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Dictionary learning for M/EEG multidimensional data

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1. Jitter-adaptive dictionary learning model (JADL)

JADL is a dictionary learning framework

- There is no need for knowing the latency and phase of atoms.
- Atoms learned by JADL are defined on the entire signal domain.
- Hypothesis:
  - The set of signals of interest can be separated by a dictionary.
- In addition to the above assumption, JADL is able to handle small changes over time.

The algorithm solving the JADL problem, is based on an implementation in [2]

- Is still able to account for different jitters across trials.
- The algorithm solving the JADL problem is based on an implementation in [2]

2. Our modified JADL model

We propose an extension to the jitter-adaptive dictionary learning method, that:

- Is able to handle multidimensional measurements such as M/EEG.
- Detects jumps over all the channels, leading to a compressed dictionary
- Compensate for small
- Not having to select a “best” channel (as with the JADL method) is both a user simplification and allows

3. Synthetic data generation

- Create a dictionary of \( K = 3 \) synthetic atoms.
- Generate an extended dictionary of 9 signals.
  - Introducing random jitters (from the set \( \mathcal{J} \) of size \( S = 100 \) contiguous allowed shifts)
  - Select 3 source groups, each of them containing 3 neighboring sources.
  - Each source group is associated to shifted versions of the same atom.
- Combine the generated signals with a lead field matrix \( C \) computed from real EEG measurements [3].
  - \( \mathbf{d} = \mathbf{C} \cdot \mathbf{x} \)
  - \( \mathbf{d} \in \mathbb{R}^{M \times N} \) is the measurement matrix either MEG or EEG, \( C \in \mathbb{R}^{M \times N} \) is the sources matrix, \( K \) and \( N \) are the numbers of channels, sources and time samples respectively.
- Perform the above procedure for \( M \) trials.
  - Introducing new random jitters to the dictionary of \( K = 3 \) synthetic atoms.
  - Generated clean M/EEG measurements of \( C = 6 \) channels, \( M = 200 \) trials and \( N = 515 \) time samples.

4. Results on lead field synthetic data

A comparison between the original and our multi-dimensional JADL model

- Both algorithms are executed with the same signals, initial random dictionary and latency parameters.
- The multi-channel algorithm is executed using all the channels from the input data, while the single-channel algorithm is executed several times, each time using a different channel.

The results of our multi-channel algorithm show:

- A very good fit of the learned dictionary to the generated one.
- A good fit also in the case where the signals were contaminated by noise.

5. Results on real data

The multi-dimensional approach is tested using real MEG and EEG data:

- \( C = 200 \) channels,
- \( M = 63 \) trials,
- \( N = 541 \) time samples,
- contaminated by ambient noise.

Input parameters:

- \( S = 103 \) contiguous allowed shifts,
- \( K = 3 \) atoms.

6. Conclusions

- The method shows superior performance and less noisy estimated waveforms compared to the original single-channel JADL framework, both on synthetic and real data.
- It is more robust to various levels of noise.
- Using the JADL framework allows one to deal with signal variations such as jitters which is difficult to do with standard methods such as PCA or ICA.
- Not having to select a “best” channel (as with the JADL method) is both a user simplification and allows the exploitation of all the available information for M/EEG trial by trial signal decomposition. This thus provides better estimations of waveforms in the dictionary.

References