity is largely oscillatory in nature, spectral measures are effective in quantifying and summarizing EEG data. The standard calculation of the power spectrum involves cutting the desired region of data into segments and then averaging the magnitude-squared of the estimated Fourier components across segments. This approach is optimal with clean data; however, it is highly sensitive to artifacts of the type discussed above.

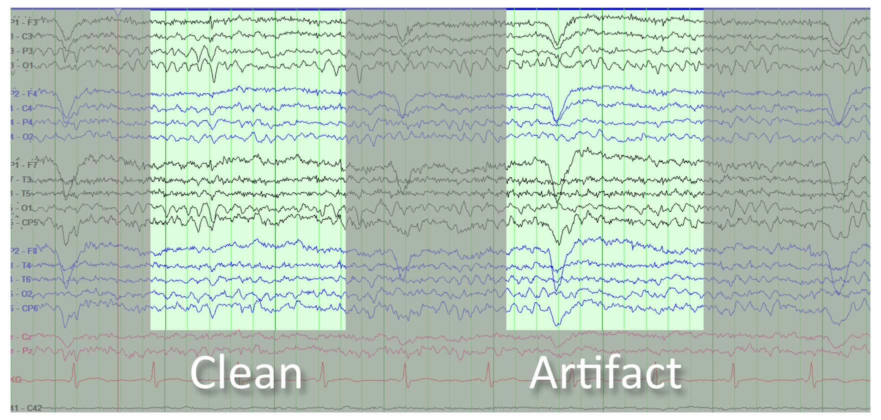



**FIGURE 1** A typical run of EEG with both clean and noisy segments. A typical clean segment is highlighted on the left; artifact (in this case an eye blink) is highlighted on the right.

Cleaning the data "by hand" works well but is time-consuming, discards large portions of data, and is subject to human bias. We devised a new method that uses robust statistics to reduce the effect of contamination on the power spectral calculation that does not have these drawbacks.

## Background

A robust statistic is defined as a one that is insensitive to outliers. The median is one such estimator.

For Gaussian-distributed data, both the mean and the median accurately estimate the true center of the distribution. However when outliers are introduced, such as when a fraction of the data come from a different distribution, the mean is affected more drastically than the median.

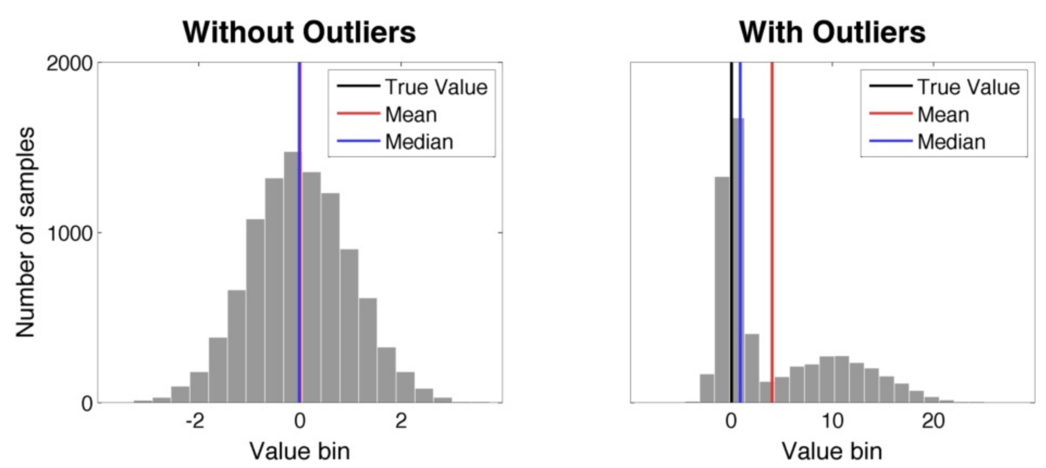



**FIGURE 2** Effect of outliers on location estimates of a univariate distribution. In the absence of outliers, both the mean and the median perform well; when outliers are present, the median performs better.

This extends to the 2-D case, such as when estimating the magnitude of Fourier components.

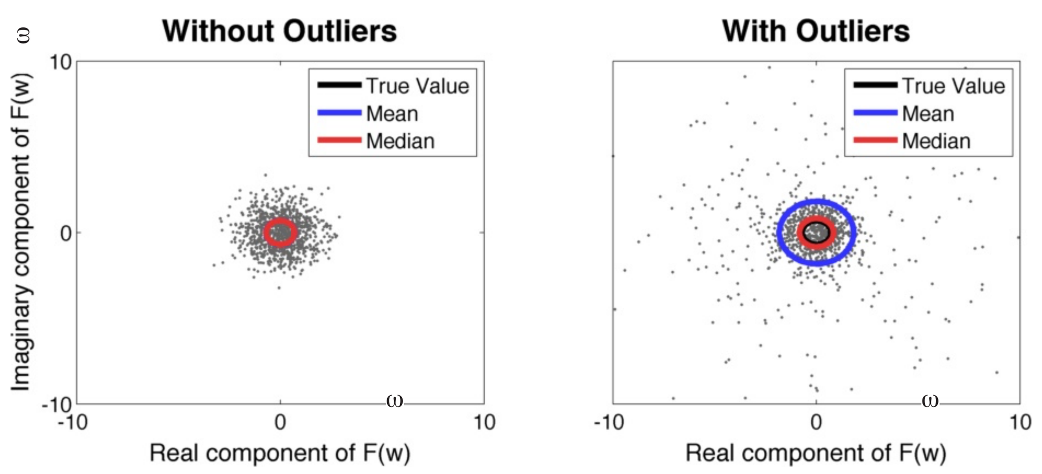
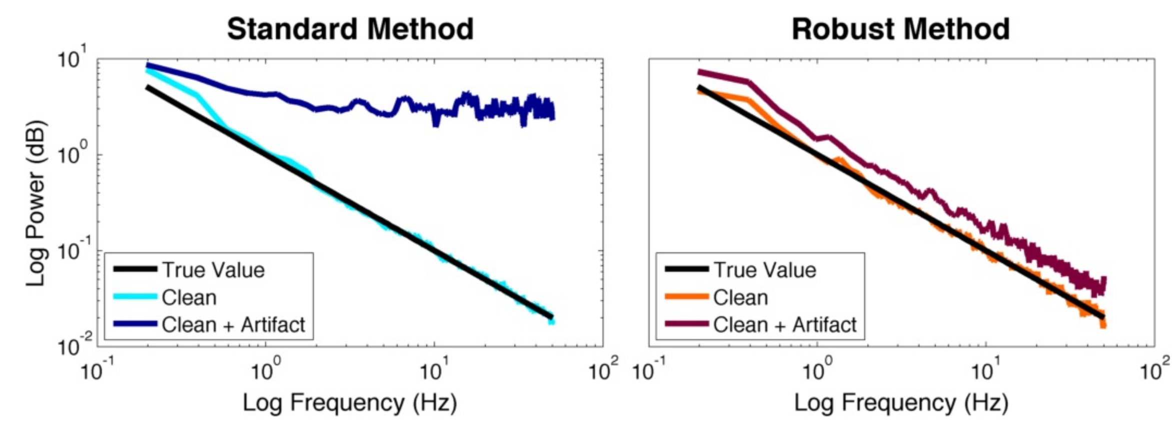



**FIGURE 3** The 2D Gaussian. When there are no outliers, the mean (standard estimator) works well (left); when outliers are present the median-based (robust) estimator performs better.

## Results: Simulated Data

On simulated data with a known power spectrum, both the standard and robust methods are effective in recovering the true power spectrum. However in the presence of contamination by noise, the robust method recovers the power spectrum with greater accuracy.



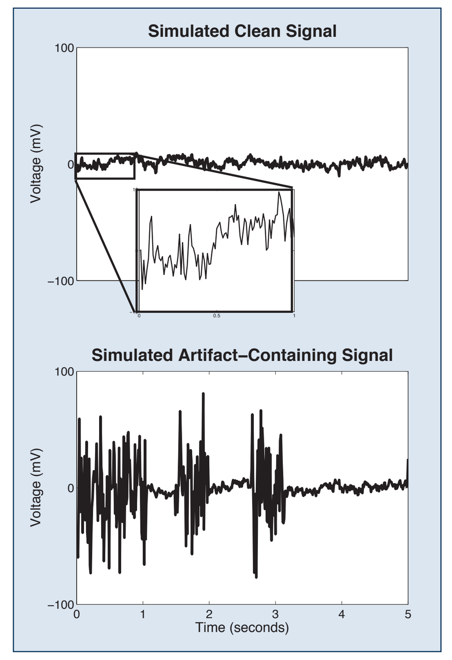




**FIGURE 4** Power spectra calculated using the standard and robust method on simulated data, with and without contaminant noise. Right panel: clean and artifact-containing segments in the time domain.

## Results: Human EEG Data

The robust method was tested on data from an awake healthy control. The EEG record was cut into three-second-long segments. Data sets were generated by pooling 20 segments, with varying proportions of clean and artifact-containing segments, thus simulating varying levels of artifact.

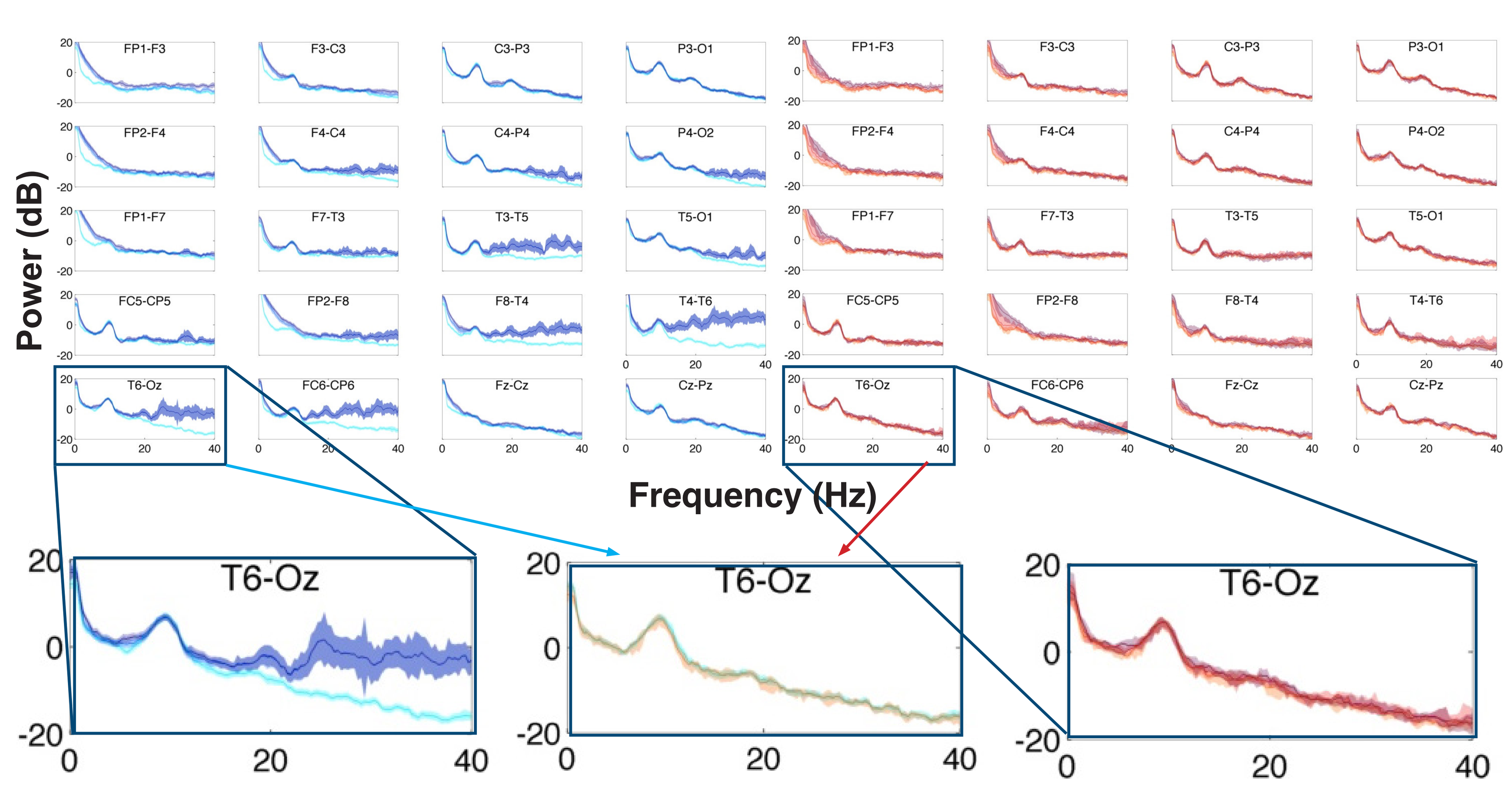



**FIGURE 5** Comparison of standard and robust method on EEG from a healthy control. Power spectra calculated from clean segments only are shown in light color; power spectra calculated from only artifact-containing segments are shown in dark color; power spectra calculated from a 50:50 mixture of clean and artifact-containing segments are shown in intermediate color. Shaded area around each trace represents the 95% confidence intervals.

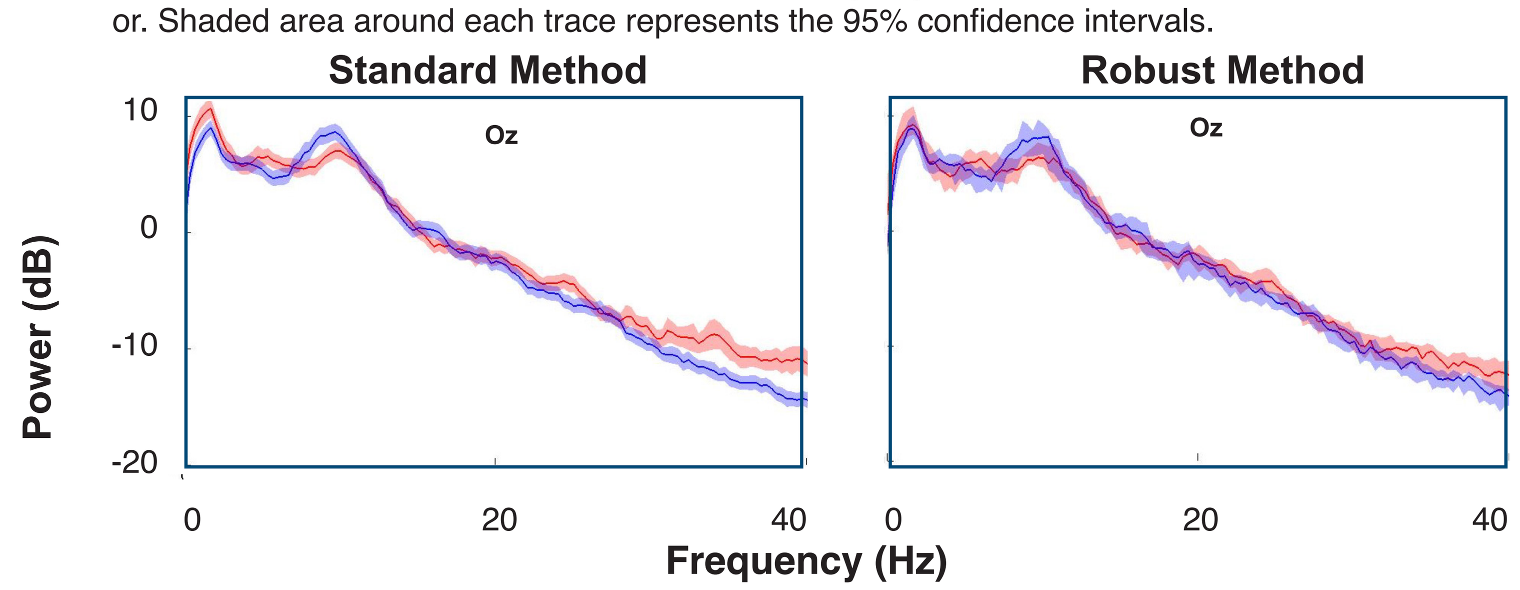



**FIGURE 6** Comparison of standard and robust method on EEG from a patient subject, without hand cleaning. Red: 90 sec of data during listening to unfamiliar music, blue: 90 sec of data during listenting to familiar music. See Fidali et al., poster 703.05. Shaded area around each trace represents the 95% confidence intervals.

## Technical Details

### *Robust Power Spectral Estimation*

Standard power spectral estimation via the multitaper method[1,2] is given by

$$S_x(\omega) = \frac{1}{B}\sum_{b=1}^{B}\frac{1}{K}\sum_{k=1}^{K}\underbrace{\frac{1}{T}\left|\int_0^T x_b(t)a_k(t)e^{-i\omega t}dt\right|^2}_{F_{b,k}(\omega)}$$

where $B$ is the number of samples; $K$ is the number of tapers; $x_b(t)$ is the time-domain signal; $a_k(t)$ is the $k^{th}$ Slepian taper; $T$ is the length of $x_b(t)$; and $S_x(\omega)$ is the power spectral density at the frequency $\omega$. This can be represented as the mean over tapers followed by a mean over trials:

$$S_x(\omega) = mean_{b=1}^{B}\left(mean_{k=1}^{K}\left(F_{b,k}(\omega)\right)\right)$$

By replacing the **mean** over trials with the **median** over trials, we get the robust estimator

$$S_x(\omega) = median_{b=1}^{B}\left(mean_{k=1}^{K}\left(F_{b,k}(\omega)\right)\right)$$

### *Confidence Limits*

Since the median depends discontinuously on the data, typical methods such as the jackknife and bootstrap lead to highly variable results for confidence intervals.

We instead use a Bayesian approach assuming an uninformative (flat) prior[3]. The procedure is as follows:

1. Label the samples so that they are ranked in ascending order, $Y_1, \ldots, Y_n$.
2. By the binomial distribution, the probability that the true $q$th quantile, $P_q$, lies between $Y_i$ and $Y_{i+1}$ is

$$P\left(Y_i < P_q < Y_{i+1}\right) = \binom{n}{i} q^i (1-q)^{n-i}$$

3. Sum over intervals. Find the maximum $j$ and the minimum $k$ such that

$$\sum_{i=j}^{k} P\left(Y_i < P_q < Y_{i+1}\right) \geq 1-\alpha$$

where $1-\alpha$ is the desired confidence interval, i.e. $\alpha = 0.05$ for the 95% confidence interval. When $q = 0.5$, this yields the confidence interval for the median.

### *Coherence*

A previous study by Wong et al[4]. has shown that robust methods can be used to improve estimates of coherence magnitude. Multivariate extensions of the approach described here, utilizing the minimum covariance determinant[5], can be used to determine coherence phase as well. We are developing methods for determination of confidence limits for these estimators.

#### References

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