Study of Structured Noise Stationarity in fMRI Using Independent Component Analysis

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The structured noise in fMRI data originates from multiple sources. These noise sources generate signals that fluctuate at different frequencies and with varying amplitude over time. The cardiac and respiratory cycles, along with low-frequency BOLD related fluctuations all contribute to the baseline signal [1,2]. It is unlikely that this combination of noise sources remains stationary over time and their presence could potentially affect detection of stimulus-evoked activation. In this study a combination of Independent Component Analysis and a stationarity metric termed the Wide Sense Stationarity (WSS) quotient [3] was used to examine the temporal stationarity of fMRI baseline noise.

Methods

Four sets of baseline noise data were acquired from cross-sectional human brain images via a sinusoidal EPI sequence using the UAB/Bruker 4.1 T whole-body scanner (64X64, FOV=22X22X.5 cm, 600 reps, TR/TE 250 ms/38.5 ms for two sets, TR/TE 1s/38.5ms for two sets). Two additional sets of data with an effective TR of 2s were generated by taking every odd image in the 1s TR datasets. All images were reconstructed with in-house software and analysis was performed using Matlab (The Mathworks, Inc.).

ICA (Hyvrinen's fixed point [2]) was used to decompose the data into 20 components with associated component time-courses. The WSS test is performed by dividing each component time-course into S equal segments of size N [3]. Each segment was compared to the others via the t-statistic and the F-statistic. The results were counted as follows:

$$p_{ij} = \begin{cases} 1 & if\,|T| \le t_{\upsilon,\frac{\alpha}{2}}\, and\, F_{\upsilon_1,\upsilon_2,\frac{1-\alpha}{2}} \le F \le F_{\upsilon_1,\upsilon_2,\frac{\alpha}{2}}, \\ 0 & otherwise \end{cases}$$

Once p was calculated, the WSS was determined by:

$$WSS = \frac{2}{S(S-1)} \sum_{i=1}^{S-1} \sum_{j=i+1}^{S} p_{ij}$$

A confidence level of 0.9 was chosen, therefore, if the value of WSS was above 0.9, the time-course was considered stationary. The time-courses in each dataset were drift-corrected prior to decomposition. Each component time-course was tested using S= 2, 5, 10, and 20 segments.

Results and Discussion

Figure 1 shows the results of the WSS test. Testing using only 2 segments resulted in the lowest percentage of non-stationary components in all datasets. The percentage of non-stationary components increased to over 85% in all datasets when the data was segmented into 5 or more segments. At S=10, all components of five of the datasets were non-stationary. It is not surprising that the greatest number of stationary components were found at S=2, given that many of the fluctuations in mean and variance will average out over large segments. As the number of segments increases, there will be less averaging and the fluctuations will have greater influence on the mean and variance of each segment. It is important to take the effect of non-stationarity into account when analyzing fMRI experiments. This is particularly important with short stimuli and/or short control periods. The stationarity in the interstimulus interval can be critically important, because a variation in the baseline occurs between events or at the activation onset, the size and shape of the true activation could become distorted or occluded.

One of the difficulties in studying the statistical nature of the fMRI baseline is the large number of time-courses in a typical study. ICA allows the noise to be projected onto relatively few time-courses, which can be analyzed separately. While the current study only looked at one aspect of fMRI noise, ICA provides a foundation for more detailed temporal and spatial analysis. Human studies were made under an institutional-review-board-approved protocol.

Conclusion

ICA was used to reduce the complexity of studying the stochastic properties of fMRI baseline data. It was found that the six fMRI baseline noise datasets produced temporally non-stationary component time-courses. This suggests that analyses of structured noise in fMRI should be based on a non-stationary model.

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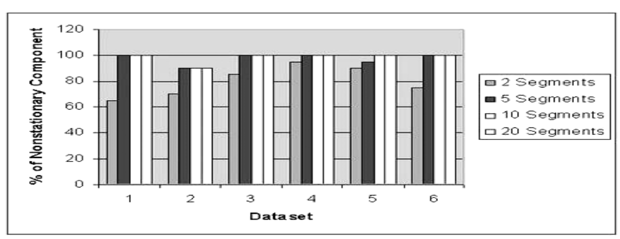

Figure: Percentage of nonstationary time courses for a 20-component decomposition of six fMRI datasets