Editorial

Brain decoding: Opportunities and challenges for pattern recognition

ABSTRACT

The neuroimaging community heavily relies on statistical inference to explain measured brain activity given the experimental paradigm. Undeniably, this method has led to many results, but it is limited by the richness of the generative models that are deployed, typically in a mass-univariate way. Such an approach is suboptimal given the high-dimensional and complex spatiotemporal correlation structure of neuroimaging data.

Over the recent years, techniques from pattern recognition have brought new insights into where and how information is stored in the brain by prediction of the stimulus or state from the data. Pattern recognition is intrinsically multivariate and the underlying models are data-driven. Moreover, the predictive setting is more powerful for many applications, including clinical diagnosis and brain–computer interfacing. This special issue features a number of papers that identify and tackle remaining challenges in this field. The specific problems at hand constitute opportunities for future research in pattern recognition and neurosciences.

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1. Introduction

During the past 10 years, the neuroscience community has largely embraced techniques and methods from pattern recognition to help analyzing and interpreting neuroimaging data. The investigation of how the human brain deals with information responding to continuous and complex external stimuli or behavior can not only lead to better understanding of human brain function, but also to practical solutions in brain–computer interfacing (BCI), or to the development of new clinical markers for disorder and disease.

Non-invasive measurements of the human brain at work have been enabled by a number of neuroimaging techniques among which the most relevant ones for this special issue are high-field functional magnetic resonance imaging (fMRI) and electroencephalography (EEG). Using the measured brain function, the spatiotemporal patterns of the corresponding neuronal activities should subsequently be analyzed to "decode" where and when the activities were presented in the context of the information processing. This information-discovery process is data-driven, multivariate and much more flexible than conventional hypothesis-driven statistical testing that is typically applied in a univariate way [1]. Moreover, the performance of pattern recognition techniques is assessed using cross-validation, which evaluates the predictive value of the algorithm, highly relevant for BCI and clinical applications.

In the fMRI community, the work of Haxby et al. [2] on how image categories are represented by different distributed spatial patterns has been extremely influential. Since then, the methodology for brain decoding has been continuously improved to maximally exploit the hidden information of the neuronal activities toward the automated recognition of the human brain functions. However, the statistical methods for brain decoding are still under development due to the fact that the signal patterns of the measured brain functions are intrinsically high-dimensional, multivariate, nonlinear and non-stationary. This is where advanced pattern recognition methods can play a central role to enable more accurate and efficient brain decoding. Brain decoding techniques bring tremendous opportunities for applications, including early diagnosis of neuropsychiatric disorders.

The field of BCI has deployed machine learning techniques since its early days [3]. Better decoding from brain signals acquired with versatile techniques such as EEG should ultimately lead to systems that will allow us to interact with the external worlds uniquely via the thought processes, obviously with a high potential for neuroprosthetic devices.

The application of pattern recognition techniques to neuroimaging is also challenging in various aspects. First of all, the datasets are typically high dimensional in space and/or time (typically between 1000 and 100,000 features) while the number of observations is low (in the order of 10–100). To cope with the curse of dimensionality, appropriate feature selection and regularization are necessary. Secondly, often the purpose of brain decoding is to obtain new insights in brain function that could give rise to new hypotheses and experiments. Therefore, the interpretation and visualization of the results – e.g., hidden within the "black box" of the classifier – is a crucial final step that should not be overlooked. The solutions to these challenges often require an interdisciplinary approach integrating domain-specific knowledge.

We hope that this special issue will be inspiring for ongoing and future work in this compelling and interdisciplinary field.

2. Overview of the special issue

The special issue presents in total ten papers that address different aspects of the brain decoding methodology and that propose new advances and solutions.

The first series of papers are related to decoding of fMRI data. Feature selection is studied using clustered random sampling [4], which shows that distributed yet local patterns are most informative, or by hierarchical clustering [5] to construct and take advantage of spatial relationships. Rodriguez et al. [6] extend independent component analysis (ICA) to take into account the phase information of fMRI data; ICA can be used as feature extraction based on the training data or in a semi-supervised way. Cabral et al. [7] investigate ensembles of classifiers for decoding of visual information, and Olivetti et al. [8] study the statistical significance of classification results evaluated within the Bayesian framework. The optimization of the regularization parameter, which highly influences brain maps that can be extracted from the decoder, should not consider classification accuracy as a sole criterion, but also measures of reproducibility [9]. When training data becomes very limited, such as in real-time fMRI, a new paradigm that uses feedback to modulate brain activity, performance can be boosted using naive labeling [10].

The next three papers focus on EEG data. The spatial relationship between the EEG electrodes can be exploited using voltage topographies in the context of evoked response potentials [11], or for BCI using connectivity as measured by phase synchronization [12]. Finally, the selection of the best time segment and frequency subband for single-trial EEG decoding using mutual information is considered by Ang et al. [13].

References

[1] K.J. Friston, A.P. Holmes, K.J. Worsley, J.P. Poline, C.D. Frith, R.S.J. Frackowiak, Statistical parametric maps in functional imaging: a general linear approach, Human Brain Mapping 2 (1995) 189–210.

[2] J. Haxby, M.I. Gobbini, M.L. Furey, A. Ishai, J.L. Schouten, P. Pietrini, Distributed and overlapping representations of faces and objects in ventral temporal cortex, Science 293 (5539) (2001) 2425–2430.

[3] B. Blankertz, G. Curio, K.-R. Müller, Classifying single trial EEG: towards brain computer interfacing, in: T. Diettrich, S. Becker, Z. Ghahramani (Eds.), Advances in Neural Information Processing Systems (NIPS, vol. 14, 2002, pp. 157–164.

[4] M. Björnsdotter, J. Wessberg, Clustered sampling improves random subspace brain mapping, Pattern Recognition, this issue, doi:10.1016/j.patcog.2011.04.005.

[5] V. Michel, A. Gramforta, G. Varoquaux, E. Eger, C. Keribin, B. Thirion, A supervised clustering approach for fMRI-based inference of brain states, Pattern Recognition, this issue, doi:10.1016/j.patcog.2011.04.006.

[6] P.A. Rodriguez, V.D. Calhoun, T. Adali, De-noising, phase ambiguity correction and visualization techniques for complex-valued ICA of group fMRI data, Pattern Recognition, this issue, doi:10.1016/j.patcog.2011.04.033.

[7] C. Cabral, M. Silveira, P. Figueiredo, Decoding visual brain states from fMRI using an ensemble of classifiers, Pattern Recognition, this issue, doi:10.1016/j.patcog.2011.04.015.

[8] E. Olivetti, S. Veeramachaneni, E. Nowakowska, Bayesian hypothesis testing for pattern discrimination in brain decoding, Pattern Recognition, this issue, doi:10.1016/j.patcog.2011.04.025.

[9] P.M. Rasmussen, L.K. Hansen, K.H. Madsen, N.W. Churchill, S.C.Strother, Model sparsity and brain pattern interpretation of classification models in neuroimaging, Pattern Recognition, under review.

[10] C.O. Plumpton, L.I. Kuncheva, N.N. Oosterhof, S.J. Johnston, Naive random subspace ensemble with linear classifiers for real time classification of fMRI data, Pattern Recognition, this issue, doi:10.1016/j.patcog.2011.04.023.

[11] A. Tzovara, M.M. Murray, G. Plomp, M.H. Herzog, C.M. Michel, M. De Lucia, Decoding stimulus-related information from single-trial EEG responses based on voltage topographies, Pattern Recognition, this issue, doi:10.1016/j.patcog.2011.04.007.

[12] I. Daly, S.J. Nasuto, K. Warwick, Brain computer interface control via functional connectivity dynamics, Pattern Recognition, this issue, doi:10.1016/j.patcog.2011.04.034.

[13] K.K. Ang, Z.Y. Chin, H. Zhang, C. Guan, Mutual information-based selection of optimal spatial-temporal patterns for single-trial EEG-based BCIs, Pattern Recognition, this issue, doi:10.1016/j.patcog.2011.04.018.

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