Empirical Mode Decomposition and Instantaneous Frequency for MEG analysis.

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Summary

Empirical Mode Decomposition is a data-driven algorithm which splits an oscillatory signal into as set of Intrinsic Mode Functions with minimal distortion to non-linear and non-stationary properties.

Here we apply a masked EMD analysis to MEG recordings of Occipital Alpha at rest and Sensorimotor Beta during a finger tapping task (data taken from the SAILS toolbox example data: https://gitlab.com/sails-dev/sails-example-data)

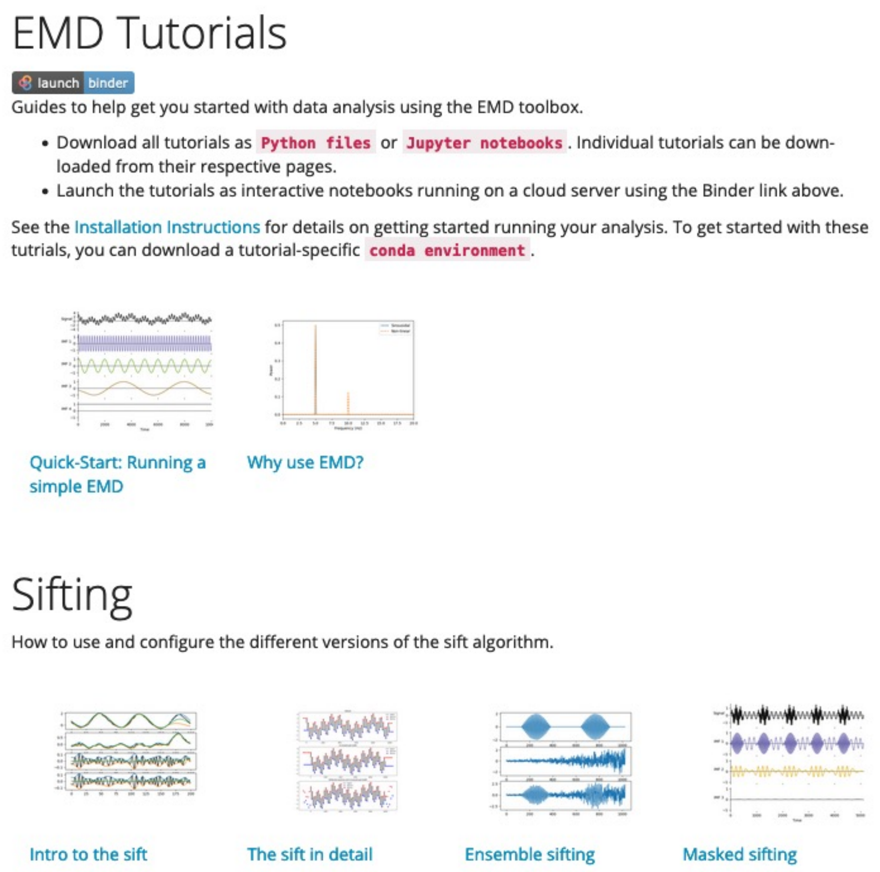
High resolution time-frequency plots are constructed using the Hilbert transform to compute the instantaneous frequency and amplitude of each IMF.

Software

All analyses are carried out in the python 3.7 in using the python EMD toolbox. Software installation and documentation can be found online at:

https://emd.readthedocs.io

Click on the 'Binder' link to run the tutorials in an interactive web-notebook - no install required!



References

Huang, N. E., Shen, Z., Long, S. R., Wu, M. C., Shih, H. H., Zheng, Q., Yen, N.-C., Tung, C. C., & Liu, H. H. (1998). **The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis.** Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences, 454(1971), 903–995. https://doi.org/10.1098/rspa.1998.0193

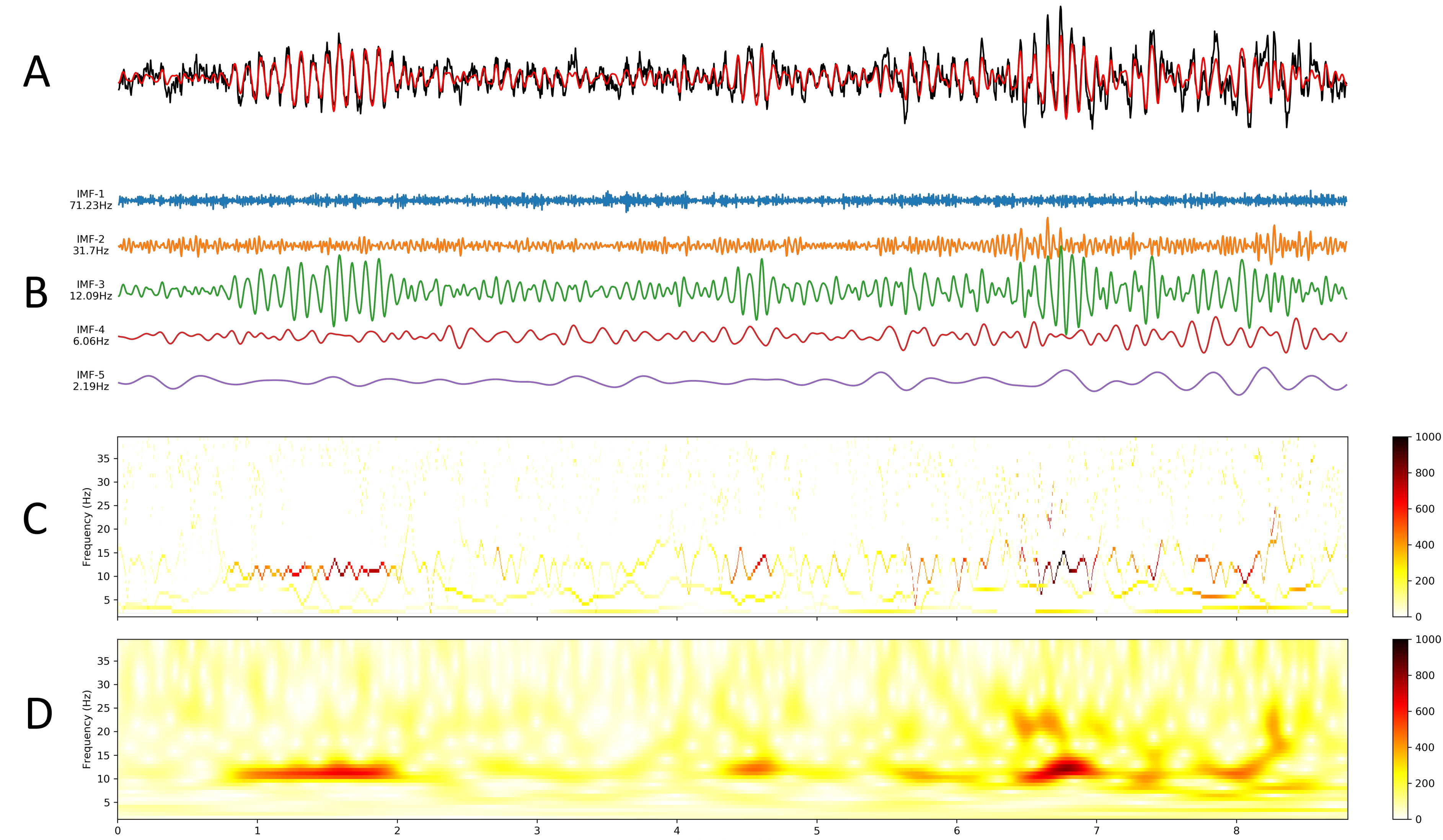
Andrew J. Quinn, Vitor Lopes-dos-Santos, Norden Huang, Wei-Kuang Liang, Chi-Hung Juan, Jia-Rong Yeh, Anna C. Nobre, David Dupret & Mark W. Woolrich (April:2021) **Within-cycle instantaneous frequency profiles report oscillatory waveform dynamics** *bioRxiv*

Andrew J. Quinn, Vitor Lopes-dos-Santos, David Dupret, Anna Nobre & Mark Woolrich (March:2021) **EMD: Empirical Mode Decomposition and Hilbert-Huang Spectral Analyses in Python** Journal of Open Source Software

Marco S Fabus, Andrew J Quinn, Catherine E Warnaby & Mark W Woolrich (July:2021) **Automatic decomposition of electrophysiological data into distinct non-sinusoidal oscillatory modes** *bioRxiv*

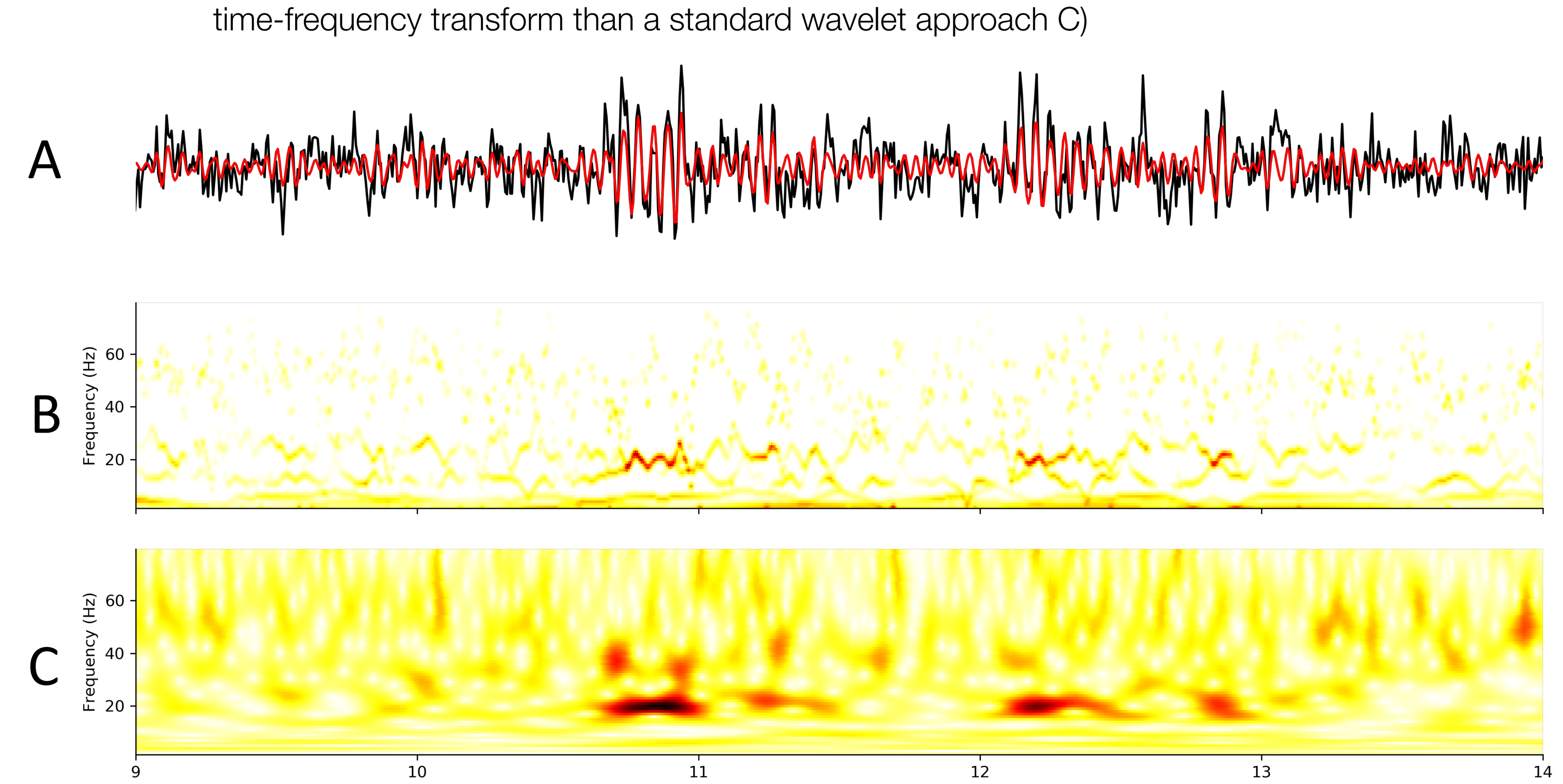
Occipital Alpha

A segment of MEG data reconstructed at an occipital source can be seen below (A). The IMFs identified by mask EMD are shown (B) and red in (A) which clearly isolate a prominent alpha rhythm in IMF-3. The Hilbert-Huang transform represents the distribution of power in these IMFs as a function of time and instantaneous frequency (C). This is much higher resolution than standard approaches such as Morlet Wavelets (D).



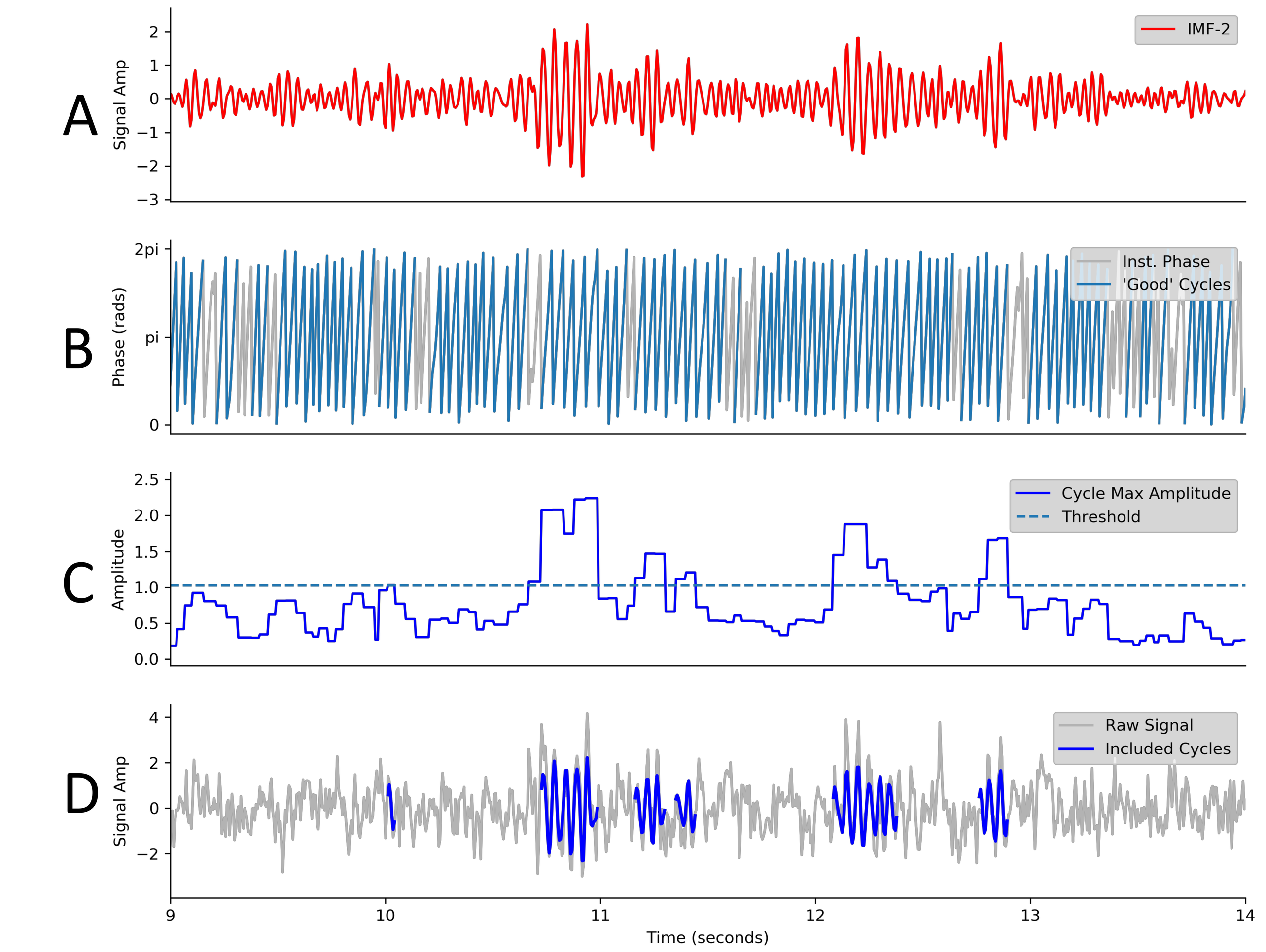
Motor Beta Rebound

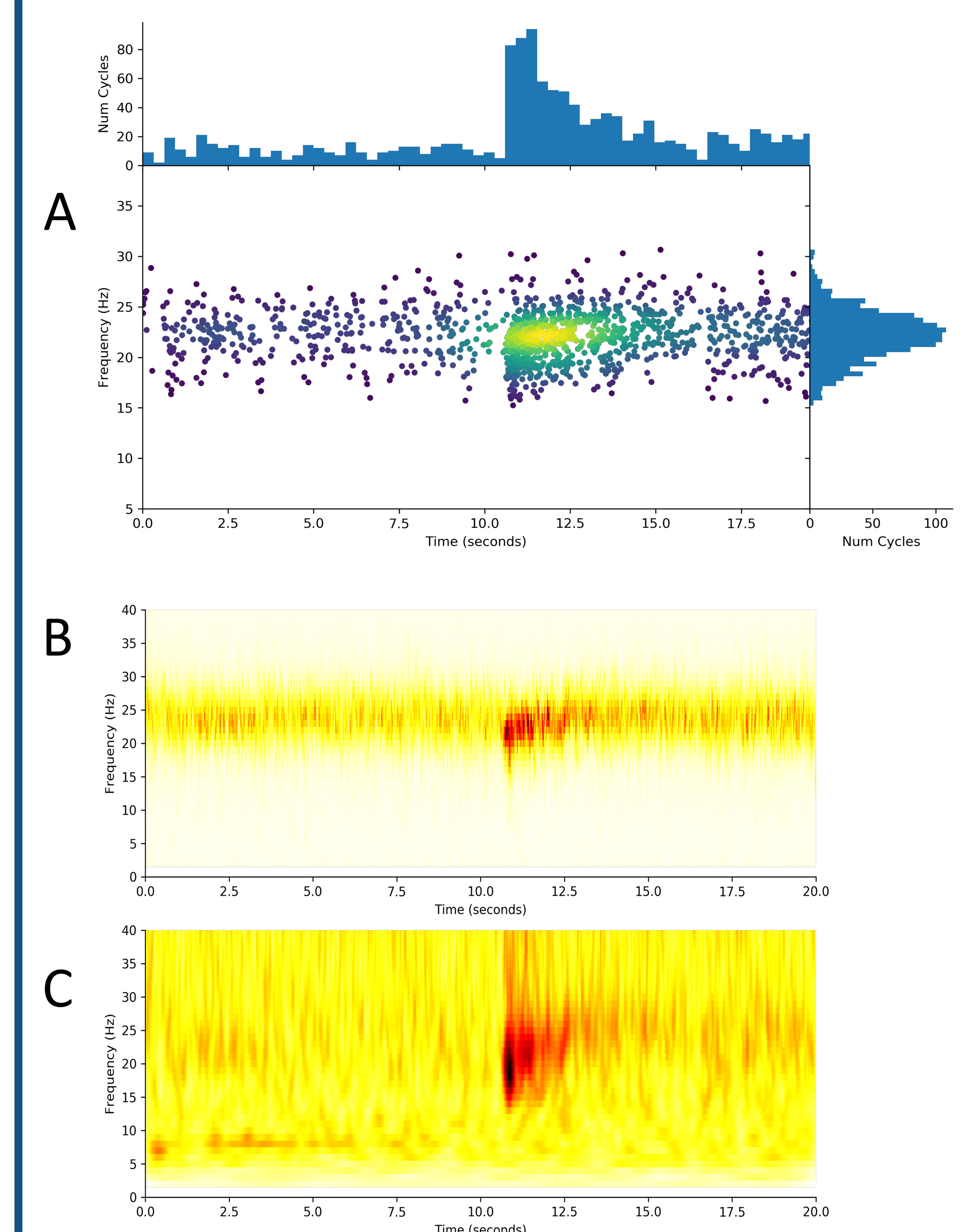
A segment of sensor space MEG data from a sensorimotor channel recorded during a finger-tapping task. The raw trace and second IMF show prominent beta oscillations (A). As with the alpha signal the Hilbert-Huang transform (B) provides a higher resolution time-frequency transform than a standard wavelet approach C)



Cycle Selection

The IMFs identified by EMD make a good basis for single cycle analyses. The beta IMF (A) is used for cycle selection here. First the Hilbert transform is used to identify the instantaneous phase (B). Cycles with incomplete or distorted phases are discarded. Secondly, the maximum instantaneous amplitude of each cycle is computed and thresholded by a percentile to remove small cycles C). These criteria are combined to identify events in which high amplitude bursts of clear oscillatory activity occur (D)





These single cycles can then form the basis for further analysis, in this case we look at a post-movement beta rebound response averaged over 30 trials. The participant taps their finger for 10 seconds before resting for 10 seconds.

A) A scatter plot indicating the timing and frequency of each identified cycle over the 30 trials. Hotter colours indicate a greater density of cycles. The top histogram indicates the average timing of cycles, showing a clear increase in number around 1 second after movement stops. The right histogram shows the distribution of cycles frequencies - indicating an average of around 22Hz.

B) The averaged Hilbert-Huang transform of the beta IMF across 30 trials.

C) The averaged wavelet transform across the 30 trials.