High Performance Prediction of 3D-Trajectory of Hand From ECoG With Recursive N-way Partial Least Squares for BCI Application

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Abstract. In the present article a tensor-input/tensor-output blockwise Recursive N-way Partial Least Squares algorithm for recursive tensor factorization and multi-linear regression is applied for prediction 3D-trajectory of hand from the ElectroCorticoGram (ECoG) for Brain Computer Interface (BCI) applications. The method combines the Multi-way (tensors) decomposition with a consecutive calculation scheme and allows blockwise treatment of tensor data arrays of huge dimensions as well as the adaptive modeling of time dependent processes with tensor-input and tensor-output variables. Applied to BCI, the algorithm provides an efficient adjustment of the decoding model. This algorithm will be used in CLINATEC® BCI platform which is designed to allow a tetraplegic subject to pilot an exoskeleton thanks to ECoG recording by means of a wireless fully implantable device: WIMAGINE®.

Keywords: Adaptive Control, BCI, Multi-Way Analysis, Partial Least Squares, Recursive Calculation, Tensor Factorization

1. Introduction and Method

Neuronal signal decoding represents a challenging task. For the real-life applications, the need for an easy use Brain Computer Interface (BCI) system is one of the crucial problems. The Recursive N-way Partial Least Squares (Recursive NPLS, RNPLS) algorithm [Eliseyev et al., 2011] was proposed for adaptive, fast and easy BCI system calibration in the case of tensor-input and vector-output data.

In this article, the generalized tensor-input/tensor-output RNPLS algorithm was applied to predict 3D-trajectory of the monkey's right hand from its ECoG recordings. The Recursive NPLS method is derived from the N-way Partial Least Squares [Bro, 1996] and Recursive Partial Least Squares [Qin, 1998] approaches. It unites both the multi-way data representation of the first one with the recursive calculation scheme of the second one. In the recursive method, the information of decomposition of observation tensors ($\underline{\mathbf{X}}$ and $\underline{\mathbf{Y}}$) is captured by their loading tensors, as well as by the coefficient matrix. They are iteratively updated according to the new data. The size of the loading tensors and the matrix of coefficients are defined by the dimensionality of the variables and do not depend on the number of observations. As a result, the algorithm always keeps the size of the processing data.

2. Data

Data used in the experiments was taken from the publicly available database (http://neurotycho.org/data/20100802s1epidural-ecogfood-trackingbkentaroshimoda). It contains the ECoG signals of Japanese macaque recorded simultaneously with continuous 3D trajectories of its hands. The ECoG signals were recorded from the 64 electrodes implanted in the epidural space of the left hemisphere of the monkey. The hand motion was recorded by means of an optical motion capture system. This system registered positions in 3D of the markers attached to shoulders, elbows, and wrists of the monkey. Precise description of the experiment and the dataset can be found in [Shimoda et al., 2012]. For the tests, one recording (about 17 minutes, sampling rate 1000 Hz) was chosen randomly from the database.

To train the algorithm, 5000 time epochs were randomly selected among recorded time moments. As a result the training set includes 0.5% of the entire recording. The test set contains 3000 random epochs of the same file out of training.

To form a feature tensor $\underline{\mathbf{X}}$, each ECoG epoch was mapped to temporal-frequency-spatial space by continuous wavelet transform. The frequency band consisted from 3 sub-bands, namely, [0.6, 7.8] Hz with step $\delta f = 0.2$ Hz, [8, 48] Hz with step $\delta f = 2$ Hz, and [50, 300] Hz with step $\delta f = 10$ Hz. Sliding windows $[t - \Delta\tau, t]$, $\Delta\tau = 1$ s with step $\delta\tau = 0.005$ s were considered for all electrodes $c = 1, 2, ..., 64$. The resulting dimension of a point is (84x201x64) ≈ 10^6, whereas the training tensor $\underline{\mathbf{X}}^{training} \in \Re^{5000\times84\times201\times64}$. The response tensor $\underline{\mathbf{Y}}^{training} \in \Re^{5000\times3\times3}$ (5000 epochs with 3 coordinates for 3 markers on the monkey hand). Thus, the dimensional of the training dataset $\{\underline{\mathbf{X}}^{training}, \underline{\mathbf{Y}}^{training}\}$ justifies the choice of the RNPLS algorithm for the model identification.

Any preprocessing technics (chewing artifacts extraction, common average reference, etc.) was not applied. To identify the decoding model with RNPLS, the training set was split into 5 subsets of 1000 points.

3. Results

To validate the generalization ability, the identified RNPLS model was applied to the test data set $\{\underline{\mathbf{X}}^{test}, \underline{\mathbf{Y}}^{test}\}$, $\underline{\mathbf{X}}^{test} \in \Re^{3000\times84\times201\times64}$, $\underline{\mathbf{Y}}^{test} \in \Re^{3000\times3\times3}$. Predicted motion of the right hand was correlated with its real position. The resulted correlations between the observed and predicted coordinates are: Shoulder: (R_X^2, R_Y^2, R_Z^2)=(0.62, 0.80, 0.85); Elbow: (R_X^2, R_Y^2, R_Z^2)=(0.54, 0.84, 0.83); Wrist: (R_X^2, R_Y^2, R_Z^2)=(0.63, 0.85, 0.82). On average (R_X^2, R_Y^2, R_Z^2)=(0.60 ± 0.05, 0.83 ± 0.03, 0.83 ± 0.02).

4. Discussion

The RNPLS algorithm performs multimodal data analysis, i.e. it can be applied to the multi-way data and preserves the structure of the data, improves robustness of the results as well as allows identifying relative impact of each dimension.

The algorithm is an efficient approach for BCI system calibration. It allows easy adjustment of the BCI system to the changing in neural signals as well as preserves the structure of the data that simplifies results interpretation. Moreover its prediction accuracy is comparable or outperforms the results previously reported for the given database (wrist coordinates correlations: 0.47 ± 0.12, 0.56 ± 0.10, 0.68 ± 0.06 with Unfold-PLS [Shimoda et al., 2012]; 0.52 ± 0.13, 0.67 ± 0.04, 0.74 ± 0.04 with Higher-Order Partial Least Squares [Zhao et al., 2012]; 0.50 ± 0.13, 0.67 ± 0.04, 0.73 ± 0.04 with NPLS [Zhao et al., 2012]; 0.50 ± 0.12, 0.67 ± 0.04, 0.74 ± 0.03 with Unfold-PLS [Zhao et al., 2012]).

This algorithm will be used in CLINATEC® BCI project which includes the realization of a fully implantable device, WIMAGINE®, to measure and transmit ECoG data wireless to a terminal, and means for a tetraplegic subject to pilot effectors with a large number of degrees of freedom, such as an exoskeleton, after training.

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