

Bayesian Component number estimation while applying ICA to functional MRI

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Introduction

Independent component analysis (ICA) has been applied to analyze a series of magnetic resonance images (MRI) [1,2,5,6]. With minimal signal assumption, ICA is advantageous for extracting potential signal source from data sets [3]. However, since no prior information is adapted for analysis, the number of components decomposed remains to be determined before a stable and satisfactory result is achieved. Previous study applied Bayesian Information Criteria (BIC) to estimate the most probable component number to analyze brain perfusion MRI [5]. In this report, we used BIC to evaluate an appropriate component number with functional MRI (fMRI). ICA was performed with varied component number to compare results and examine the effectiveness of BIC.

Material and Method

Five fMRI data sets from volunteers (male, 28-35yr) were adopted in this study. Data were acquired with T2* weighted echo-planar-imaging (EPI) on a Siemens 1.5Tesla system (Siemens Magnetom Vision+, Erlangen, Germany). Each data set contained eighty consecutive images (TE=66ms, FOV = 384mm, matrix size = 128x128, slice number = 6, slice thickness = 4mm) with 1 sec time interval. Experiment paradigm was designed to repeat on-off blocks, each with 8 images with visual stimulus followed by the other 11 images without stimulus.

Bayesian information criteria compute the best fit log likelihood from the results of ICA and contain three terms:

$$\log P(k) = \log[\text{likelihood of ICA}] - \log[\text{likelihood of PCA reduced space}] - 0.5 \cdot \text{dim} \cdot \log[N] \quad (1)$$

where dim is the total number of parameters to estimate and N is the data sample number, voxel number in this study [4]. Both BIC-ICA [4] and FastICA [3] were applied to analyze data for comparison. In global analysis, one slice out of six was selected. In local analysis, voxels were selected by correlating each voxel signal with paradigm function. Independent component (IC) number was set from 1 to 10. Analysis results were checked to find components corresponding to activation in visual cortex. Activation reference function was obtained by calculating the mean time curve of all voxels selected in local analysis. Correlation coefficients (CC) between activation reference function and each component time curve were then calculated.

Result

Table 1 showed the component number estimated by BIC in all data sets. Note that in local analysis, BIC estimated more or equal independent sources than in global analysis. In global analysis of all data sets, components analyzed according to BIC estimation, shown in Table 1, were not able to locate a component relating to blood oxygen level dependent (BOLD) signal. By increasing component number to 7, fMRI experiment related component can constantly be found. In local analysis, a fMRI experiment related component was constantly found with IC number estimated by BIC, with CC ranged from 0.87 to 0.91. Figure 1 showed data set 2 analyzed. Global analysis was performed over slice 3 and local analysis was performed over colored voxels, as shown in Fig. 1(a). Fig. 1(b) showed the activation reference function. Figure 2 showed the highest CC varied with component number analyzed. In global analysis, the minimum IC number required to resolve experiment related component is seven, which is larger than two as estimated by BIC. While in local analysis, BIC estimated a correct IC number to reveal BOLD signal. Both BIC-ICA and FastICA algorithms agreed with the minimum component number required.

Discussion

While analyzing MRI with ICA, reducing component number alleviates computational consumption and improves the ease of reviewing analysis result. Bayesian Information Criteria (BIC), which penalizes inference models with too many parameters [4], is useful to find the simplest and most informative independent component set. Previous study successfully analyzed perfusion MRI with component number estimated by BIC [6]. In our study, the component number estimated by BIC in global analysis was not able to resolve BOLD signal. We may speculate that this is because the BOLD signal is smaller and more localized to be regarded as effective information in BIC, compared with signal variance caused by contrast administration. In local analysis, however, BIC estimated the correct IC number to give a stimulus-related independent component. We, therefore, suggest the combination of ROI analysis and BIC for fMRI analysis when computing power or time is limited, such as in online fMRI analysis.

Reference

[1] McKeown M.J., et al. *Hum. Brain Mapp.*, 6:160-188, 1998 [2] McKeown M.J., et al. *Hum. Brain Mapp.*, 6:368-372, 1998 [3] Aapo, H. et al. *Neural Networks*, 13:411-440, 2000 [4] Kolenda T., et al. *Proc. ICA*, 540-545, 2001 [5] Kao Y.H., et al. *Magn. Reson. Med.*, 49:885-894, 2003 [6] Calamante F., et al. *Magn. Reson. Med.*, 52:789-797, 2004

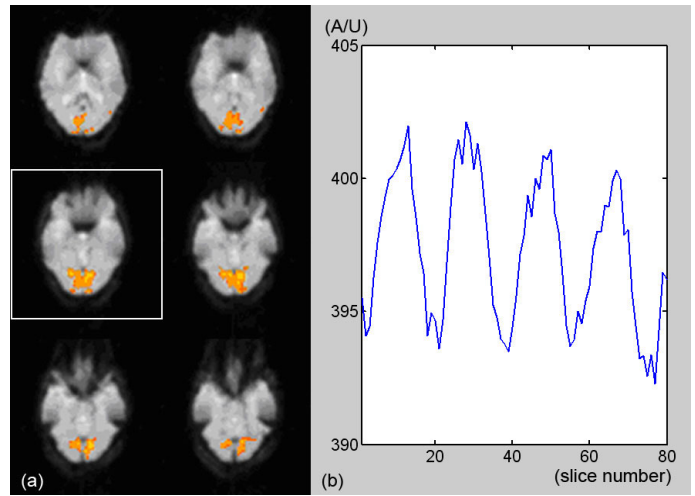


Figure 1. Data set 2 analyzed. (a) Slice 3, framed, was selected in global analysis. In local analysis, all colored voxels in six slices were selected. (b) Activation reference function by calculating the mean time curve of all colored voxels in (a).

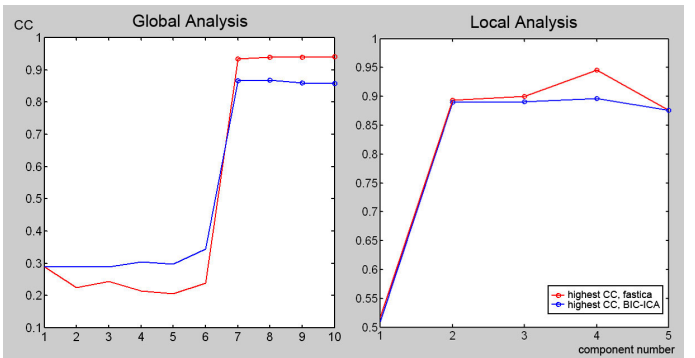


Figure 2. Analysis results from data set 2. Highest CC among all independent components was plotted with varied IC number analyzed. Circles in lines represented the component with highest CC was checked to be stimulus related. Note in global analysis a minimum required IC number to find stimulus-related component is 7, which is larger than 2 as estimated by BIC. In local analysis, BIC estimated correctly the minimum IC number. Both BIC-ICA and FastICA algorithms agreed with the results.

	Data Set 1	Data Set 2	Data Set 3	Data Set 4	Data Set 5
Global Analysis	2IC, P=0.90	1IC, P=0.95	2IC, P=0.67	1IC, P=0.60	1IC, P=0.55
Local Analysis	2IC, P=0.74	2IC, P=0.77	3IC, P=0.55	2IC, P=0.69	2IC, P=0.68

Table 1. Independent component number estimated by Bayesian Information Criteria (BIC) while performing global and local analysis of fMRI data sets.