NeuroImage 173 (2018) 434–447

Contents lists available at ScienceDirect

NeuroImage

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

Multivariate pattern analysis for MEG: A comparison of dissimilarity measures

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ARTICLE INFO

Keywords:
MEG
EEG
Multi-voxel pattern analysis
Decoding
Representational similarity analysis
Cross-validation
Noise normalisation
Machine learning

ABSTRACT

Multivariate pattern analysis (MVPA) methods such as decoding and representational similarity analysis (RSA) are growing rapidly in popularity for the analysis of magnetoencephalography (MEG) data. However, little is known about the relative performance and characteristics of the specific dissimilarity measures used to describe differences between evoked activation patterns. Here we used a multisession MEG data set to qualitatively characterize a range of dissimilarity measures and to quantitatively compare them with respect to decoding accuracy (for decoding) and between-session reliability of representational dissimilarity matrices (for RSA). We tested dissimilarity measures from a range of classifiers (Linear Discriminant Analysis – LDA, Support Vector Machine – SVM, Weighted Robust Distance – WeiRD, Gaussian Naïve Bayes – GNB) and distances (Euclidean distance, Pearson correlation). In addition, we evaluated three key processing choices: 1) preprocessing (noise normalisation, removal of the pattern mean), 2) weighting decoding accuracies by decision values, and 3) computing distances in three different partitioning schemes (non-cross-validated, cross-validated, within-class-corrected). Four main conclusions emerged from our results. First, appropriate multivariate noise normalization substantially improved decoding accuracies and the reliability of dissimilarity measures. Second, LDA, SVM and WeiRD yielded high peak decoding accuracies and nearly identical time courses. Third, while using decoding accuracies for RSA was markedly less reliable than continuous distances, this disadvantage was ameliorated by decision-value-weighting of decoding accuracies. Fourth, the cross-validated Euclidean distance provided unbiased distance estimates and highly replicable representational dissimilarity matrices. Overall, we strongly advise the use of multivariate noise normalisation as a general preprocessing step, recommend LDA, SVM and WeiRD as classifiers for decoding and highlight the cross-validated Euclidean distance as a reliable and unbiased default choice for RSA.

Introduction

The investigation of the rapid neural dynamics underlying cognitive functions requires a combination of high-temporal resolution neural measurements with analytical methods that systematically and efficiently probe the information encoded in measured brain activity. A promising approach is the application of multivariate pattern analysis methods (MVPA) to magnetoencephalography (MEG), combining the sensitivity of pattern-based methods with the high temporal resolution of MEG. Two prominent MVPA methods are multivariate decoding (Cox and Savoy, 2003; Haxby et al., 2001; Haynes and Rees, 2005; Kamitani and Tong, 2005), which quantifies the discriminability of condition-specific activation patterns, and representational similarity analysis (RSA) (Diedrichsen and Kriegeskorte, 2017; Kriegeskorte, 2009; Kriegeskorte et al., 2008a, 2008b; Kriegeskorte and Kievit, 2013). RSA characterizes the similarity of measured responses to experimental conditions in representational dissimilarity matrices (RDMs). As RDMs can in principle be computed for any measurement modality, RSA on MEG opens the way to quantitatively relate rapidly emerging brain dynamics to other data, such as fMRI (Cichy et al., 2016b, 2013) in order to localize responses; computational models (Cichy et al., 2017a, 2016a; Kietzmann et al., 2017; Pantazis et al., 2017; Seeliger et al., 2017; Su et al., 2012; Wardle et al., 2016) in order to understand the underlying algorithms and representational format; to behaviour (Cichy et al., 2017b; Furl et al., 2017; Mur et al., 2013); and across species (Cichy et al., 2014).

At the core of MVPA is the dissimilarity measure used to quantify the

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https://doi.org/10.1016/j.neuroimage.2018.02.044
Received 4 August 2017; Accepted 22 February 2018
Available online 27 February 2018

discriminability (decoding) or the dissimilarity structure (RSA) of evoked activation patterns, fundamentally affecting both the accuracy and the interpretability of results. Yet little is known about the performance and characteristics of different dissimilarity measures for MEG MVPA. Inspired by previous work comparing different dissimilarity measures for fMRI (Walther et al., 2016), we conducted a comprehensive and systematic investigation of dissimilarity measures for MEG to close this gap.

To this end, we compared a set of dissimilarity metrics comprising classifiers (Linear Discriminant Analysis – LDA, Support Vector Machine – LDA, Weighted Robust Distance – WeiRD, Gaussian Naïve Bayes – GNB) and distance measures (Euclidean distance, Pearson correlation). This comparison was done qualitatively, by characterizing dissimilarity time courses, and quantitatively, by comparing decoding accuracies (decoding) and session-to-session reliabilities of RDMs (RSA). We further evaluated the effects of three main processing choices that affect dissimilarity estimation: 1) preprocessing (noise normalisation, removal of the pattern mean), 2) the use of classification decision values to preserve gradual information in classification-based MVPA, and 3) data partitioning (non-cross-validated; cross-validated; within-class-corrected, i.e. subtracting within-from between-condition distances).

Our results give rise to four straightforward recommendations for MVPA in MEG research. First, multivariate noise normalisation is strongly recommended as a general preprocessing step when considering a number of methodological intricacies. Second, for decoding we recommend LDA, SVM and WeiRD, which achieved high accuracies. Third, we show that a previously reported impairment of pattern reliability for decoding accuracy (Walther et al., 2016) can be mitigated by weighting correct and incorrect predictions with classifier decision values. Fourth and finally, concerning distance-based dissimilarity measures for RSA, we recommend the cross-validated Euclidean distance as a robust, gradual, reliable and largely unbiased default choice.

Materials and methods

Data set

The present study is based on a previously published MEG data set (Cichy et al., 2014). This data set was chosen for two reasons. First, the data set has two experimental sessions per participants, enabling us to compute inter-session reliabilities of our measures. Although it is possible to split a single experimental session into subparts to compute reliability, we reasoned that two independent sessions more realistically probe the robustness of a measure with respect to measurement quality (e.g., noise level of individual channels) or daily conditions of participants (e.g. wakefulness or motivation). Second, the employed stimulus set has been used in a number of previous studies (Cichy et al., 2016b, 2014; Cichy and Pantazis, 2016; Khaligh-Razavi and Kriegeskorte, 2014; Kiani et al., 2007; Kriegeskorte et al., 2008b; Mur et al., 2013; Walther et al., 2016), facilitating the comparison of our results with previous literature.

We briefly summarize the most relevant aspects of experimental design and acquisition underlying the present data set (for a detailed description, see Cichy et al., 2014). Participants viewed coloured images of 92 different objects on a grey background presented at the centre of a screen (2.9° visual angle, 500 ms duration), overlaid with a dark grey fixation cross. For each of two MEG sessions, participants completed 10 to 15 runs of 420 s duration each. Each image was presented twice in each MEG run in random order, with a trial onset asynchrony of 1.5 or 2 s. To control vigilance and eye blink behaviour, participants were instructed to press a button and blink their eyes in response to a paper clip that was shown randomly every 3 to 5 trials (average 4). Paper clip trials were excluded from further analysis.

During the experiment, continuous MEG signals from 306 channels (204 planar gradiometers, 102 magnetometers, Elekta Neuromag TRIUX, Elekta, Stockholm) were acquired at a sampling rate of 1000 Hz. Recorded MEG signals were filtered in a frequency range of 0.03–330 Hz (default setting of Elekta). The lower frequency serves to remove direct current (DC) drifts and its precise value is not critical as long as it is small enough to avoid distortions of event-related responses (see Rousselet, 2012). The higher frequency serves to prevent aliasing. To protect from filter imperfections, the Elekta default value is set to 330 Hz, i.e. below the theoretical Nyquist frequency of 500 Hz. As to our knowledge there are no known informative visually evoked brain signals above the upper limit of the gamma band, i.e. 100 Hz, the precise value of the higher frequency is likewise not critical.

For spatiotemporal filtering we used the MaxFilter software (Elekta, Stockholm), which has been shown to reduce noise and remove artefacts without altering the field patterns of brain signals (Taulu et al., 2004; Taulu and Simola, 2006). We used default parameters (harmonic expansion origin in head frame = [0 0 40] mm; expansion limit for internal multipole base = 8; expansion limit for external multipole base = 3; bad channels automatically excluded from harmonic expansions = 7 s.d. above average; temporal correlation limit = 0.98; buffer length = 10 s). Intuitively, a spatial filter was applied that separated signal data from distant noise sources outside the sensor helmet. Subsequently, a temporal filter was applied that discarded time series components of the signal data that were strongly correlated with noise data.

Finally, raw MEG trials were extracted with 100 ms baseline and a 1000 ms post-stimulus period (i.e., 1101 ms length), yielding 306-dimensional pattern vectors for each time point of a trial. In addition, raw trials were down-sampled by averaging across consecutive 10 ms bins to decrease the computational costs and to increase the signal-to-noise ratio.

General analysis pipeline

We first introduce the general analysis pipelines underlying the comparison of dissimilarity measures for decoding and RSA and thereafter describe each step of the pipeline in detail. As shown in Fig. 1A, in a first step, trials were combined to *pseudo-trials* to improve the overall signal-to-noise ratio. In a second step, pseudo-trials were submitted to an optional preprocessing stage: *multivariate noise normalisation* and/or *removal of the mean pattern*. In a third step, the dissimilarity measures were applied to pseudo-trials, separately for each pairwise combination of conditions and either in a *cross-validated* procedure or a *non-cross-validated* procedure (Fig. 1B). The first three steps were performed for overall 20 randomized assignments of trials to pseudo-trials (*permutations*) and for both sessions of each participant. In a fourth and final step, dissimilarity measures were compared. For decoding, classifiers were compared based on average decoding accuracy (averaged across condition pairs, permutations and sessions). For RSA, dissimilarity measures were compared by means of the session-to-session reliability of representational dissimilarity matrices (averaged across permutations).

Pseudo-trials

To increase the signal-to-noise ratio, for each of the N_C (=92) conditions we created 5 *pseudo-trials* by dividing randomly ordered preprocessed raw trials into 5 approximately equinumerous partitions and then averaging across raw trials within partitions (Fig. 1A). To minimize effects caused by the arbitrariness of this ordering, the procedure was repeated for 20 random orderings of raw trials (henceforth referred to as *permutations*).

Optional preprocessing of pseudo-trials

Prior to MVPA, the MEG data may undergo additional preprocessing. Here, we assessed two popular preprocessing choices: 1) noise normalisation to improve the quality of the data, and 2) removal of the mean pattern to eliminate condition-nonspecific response components.