Electro-Metabolic Coupling Investigated with Jitter Invariant Dictionary Learning

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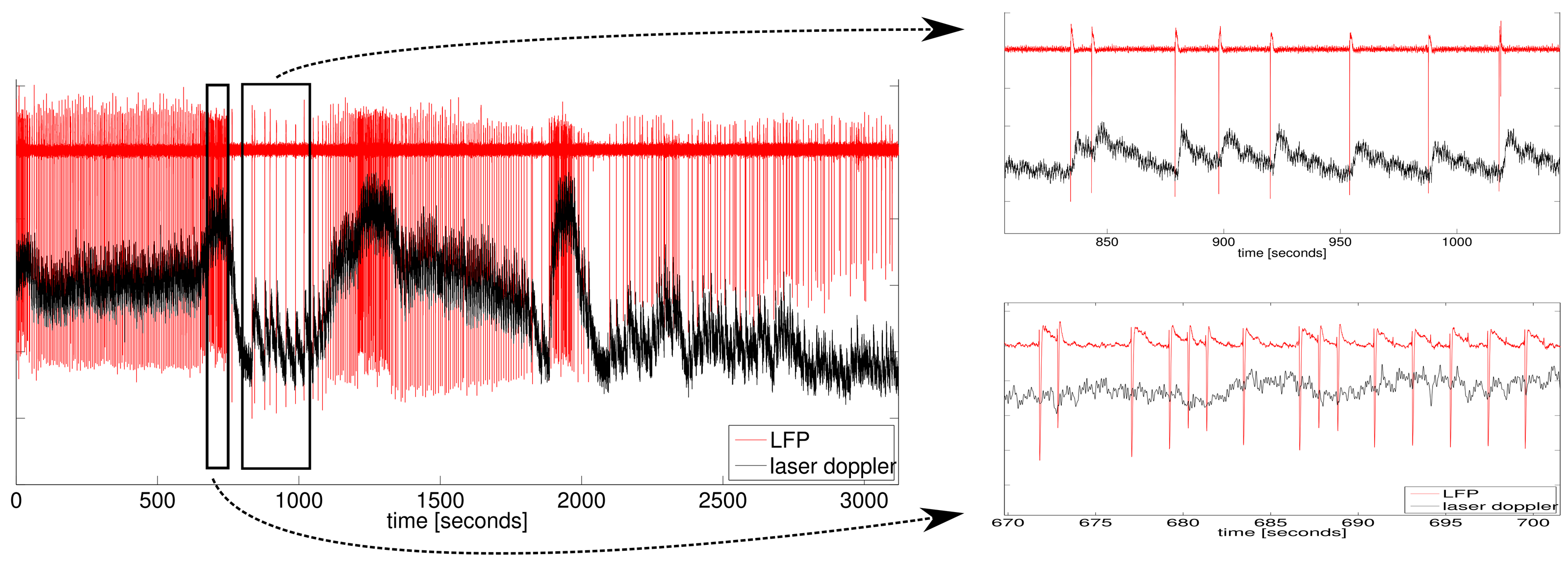
This work aims at establishing a relationship between neurophysiological and hemodynamic activity in an animal model of epilepsy. For the analysis, we propose a novel algorithm that is suited to learn meaningful representations of the multimodal datasets. As a result, we are able to learn a hemodynamic response and discover spike synchronization with hemodynamic activity.

Goals and Challenges

Goals:

- Investigate neurophysiological and hemodynamic activity.
- Establish relationship between the two.



Data: ~ 1 hour of simultaneous recordings of lead field potential (LFP) and laser doppler (LD) in Winster-Han rat. Biccuculine (a blocker of inhibition) was injected in the cortex to elicit epileptic-like discharges.

Difficulties:

- Large dataset with several hundred epileptic spikes.
- Spikes change over time (shape, amplitude, spiking rate).
- Overlaps in spikes and hemodynamic responses.

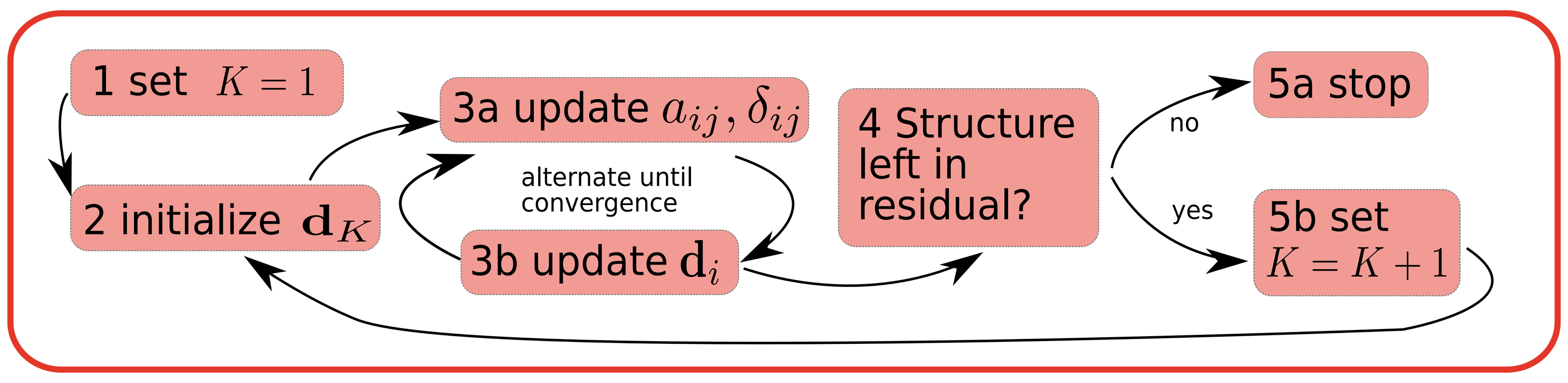
Processing LFP Data: Two Approaches

A) Epoching: LFP data is segmented into time windows centered around spikes [1] Drawbacks: (a) spikes need to be detected previously, (b) overlaps are not properly treated.

B) Continuous model: LFP data $\mathbf{x}$ is composed of K spike shapes $\{\mathbf{d}_i\}_{i=1}^K$ repeated at different latencies δ_{ij} with varying amplitudes a_{ij} plus some noise ϵ:

$$\mathbf{x} = \sum_{i=1}^{K} \sum_{j=1}^{M_i} a_{ij} \mathbf{d}_i(\cdot - \delta_{ij}) + \epsilon$$

Calculate $a_{ij}, \delta_{ij}, \mathbf{d}_i$ using K-hierarchical alternate minimization:



Algorithm 1: Outline for learning waveforms (here spikes) and their latencies δ_{ij} and amplitudes a_{ij}. Algorithm starts learning a single waveform $\mathbf{d}_1$, which is initialized with e.g. an arbitrary spike in the data (2). Then all spikes are detected and their latencies δ_{ij} and amplitudes a_{ij} are calculated (3a, details below). The a_{ij}, δ_{ij} are now used to update waveforms $\mathbf{d}_i$. Steps 3a and 3b are repeated until convergence. If the residual still contains much structure, the previous steps may be repeated with an additional waveform.

Core of Algoritm 1 - alternate minization

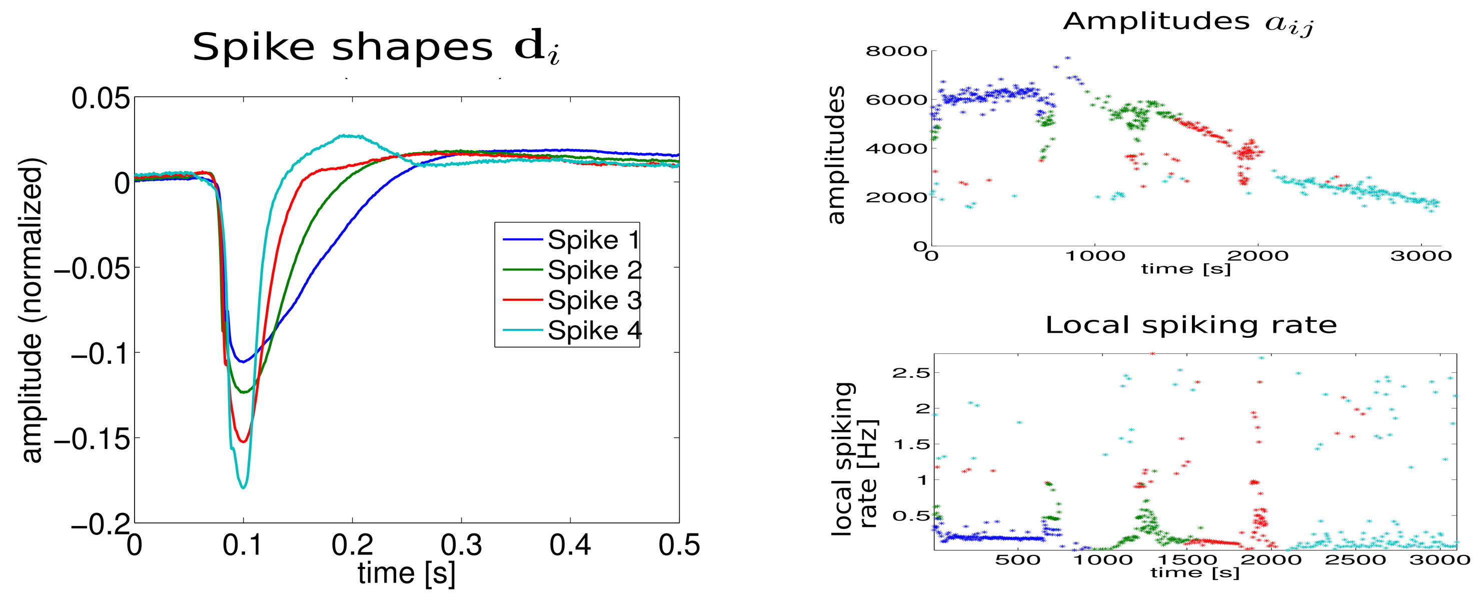
3a Correlation based detection of waveforms, can be solved by sparse coding (e.g. LARS [2]) with all possible shifts of the $\mathbf{d}_i$.

3b Simple averaging if detected waveforms are not overlapping. Otherwise overlaps are accounted for in linear system (discrete deconvolution), which may be ill-conditioned for strong overlaps.

References :
[1] Hitziger et al. Jitter-Adaptive Dictionary Learning - Application to Multi-Trial Neuroelectric Signals, *ICLR* (2013)
[2] Efron et al. Least Angle Regression, The Annals of statistics 32.2 (2004): 407-499

Results on LFP

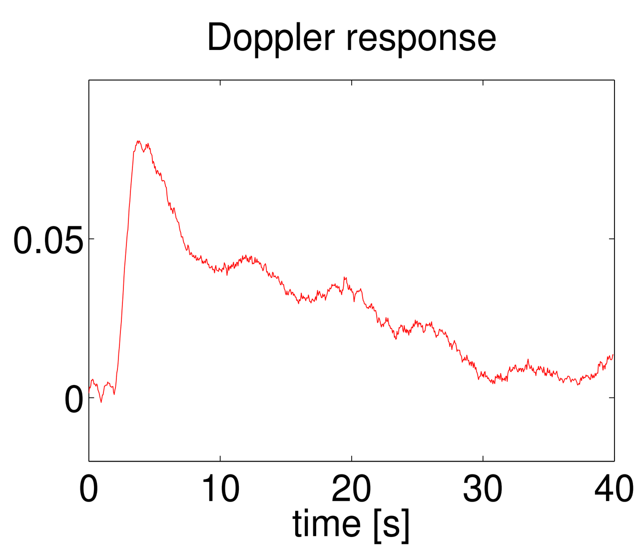
Algorithm 1 produces a compact representation of the data, providing additional insight.



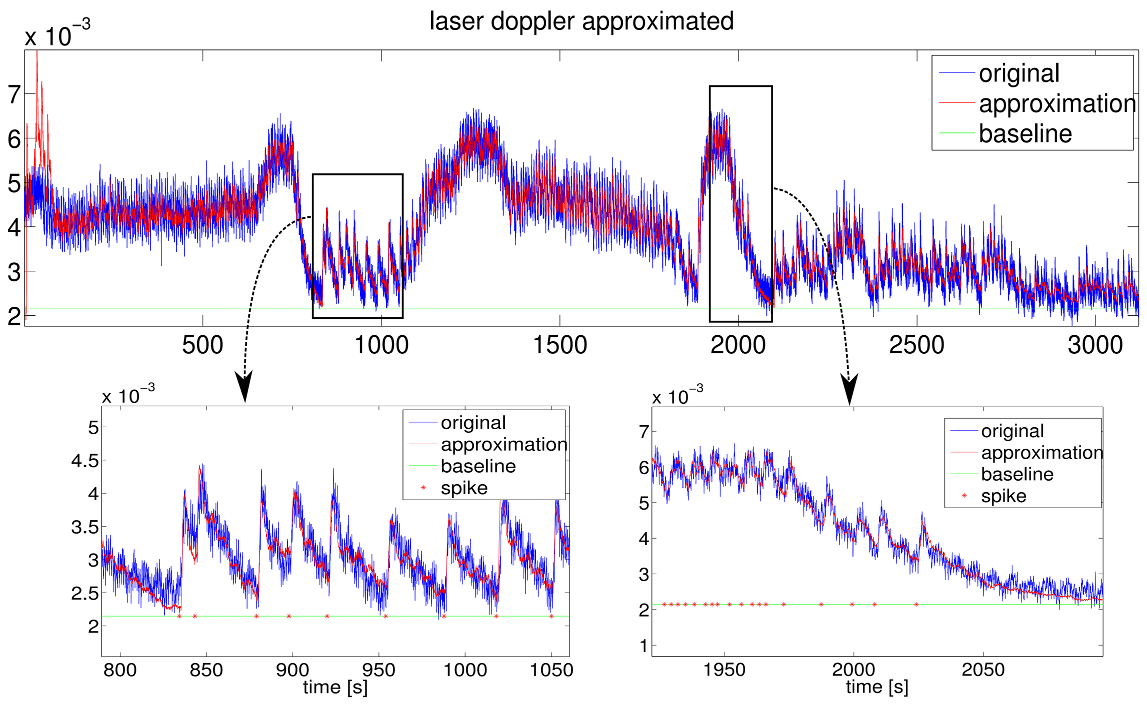
Left: four spikes were learned on the data, note that their amplitudes are normalized. Their shapes differ mainly in duration. Right: amplitudes of detected spikes (top) are decreasing with time. They appear strongly negatively correlated with their local spiking rate (defined as 1 / distance to previous spike [s]).

LFP vs. Laser Doppler

Hemodynamic response is learned using Algorithm 1, where we take as δ_{ij} the previously detected spike latencies.

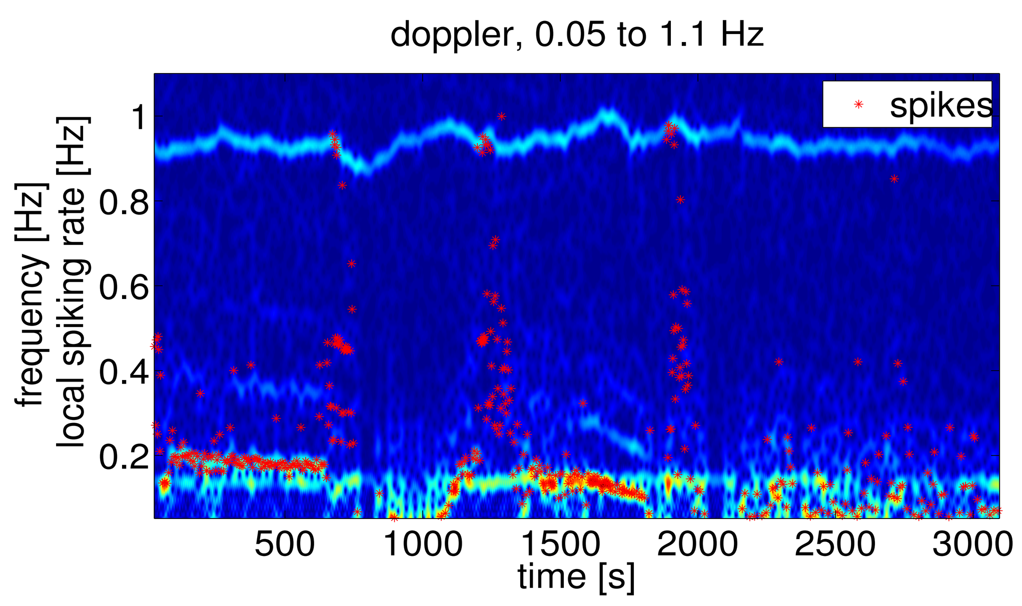


Hemodynamic response learned on laser doppler using Algorithm 1 with $K = 1$ and δ_{ij} the learned spike latencies. The presence of the oscillations with 7s period probably result from strong overlapping effects due to high spiking rates and long doppler response.



The figures show the laser doppler data (blue) and the appoximation (red) given by the learned representation. During learning with Algorithm 1 we included a constant waveform $\mathbf{d}_0$, see green baseline. Note that relation between spike occurence (red asterisk, bottom figures) and doppler response is only clearly visible during low spiking rates.

Time-frequency analysis reveals synchronization of spikes with 0.9-1 Hz rhythm in hemodynamics, probably related to respiration.



Local spiking rates (1/distance [s] to previous spike) are plotted on time-frequency map of laser doppler. During the three spike outbursts around 750, 1250, and 1900 seconds the spikes appear to synchronize with 0.9-1 Hz activity in the doppler. Around 750 seconds local spiking rates even clearly correspond to the subharmonics of this rhythm.

Summary

Proposed algorithm

- Produces informative data representations suited to analyze and compare multimodal data.
- Stepwise structure makes it flexible and allows integration of prior information.

Electro-Metabolic Coupling

- Hemodynamic response was learned that well explains the data.
- Synchronization of spiking rates with periodic activity of 0.9-1 Hz in laser doppler becomes apparent in time-frequency map.

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