Recursive Multi-Way PLS for Adaptive Calibration of Brain Computer Interface System

Andrey Eliseyev\textsuperscript{1,2}, Alim-Louis Benabid\textsuperscript{2}, and Tatiana Aksenova\textsuperscript{1,2}

\textsuperscript{1} Foundation Nanosciences, Grenoble, France
\textsuperscript{2} Clinatec/LETI/CEA, Grenoble, France
{andriy.yelisyeyev,alim-louis.benabid,tetiana.aksenova}@cea.fr

Abstract. In the present article a Recursive Multi-Way PLS algorithm for adaptive calibration of a BCI system is proposed. It combines the NPLS tensors decomposition with a scheme of recursive calculation. This Recursive algorithm allows treating data arrays of huge dimension. In addition, adaptive calibration provides a fast adjustment of the BCI system to mild changes of the signal. The proposed algorithm was validated on artificial and real data sets. In comparison to generic Multi-Way PLS, the recursive algorithm demonstrates good performance and robustness.

Keywords: Partial least square, recursive estimation, multi-way analysis tensor factorization, brain-computer interface (BCI), adaptive control.

1 Introduction

Movement related Brain Computer Interfaces (BCI) aim to provide an alternative non-muscular communication pathway for individuals with severe motor disability (such as post-traumatic quadriplegia) to send commands to effectors of the external world originating from measures of the brain neuronal activity. During the last decades, several approaches were developed to face the problem of neuronal signal decoding. In particular, multi-way analysis was reported recently as an effective tool for neuronal signal processing. It allows simultaneous treatment of data in several domains. For instance, multi-way analysis was applied recently at the self-paced BCI in natural environment in freely moving animals ([1], [2]). Signals of neuronal activity were mapped by continuous wavelet transformation to the temporal-frequency-spatial space. Then the Iterative N-way PLS (INPLS) was applied to extract the predictors (neural electrical features preceding an intention to act). One of the major problems of BCI studies is the variability of neuronal signals, due in particular to the brain plasticity. These changes in neuronal activity require recalibration of BCI systems. The full system recalibration is a time and labor consuming procedure. Adaptive calibration aims to provide a fast adjustment of the BCI system to mild changes of the signal. Although the INPLS allows treating data arrays of huge dimension, this method cannot be applied for adaptive learning. In this paper a Recursive NPLS (RNPLS) algorithm is proposed. It allows online processing of multi-modal data. Moreover, weighted RNPLS can be applied for adaptive learning to treat time-dependent recordings. This algorithm can be efficiently used for numerous applications beyond BCI.
2 Methods

The RNPLS algorithm combines the NPLS tensors (multi way arrays) decomposition and modeling [3] with the scheme of recursive calculation [4].

2.1 Generic PLS

Partial Least Squares (PLS) is a statistical method for data analyses, particularly suited to the case of high dimensions of observations [5]. PLS regression is an approach for modeling the linear relationship between the vector of dependent (output) variables \( y \) and the vector of independent (input) variables \( x \) on the basis of matrices of observations \( X \) and \( Y \): \( Y = XC + V \), where \( V \) and \( C \) are noise and coefficient matrices. To build the model, the observations are projected into low dimensional spaces in such a way that the maximum variances of \( X \) and \( Y \) are explained simultaneously. PLS represents the iterative procedure. At the first step, the matrices \( X \) and \( Y \) are presented as bilinear terms:

\[
X = t_i p_i^T + E_i, \quad Y = u_i q_i^T + F_i,
\]

where \( t_i \) and \( u_i \) are the latent variables (score vectors), whereas \( p_i \) and \( q_i \) are the loading vectors. \( E_i \) and \( F_i \) are the matrices of residuals. The score vectors are linear transforms of the matrices of observation in a way to maximize the covariance of \( t_i \) and \( u_i \) [5]. The score vectors are related by a linear model minimizing the norm of the residuals \( r_i : u_i = b_i t_i + r_i \). The same procedure is applied iteratively to the residual matrices. It is repeated \( F \) times.

Let us note that latent variables could be constructed as orthonormal [4]:

\[
T^T T = I_r,
\]

where \( T = [t_1, \ldots, t_r] \), \( I_r \) is identity matrix.

2.2 Recursive PLS

The recursive PLS algorithms were invented to take into account time-dependent changes of data as well as to be able to handle large data sets. Qin [4] and by Dayal and MacGregor [6] introduced the most known approaches. The Dayal and MacGregor algorithm exhibits a better performance but it stores in the memory the covariance matrix \( XX^T \), the size of which is equal to the square of the dimension of variable \( x \). Thus the method is not suited to the case of high dimension of the variable \( x \). In our BCI program, we are particularly interested in multimodal data analyses. In this case, the data dimensionality is extremely large (in the order of hundreds of thousands). That is why we chose Qin’s algorithm [4] as a basic approach. This article is devoted to the extension of this method to multimodal data.

According to the algorithm of Qin [4], matrices \( X \) and \( Y \) are decomposed by the batch-wise PLS algorithm with orthonormal latent variables (1):