NeuroImage 108 (2015) 203–213

Contents lists available at ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/ynimg

Multivariate detrending of fMRI signal drifts for real-time multiclass pattern classification

Dongha Lee [a,b,c], Changwon Jang [a,b], Hae-Jeong Park [a,b,*]

[a] BK21 PLUS Project for Medical Science, Yonsei University College of Medicine, Seoul, Republic of Korea
[b] Department of Nuclear Medicine, Department of Radiology, Department of Psychiatry, Severance Hospital, Yonsei University College of Medicine, Seoul, Republic of Korea
[c] Severance Biomedical Science Institute, Yonsei University College of Medicine, Seoul, Republic of Korea

ARTICLE INFO

Article history:
Accepted 24 December 2014
Available online 5 January 2015

Keywords:
Multi-voxel pattern analysis (MVPA)
Voxel-wise detrending
Real-time fMRI
Multi-voxel fMRI classification
Support vector machine (SVM)

ABSTRACT

Signal drift in functional magnetic resonance imaging (fMRI) is an unavoidable artifact that limits classification performance in multi-voxel pattern analysis of fMRI. As conventional methods to reduce signal drift, global demeaning or proportional scaling disregards regional variations of drift, whereas voxel-wise univariate detrending is too sensitive to noisy fluctuations. To overcome these drawbacks, we propose a multivariate real-time detrending method for multiclass classification that involves spatial demeaning at each scan and the recursive detrending of drifts in the classifier outputs driven by a multiclass linear support vector machine. Experiments using binary and multiclass data showed that the linear trend estimation of the classifier output drift for each class (a weighted sum of drifts in the class-specific voxels) was more robust against voxel-wise artifacts that lead to inconsistent spatial patterns and the effect of online processing than voxel-wise detrending. The classification performance of the proposed method was significantly better, especially for multiclass data, than that of voxel-wise linear detrending, global demeaning, and classifier output detrending without demeaning. We concluded that the multivariate approach using classifier output detrending of fMRI signals with spatial demeaning preserves spatial patterns, is less sensitive than conventional methods to sample size, and increases classification performance, which is a useful feature for real-time fMRI classification.

Introduction

Multi-voxel pattern analysis (MVPA) of functional magnetic resonance imaging (fMRI) signals is a popular method for analyzing brain activity using (neural activity-induced) blood-oxygen-level-dependent (BOLD) signal patterns (Norman et al., 2006). MVPA has been used to classify various patterns of visual objects (Haxby et al., 2001, Haynes and Rees, 2006, Diana et al., 2008), word semantics (Mitchell et al., 2008), subjective experience of sound (Meyer et al., 2010), episodic memory (Chadwick et al., 2010), mental imagery (motor, mood, and object) (LaConte et al., 2007, Reddy et al., 2010), and emotions (happiness, disgust, and sadness) (Sitaram et al., 2011).

In its application to fMRI, the classification performance of MVPA depends on several factors in the preprocessing step, such as spatial smoothing (Misaki et al., 2013), temporal compression, data partitioning, resampling (Strother et al., 2002), realignment (LaConte et al., 2003), and detrending signal drift (Etzel et al., 2011). The latter in particular is necessary to enhance classification accuracy, especially for long-time fMRI acquisition.

Signal drift in fMRI can be attributed to the temporal variation in scanner magnetic fields (Smith et al., 1999) or physiological factors (Biswal et al., 1996, Kiviniemi et al., 2000). Considering that these factors affect signals in the entire brain, a simple approach has been to remove spatially global effects of drift by regressing out, or proportionally scaling out, spatial mean signals from fMRI signals (Macey et al., 2004). However, this approach does not account for local variability of fMRI drifts. The most common solution these days is to linearly detrend signal drifts in each voxel, and is called voxel-wise linear detrending (Tanabe et al., 2002, Hassabis et al., 2009, Pereira et al., 2009, Chadwick et al., 2010, Reddy et al., 2010, Sitaram et al., 2011, Etzel et al., 2011, Andersson et al., 2013, Bonnici et al., 2013). However, voxel-wise linear detrending of fMRI drift is limited in MVPA, since linear trend estimation is vulnerable to noise, can alter spatial patterns (Misaki et al., 2010, Etzel et al., 2011), and may affect classification performance (LaConte et al., 2005).

Voxel-wise detrending leads to a more critical problem in real-time fMRI (Sitaram et al., 2011, Andersson et al., 2012). In real-time fMRI, the drift should be estimated from online sample data, i.e., a mixture

* Corresponding author at: Department of Nuclear Medicine, Radiology, Psychiatry, Yonsei University College of Medicine, 50 Yonsei-ro, Sinchon-dong, Seodaemun-gu, Seoul 120-752, Republic of Korea. Fax: +82 2 393 3035.
E-mail address: parkhj@yonsei.ac.kr (H.-J. Park).

http://dx.doi.org/10.1016/j.neuroimage.2014.12.062
1053-8119/

of drifts and signals. Online estimation of drift using incomplete data may result in unstable spatial patterns in recursive voxel-wise detrending algorithms (Andersson et al., 2012, Andersson et al., 2013).

In this study, we investigate whether class-specific multi-voxel (multivariate) detrending can mitigate the problems in the two extreme methods mentioned above, i.e., (spatially) global signal removal methods and voxel-wise detrending methods. The former ignores regional variations in signal drifts; whereas the latter is too sensitive to voxel-wise artifacts without considering the similarity of drift effects in the neighborhood of each voxel.

An example of the multivariate detrending approach is a binary classifier output detrending method proposed by LaConte et al. (2007) based on a support vector machine (SVM) (Boser et al., 1992, Cortes and Vapnik, 1995), a supervised machine learning method for MVPA. As the average of SVM classifier outputs should be centered at zero, classifier output drifts (caused by signal drifts) can be regressed out by a recursive least-square fit of a straight line for the outputs (LaConte et al., 2007). Since the classifier output is a weighted sum of signals at multiple voxels for each class, detrending classifier outputs takes advantage of robustness against pattern distortions caused by inconsistent voxel-wise detrending.

A growing number of recent fMRI-based MVPA studies have addressed multiclass problems. To deal with multiclass problems using SVM, two different strategies have been used to combine multiple binary classifiers or to put all data together ("all-together") in the design of a SVM classifier. Examples of the multiple binary classifiers approach are one-versus-all, one-versus-one, directed acyclic graph SVM (Platt et al., 2000), and error-correcting code (Dietterich and Bakiri, 1995). Several "all-together" SVM algorithms are also available (Bredensteiner and Bennett, 1999, Mayoraz and Alpaydin, 1999, Weston and Watkins, 1999, Crammer and Singer, 2002, Lee et al., 2004); however, these require generally higher computational costs than multiple binary classifiers. Thus, for general multiclass SVM applications, the one-versus-all and one-versus-one approaches are common choices due to their simplicity. In the one-versus-all approach, each binary classifier deals with data divided into a class and the rest classes. The classifier with highest output (among all the classifiers) determines the class label of the data (a winner-take-all strategy). In the one-versus-one approach, each binary classifier is specialized to classify pairs of all class labels. The final class label is chosen by counting votes from all the classifiers (a max-wins voting strategy). So far, various approaches have been applied to multiclass fMRI classification: for example, the one-versus-all approach (Reddy et al., 2010), the one-versus-one approach for four classes (Andersson et al., 2012), and the error-correcting code method for four-way position classification (Hassabis et al., 2009).

However, no multivariate detrending method has been introduced to improve multiclass classification of fMRI data. Furthermore, the effectiveness of the multivariate detrending method for multiclass fMRI data remains to be assessed, especially for the purpose of real-time application.

In this paper, we propose a multivariate real-time detrending method to reduce the temporal inconsistency of the spatial patterns that occur in a voxel-wise fMRI detrending method. The proposed method includes a spatial demeaning at each scan and a temporal detrending of drifts in the multiclass classifier outputs (in this study, the outputs of linear SVMs). Using a binary classification of motor movements and a multiclass classification study of four motor imageries (i.e., walking forward, turning left, turning right, and catching a cup), we show that classification performance can be significantly improved by detrending classifier outputs (thus removing class-specific multivariate drifts), especially in multiclass MVPA. We also show that spatial demeaning is an important step to optimally train classifiers, through a greater emphasis on the spatial pattern itself rather than the signal offset, and to thus improve classification performance.

Material and methods

Generalized classifier output linear detrending

The generalized multiclass classifier output linear detrending algorithm (GCLD) that we propose in this study combines the spatial demeaning and linear detrending of classifiers outputs through the following steps. Here, we explain the general concept and procedure of GCLD; more details will follow in the Evaluation section.

STEP 1: spatial demeaning (DM) of a training data set

For a set of raw scanned data $\{\mathbf{S}_t\}_{t=1,\ldots,T}$, we derive a voxel intensity vector $\mathbf{s}_t = \{s^t{}_1, s^t{}_2, \ldots, s^t{}_R\}$ corresponding to intensities $\mathbf{S}_t(\mathbf{v})$ at scan time t at voxels $\mathbf{v} = \{v_i | v_i \in ROI\}$ within a target brain region of interest (ROI) (R voxels within the ROI). To focus on the overall procedure of GCLD, details of ROI selection will be explained later.

To remove global drifts commonly affecting voxels within the target ROI at each scan, we subtract a mean intensity of voxels within the ROI (μ_t) from the voxel intensity vector $\mathbf{s}_t$.

$$\mathbf{x}'_t = \mathbf{s}_t - \mu_t = \left\{ s^t{}_e - \mu_t \right\}_{e=1,\ldots,R}, \quad \mu_t = \frac{1}{R}\sum_{e=1}^{R} s^t{}_e \tag{1}$$

STEP 2: feature selection and training multiclass SVMs

Feature selection. From the demeaned voxel intensity vector set $\{\mathbf{x}'_t\}_{t=1,\ldots,I}$ extracted from a training data set (with a set size of I), we selected a feature vector $\mathbf{x}_t$ (a subset of $\mathbf{x}'_t$) that was composed of statistically meaningful voxels, using a searchlight strategy. Feature selection will be explained in detail in the Evaluation section.

A binary SVM and the binary classifier output detrending method. We use a binary linear SVM (Boser et al., 1992, Cortes and Vapnik, 1995) as a basic classifier that produces a linear discriminant function f with the largest possible margin for a given feature data set $\{\mathbf{x}\}$ (with a vector dimension D), defined below:

$$f(\mathbf{x}) = \mathbf{w}\mathbf{x} + b \tag{2}$$

where $\mathbf{w} = (w_1, \ldots, w_D)$ is the normal weight vector of the separating hyperplane, and b is the bias that translates the hyperplane away from the origin of the feature space. For a training set $(\mathbf{x}_i, y_i)$ for $i = 1, \ldots, I$, $y \in \{1, -1\}^I$, the SVM searches for optimal values of $\mathbf{w}$ and b to find a hyperplane that maximizes the margin magnitude $\frac{\|w\|}{2}$ as follows:

$$[\mathbf{w}^*, b^*, \xi] = \min_{w,b,\xi} \frac{1}{2}\mathrm{w}^T\mathrm{w} + \mathrm{C}\sum_{i=1}^{I}\xi_i, \text{ subject to } \mathrm{y}_i\left(\mathrm{w}^T\mathbf{x}_i + b\right) \geq 1 - \xi_i,\ \xi_i \geq 0. \tag{3}$$

C is a regularization parameter that controls costs between the margin maximization and the classification error minimization on the training data and should be optimized before training SVM. Details of the optimization process of C will be dealt with in the Evaluation section. For a testing set $\{\mathbf{x}_i\}_{i=1,\ldots,J}$, the classifier output is $f(\mathbf{x}_i) = \mathbf{w}^*\mathbf{x}_i + b^*$, and the class label for an input feature vector $\mathbf{x}_i$ is assigned according to the sign of $f(\mathbf{x}_i)$, i.e., greater than or less than zero.

The binary classifier detrending method proposed by LaConte et al. (2007) was to remove drifts in the classifier output $f(\mathbf{x}_i)$ at scanning time t_i to make the average classifier outputs to zero by recursive detrending. That method can be written as the following equation:

$$g(\mathbf{x}_i) = f(\mathbf{x}_i) - \alpha t_i - \beta = \mathbf{w}^*\mathbf{x}_i + b^* - \alpha t_i - \beta \tag{4}$$

For a feature vector $\mathbf{x}_i$ at time t_i, the slope (α) and intercept (β) was recursively estimated using history samples of $\{f(\mathbf{x}_j)\}$ for $t_j \leqslant t_i$. A feature