A unifying algorithm for the identification of kinematic and electromyographic motor primitives

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Introduction

- Multiple definitions of motor primitives have been described in literature.
- Different definitions of primitives rely on different generative models.
- Multiple algorithms can be used to identify the same kind of primitives. Each algorithm puts however different constraints on the parameters.

Synchronous primitives

\[ m(t) = \sum_{j=1}^{\infty} \alpha_j \cdot s_j(t - \tau_j) \]

Ivanenko et al. (2005)

Time-varying primitives

\[ m(t) = \sum_{j=1}^{N} w_j(t - \tau_j) \]

d’Avella et al. (2003)

Kinematic primitives

\[ x_i(t) = \sum_{j=1}^{N} a_{ij} \cdot s_j(t - \tau_j) \]

Omlor (2010)

Goals

- To relate different definitions of motor primitives to each other.
- To allow the use of a single algorithm to identify motor primitives based on a single generative model.
- To facilitate the comparison of results across different studies.
- To provide researches with a comprehensive tool suitable for the extraction of several kinds of motor primitives.

Methods

All definition of primitives can be derived from a unique generative model, usually referred to as anechoic mixture model

\[ x_i(t) = \sum_{k=1}^{M} c_{ik} \cdot e^{j\omega_k t} \]

They differ from each other only for the constraints imposed on the parameters of the model (e.g. non-negativity or equality constraints, presence of delays).

Approximating the signal and the delayed sources by truncated Fourier series we obtain

\[ x_i(t) = \sum_{k=1}^{M} c_{ik} \cdot e^{j\omega_k t} \]

\[ s_j(t - \tau_j) = \sum_{k=1}^{N} v_{jk} \cdot e^{-j\omega_k \tau_j} \cdot e^{j\omega_k \tau_j} \]

where \( M \) is an integer and \( c_{ik} \) and \( v_{jk} \) belong to the complex space. The last equations imply

\[ |c_{ik}|^2 = \sum_{j=1}^{N} |\alpha_j|^2 \cdot |v_{jk}|^2 \]

and the relationship

\[ c_{ik} = \sum_{j=1}^{N} \alpha_j \cdot v_{jk} \cdot e^{-j\omega_k \tau_j} \]

Weighting coefficients and delays can be retrieved through a classical cross-correlation procedure

\[ (\tau_j, A_j) = \arg \min_{(\tau_j, A_j)} \| s_j(t - \tau_j) - A_j \cdot S(\tau_j) \| \]

where \( S(\tau_j) = (s_j(t - \tau_j), \ldots) \) and \( A_j = (\alpha_j, \ldots) \).

References


FADA: Fourier-based Anechoic Demixing Algorithm

1. Identification of the absolute values of the Fourier coefficients of the sources (NMF or non-negative ICA to obtain independent primitives)

2. Identification of phases of the Fourier coefficients of the sources (non-linear quadratic optimization, non-negativity constraints can be imposed here)

3. Identification of weighting coefficients and delays ensuring that the sources are known (standard cross-correlation procedure)

Work in progress (in collaboration with Dominik Endres)

Development of new Bayesian criteria for:
- Model selection
- Estimation of model complexity (# of primitives)
- Most likely type of smoothness prior

Log-likelihood of data (Graupe approx.)

Example: estimate of complexity

Results

To test the performances of the new algorithm we proceeded as it follows:
- Artificial data sets with well-specified statistical properties were synthesized. The generative processes combined linearly, and partially with time delays, a small number of basic primitives whose properties were optimized in order to mimic the basic statistical properties of electromyographic and electromyographic data.
- FADA and other standard algorithms were applied to the generated data set and their capability to identify the original sources was assessed.
- Robustness of algorithm performances to signal dependent noise were assessed.

Conclusions

- The new algorithm is based on one single generative model but it allows the identification of multiple kinds of primitives.
- Its identification performances are at least as good as those of other standard unsupervised learning algorithms.
- It works on a lower number of parameters: more robust to noise.
- Very good trade-off between performances and flexibility.
- To be distributed soon in form of freeware Matlab toolbox (Chiovetto et al. 2013, in preparation).

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