

# Spatial Independent Component Analysis for Multi-task Functional MRI Data Processing\*

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**Abstract.** Multi-task in one epoch usually exists in our life, but the brain functional activation response is few analyzed. One key problem is that the multi-task response data processing has not been addressed. In this paper, spatial independent component analysis (sICA) is presented to separate the different response of the complex visual-movement task by analyzing the unmixing matrices temporal components corresponding to spatial separated pattern. An *in vivo* fMRI experiment, with ten subjects (five male, five female) with the visual stimulation and hands' movement synchronously, is performed. Separated component patterns of the spatial ICA are chosen by computing the relation between the unmixing matrices temporal component corresponding to spatial separated pattern and experiment pattern. The result shown that the spatial ICA can separate the two response activation patterns, and the response of the unmixing matrices temporal information corresponding to spatial component patterns between two tasks are obvious different. The visual response is obvious faster than the movement response by analyzing relation between the neuron dynamic response and unmixing matrices temporal response.

**Keywords:** functional MRI, spatial ICA, separation, unmixing matrices, brain activation, visual-movement stimulation.

## 1. Introduction

Multi-task, for example, visual and auditory stimulation, visual and hand movement stimulation, etc. in one epoch usually exists in our life. Current fMRI experiment is mostly only single task in one epoch for simplifying experiment and data process. One of alternating multi-task between left hand movement and right hand movement stimulation has been finished [1]. Reason is that the multi-task brain functional activation response data processing is difficult to be analyzed.

At present, the primary approaches for fMRI data analysis could be divided into two kinds: hypothesis-driven and data-driven methods. Firstly, the hypothesis-driven method, such as statistical parametric mapping (SPM) based on the general linear model (GLM) [2, 3] which is a powerful tool for the analysis of function mapping paradigm requires statistical inference and hypothesis test. Similarly, t tests and F test that are statistical test methods need accurate time information corresponding task paradigm to measure the temporal correlation [4] of response to observe BOLD signals. Secondly, another analysis approach is so-called data-driven method, which does not require any prior assumption about task paradigm. Here, they have been utilized to functional task experiments in the context of principal component analysis (PCA) [5], blind source separation (BSS) [6, 7], and the temporal clustering analysis (TCA) [8]. Those methods emphasize on the intrinsic character and direct analysis of the fMRI data sets. Among all multivariate approaches, independent component analysis (ICA) is the predominance recently and is a valuable tool for the multivariate data-driven analysis of fMRI data [9, 10].

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ICA enables powerful exploratory analysis on fMRI data by extracting spatially and temporally independent patterns or mapping to both task-related activations (experimental conditions) and noise components, which come from stochastic noise (e.g., physiologic noise and scanner noise) and systematic noise (e.g., motion artifact noise, drift noise and distortion noise) [11,12]. The value distribution of the fMRI signals in space and time is to be considered: the spatial ICA (sICA) whose statistical distribution of signal is sampled in number of voxels, and the temporal ICA (tICA) whose statistical distribution of signal is sampled in observed time course. Presently, most contributions report the detection of the locations of the brain activations when subjects performed a cognition task using sICA [13], tICA [14, 15] or spatiotemporal ICA (stICA) [16], which make use of the separated source matrix only [17, 18]. But the choice of separated components using both source and unmixing matrices for block task paradigm was few adopted. A practical fMRI BOLD responsive signal may be composed of asynchronous response or different responsive patterns caused by the difference of local vessel structures and functions of the brain during the subject performing the various task. The BOLD signals, especially in the performance with multi-tasks at the same time, originates from different spatial positions and specific temporal characteristic may be different in statistics; so, naturally, approaches both using the source matrix information for detecting and localizing spatial position and using the unmixing matrix for comparing and analyzing time course are feasible in practice.

In our prior study, the spatial ICA is used to separate fMRI data composed of asynchronous response or different responsive patterns by analyzing the separated component pattern and the temporal signal of activation voxels [18]. In this study, spatial ICA algorithm is presented to separate the different activation patterns of the complex synchronous visual stimulation and the hands' movement task by analyzing the temporal information of unmixing matrix corresponding to spatial component patterns. Firstly, spatial ICA approach and fMRI experiment is shown in material and method section. Then, vivo fMRI data analysis results are shown in result section. Final section is the result discussion.

## 2. Material and Methods

### 2.1. Spatial ICA Model

In spatial ICA, fMRI data sets firstly are assumed to be a linear mixture of spatially independent component patterns including background Gaussian noises and brain activation signals which evoked asynchronous excitations of voxels [9, 11, 19], thus, the signal model of the spatial-ICA is presented as

$$x(l,t) = As(l,t), l = 1, \dots, L, t = 1, \dots, N \quad (1)$$

where  $l$  is the index of voxels,  $L$  is the total number of voxels at one volume, such as 94208 in this work, and  $s(l,t) = \{s_1(l), s_2(l), \dots, s_N(l)\}$  is a set of spatially independent patterns which are assumed to be spatial independent. Also,  $x(l,t) = \{x_1(l), x_2(l), \dots, x_N(l)\}$  is the observed temporal fMRI time course, in this work,  $N=120$ .  $A$  is a  $N \times N$  unknown time-invariant mixing matrix. The separated spatial pattern matrix estimated are then written as

$$Y(l,t) = A^{-1}x(l,t) = Wx(l,t), l = 1, \dots, L, t = 1, \dots, N \quad (2)$$

where  $W$  is a  $N \times N$  unmixing matrix temporal course corresponding to spatial component patterns  $Y(l,t)$ , here,  $N=120$ .

The aim of the spatial ICA is to find the linear unmixing matrix  $W$  and the separated source matrix  $Y$  and then to get the original mutually independent signals or patterns  $S$ . To estimate the matrix  $W$  and matrix  $Y$ , in this work, the fast-fixed ICA algorithm was utilized for the spatial ICA [20].

### 2.2. Data Acquisition

Ten healthy subjects participated fMRI experiment (five male, five female, mean age 30). The experiment was conducted at University of Texas health center at San Antonio, with SIEMENS 3 TESLA MAGNETOM TRIO. The gradient echo EPI sequence's parameters are as follows: 23 slices, TR=2000 ms, TE=40 ms, FOV=24 cm, matrix=64×64, in-plane resolution=2×2 mm, flip angle=90°. The paradigm of the experiment

are epochs, each epoch is composed of 10 scans (20 s/epoch). Totally, there are six cycles (12 epochs), as shown in Fig.1, thus, and 120 scans acquired.

### 2.3. Task

The condition for successive blocks alternated between rest and simultaneous visual stimulation and hands' movement, moreover, starting with rest. Visual stimulation was presented at the center of the visual field with frequency of 8 Hz, light intensity of 200 cd/cm<sup>2</sup>, and visual angle of 2°. Also, visual stimulation signals act as the trigger to start the hands' movement.

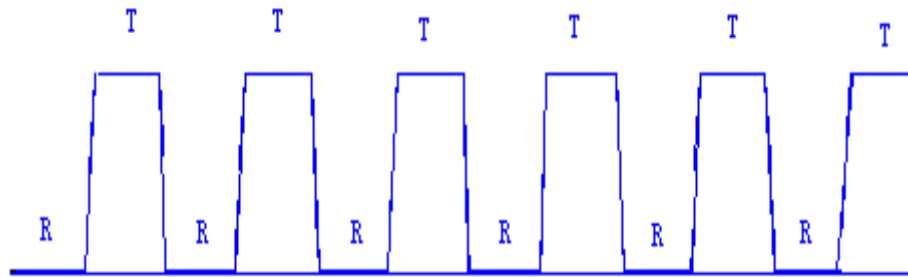


Fig.1: Epoch patterns. The letters R and T correspond to rest and task, respectively.

### 2.4. Data Analysis

Firstly, the experimental data was disposed by SPM2 software package [www.fil.ion.ucl.ac.uk/spm] [3]. Spatial transformation mostly including realignment and spatial normalization was performed to correct for head motion. And the data was smoothed spatially with a Gaussian filter (8 mm FWHM kernel). The preprocessed data does not affect spatial ICA results in general [1, 11]. Then, using the spatial ICA algorithm, where observed matrix  $x(l, t)$ , see (1),  $l = 64 \times 64 \times 23, t = 120$ , 120 separated component maps were obtained for the data of one volume. According to the above spatial ICA method, the voxels with z-score values (here,  $|z| > 5.0$ , approximately,  $p < 0.05$ ) were specified as the active voxels, and, whose spatial position overlaid the anatomical images.

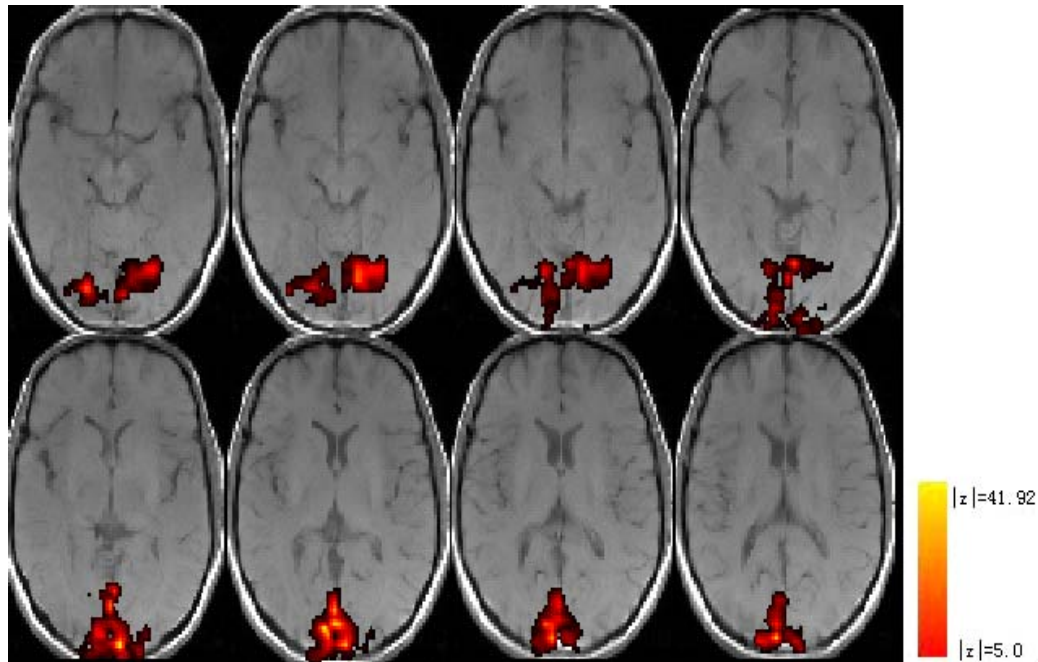
Finally, by validating the availability of spatial ICA approach, the intrinsic character of the unmixing time course matrix  $W(N, N)$ , see (2), elicits the time course information corresponding to the fixed spatial components. Introducing the specific time course vector into the SPM as restructured design matrix, thus, SPM could compute the special active areas using the statistic t-tests ( $p < 0.001$ , uncorrected) based on the new design matrix mentioned above.

### 3. Results

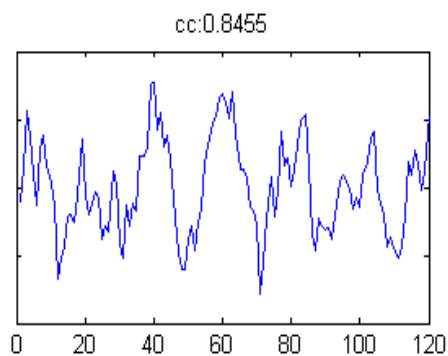
In the same way, the spatial ICA approach is implemented according to we mentioned above, the voxels with z-score values ( $|z| > 5.0$ ) were in the light of the active voxels and overlaid the anatomical image. Fig.2 shows the activation positions whose BOLD signals responded under the experimental paradigm, where Fig.2a are the spatial separated components of the preprocessed fMRI data when the spatial separated components corresponding time course had high correlation coefficient with visual stimulation and hands movement. Fig.2a expresses that activation areas are mostly the visual area not including the motor area. At the same time, this activation areas' time course bear high correlation coefficient and Fig.2b means that time course separated by the spatial ICA had correlation with the experiment paradigm's time course, which can not replace the actual brain activation pattern absolutely. The active cortex obtained by sICA for the visual stimulation results is showed in the Fig.2c.

After that, we selected another time course possessing the high correlation from the 120 spatial separated components, and let voxels with z-score values ( $|z| > 5.0$ ) overlay the anatomical image. Fig.3 shows that the

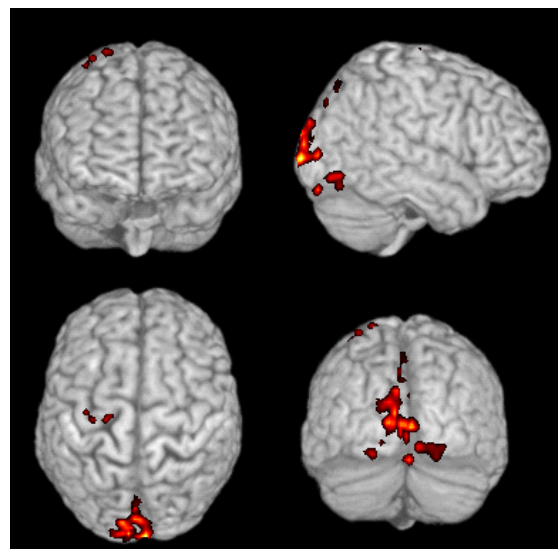
subject's bilateral sensorimotor areas and a fraction of visual areas are activated [21, 22]. The Significant functional brain activations from sICA and corresponding Brodmann's areas and areas for local maximum's Talairach coordinate are shown in Table 1.



(a)

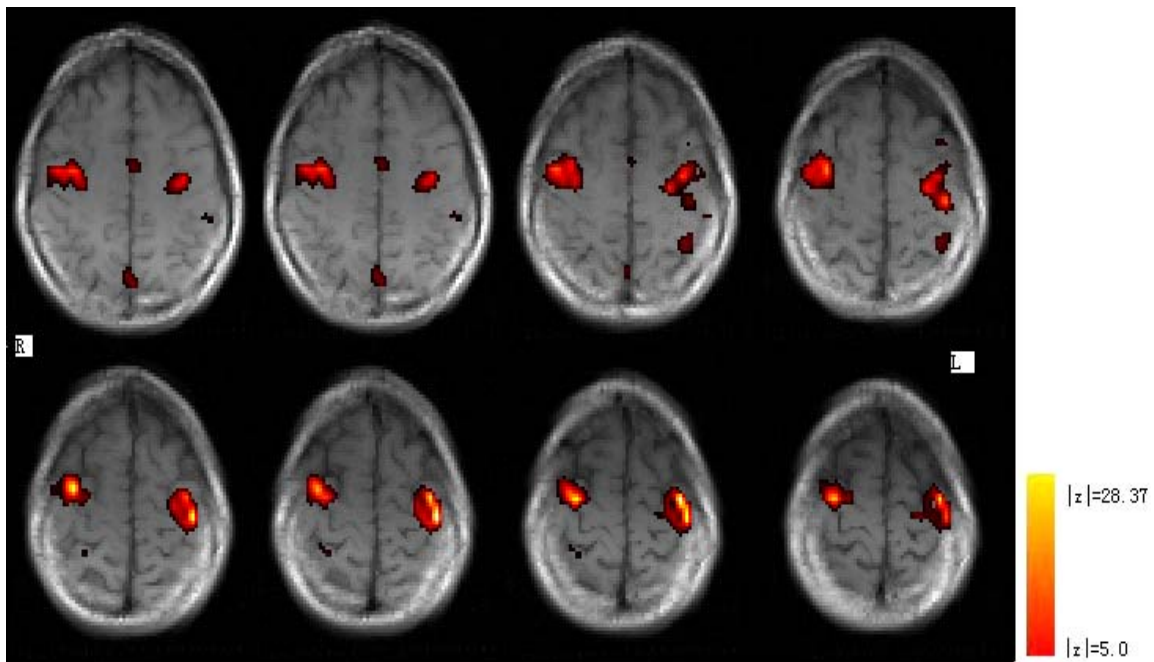


(b)

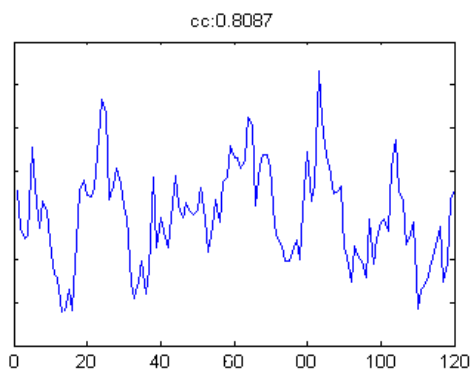


(c)

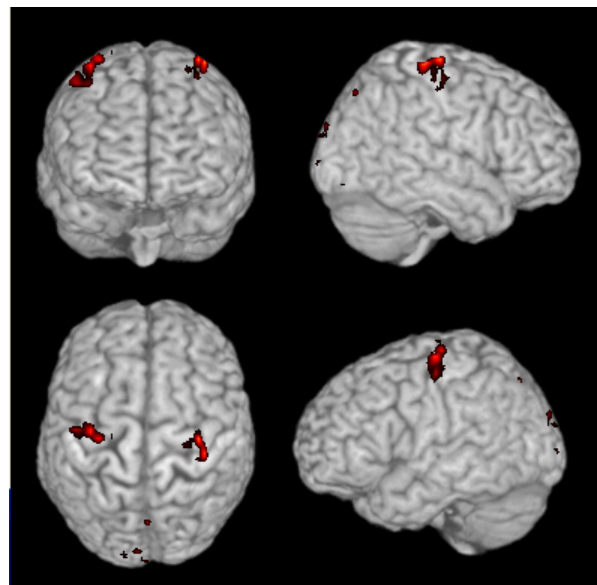
Fig.2: Imaging results by spatial ICA. (a) Imaging maps of the one of the time course high correlation to the experimental paradigm separated component. (b) Time course of the former separated components had  $cc=0.8455$  with the paradigm time course. (c) The active cortex obtained by sICA for the visual stimulation.



(a)



(b)



(c)

Fig.3: Imaging results by spatial ICA. (a) Imaging maps of another high correlation separated components. (b) Time course of the second spatial component had  $cc=0.8087$  with the paradigm time course. (c) The active cortex obtained by sICA for the hands' movement.

Table 1. Significant functional brain activations from sICA.

Cluster	Area for local maxima	Brodman's area	Z  value	Talairach coordinate (mm) of max voxel (x,y,z)
sICA-IC1	RC OL lingual gyrus	BA 18	15.36	16, -78, -10
	RC OL cuneus	BA 18	41.92	6, -102, 2
	RC OL cuneus	BA 17	16.93	6, -98, 0
	LC OL fusiform	BA 18	21.65	-22, -86, -16
	LC OL cuneus	BA 18	31.7	-6, -100, 2
	LC OL cuneus	BA 19	23.53	-4, -96, 26
sICA-IC2	RC FL medial frontal	--	10.2	2, -12, 54
	RC FL precentral	BA 4	15.12	34, -24, 52
	RC FL precentral	BA 6	12.19	36, -8, 56
	LC FL precentral	BA 4	19.04	-38, -14, 54
	LC FL precentral	BA 6	17.81	-26, -10, 50

Note. Two independent components be separated by sICA, IC1, IC2 represents the visual stimulation and hand's movement spatial component, respectively. Abbreviation used: LC, left cerebrum; RL, right cerebrum; FL, frontal lobe; OL, occipital lobe.

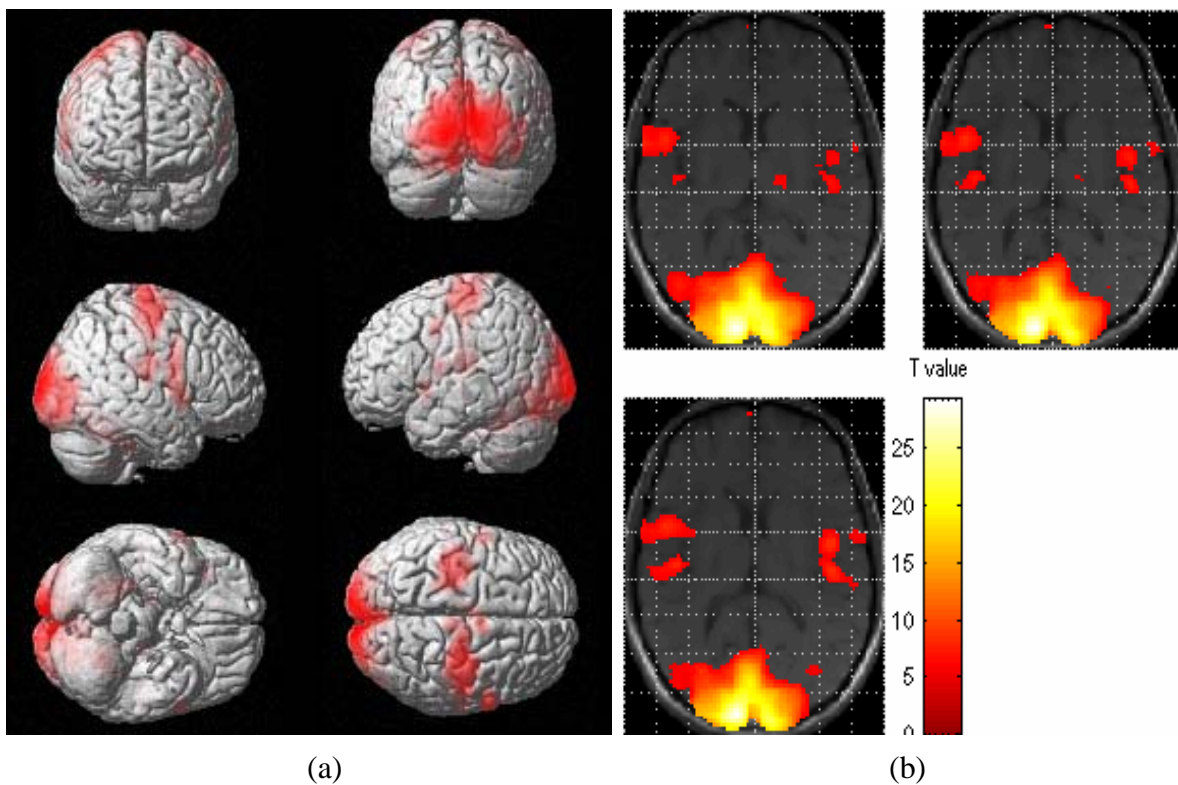


Fig.4: SPM results. (a and b) the visual areas and the motor areas be activated, synchronously.

## 4. Discussion

### 4.1. Comparison with SPM

By applying the spatial ICA to the in vivo fMRI data set, we found that where do exist different BOLD signal in different brain regions of different vessel structures and neural masses in one stimulation condition [18]. Aiming to block experiment, statistical parametric mapping (SPM), using the general linear model (GLM) as a pure hypothesis-driven which needs prior information to analyze fMRI data, is a very available

method. Here, our experimental paradigm of the design matrix of the GLM shown in Fig 1 is an alternating task between rest and simultaneous task with visual stimulation and two hands movement. The SPM results shown in Fig.4 indicate that those areas are activated synchronously, but SPM can not distinguish the visual areas and motor areas respectively. In principle, brain activations of the visual and motor areas have different response to the task. More complex movement has also been studied using fMRI. Activation of primary motor cortex was firstly reported by Rao et al. [23]. On the other hand, Boecker et al. [24] showed that the SMA was activated by simple repetitive movement and argued that it is involved in self-paced finger tapping and not exclusively reserved for more complex motor control. More extend and consistent activation during self-initiated movement than during visually triggered movement was observed in the anterior SMA, the rostral part of the cingulated motor zone (RCZ) and the caudal part of the cingulated motor area (CCZ), whereas more complex movement was associated with more extensive activation than the simple movement in the posterior part of the SMA and the CCZ.

Table 2. Significant functional brain activations from different methods.

Cluster	Cluster volume (cm <sup>3</sup> )	Cluster <i>p</i> value	Area for local maxima	Brodman's area	T value	Talairach coordinate (mm) of max voxel (x,y,z)
<b>A. Canonical SPM</b>						
1. Visual cortex	31.4	<0.001	RC OL cuneus	BA 18	29.26	10, -100, 10
		<0.001	RC OL cuneus	BA 17	16.33	4, -76, 12
		<0.001	RC TL suproior temporal	BA 22	13.38	54, 10, -4
		<0.001	LC OL middle occipital	BA 18	22.97	-12, -100, 18
		<0.001	LC OL cuneus	BA 17	15.51	-4, -80, 6
2. Left hemisphere sensorimotor areas	17.29	<0.001	LC PL postcentral gyrus	BA 3	9.34	-36, -26, 56
		<0.001	LC FL precentral gyrus	BA 4	8.97	-36, -24, 60
		<0.001	LC PL postcentral gyrus	BA 6	8.31	-54, 0, 42
		<0.001	LC TL superior temporal	BA 42	6.78	-60, -28, 16
3. Right hemisphere sensorimotr areas	25.06	<0.001	RC FL precentral gyrus	BA 6	12.78	30, -14, 60
		<0.001	RC PL postcentral gyrus	BA 3	9.05	46, -18, 48
		<0.001	RC FL precentral gyrus	BA 4	8.28	44, -16, 44
		<0.001	RC sub-lobar insula	BA 40	6.42	50, -22, 14
<b>B. IC1-SPM</b>						
Visual cortex	17.08	<0.001	RC OL cuneus	BA 18	6.48	2, -90, 12
		<0.019	RC OL cuneus	BA 17	4.80	4, -78, 12
		<0.001	LC OL cuneus	BA 18	6.25	-2, -86, 18
		<0.004	LC OL cuneus	BA 17	3.98	-4, -78, 10
<b>C. IC2-SPM</b>						
1. Left hemisphere sensorimotor areas	6.91	<0.001	LC FL precentral gyrus	BA 6	6.73	-38, -6, 36
		<0.002	LC FL precentral gyrus	BA 4	5.17	-34, -18, 48
2. Right hemisphere sensorimotor areas	5.66	<0.001	RC FL precentral gyrus	BA 6	6.52	46, -10, 30
		<0.002	RC FL precentral gyrus	BA 4	4.94	46, -18, 42
3. Other areas	2.40	<0.008	LC OL cuneus	BA 18	6.38	-2, -70, 30
		<0.011	LC OL cuneus	BA 7	4.80	-10, -70, 18

Note. Canonical SPM indicates experiment fMRI data analyzed SPM2 using experiment paradigm time course as the design matrix; IC1-SPM indicates SPM2 use the 1st ICs corresponding the visual stimulation spatial component as the design matrix; IC2-SPM indicates SPM2 use the 2nd ICs corresponding the hands' movement spatial component as the design matrix. Abbreviation used: LC, left cerebrum; RL, right cerebrum; FL, frontal lobe; OL, occipital lobe; PL, posterior lobe; TL, temporal lobe.

To compare the results of our spatial ICA approach and time course information of the unmixing matrix, we restructure the columns of design matrix of SPM using the first and the second components corresponding time course, see Fig.2b and Fig.3b. The SPM results are shown in Fig.4. Fig.5a shows that most activated areas are visual areas not including other brain activated areas using the time course of the first spatial component, and the same brain activated areas with directly using the spatial ICA method, see Fig.2a. Whereas, using the time course of the second spatial component as columns of design matrix, the SPM results shown in Fig.5b illuminated that activated areas not only were involved in the bilateral motor areas corresponding to the two hands movement, but also contained some activated visual areas whose time course should not be comprise in the time course of the second spatial component. Yet, the alike results of SPM, see Fig.5b, and the spatial ICA results, see Fig.3a.

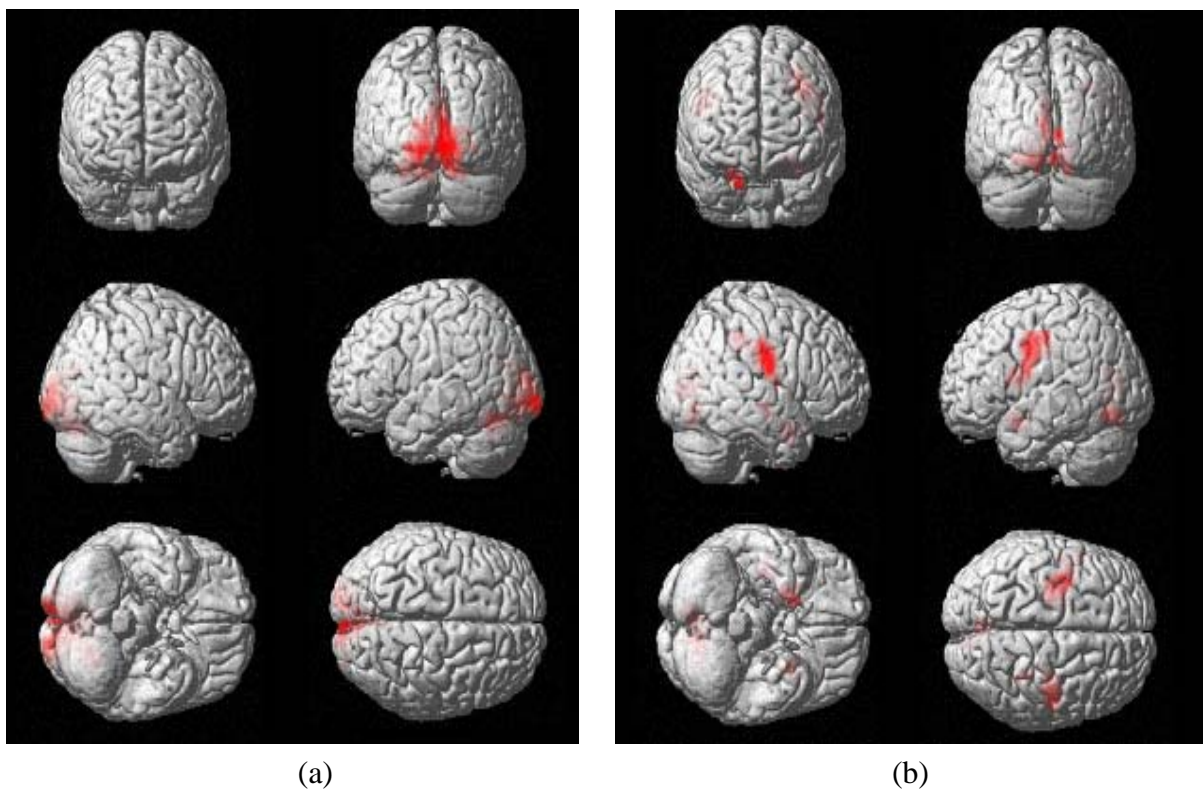
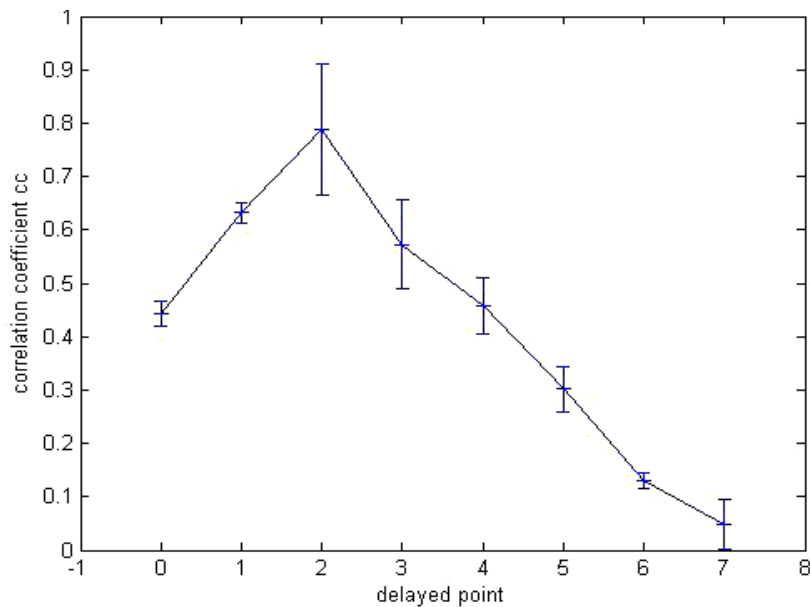


Fig.5: Brain activated areas. (a) Using the time course of the first spatial component. (b) Using the time course of the second spatial component.

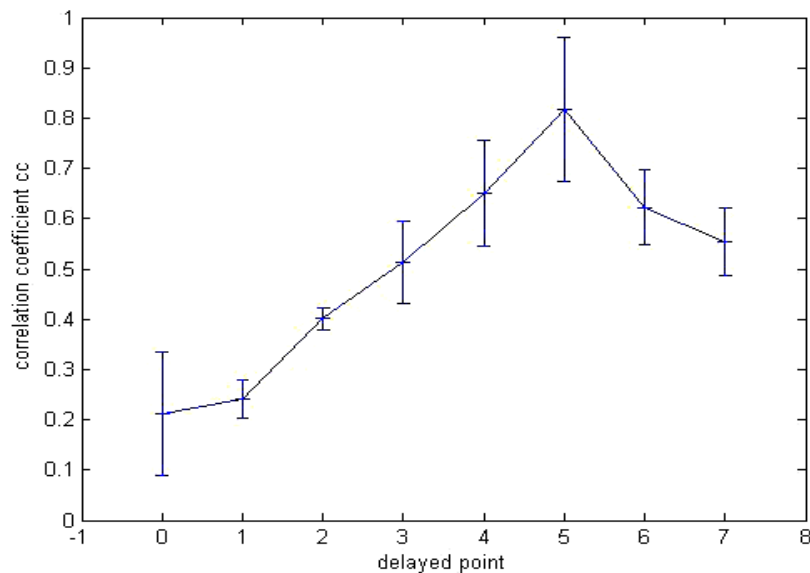
However, spatial ICA can distinguish the visual and motor areas; see Fig.2a and Fig.3a, even if these two tasks are completed in one epoch. Our conclusion is that spatial ICA is a useful tool for discrimination of the activations in different brain region, especially, in the multi-task performance in one epoch. Significant functional brain activations computed by different methods are show in Table 2.

To analyze the fMRI data as multi-task in one epoch, canonical HRF convoluted paradigm time course was commonly regarded as the brain activation mode, which does not consider that there are different brain activation modes from area to area of the brain or from person to person. Here, visual cortex, left and right hemisphere sensorimotor areas, which bear  $31.4 \text{ cm}^3$ ,  $17.29 \text{ cm}^3$  and  $25.06 \text{ cm}^3$  cluster volume, respectively, where the max statistical voxel is left cerebrum occipital lobe cuneus, left cerebrum posterior lobe postcentral gyrus and right cerebrum frontal lobe precentral gyrus, respectively, were activated synchronously by using canonical-SPM method. Moreover, visual cortex bear  $17.08 \text{ cm}^3$  cluster volume and max statistical areas is right cerebrum occipital lobe cuneus by using the IC1-SPM. Finally, left and right hemisphere sensorimotor areas bear  $6.91 \text{ cm}^3$  and  $5.66 \text{ cm}^3$  cluster volume and max statistical areas are left

cerebrum frontal lobe precentral gyrus and right cerebrum frontal lobe precentral gyrus, respectively, by using IC2-SPM. Our results show that cluster volume using IC1- and IC2-SPM to calculate activation areas is more exact and precise, and smaller than using canonical-SPM. So, this sICA have even more hold predominance to analyze and process fMRI data sets that have no specific time course, such as epilepsy, schizophrenia, Alzheimer's disease.



(a)



(b)

Fig.6: Results of the delayed correlation. (a) Time course of the visual stimulation component of delay correlation with paradigm time course. (b) Time course of the two hands movement component of the delay correlation with paradigm time course.

## 4.2. Comparison of the Temporal Responses between Visual Stimulation and Hands' Movement

In former investigation, the combined GLM and ICA method was employed to analyze the visual-perception task [25]; the SPM-ICA was used to distinguish the left and right hand experiment fMRI data analysis [1]; the spatio-temporal was employed to analyze visual fMRI data [26]. They are only using the separated signal or the separated temporal pattern, not using the unmixing matrix time course information. The unmixing matrix temporal information can show the temporal response process corresponding to spatial separated pattern. Unmixing matrix information that is not only simply computed correlation with experiment paradigm, but also computed delay correlation with experiment, then ensured spatial components based on the high correlation values corresponding to the components. Neurons response have some time delay, so, we let unmixing matrix time course delay the zero to the seven points (0-14 s) to compute the correlation coefficient with paradigm time course convoluted with canonical hemodynamic response functions (HRF) [27, 28]. Fig.6a indicated that time course of the visual stimulation component has the highest correlation coefficient when delayed by two points (4 s). Comparatively, Fig.6b indicated that when delayed by five points (10 s), the highest correlation coefficient arose. Thereby, unmixing matrix time course do not stand our experimental paradigm time course, but stand the real neurons response to the performance task of brain areas. This result shows that the visual response is faster than movement response.

## 5. Conclusion

In this paper, the spatial independent component analysis is presented to separate the different response of visual-movement by analyzing unmixing temporal information. Our results show that spatial ICA method could separate two independent component patterns corresponding to each task in multi-task experiment and the brain functional visual response is faster than movement response.

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