Counting temporal classes in a resting-state fMRI exam

Alberto Arturo Vergani[1]
[1]Middlesex University, London (UK)
a.vergani@mdx.ac.uk

[Introduction/Motivation:]

This work aims to compute the number of temporal classes within a resting state fMRI examination. Researchers are interested in investigating the bio-markers underlying the fMRI resting functional state, that are co-related spatial networks [1], focusing on the physiological regularities in healthy subjects and pathological alterations in patients. Clustering is an unsupervised learning method used to study the network connectivity in the resting state experiment [2] . The classical way to apply clustering algorithms is in finding homogeneous classes of signal signatures, i.e., the so-called *spatial clustering* or clustering of spatial patterns. Moreover, the crossed clustering [3] is the adoption of both spatial clustering and temporal clustering, where the *temporal clustering* is the detection of homogeneous classes of temporal patterns, that are represented by brain volumes sharing a common brain status. In this work the perspective of temporal clustering is adopted to investigate how many temporal classes are in a resting state fMRI experiment.

[Methods:]

The data used is from the fMRI NITRC repository [4] and regard one subject (Female, 31 years-old, healthy). The processing pipeline adopted encompassed temporal and spatial filtering, motion correction, standard registration and ICA-based noise removal [5] . The clustering algorithm used is the fuzzy c-means (FCM) [6] . The validation of the clustering outcomes has been made by the fuzzy partition coefficient (FPC) [7] . The experimental procedure regards the computation of the fuzzy partition matrix varying the exponent M from 1.1 to 2 and the number of clusters with the range 2, 5, 10, 20, 50, 100. The result is a clustering evaluation matrix.

[Results and Discussion:]

Figure 1 shows the complete clustering outcomes of the computational experiments. Since the best clustering has the FPC value close to 1, the clusters that are associated with the highest FPC values are the optimal number of temporal classes, given a specific configuration of the FCM algorithm. The lower values of the fuzzy exponent M (1.1-1.3) are associated with the highest FPC values (>0.6) in combination with all the range of clusters (2,5,10,20,50,100). Instead, values of M greater then 1.3 combined with a low number of clusters (2,5) are associated with medium FPC values (0.4-0.6) or with low FPC values (<0.4) if there are high number of clusters (10,20,50). Considering that the lowest values of the exponent M are an extreme experimental cases, the other values of M associated with good FPC are the ones related with the lowest number of clusters. Therefore, the number of clusters that represents the candidate number of temporal classes of a resting state are 2 and 5. The limitations of this study are the usage of one subject and the adoption of a specific clustering algorithm with a related validation measure. In the extension of this work, there will be a comparison of results obtain with multiple subjects and the adoption of other validation measures for fuzzy clusters (given the results in [8]), taking also in to account different steps for number of clusters and the fuzzy exponent M. Other future works could regard a comparison of spatial clustering with the temporal clustering of resting state fMRI data (see [3] for a example) and active fMRI studies.

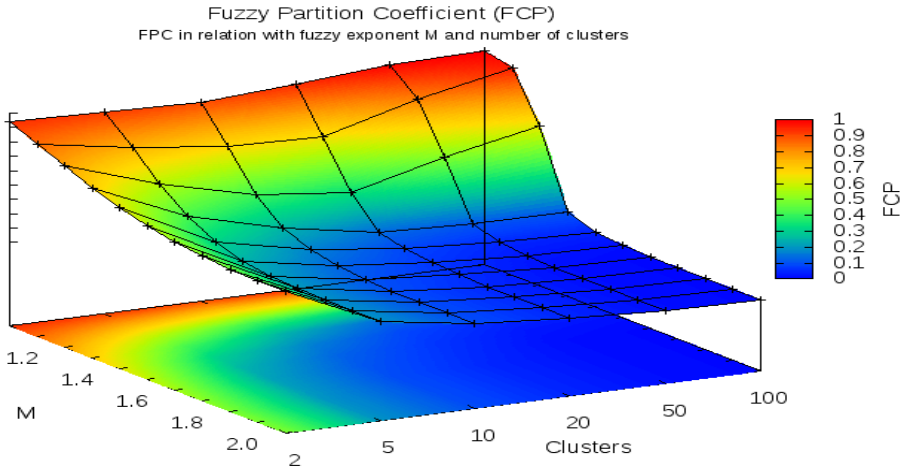

Figure 1 shows the relation of the fuzzy partition coefficient FCM with the fuzzy exponent M and number of clusters. Since the best clustering has the FPC value close to 1, the clusters that are associated with the highest FPC values are the (optimal) number of classes, given a specific configuration of the FCM algorithm. The lower values of the fuzzy exponent M (1.1-1.3) are associated with the highest FPC values in combination with all the range of clusters (2,5,10,20,50,100) (red colour). Instead, greater values of M combined with low number of clusters (2,5) are associated with medium FPC values (green colour), whereas if the number of cluster increases (10,20,50), the FPC values decrease close to the minimum values (blue colour).

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