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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.

- Atoms learned by JADL are defined on the entire signal domain.
- The set of signals of interest \(x_j \in \mathbb{R}^m\) can be generated by a dictionary.
- Atoms present in a signal can suffer from unknown time delays (jitter).
- The algorithm solving the JADL problem is based on an implementation in [2].

The dictionary learning framework iteratively alternates between:

1. Atom Selection: The best shifted versions of the atoms contained in the extended dictionary \(D^e\) are selected, over all the channels, leading to a compressed dictionary \(D_{c}\).

2. Dictionary update: finding the shapes \(a_i\) that minimize:

   \[
   \sum_{j} \sum_{i} \|a_i x_j - d_i^j\|^2 + \lambda \sum_{i} \|d_i\|^2
   \]

   subject to \(\|a_i\|_0 \leq 1, i = 1, \ldots, K\).

3. Synthetic data generation

   - Create a dictionary \(K = 3\) synthetic atoms.
   - Generate an extended dictionary of 9 signals.
     - Introducing random jitters (from the set \(\Delta = \{\Delta \mid \Delta < 103\} \) contiguous allowed shifts) to the dictionary atoms.
     - 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].

   - 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.

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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.

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 decoposition. Thus it provides better estimations of waveforms in the dictionary.

References


SNR
-36.107
-16.700
0.998
0.462

Figure 3: The single-channel (left) and the multi-channel method (right).