A regularization algorithm for decoding perceptual profiles

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Introduction

We have tested and optimized a machine learning approach on fMRI data, based on new regularization learning algorithms [1] for regression problems. In this study, we have evaluated the feasibility of predicting the perceived pain intensity in healthy volunteers, from fMRI signals collected during an experimental model of acute prolonged (tonic) pain lasting several minutes [2,3].

Learning and regularization

Learning from examples: given a training set
\[ \{(x_i, y_i) \in X \times Y : i = 1, \ldots, n\}, \ X \subseteq \mathbb{R}^m, \ Y \subseteq \mathbb{R} \]
find the decision function \( f : X \rightarrow Y \) to predict the label \( y \) of new examples \( x \) by solving [4]

\[
\min_{f \in \mathcal{H}} \left \{ \frac{1}{n} \sum_{i=1}^{n} V(y_i, f(x_i)) + \lambda \|f\|_K^2 \right \}
\]

where:
- \( V \) is a loss function
- \( \mathcal{H} \) is a Reproducing Kernel Hilbert Space with Mercer kernel \( K \) [5]
- \( \lambda \) is a positive regularization parameter.

If we consider the quadratic loss \( V(y, f(x)) = (y - f(x))^2 \) and the sampling operator \( S_x : \mathcal{H} \rightarrow \mathbb{R}^n \) defined by \( (S_x f)_i = f(x_i) \), problem (1) becomes

\[
\min_{f \in \mathcal{H}} \|S_x f - y\|_2^2 + \lambda \|f\|_K^2
\]

where \( \| \cdot \|_n \) is 1/n times the Euclidean norm in \( \mathbb{R}^n \) and \( y = (y_1, \ldots, y_n)^T \). The solution of (2) is the Tikhonov regularized solution of the linear inverse problem \( S_x f = y \) whose explicit form is given by [6]

\[
f(x) = \sum_{i=1}^{n} \alpha_i K(x, x_i)
\]

Tikhonov regularization algorithm:
\( \alpha = (K + n\lambda I)^{-1} y \), where
\( K_{ij} = K(x_i, x_j), \quad \alpha = (\alpha_1, \ldots, \alpha_n)^T \)

\( \alpha = 0 \) method [7]:
\[
\alpha(i)^{(1)} = \alpha(i)^{(1)} + \frac{1}{i} \omega_i \alpha(i)^{(1)} - \frac{1}{i+1} \omega_i \alpha(i+1)^{(1)} + \omega_i \alpha(i-1)^{(1)}
\]

\( \omega_i = \frac{(i-1)(i+2)}{(i+2)(i+3)} \)

Crucial parameters: the role of the regularization parameter \( \lambda \) is played by the number of iterations \( t \). The fast convergence together with the very simple definition of each iteration (which involves only a matrix-vector product) makes the \( v \)-method less computationally expensive than state-of-the-art approaches as SVM [8].

Data pre-processing and the input features

- Corrections of head movements, temporal filtering (gaussian 15 points, \( \sigma = 100 \)) and linear detrending
- Features: for each ROI the first principal singular vector (1st-SVD) of the time series was computed using the AFNI S/W package. To roughly recover the original signal variation, each 1st-SVD was multiplied by the median of the standard deviations of the time courses of each ROI voxel, computed over an interval of 6.5 min, starting from 30s before stimulation

Experimental dataset (14 subjects x 300 TR)

14 volunteers were injected subcutaneously with a dilute ascorbic acid solution into the thenar eminence of the left hand

The fMRI experiment

- pain intensity was recorded by moving a computer-controlled visual analogue scale (VAS in 0-100) with the right (unstimulated) hand
- functional images were acquired by a GE 1.5T scanner, using an EPI BOLD-sensitive sequence (TR=4s, 3.75s, 7.5mm slice thickness to 2x2x2mm)
- 300 brain volumes (in 20 min) were collected from 24 contiguous axial planes covering the diencephalon and telencephalon
- 10 regions of interest (ROIs) -based on a priori hypothesis- were identified in both hemispheres on anatomical brain images, acquired in the same experimental session. They included the thalamus, basal ganglia, parietal operculum, insular and cingulate cortical areas.

Results

Performance evaluation

• relative reconstruction error \( r^2(f, x, y) = \| y - f(x)/\|y \|_2 \|
• Pearson cross-correlation coefficient \( p(f, x, y) \)

Predicted pain profile compared to the real target for two representative subjects

TEST

\[
P_1 = 0.73, 0.74, 0.92, 0.50, 0.50, 0.53, 0.66, 0.68, 0.38, 0.80, 0.77, 0.58, 0.67, 0.83
\]

\[
P_2 = 0.87, 0.71, 0.44, 0.88, 0.84, 0.90, 0.68, 0.82, 0.97, 0.81, 0.79, 0.70, 0.83
\]

CONCLUSIONS

- Albeit preliminary, these results show that the proposed algorithm is potentially useful for inter-subject prediction of perceptual profiles from fMRI data.
- Given its fast convergence rate, the \( v \)-method is suitable for regression or multiple classification problems in the fMRI field.

[1] Le Cun G., et al. (2008), Spectral algorithms for supervised learning, Neural Computation 20, 1873-1897