DATA DOWNSAMPLING FOR TIME-EFFICIENT AND ROBUST ESTIMATION OF ICA MODEL ORDER USING BOOTSTRAP STABILITY ANALYSIS OF PRINCIPAL COMPONENTS

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Target Audience: Functional MRI (fMRI) and signal/image processing communities.

Purpose: Independent component analysis (ICA) is frequently used for data driven analysis of functional MRI (fMRI) data for task-related as well as resting state studies [1]. Correct estimation of the number of independent components (nIC) is essential, since nIC strongly influences the results of ICA [2]. Previous studies have suggested that bootstrap stability analysis of the principal modes (BSA) provides a more accurate and reproducible estimate of nIC [3, 4]. However, application of BSA imposes a much larger computational burden when compared with the most commonly used methods of nIC estimation such as the Minimum Description-length (MDL) criterion. Since low-pass filtering can be employed to improve contrast-to-noise ratio prior to ICA [4, 5], we explored whether data downsampling following low-pass filtering reduces BSA processing time without compromising nIC estimation or ICA.

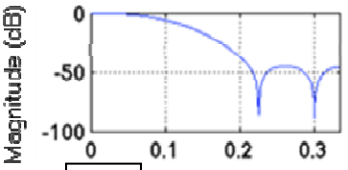

Fig 1

Methods: Activation data sets were collected from primary somatosensory cortex of anesthetized squirrel monkeys receiving blocks of vibrotactile finger tip stimulation under a well established IACUC-approved protocol. Monkeys (n = 2, two imaging sessions per monkey) were anesthetized and prepared for imaging as described in [6]. An i.v. bolus of dextran coated MION (30 nm particle size,12-16 mg Fe/kg) in saline was injected intravenously to provide cerebral blood volume (CBV) weighted contrast. Piezoceramic actuators (Noliac, Kvistgaard, Denmark) delivered a vertical indentation of a 2 mm diameter probe with 0.34 mm displacement to individual distal fingerpads of digits 1 (D1) and 3 (D3) simultaneously. Seven alternating 30s blocks of baseline and vibrotactile stimulation were delivered per imaging run. Three to six runs of 2-shot, multi-slice gradient echo planar image series were acquired during the stimulation with the following parameters: TR/TE 750/10ms, in-plane resolution of 273x273 μm^2 and 300 volumes. Motion correction was performed using AFNI. All the images in the series were blurred using a 3x3 Gaussian kernel with $\sigma = 2$ pixels. Motion parameters as well as 5 principal components of the signals from the skin were regressed out of the data. Individual time-courses were low-pass filtered ($f < 0.1$ Hz). nIC estimation and ICA were performed on complete and two-fold down-sampled time series consisting of 1) the average of all the runs within a session (nIC_{avg} and ICA_{avg}); 2) the concatenation of all the runs within a session (nIC_{cat} and ICA_{cat}). ICA was performed using Group ICA for fMRI Toolbox (GIFT) [1]. BSA and MDL were used for nIC estimation. The number of replicates (100 for real datasets, 500 for null-hypothesis datasets) and sampling density for BSA bootstrapping (~55% of the total time-points for nIC_{avg}, ~35% of total time points for nIC_{cat}) were kept the same in all cases.

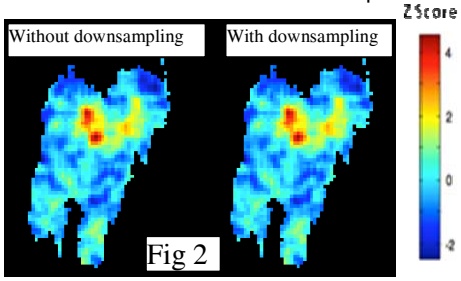

Fig 2

Results and Discussion: Fig 1 shows the frequency response of the low-pass filter used in preconditioning of time-series data for this study. The filter provides high attenuation (22 dB) at f = 0.167 Hz, and therefore downsampling the data by a factor of 2 (effective sampling rate of 1/3 Hz) does not generate significant aliasing. The average time required for BSA estimation of nIC without downsampling was 2 hours for concatenated data and 3.89 min for averaged data. nIC was computed much more efficiently using BSA when downsampled data were used (20.2 mins for concatenated data; 1.45 mins for averaged data). The greater fractional reduction for the larger (concatenated) dataset arises from the reduced time required for PCA as well as the smaller number of samples per bootstrap for the same bootstrap sampling density. Table 1 shows that the nIC estimates (obtained using BSA) with and without temporal downsampling agreed well (with a difference ranging from only 1 to 4 components). Task-related maps obtained using ICA_{avg} and ICA_{cat} with and without temporal downsampling are almost identical (average cross correlation =0.95±0.08 for ICA_{avg} and 0.90±0.13 for ICA_{cat}), when nIC was estimated using BSA. Task-related maps obtained using ICA_{avg} showed the expected pattern of focal activation of D1 and D3 regions in area 3b. In contrast, nIC estimates obtained using MDL with temporal downsampling differed significantly (Table 2), and show high variability, even though information loss due to aliasing arising from downsampling was negligible. Our results indicate that when the data are appropriately low-pass filtered in preprocessing stage, nIC and ICA maps obtained after downsampling the data (while satisfying Nyquist's criterion to a reasonable degree) are in agreement with those obtained without downsampling when BSA is used, while requiring much less processing time. Although we have used a downsampling factor of 2, greater factors are achievable when filters with stricter specifications are used.

Table 1

	Averaged Data		Concatenated Data	
	Without Downsampling	With Downsampling	Without Downsampling	With Downsampling
Sub1,Sess1	9	9	16	14
Sub1,Sess2	8	11	20	18
Sub2,Sess1	14	11	23	22
Sub2,Sess2	14	12	26	22

Table 2

	Averaged Data		Concatenated Data	
	Without Downsampling	With Downsampling	Without Downsampling	With Downsampling
Sub1,Sess1	16	3	559	43
Sub1,Sess2	20	3	1685	37
Sub2,Sess1	176	4	1066	52
Sub2,Sess2	176	5	1062	44

Conclusions: BSA is the preferred method for nIC estimation but at a cost of (possibly prohibitively) long computation times. However, significant reductions in computation time can be achieved by filtering the data followed by downsampling, thus making it a feasible method of nIC estimation for larger datasets. Filtering and downsampling results in negligible loss of information of interest when the stimulus-driven response consists of low frequency components or when LFFs are being studied (falling in 0-0.1 Hz range).

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