Accurate estimation of physiologic noise using temporal ICA-derived spatial measures

E. B. Beall[1] and M. J. Lowe[1]

[1]Radiology, Cleveland Clinic, Cleveland, OH, United States

Introduction

It has been reported [1-2] that BOLD-weighted MRI timeseries data contain fluctuations from non-neuronal physiologic sources such as cardiac and respiration. Retrospective removal of the effect of physiologic noise requires information from parallel measurement of pulse and respiration. In some cases, this parallel measurement is not available or is difficult or impossible due to the experimental paradigm. We present a method to extract the pulse and respiratory information from spatially co-registered fMRI timeseries data using Independent Component Analysis (ICA) to determine an independent spatial weighting matrix. We show that temporal ICA [3] can reliably identify the spatial and temporal patterns of respiratory physiologic noise if the parallel measurement is made in at least one spatially co-registered data set. The spatial patterns thus determined can be used on a separate scan of the same subject or of other spatially co-registered subjects to produce the temporal pattern specific to physiologic noise for that scan.

Theory:

fMRI data can be assumed to be a linear combination of an unknown number of sources. These sources are linearly mixed through a weight matrix such that X=MC, where X is a 2D data matrix (voxels×time), M is a linear mixing matrix (voxels×components) and C is the matrix of sources (components×time). ICA is an algorithm to determine the unmixing matrix (W, the inverse of M), which maximizes the statistical independence of a given number of sources in the temporal domain. Selecting the j^{th} component is accomplished by taking the j^{th} column of the unmixing matrix W. This unmixing vector can be applied directly to the data to obtain the j^{th} temporal component by $W_jX=C_j$. If the spatial representation of the j^{th} source remains constant for a second data set Y, then the temporal component represented by that spatial map can be obtained using the unmixing vector by $W_jY=C_j^Y$. Cardiac and respiratory noise sources will be present in all slices of the data, but due to the temporally offset acquisitions of 2D EPI, sampling of the physiologic effects will be staggered across the slices according to the acquisition order. If the temporal sources can be accurately determined for each slice, then an accurate direct-sampled physiologic signal can be reconstructed by variance normalizing the sources prior to re-ordering in slice-acquisition order.

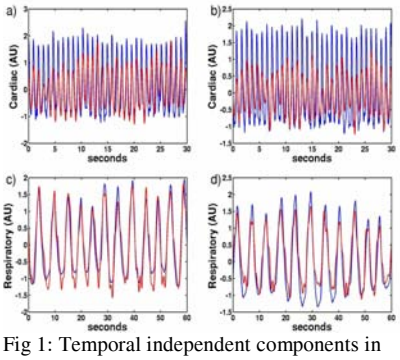

Fig 1: Temporal independent components in red, variance normalized and placed in slice-acquisition order for method 1, plotted with physiologic data in blue. 1a) cardiac components for scan used to select unmixing matrix, 1b) cardiac components for independent scan, 1c) respiratory components for scan in Fig 1a, 1d) respiratory for independent scan.

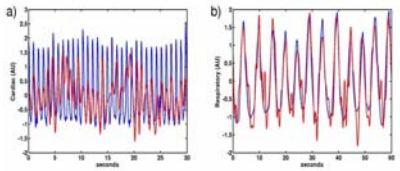

Fig 2: Independent components chosen with method 2. 2a) cardiac, 2b) respiratory components in red, physiologic data in blue.

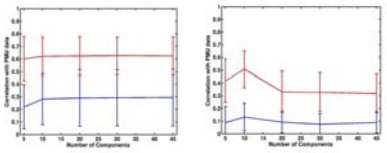

Fig 3: Dependence upon number of components used in ICA decomposition. 3a) method 1. 3b) method 2 mean and standard

Methods and Materials

Two gradient echo EPI resting BOLD-weighted studies at 3T were performed on 16 healthy volunteers. One hundred-thirty two volumes of 31-4mm thick axial slices (TE/TR/flip=29ms/2000m/90°, matrix=64x64, 256mm x 256mm FOV, receive bandwidth=125KHz). Pulse and respiratory information was recorded in parallel using a pulse plethysmograph and respiratory bellows.

Method 1

Temporal ICA was performed on each slice separately, decomposing a range of components from 5 to 45. These components were correlated with the parallel physiologic data to obtain the spatial unmixing vectors for cardiac and respiratory sources. The unmixing vector for each slice was applied to the independent scan data to obtain the source component for each slice. These source components were variance normalized and ordered in slice acquisition order and low-pass filtered to obtain direct-sampled independent estimators of the physiologic noise.

Method 2

The unmixing maps were transformed to the common stereotaxic frame of Talairach and Tournoux[4] and for each subject, all other subject unmixing maps were averaged together to create an average unmixing map for cardiac and for respiratory, free from the presence of the present subject's spatial maps. The average map was transformed to the subject's original scan space and for each scan, the columns of that scan's unmixing matrix W were correlated with the average unmixing vector to determine the physiologic unmixing vectors for that subject. The component columns of C corresponding to the chosen unmixing vectors were variance normalized and placed in slice-acquisition order and low-pass filtered to obtain direct-sampled spatial average estimators of the physiologic noise.

Results Method 1:

For respiratory source estimation, 32/32 analyses returned a significantly correlated respiratory trace, while in 24/32 of the attempts, a significantly correlated cardiac trace was returned. A plot of a typical subject's independent estimators and pmu data is shown in Fig 1. Note that the pmu data displayed in Fig 1b and 1d (independent scan) is the one actually measured for the scan, but was not used to determine the estimator, and in the case of the respiratory estimator, accurately estimates the measured data. This is the basic finding. The correlation of the independent estimators with the PMU data was 0.624±0.153 for respiratory and 0.291±0.225 for cardiac.

Results Method 2:

For respiratory source estimation, 32/32 returned significantly correlated respiratory traces, while the cardiac was significant for 16/32 scans. The correlation of the spatial average estimators with the PMU data was 0.508±0.145 for respiratory and 0.132±0.110 for cardiac. A plot of a typical subject's spatial average estimator and the PMU data is shown in Fig 2. The number of component used in the ICA decomposition was varied from 5 to 45, and the full analysis repeated. Little effect was seen in increasing the number of components beyond 10 for method 1, but method 2 was optimal near 10 components, and the mean and standard deviation correlation versus number of components for the two methods is shown in Fig 3.

Discussion and Conclusion

We have shown a robust methodology to obtain respiratory physiologic noise signals using the fMRI data and an independently acquired spatial pattern of physiologic signals, whether of the subject currently under study or an ensemble spatial pattern created from independent subjects. The results for cardiac do not yield a suitable estimation, but merit further investigation. This method may also be useful for near real-time display of a source, whether physiologic, functional task or functional connectivity signal, depending on the correlate used with the ICA components.

References

1) Jezzard et al 1992, presented at 12th SMRM, New York, 2) Weisskoff et al 1992, presented at 12th SMRM, New York, 3) McKeown et al 1998, Proc Natl Acad Sci USA 95**,** 803-810, 4) Talairach and Tournoux, Co-Planar Stereotaxic Atlas of the Human Brain, 1988