

# **ELECTRONIC APPENDIX**

This is the Electronic Appendix to the article

## **The local mean decomposition and its application to EEG perception data**

by

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*J. R. Soc. Interface* ([doi:10.1098/rsif.2005.0058](https://doi.org/10.1098/rsif.2005.0058))

Electronic appendices are refereed with the text; however, no attempt is made to impose a uniform editorial style on the electronic appendices.

## Appendix

### 1. Smoothing of the local means and the local magnitudes

The smoothing of the local means and the local magnitudes to form a continuous, smoothly varying local mean function estimate and a corresponding envelope function estimate, can be accomplished in the following way. As can be seen from appendix figure 1a, the endpoints (shown as blue dots) of the local means of the data overlap. In this paper, the right endpoint of each local mean is averaged with the left endpoint of the next local mean. The averaged endpoints are shown as blue dots in appendix figure 1b. The resulting local mean function shown in appendix figure 1b can now be smoothed using moving averaging. For this paper the length of the moving average was set to be one third of the length of the longest local mean, shown at 0.15 s in appendix figure 1a. The local mean function was then repeatedly smoothed using this length of moving average until no two successive points had the same value. Six applications of a 22-point moving average were required to obtain the local mean shown in figure 1a (main text). The smoothing process is shown in appendix figure 2a-f. Exactly the same smoothing regime should be applied to the corresponding local magnitudes.

It should be noted that varying the length of the moving average can affect the shape of the final envelope, or the frequency of the final frequency modulated signal. For example, an envelope obtained using one length of moving average may oscillate slightly differently during a period of time, compared to an envelope obtained using a different length of moving average. However, these variations tend to be localized, and the envelopes obtained using different lengths of moving average for the EEG data appear to be largely similar. Furthermore, a similar issue affects wavelets. If data is analysed using one sort of wavelet, for example a Morlet wavelet, a result is obtained which is different to the result obtained using another sort of wavelet.

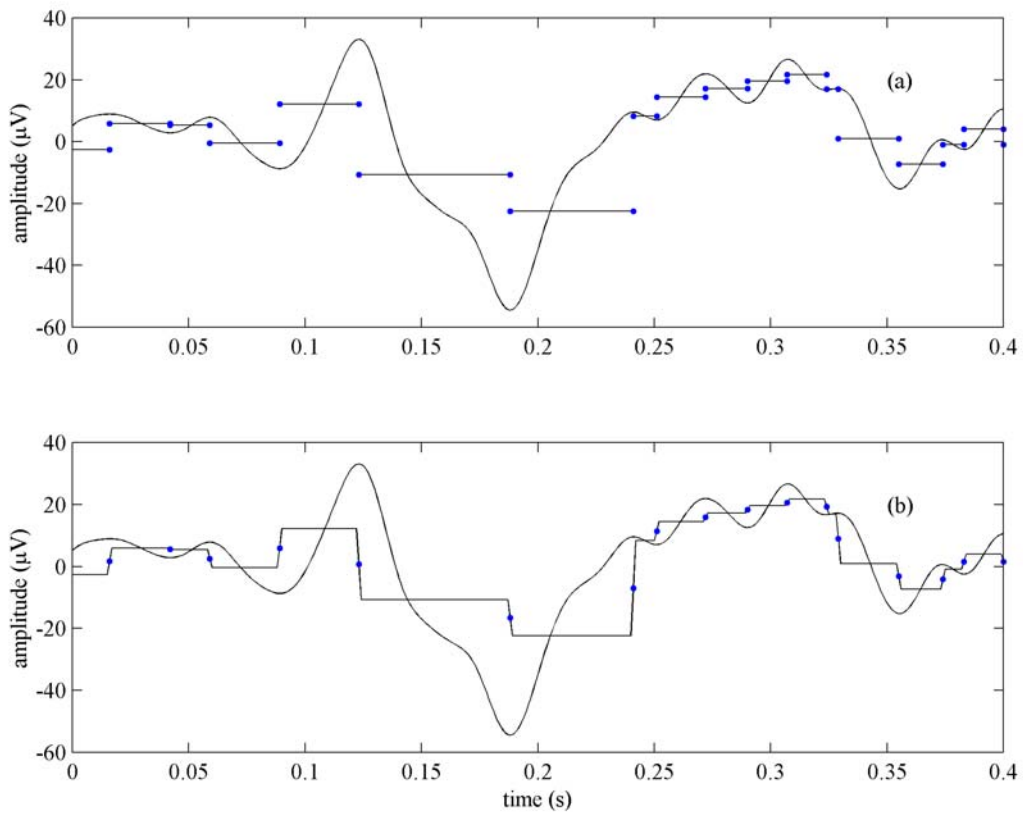
### 2. Calculation of the significance levels of the circular variance ratios

The various circular variance ratio significance levels used in this paper were calculated by randomizing the perception and no perception trials. For figure 9 (main text) the 576 ( $6 \times 96$ )

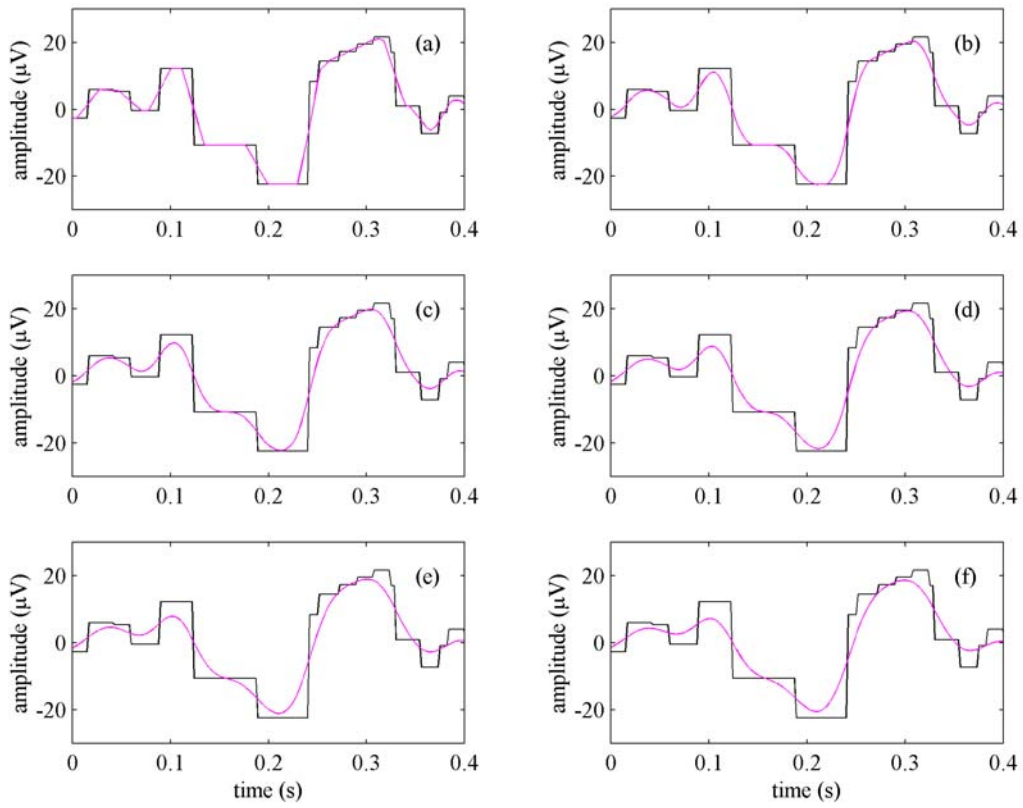
occipital (O1, O2, and OZ) perception and no perception LMD second product function (PF2) instantaneous phase values were randomized over the 576 trials at each instant in time. These 576 randomized phases were then split into two groups of 288. At each instant the circular variances of each of these two groups of phases was calculated according to equations (3.1) and (3.2). The ratio of these two circular variances was then calculated according to equation (3.3). The maximum circular variance ratio value over the 1.5 s length of the trials was then noted. The randomization procedure was repeated 100 times, and the circular variance ratio values for these 100 randomizations were collected. The 1% significance level was set equal to the largest value of these maximum ratio values. This 1% significance level is shown on figure 9 (main text). For figure 10 (main text) the 576 occipital perception and no perception STFT instantaneous phase values corresponding to the 5 Hz frequency bin were randomized over the 576 trials at each instant in time. The circular variance ratio value 1% significance level for these 5 Hz STFT phases was calculated in the same way as for the LMD phases described above.

### 3. Comparison between LMD and EMD

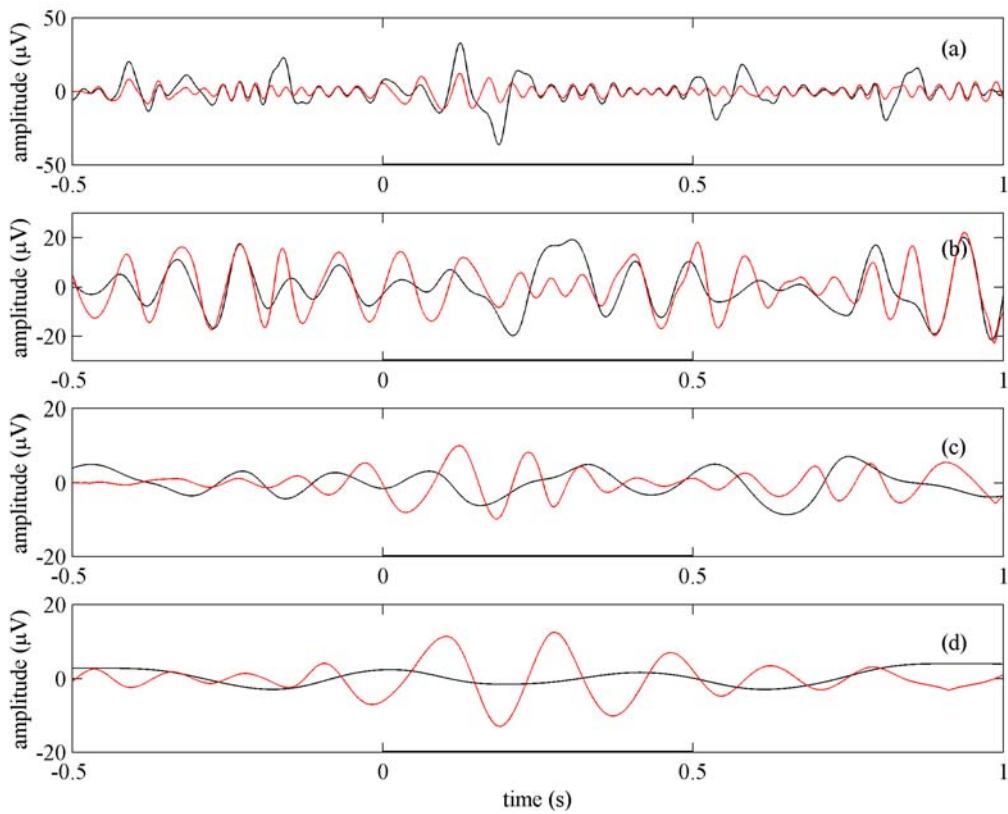
The LMD method appears to be a much gentler way of decomposing data, compared to the cubic spline iteration approach used in the empirical mode decomposition (EMD) scheme. The LMD product functions seem to retain more of the frequency and envelope information present in the original signal than the EMD intrinsic mode functions (IMFs) do. This can be seen in appendix figure 3, which contrasts the product functions calculated from the sample EEG signal, with the equivalent EMD IMFs (shown in red). On average, the LMD approach results in the EEG energy appearing to be more concentrated in the time-frequency plane at 10 Hz prior to stimulus onset, and in the form of a chirp following stimulus onset (figure 6d, main text), than it is in the Hilbert spectrum (figure 6c, main text).



Appendix figure 1. Averaging of overlapping endpoints. Plot 1a shows a portion of the sample EEG signal analysed in the main text, and its corresponding local means, plotted as straight lines extending between successive extrema of the signal. The endpoints of the local means (marked as blue dots) overlap. Plot 1b shows the averages of the endpoints and the resulting continuous local mean function.



Appendix figure 2. Smoothing of the local mean function. Plots 2a-f show the smoothing, using successive applications of a moving average, of the local mean function shown in appendix figure 1b. The final smoothed local mean function (pink curve, plot 2f) is also shown in figure 1a in the main text.



Appendix figure 3. Comparison between LMD product functions and EMD intrinsic mode functions. This figure shows the four LMD product functions (also shown in figure 3, main text) generated from the 1-45 Hz filtered EEG sample signal analysed in the main text, compared with the four EMD IMFs generated from the same signal (shown in red).