Improved performance in fuzzy clustering of functional MRI datasets by effective processing strategies

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Introduction

Exploratory data analysis (EDA) of functional MRI datasets is becoming more common as it allows researchers to identify activation areas without having to specify all the experimental parameters, expected haemodynamic response and noise characteristics of the dataset prior to analysis [1]. A previous study reported on the effectiveness of various clustering techniques by using statistically established ranking association coefficients on simulated and hybrid datasets where the true activation pixels are known [2]. This study demonstrates that by using pre-processing methods such as spectral peak dataset partitioning, clustering modifications such as cluster merging, and post-processing techniques such as spatio-temporal region growing, EDA with fuzzy c-means clustering is vastly improved.

Methods

The artificial datasets simulated a transversal brain slice (128x128 pixels) with 35 time-points series over a time invariant texture. Three datasets, each with the same regions of activation (49 pixels), were created by adding 3% Gaussian noise and with functional contrast-to-noise (CNR) levels of 1.33, 1.66, and 2.0; values common in fMRI experiments of the human brain. Three hybrid datasets were also analyzed, consisting of 25 activation pixels overlaid on an in vivo single slice MRI (64x64 pixels). Simulated 140 time-points series were added with the same effective CNR used on the artificial datasets, 1.33, 1.66 and 2.0. Data sets are available at http://www.ci.tuwien.ac.at/research/oenb/oenb_data.html. For each cluster analysis run, two association coefficients were calculated, a weighted Jaccard coefficient (JC) and the correlation coefficient (CC) as described in [2].

EROICA [3], part of the EvIdent software package, is an EDA approach specifically designed to improve the efficacy of fuzzy c-means clustering for functional MRI datasets. Using spectral peak (SP), a frequency-domain solution to finding periodic signals buried in noise, EROICA takes advantage of the fact that most functional MRI experiments result in periodic (or nearly periodic) activation time-courses (TC) to separate the original region of interest into a "noisy" set and a "potentially interesting" set. Fuzzy clustering is performed on the latter subset, which is likely to contain periodic activations. With clustering EDA methods such as fuzzy c-means and neural gas, users specify the expected number of clusters in the dataset. EROICA implements cluster merging, where clusters with similar TC centroids are amalgamated, thus the user can safely specify a large number of initial clusters and not impair computational performance as similar clusters are merged. For all datasets, analysis runs were performed with 5, 10 and 20 as the initial number of clusters using EROICA, fuzzy c-means and neural gas. No pre-processing of the time courses, other than normalization, was performed using the latter two methods.

Results

	Artificial – CC / wJC			Hybrid - CC / wJC		
EROICA	0.97/0.98 (5)	0.97/0.98 (10)	0.97/0.98 (20)	0.93/0.95 (5)	0.94/0.95 (10)	0.94/0.95 (20)
neural-gas	0.81/0.40 (5)	0.93/0.81 (10)	0.98/0.95 (20)	0.47/0.24 (5)	0.84/0.74 (10)	1.0/0.96 (20)
fuzzy c-means	0.43/0.31 (5)	0.46/0.55 (10)	0.50/0.68 (20)	0.38/0.08 (5)	0.46/0.74 (10)	0.56/0.81 (20)

Table 1: Average CC /wJC for the artificial and hybrid datasets for all CNR at various initial clusters, 5, 10 and 20, for EROICA, neural-gas and fuzzy c-means.

Table 1 shows the average CC and wJC of all CNR in the artificial and hybrid datasets for 5, 10 and 20 initial clusters using EROICA, neural-gas and fuzzy c-means. The performance values for nerual gas and fuzzy c-means were computed in [2]. The table illustrates that for 5 and 10 clusters EROICA outperforms neural gas for both the hybrid and artifical datasets, and is a vast improvement over fuzzy c-means. As the number of clusters is increased, the performance of fuzzy c-means and neural gas improves, as false negatives will be moved to other clusters and will not be included in the activation cluster. It is difficult to know a priori the number of initial clusters to use, so it is common to specify a large number, unfortunately computation time also increases. Fuzzy c-means was 5 times slower than EROICA for 20 clusters and neural gas was 25 times slower. The results indicate that when using SP pre-selection, along with cluster merging, the number of initial clusters does not affect the resulting activation cluster and calculation times are dramatically reduced.

After applying the SP pre-selection step, the analysis subset was 523 pixels out of 1131 for the hybrid datasets and 155 out of 4260 for the artificial datasets. For the artificial dataset the SP filter resulted in a significantly smaller analysis subset, and the activation cluster had fewer member pixels (true-positives) after the clustering step. Spatio-temporal region growing [4] was used to recover some of the activation pixels rejected by the SP filter. In region growing, the neighbouring pixels of the initial cluster seed pixels are compared in the temporal dimension with the cluster centroid and added to the cluster if they pass a user specified similarity threshold based on correlation. The default threshold value of 0.35 was used for region growing. The same display threshold used for the EROICA analysis, equivalent to a p-value of 0.01, was used to determine the final activation cluster. A significant number of true positives were recovered with region growing on the artificial dataset. With the hybrid datasets, region growing did not have a noticeable impact on the final activation cluster area for all 3 CNR datasets, as the SP filter did not exclude as many TC before the primary cluster analysis.

Discussion and Conclusion

Using frequency filter (SP) and cluster merging resulted in more robust clustering; similar clusters were found for 5, 10, or 20 initial clusters in a considerable shorter amount of time. With EROICA, very good performance measures where achieved regardless of the initial number of clusters, which is an input that must be selected a priori by the user. When using SP pre-selection and region growing additional assumptions are made concerning the structure of the time series in functional MRI datasets, namely a periodic structure to the time courses and spatial connectivity in the activation pixels. These valid assumptions lead to faster and more robust data processing and results in higher validity measures for exploratory data analysis using fuzzy clustering.

References

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