

# Cortical responses evoked by wrist joint manipulation

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## 1. Introduction

This benchmark dataset features the response in the human cortex to robotic manipulations of the wrist joint. The wrist joint manipulations are encoded by sensory organs in the periphery and transmitted via the spinal cord to the brain (i.e. the somatosensory cortex contralateral to the manipulated wrist). The evoked cortical responses can be measured on the scalp using electroencephalography (EEG). Since the cortical responses to joint manipulations are associated with sensory processing of external input, modeling this response could be useful to detect and monitor abnormal sensory processing due to diseases, such as stroke, spinal cord injury and Parkinson's disease

However, several challenges are noted in modeling the cortical response recorded using EEG. The sensory organs and neurons in the nervous system are highly nonlinear and exhibit complex dynamics. Also, the signal-to-noise ratio of EEG is poor, ranging from -10 to -40 dB.

This benchmark provides a dataset for developing and testing new methods for EEG signal processing. The dataset was originally introduced in:

- Vlaar MP, Birpoutsoukis G, Lataire J, Schoukens M, Schouten AC, Schoukens J, van der Helm FCT, *Modeling the Nonlinear Cortical Response in EEG Evoked by Wrist Joint Manipulation*, IEEE Trans Neural Syst Rehabil Eng 26:205-305, 2018
- Vlaar MP, Solis-Escalante T, Vardy AN, van der Helm FCT, Schouten AC, *Quantifying Nonlinear Contributions to Cortical Responses Evoked by Continuous Wrist Manipulation*, IEEE Trans Neural Syst Rehabil Eng 25: 481-491, 2017.

The next sections describe the experiment procedures (Section 2) and the structure of the dataset (Section 3). The figures of merit that are used in this benchmark are presented in Section 4. Finally, the results and the expected challenges during the identification process are listed in Section 5.

## 2. Experiment procedures

The experimental data was acquired on ten healthy volunteers (all right-handed) at the Delft University of Technology. The experimental procedure was approved by the Human Research Ethics Committee of the Delft University of Technology.

Participants were seated with their right forearm fixated to an arm support and their hand strapped to the handle of a robotic manipulator, see Figure 1. For the experiment, participants were instructed to relax their wrist and not to react to the continuous angular perturbation applied by a robotic manipulator. Cortical activity was sampled at 2048 Hz from 126 electrodes. The handle angle and torque of the robotic manipulator were recorded, via a galvanic isolation transformer, by the same amplifier as the EEG.

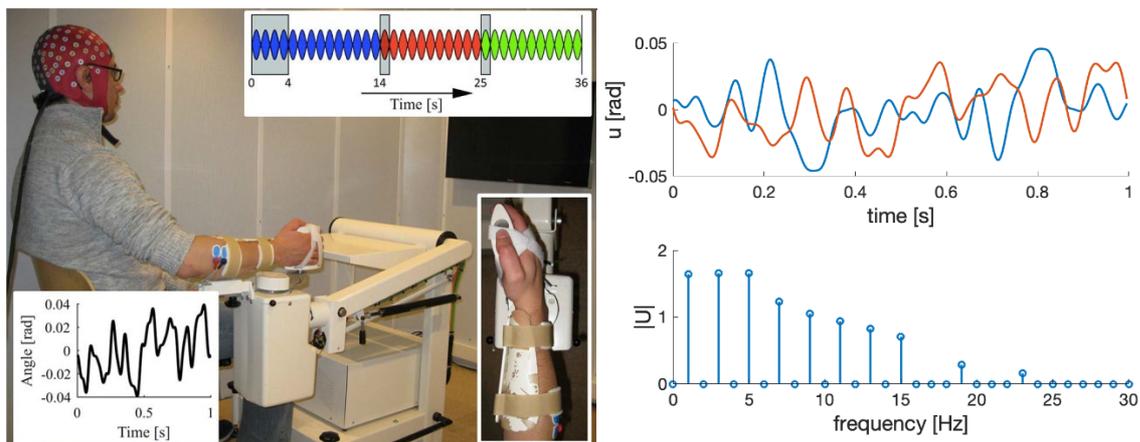


Figure 1: Experimental setup and overview. Left: participants were seated with their right forearm fixated to an arm support and their hand strapped to the handle of a robotic manipulator (figure from Vlaar et al., 2018). The top-right insert in the picture shows a schematic representation of the composition of one 36s trial. Each lobe represents one 1s period of the perturbation signal and the three different colors represent different multisine realizations. Highlighted periods are excluded, leaving ten periods per realization in each trial for analysis. Right-upper: two realizations of the angular perturbation. Right-lower: frequency content of the perturbation signals.

The perturbation signals were multisine signals, i.e., the sum of multiple sinusoids, with frequencies of 1, 3, 5, 7, 9, 11, 13, 15, 19, and 23 Hz, with a period of 1 s. The excited frequencies cover the frequency band of neural activity in the human sensorimotor system. Seven different realizations ( $M=7$ ) of the multisine signals (with the same frequencies) were generated using different (random) phase realizations. All signals had the same root-mean-square (0.02 radians). The signals were designed to have equal power on the first three frequency components (i.e. 1, 3, 5 Hz) and a decaying power spectrum (-20dB/decade) for the remaining frequency components, i.e. a flat velocity spectrum. This design is a trade-off between reduced predictability of the signal (to prevent anticipation of participants during the experiment) and the sensitivity of the muscle spindles.

Seven trials of 36s were recorded. To reduce the effect of transient dynamics, 4s from the beginning and two times 1s in between a trial were removed (at the transition from one realization to the other, see the grey areas in the insert in Fig. 1). Eventually 210 periods ( $P=210$ ) per realization ( $M=7$ ) were recorded for each participant.

A detailed description of the experimental protocol can be found in the articles (Vlaar et al. 2017, Vlaar et al. 2018).

### 3. Data description

Due to volume conduction, EEG signals recorded from the scalp are linear mixtures of multiple activities (e.g. different cortical areas, yet also eye movements, muscle activity, cardiac activity, and movement). Independent component analysis (ICA) is a widely used processing technique to separate the cortical and non-cortical contributions to the EEG signal, based on the assumption of temporal independence and spatial stationary (Makeig et al. 2004). Before applying ICA, the EEG signals were filtered by a 1–100 Hz zero-phase shift band-pass filter to remove high-frequency noise and slow trends in the data (e.g. blood pressure, heartbeat, breathing and sweat potentials). Subsequently, all signals were downsampled to 256 Hz and segmented into 1 s periods, i.e. the period of the perturbation signal. The signal-to-noise (SNR) for each ICA component was calculated and for each participant, the ICA component with the highest SNR was used as the output. Standard source localization methods were used to verify that the likely cortical sources of the selected ICA components were located in the left hemisphere near the primary somatosensory cortex.

The data is provided as Matlab files (.mat) in three different configurations:

1. Small (<1Mb): for every participant and multisine realization the averaged (over periods) input signal (handle angle) and output signal (ICA component with highest SNR) are given. The data is available for download as supplementary material with the article of Vlaar et al. 2018 ([ieeexplore.ieee.org/document/8036235/media](https://ieeexplore.ieee.org/document/8036235/media)) and at [www.nonlinearbenchmark.org](http://www.nonlinearbenchmark.org).
2. Medium (around 500Mb): Similar data as 1, but the data is not averaged over the periods and sampled at the original sample rate of 2048 Hz. The data is available for download at [www.nonlinearbenchmark.org](http://www.nonlinearbenchmark.org)
3. Large (around 60Gb): The data is only filtered and segmented in 1 s periods. The data includes all 126 recorded EEG channels at the original sample frequency of 2048Hz. The ICA matrix to convert the channels to sources is included. This data is the base for the above datasets and is needed to replicate the results of Vlaar et al. 2017. The data is available for download at the 4TU Centre for Research Data (<http://data.4tu.nl>) and accessible using the following Digital Object Identifier (DOI): <http://dx.doi.org/10.4121/uuid:176d8f78-d9fd-491e-90e7-9370e249b701>.

For all datasets Matlab scripts are provided to load and plot the relevant time series.

This first data set was used in the articles to fit the nonlinear models between the stimulus and the cortical response at the component with the highest SNR (Vlaar et al. 2018, Tian et al. 2018). It is advised to start with this data set. The second dataset includes the variability over the periods and is provided at the original sample rate. The third data set includes all data channels and may also be used to investigate, for example, other source separation methods.

#### 4. Figure of merit

The goal of the benchmark is to determine the best model that can explain the cortical responses to wrist manipulations. We expect all users of the benchmark to report the following figure of merit to allow for a fair comparison between different methods:

$$VAF = \left( 1 - \frac{\text{var}(y(t) - \hat{y}(t))}{\text{var}(y(t))} \right) \cdot 100\%$$

where  $\hat{y}(t)$  is the modeled output,  $y(t)$  is the output provided in the dataset. When reporting, explicitly state which data (or realization) was used for estimation and which for validation. Also report how the response of the multiple participants were modeled; typically, one model per participant is obtained and the mean VAF  $\pm$  standard deviation over the participants is reported.

Also mention whether the modeled output  $\hat{y}(t)$  is obtained using simulation (only the input signals  $u(t)$  are used to obtain the modeled outputs) or prediction (both the input signals  $u(t)$  and the past output  $y(t)$  are used to obtain the modeled outputs). Provide both figures of merit (simulation and prediction) if the identified model allows for it.

#### 5. Results

The electrodes with the highest SNR were found over the left sensorimotor cortex (see details in Vlaar et al. 2017) and had an average SNR of -14.8 dB (10 subjects). The average evoked cortical response (averaged over periods and realizations) recorded using electroencephalography was shown to be highly nonlinear; a linear model can only explain 10% of the variance of the evoked response, and over 80% of the response is generated by nonlinear behavior (Vlaar et al. 2017).

In the second article, independent components with the highest SNR were used for modeling. The average highest SNR was -12.3 dB. A truncated Volterra series model could explain 46% of the variance of the evoked cortical response, thereby demonstrating the relevance of nonlinear modeling in EEG analysis (Vlaar et al. 2018).

In two other studies Nonlinear AutoRegressive Moving Average Models with eXogenous input (NARMAX) were applied, also using the independent components with the highest SNR as output (Tian et al, 2018). The inclusion of autoregressive terms in the NARMAX model allows for using the measured output for prediction, resulting in an average VAF of 69% for three-step ahead prediction (Tian et al. 2018).

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### Articles using the EEG benchmark data set

1. Vlaar MP, Birpoutsoukis G, Lataire J, Schoukens M, Schouten AC, Schoukens J, van der Helm FCT, *Modeling the Nonlinear Cortical Response in EEG Evoked by Wrist Joint Manipulation*, IEEE Trans Neural Syst Rehabil Eng 26:205-305, 2018
2. Vlaar MP, Solis-Escalante T, Vardy AN, van der Helm FCT, Schouten AC, *Quantifying Nonlinear Contributions to Cortical Responses Evoked by Continuous Wrist Manipulation*, IEEE Trans Neural Syst Rehabil Eng 25: 481-491, 2017.
3. Tian R, Yang Y, van der Helm FCT, Dewald JPA, *A Novel Approach for Modeling Neural Responses to Joint Perturbations Using the NARMAX Method and a Hierarchical Neural Network*, Front Comput Neurosci 12:96, 2018.

### References

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