Proceedings of the 6th International Conference on Statistics: Theory and Applications (ICSTA'24)
Barcelona, Spain – August 19 - 21, 2024
Paper No. 110
DOI: 10.11159/icsta24.110

Nonstationarity of the Hemodynamic Response Function in Event-Related Functional Magnetic Resonance Imaging

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Extended Abstract

In the analysis of event-related functional magnetic resonance imaging (fMRI) data, often an assumed hemodynamic response function (HRF) is convolved with the corresponding stimulus onset time series and then used as a regressor in a generalized linear model to model the observed signal [1]. The respective estimated beta coefficients define the shape of the HRF, which in turn is used to draw conclusions about the brain's reaction to the stimulus. The shape of the HRF can be described by different shape parameters such as peak magnitude, time to peak or nadir magnitude. It is common to assume stationarity of the HRF, that is, for a fixed stimulus its shape does not vary over time [1][2]. However, this is not necessarily true; possible sources of nonstationarity are changes in emotions, stress level or learning effects (see e.g., [3][4]).

While procedures have been developed to model a nonstationary HRF, they only account for changes in either the peak magnitude or the overall mean of the signal. Yet ignoring changes in other shape parameters leads to mismodeling the HRF's shape and thus misinterpretation of the brain's response.

In this work we aim at developing a method to answer the following questions: Can we assume stationarity of the hemodynamic response? If not, how does the HRF's shape change over time? In other words, we investigate if current methods sufficiently account for nonstationarity of the HRF. To this end, we present a procedure and apply it within the framework of category learning, where a categorization rule is learned through trial and error. Executing a categorization task can be split in two phases: the learning phase, during which the categorization rule is determined, and the application phase. We assume that the shift between these phases is the source of nonstationarity, and thus we model nonstationarity as an abrupt change.

We propose the following procedure to answer the questions posed above. To investigate nonstationarity in the HRF, we carry out change point analyses for regression models, utilizing information criteria. If change points are detected, we include them in the model of the observed signal by splitting the corresponding stimulus onset time series at the estimated change point location. Then, we estimate the shape parameters of the HRF before and after the changes and test which ones significantly differ over time. We account for the hierarchical structure of the multiple testing problem that arises from testing for changes on group level in i) multiple brain regions and ii) multiple shape parameters. The proposed procedure returns, for each brain region, a set of shape parameters which significantly change over time. Since inference on the changes in the shape parameters is made on group level, these results are generalizable. The approach is flexible in terms of the number of assumed change points. While this procedure is motivated by the example of learning as a source of nonstationarity, it can be applied to any fMRI experiment in which rapid changes in the shape of the HRF are of interest.

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