Spatio-temporal fuzzy clustering of fMRI timeseries

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Abstract

We introduce a novel fuzzy clustering algorithm, specifically tailored to the analysis of fMRI data sets. In contrast to previous approaches, our algorithm clusters fMRI time series based on both spatial and temporal information (*spatio-temporal clustering*). The probability that a voxel belongs to a cluster is expressed by a spatial function, which takes into account the neighbourhood relationships between voxels. The proposed approach is described and compared to conventional FCM on realistic simulated fMRI data sets. Results of a Receiver Operating Characteristics (ROC) analysis indicate that spatiotemporal FCM performs significantly better than conventional FCM, especially in the case of low contrast-to-noise ratio.

Introduction

Clustering techniques are used in fMRI to separate time series into several patterns according to their similarity [1]. A well known member of this category is the Fuzzy Clustering Method (FCM) [2]. In FCM as well as in similar approaches the assignment of a voxel to a specific cluster is only based on its temporal relation to the cluster centroid and information on spatial proximity of the voxels is ignored. In this study, we introduce a FCM approach tailored to the 4D nature of fMRI data sets, in which clustering of the time series is driven by both spatial and temporal information (*spatio-temporal FCM*), The proposed approach is described and compared to conventional FCM on realistic simulated fMRI data sets.

Materials

A synthetic data set was constructed by adding realistic spatio-temporal activation patterns to background noise. Activation patterns were based on results from a previous study on visuospatial mental imagery [3, 4]. Background noise consisted of fMRI time series measured at 3 Tesla during resting state (Siemens Allegra, GE-EPI, TR=1500ms, TE = 46 ms, 32 slices, 64 x 64, voxel size = 3 mm x 3 mm x 3 mm). Relative amplitude of activation and background noise was controlled using the Contrast to Noise Ratio (CNR), which was varied in the range of 1 to 3. Figure 1 shows a projection of the simulated activations on a flattened representation of the cortical sheet of the subject's brain, mimicking auditory (green), imagery (blue) and visual/motor (yellow) activation.

Methods

Fuzzy clustering attempts to partition a set of *N* voxels in *C* 'clusters' of activation. This is achieved by comparing the voxel's time courses $\boldsymbol{x}_n$ (n = 1 ... N) with each other and assigning them to representative time courses, called cluster centroids $\boldsymbol{v}_c$ (c = 1 ... C), derived during this process. Fuzziness relates to the fact that a voxel is generally not uniquely assigned to one cluster only (hard clustering), but instead, the similarity of the voxel time course to each cluster centroid is determined. This is expressed by the 'membership' u_{cn} of voxel n to cluster c. Both centroids and memberships are calculated in an iterative procedure, elaborated by Bezdek [5] and expressed by Eq. (1), where m is the fuzziness coefficient, used to `tune´ out the noise in the data and d is a distance measure. Recently, Chuang et al. [6] presented a spatial version of FCM for 2-dimensional image segmentation, incorporating into the membership function u_{cn} the spatial information from a square window that surrounds a voxel. In this study, we extended this 2-dimensional neighbourhood *NB* to a 3-dimensional cube, centred on the concerning voxel and applied it to the analysis of time-series. The probability that a voxel $\boldsymbol{x}_n$ belongs to a cluster c is expressed by the spatial function h_{cn} defined in Eq. (2). Function h_{cn} is incorporated into the membership function as described by Eq. (3). In the latter equation, p and q are parameters to control the relative importance of both functions. In this study, we fixed the algorithm's parameters to typical values: p=1, q=1, *NB*=3*3*3.

$$\mathbf{v}_c = \frac{\sum_{n=1}^{N} u_{cn}{}^m \mathbf{x}_n}{\sum_{n=1}^{N} u_{cn}{}^m} \qquad u_{cn} = \frac{1}{\sum_{k=1}^{C} \left(\frac{d(\mathbf{x}_n, \mathbf{v}_c)}{d(\mathbf{x}_n, \mathbf{v}_k)} \right)^{\frac{2}{m-2}}} \quad (1)$$

$$h_{cn} = \sum_{k \in NB(\mathbf{x}_n)} u_{ck} \quad (2)$$

$$u_{cn}{}^s = \frac{u_{cn}{}^p h_{cn}{}^q}{\sum_{k=1}^{C} u_{kn}{}^p h_{kn}{}^q} \quad (3)$$

Performance of the methods under investigation is quantified by an ROC analysis, in which the True Positive Rate (TPR) vs. the False Positive Rate (FPR) is parameterized by the membership. TPR and FPR were estimated by imposing a threshold on the membership. (i.e. hard clustering).

Results and discussion

We applied conventional and spatiotemporal FCM to the synthetic data sets and evaluated the capability of retrieving all simulated activations. Results are presented for the visual/motor activation (results for auditory and imagery activations are analogous). As illustrated in Figure 2, spatio-temporal FCM outperformed conventional FCM at low CNRs. ROC analysis also allowed determining optimal memberships threshold for each method: the membership value yielding the maximal surface of the rectangle under the ROC curve (Figure 3). Spatial FCM performs optimally in terms of TPR and FPR for u_{cn} =0.11 (square in Figures 2 and 3), whereas conventional FCM performs optimally for u_{cn} =0.27 (circle). We are currently performing additional analyses to investigate the influence of p and q, the extent of the applied neighbourhood, and the number of clusters C.

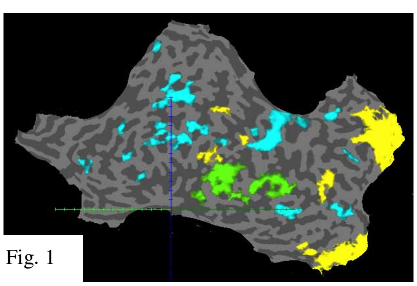

Fig. 1

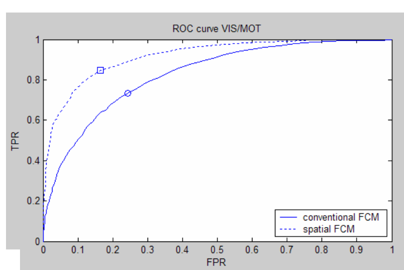

Fig. 2

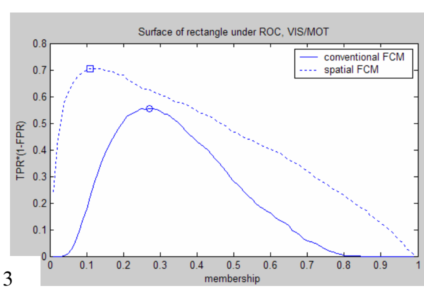

Fig. 3

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