Fuzzy Segmentation Spatiotemporal Patterns of Cognitive Potential into Microstates

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Summary: Fuzzy c-mean algorithm was applied to segment spatiotemporal patterns of brainwave into microstates and memberships. The optimal clustering number was estimated with both the trends of objective function and the eigenvalue number of microstates. Comparable spatial patterns may occur at different temporal moments in consideration of fuzzy index that is beyond the limit of serial processing. Those techniques were illustrated with multichannel event-related potentials recorded from 9 subjects during Stroop test. Statistical parametric map of F value suggested that significant task (color decision and word decision) effect involve widespread cortical regions after stimulus onset 280 ms and this result supports the hypothesis that Stroop interference derives from response competition during post-perception stage. As significant stimulus (congruent stimulus and incongruent stimulus) effect only involves several separate visual regions within 100 ms after stimulus presentation, it may reflect top-down attentional regulation.

Key words: Fuzzy c-mean algorithm; Clustering analysis; Statistical parametric map (SPM); Stroop test; Event-related potentials (ERP); Spatiotemporal pattern.

Introduction

Behavioral experiments have suggested that a cognitive process can be divided into several stages. Both Donders subtraction method and Sternberg additive factors method hypothesizes that those stages are not overlapping each other and occur serially (Coles et al. 1995). More and more experimental evidences indicate that fulfilling even a simple cognitive task involves dynamical cooperation of many cerebral structures or regions. Parallel distributed processing becomes an alternative viewpoint for understanding mechanism of cognitive processes (Mesulam 1998). To resolve this, more direct method and indexes beyond behavioral ones are needed.

As multichannel electroencephalograph (EEG) and event-related potentials (ERP) reflect functional states of cortical network, they are expected to become hopeful tools for illustrating the above problems. Ironically, it is more difficult for brainwave processing when more channel data are available. Classification is usually the first step of understanding complicated phenomena. We still stick to this rule when facing spatiotemporal pattern (STP) of brainwave. A stable and definite STP termed microstate may become the basic element for comprehending cognitive processes (Lehmann and Skrandies 1984; Lehmann 1987).

Segmentation and classification of brainwave is a fundamental work and has a rather long history. Some research focused on EEG compression, detection of epilepsy spike and sleep analysis (Bodenstein and Praetorius 1977; Bodenstein et al. 1985). Time domain methods such as parameter model and correlation analysis usually need rather long data segments and the temporal stability of time series must be considered. Furthermore, it is difficult to understand those time domain features corresponding to EEG segments.

One method of spatial domain brainwave segmentation proposed by the Zurich group depends on the position of extremum of STP after reference-free transformation (Lehmann and Skrandies 1984; Lehmann 1987). It neglects most information contained in the peaks and troughs of STPs. Recently they purposed a new method based on c-mean algorithm (CMA) (Pascual-Marqui et al. 1995). This algorithm hypothesizes that each spatial pattern just belongs to one definite microstate (clustering center or prototype). So it admits serial processing in fact

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and cannot give a satisfactory solution to some intermediate spatial patterns.

Fuzzy c-mean algorithm (FCMA) is a better clustering method derived from CMA (Bezdek 1981). In FCMA, each sample (spatial pattern) belongs to all clustering centroids or prototypes (microstates). Memberships varied between 0 and 1, consecutively providing a set of index for all samples (spatial patterns) including intermediate ones, which describe the extent of similarity between each sample and each prototype. FCMA makes it possible to investigate several neural assemblies operating simultaneous within cognitive process quantitatively.

When asked to name the color in which a word is displayed, one often has the feelings of conflict and effort if the display color and meaning of the word is incongruent (e.g., the word "red" displayed in green). A longer reaction time (RT) is observed in comparison with congruent word (e.g., the word "red" displayed in red) and neutral word (e.g., the word "dog" displayed in green) (Stroop 1935). This Stroop effect is robust and this task is often taken as either a test of selective attention or a test of stimulus-response compatibility, or even a test of semantic processing. Many accounts have been proposed (for a review, see MacLeod 1991), however the neural substrates are still not clear. Incongruence between color and meaning was not associated with a delay in the P300, even though RT was delayed (Duncan-Johnson and Kopell 1981; Ilan and Polich 1999). This phenomenon would suggest that the interference occur somewhere downstream from the system responsible for stimulus evaluation provided that P300 latency is a marker of stimulus evaluation time. A recent research using ERP found no significant waveform difference between congruent stimulus and incongruent one (Posner and Rothbart 1998). Those findings have given little neuroanatomical information. PET studies found activation in anterior cingulate associated with incongruent color-names that is still disputable (for a review, see Coull 1998).

In this paper, we would focus on FCMA and apply it to segment multichannel ERP, which were recorded during a simplified version of the Stroop test. Statistical parametric map of F statistic (SPM(F)) is employed to disclose the spatiotemporal organization of the Stroop effect.

Methods

Fuzzy c-mean algorithm

FCMA minimizes the following objective function with respect to fuzzy membership u_{in} and cluster centroid $\mathbf{v}_i (1 \le i \le C)$,

$$J = \sum_{i=1}^{C} \sum_{n=1}^{N} u_{in}^{m} \left(\left\| \mathbf{x}_n - \mathbf{v}_i \right\| \right)^2 \tag{1}$$

where $\{\mathbf{x}_n\} (1 \le n \le N)$ consist of potentials or other transform-domain values of M length and N channels ERP, C $(2 \le C \le M)$ is the number of clusters, m $(1 < m < \infty)$ is the fuzziness index. Note that $\|*\|$ is the usual Euclidean distance. FCMA is executed in the following steps.

1) Initialized $\mathbf{v}_{i,0}$ as small random number. Fixed C,m and gave a little $\varepsilon > 0$. Memberships u_{in} of $\mathbf{x}_n$ belongs to cluster i such that

$$\sum_{i=1}^{C} u_{in,0} = 1 \tag{2}$$

2) For $t = 1, 2, \ldots, t_{\max}$,

i) Compute the fuzzy membership u_{in} using

$$u_{in,t} = \left(\sum_{j=1}^{C} \left(\left\| \mathbf{x}_n - \mathbf{v}_{i,t-1} \right\| / \left\| \mathbf{x}_n - \mathbf{v}_{j,t-1} \right\| \right)^{2/m-1} \right)^{-1} \tag{3}$$

ii) Update the fuzzy centroid $\mathbf{v}_i$ using

$$\mathbf{v}_{i,t} = \sum_{n=1}^{N} \left(u_{in,t} \right)^m \mathbf{x}_n \Big/ \sum_{n=1}^{N} \left(u_{in,t} \right)^m \tag{4}$$

iii) Estimate convergent error E_t using

$$E_t = \sum_{i=1}^{C} \left\| \mathbf{v}_{i,t} - \mathbf{v}_{i,t-1} \right\|^2 \tag{5}$$

3) Repeat steps i), ii) and iii) until $E_t < \varepsilon$ or $t > t_{\max}$.

Fuzzy index m is often chosen empirically. When m is close to 1, each spatial pattern trends to be represented by just one clustering centroid (microstate) and FCMA is close to CMA. Conversely each spatial pattern trends to be represented by all clustering centroids (microstates) equivalently when m getting larger. Pal and Bezdek (1995) recommended that the best choice for m was probably in the interval [1.5, 2.5].

The result of the FCMA depends on the initial value of cluster centroid $\mathbf{v}_{i,0}$, and the objective function J often traps into local minimum. To improve this nonlinear optimal problem, one can simply execute FCMA repeatedly just by setting initial values randomly. The algorithm is fast enough and the result corresponding to the minimum objective function should be taken as the final optimal solution.

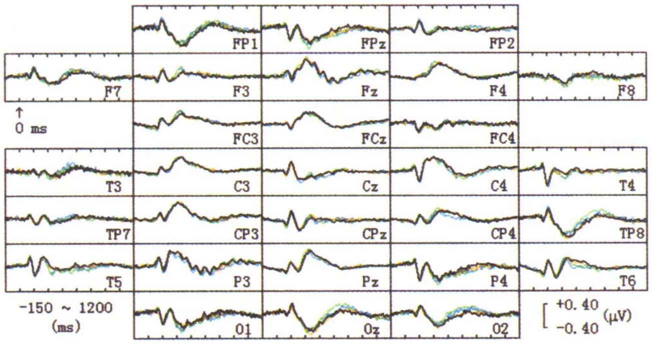

Figure 1. Four ERP waveforms of grand average over 9 subjects under different experimental conditions: color-decision task (congruent-black and incongruent-red) and word-decision task (congruent-green and incongruent-blue) are rather similar. All ERP data with correct response are processed by Hjorth transformation and normalized before grand averaging.

Determining the optimal number of cluster

The optimal cluster number can be determined by two methods. One is based on the trends of objection function against increasing microstate number. Usually it is a monotonic decreasing curve. The turning point of the curve indicates the position of the optimal number of clustering.

Shape similarity among microstates indicate their redundancy and may be reflected by their linear correlation in statistics. So another method is using decorrelation technique. After getting the cross-correlation matrix of microstates, its eigenvalues can be estimated and arranged in decreasing order. The position of optimal cluster number is determined according to the eigenvalue spectrum when using larger cluster number.

Searching for the optimal segmenting points

Each spatial pattern has several membership functions corresponding to microstates respectively. The optimal segmenting points can be defined as the time that local minimal difference between maximal membership function and sub-maximal one. As there is the possibility that such difference curves may have many peaks and troughs, the optimal segmenting points are usually more than the number of optimal clusters. The searching steps may be taken as follows:

1) Compute the deviant $\{d_n\}$ between the maximal and sub-maximal membership functions - $\max(u_{in})$, $\mathrm{sub}(u_{in})$ $(1 \le i \le C)$ - of each spatial pattern $\mathbf{x}_n$ $(1 \le n \le N)$ at each time point

$$d_n = \max(u_{in}) - \mathrm{sub}(u_{in}) \tag{6}$$

2) Compare d_{2k} and d_{2k+1} $(1 \le k \le N/2)$ and preserve the smaller of the nearest neighbors and its corresponding time of $\{d_n\}$. Thus the length of new series consisting of the smaller set reduces to half of its original $(N/2)$.

3) Repeat step 2 till the length of new series is close to $(C\text{-}1)$.

This searching strategy can shrink the region quickly and can be also used for getting other local extrema such as local maximal memberships.

Subjects, experimental paradigm and data collection

Nine healthy students (male: 4, female: 5) ranged from 21 to 27 years of age took part in the experiment. We used a simplified Stroop test consisting of four Chinese characters either "red" or "green" displayed in red or in green respectively. The duration of each character is 1200 ms and presented 30 times randomly on the center of black screen at interval 2000 ms. The distance between screen (character size 1.8 ×1.8 cm) and subjects is 50 cm, i.e. a visual angle of 2.0× 2.0°. During the color-decision session, subjects were asked to press a button with their left or right hand respectively according to the color of character. During the word-decision session, each subject responded to meaning of character. Both speed and accuracy were measured. The experimental order was balanced among subjects.

Event-related EEG was recorded from 29 channels (indexed as figure 1) with linked mastoids as reference and subjects were instructed to relax. EEG epochs from 150 ms before to 1250 ms after stimulus were amplified with cutoff frequencies of 0.1 and 100 Hz by means of a NeuroScan ERP workstation, digitized at 1000 Hz, and analyzed off-line. Electrode impedance during the experiments did not exceed 5 kΩ. Trials of 10% ~ 20% contaminated with ocular, muscular or any other type of artifacts were inspected visually and rejected.

Data preprocessing and statistical analysis method

In order to get reference-independent data, Hjorth transformation (the weighted average reference montage) was applied to average ERP waveform of each subject (Hjorth 1980; Lemos and Fisch 1991; Curran et al. 1993)

$$P_i = p_i - \sum_{j=1}^{M}\left(p_j r_{ij}^{-1}\right) / \sum_{j=1}^{M} r_{ij}^{-1}, 1 \le i \le M, j \ne i \tag{7}$$

where P_i is the potential value p_i, p_j after transformation, weight r_{ij} is the distance between recording electrode positions i and j. This reference-free transformation reduces the effect of volume conduction of remote regions and enhances the role of local activity. Before grand averaging for further statistical analysis, normalization was carried out across experimental conditions for each sub-

Table I. Reaction times (ms) and error rates (%) (M±S).

9 Subjects	Color Decision		Word Decision	
Congruent	402 ± 49	1.9 ± 2.6	439 ± 41	1.9 ± 2.1
Incongruent	420 ± 61	2.4 ± 1.9	448 ± 46	2.8 ± 3.7

ject. The minimum from each data point was subtracted and divided by the difference between maximum and minimum (where the minimum and maximum values are computed over all times and sites). After that, a biased value 0.50 was subtracted so that all amplitude of averaged ERP varied in range of [–0.50, 0.50]. This step is necessary for variance homogeneity and could avoid the extra influence of some outliers. Otherwise an individual ERP with high amplitude may have more influence on final grand average waveforms or statistical results.

Normalized amplitude of each channel was subjected to repeated measure analysis of variance (ANOVA) with two within-subjects factors, stimulus (congruent, incongruent) and task (color decision, word decision). Based on F value of each channel, SPM(F) was acquired by interpolation technique of generalized cortical imaging technique (Zhou et al. 1998). RTs and error rates were also submitted to the same ANOVA procedure.

Results

Behavioral results and spatiotemporal pattern of ERP

Table I contains both RTs and error rates. RT within 200 ~ 1000 ms was viewed as correct response. The significant effect of stimulus ($F(1, 236)=42.482$, $P<.001$) demonstrated the differences in RT produced by congruent and incongruent words. Also the significant effect of task ($F(1, 236)=7.726$, $P=0.006$) demonstrated the differences in RT produced by color-decision and word-decision. The interaction effect between stimulus and task was not significant ($F(1,236)=0.614$, $P=0.434$). No significant differences in error rate were found.

Grand average of ERPs over 9 subjects corresponding to the four experimental conditions with correct responses respectively are rather similar to each other as figure 1 shows.

Figure 2 is the spatiotemporal pattern of ERP from -100 ms to 700 ms corresponding to congruent character with correct responses during color-decision task. Each spatial pattern is an average activity of 10 ms. There is a clear repeating phenomenon: spatial patterns of 90 ~ 150 ms reappear at the interval of 190 ~ 270 ms. Those reappearance patterns are featured by a negative component symmetrical to Cz point and a positive component distributed bilateral posterior associative regions.

FCMA results

When the fuzzy exponent m gets larger, each spatial pattern of ERP has the tendency of being represented by all microstates equivalently. Figure 3 shows the influence of fuzzy exponent. The FCMA result corresponding to figure 2 consists of 4 microstates and their memberships when the fuzzy exponent equals different value respectively: (a) 1.10, (b) 1.60 and (c) 2.10. A small m makes FCMA close to CMA. The membership of CMA is actually either 1 or 0 (all-or-none). Note the corresponding microstates are still similar in spite of varied m.

Figure 4 gives the fuzzy clustering result also corresponding to figure 2 while the cluster number is 8 and the fuzzy exponent m equals 1.60. The duration of each microstate was estimated as following: -100 A 91 C 138 B 195 C 274 D 340 E 438 F 504 G 603 H 700 (ms). Each alphabet and the numerical value before and after that represent a certain microstate and its onset and offset which were determined by minimal difference between its maximal and sub-maximal memberships. Note that C microstate appear twice describing the reprise phenomenon in figure 2. The shape similarity between microstates and spatiotemporal patterns has suggested that microstates are representative. The membership set describes their extent of similarity.

The optimal number of clustering

When the cluster number gets larger, similar microstates appear more. Figure 5 (a) indicates the (objective function/cluster number) ratio decreased with increasing cluster number (2, 4, 6, 8, 10, and 12). Figure 5 (b) shows the logarithmic spectrum of eigenvalue normalized by their sum in decreased order. Eigenvalues were acquired from each correlation matrix with different microstates number (2, 4, 6, 8, 10, and 12). There appears to be a platform between cluster number 6 and 8. The position of turning point imply the optimal cluster number 6. Those results were still corresponding to the condition of congruent character and color-decision task.

Figure 6 reveals intersubject variability: clustering results come from three subjects under the condition of congruent stimulus and color decision task (cluster number 4, fuzzy exponent 1.60). The FCMA results are truly data-dependent and each microstate is always loyal to spatiotemporal patterns of some period it derived from.

SPM(F) results

When using clustering results for further statistical analysis, one has at least two choices: the advantage

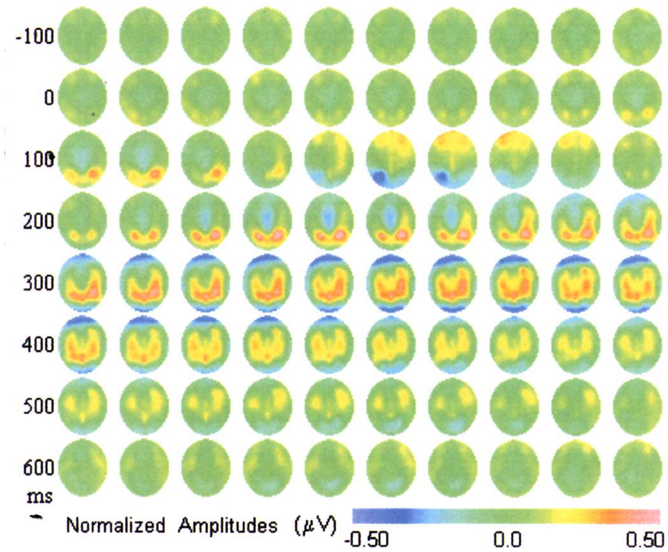

Figure 2. The spatiotemporal patterns of every 10 ms average activity during color decision task (congruent character with correct response). Note the repeat phenomenon: spatial patterns of 90 ~ 150 ms reappear during 190 ~ 270 ms. Top view and nose upwards.

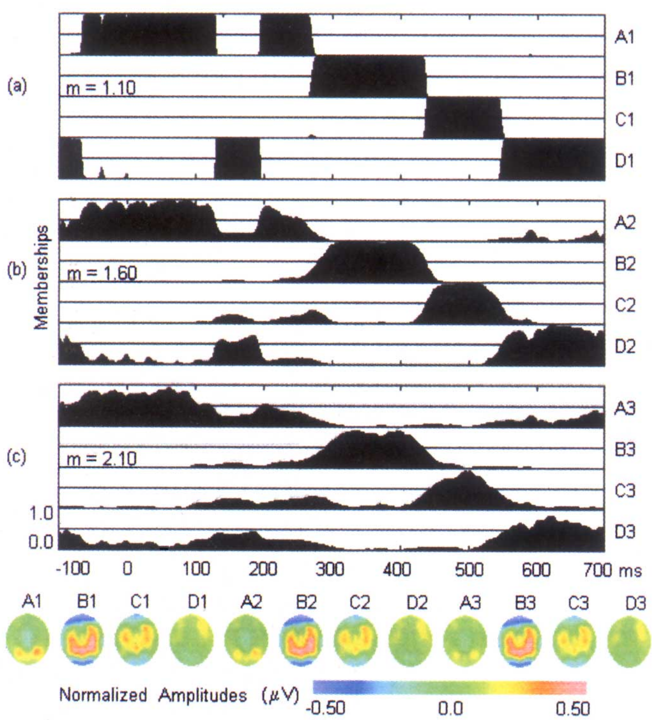

Figure 3. The FCMA results corresponding to figure 2 with 4 microstates and their memberships when the fuzzy exponent *m* equals different value: (a) 1.10, (b) 1.60 and (c) 2.10.

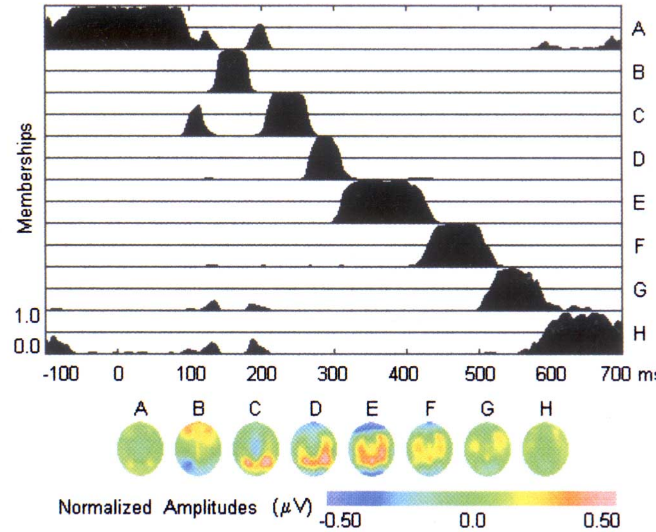

Figure 4. The FCMA results corresponding to figure 2 with fuzzy exponent 1.60, 8 microstates and their memberships. The duration of each microstate is estimated as: -100 A 91 C 138 B 195 C 274 D 340 E 438 F 504 G 603 H 700 (ms).

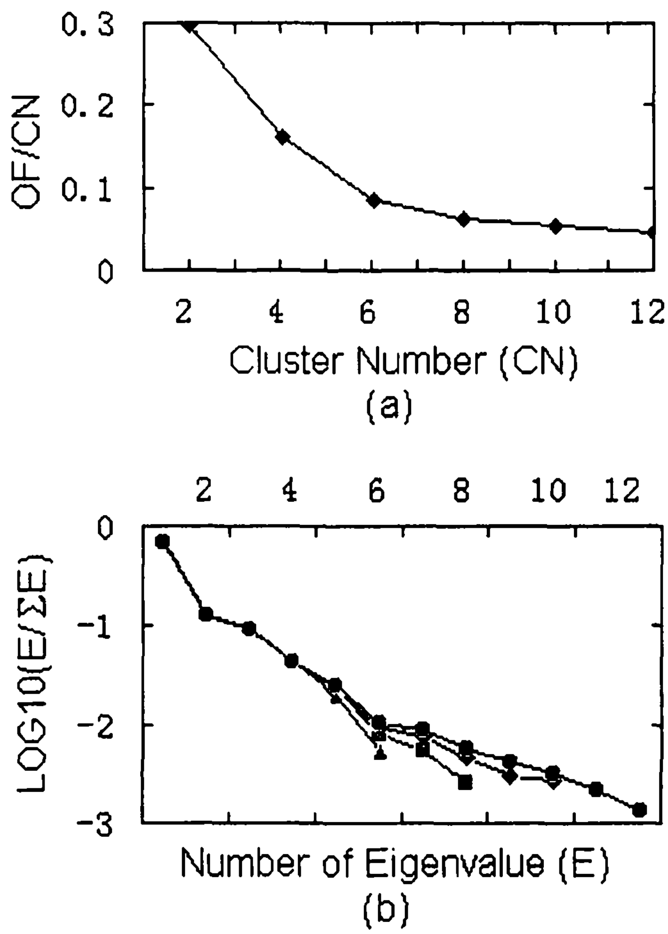

Figure 5. The platform starting from cluster number 6 implies the optimal cluster number. (a) The ratio of (objective function/cluster number) decreased with increasing cluster number. (b) The logarithmic eigenvalue spectrum of decreased order acquired from each correlation matrix of different microstates number.

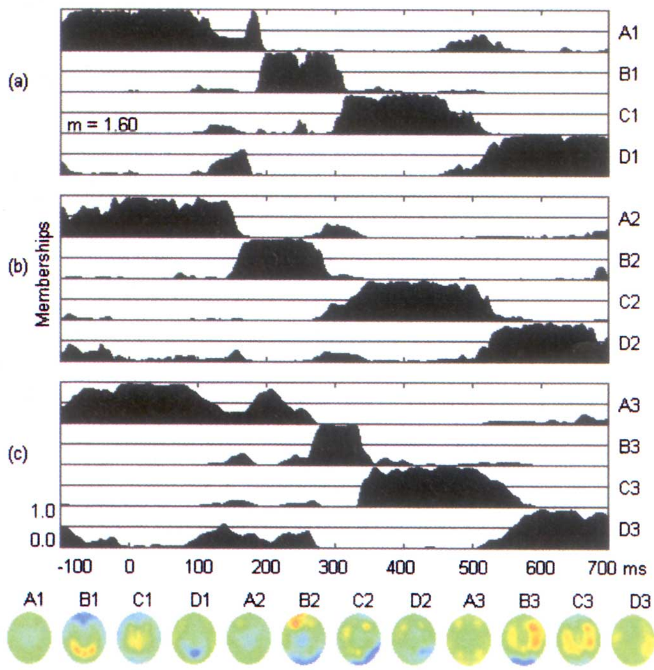

Figure 6. The FCMA results reveal intersubject variability, which derived from three subjects under the same conditions of congruent stimulus, color-decision and fuzzy exponent 1.60.

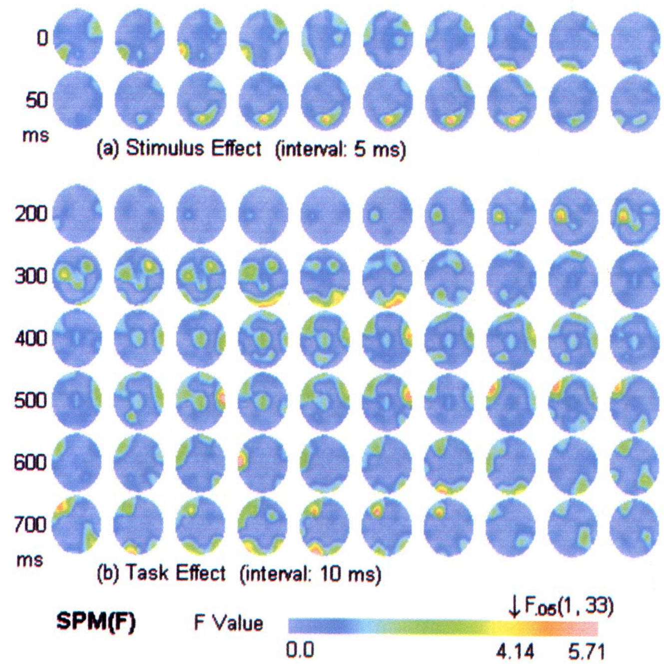

Figure 7. Statistical parametric map of F value of Stroop effects. (a) Significant stimulus effect (congruent vs. incongruent) involves several separate visual regions during early perception stage. (b) Significant task effect (color decision vs. word decision) involves widespread cortical regions during post-perception stage starting about 280 ms after stimulus onset. Top view and nose upwards.

microstate or the sum of each microstate weighted by its membership function. The latter is actually close to the situation of taking primary spatiotemporal patterns directly for comparison. Since fuzzy clustering analysis for the four grand average ERPs had similar results, SPM(F) was applied.

No significant interaction of stimulus × task in each channel was found. Figure 7 consists of spatiotemporal patterns of the F value. (a) Significant stimulus effect (congruent or incongruent) involves several separate regions of visual cortex (including occipital region, occipitotemporal and occipitoparietal regions) within 100 ms after stimuli presentation. (b) Significant task effect (color-decision or word-decision) starts about 280 ms after stimulus onset and involves widespread cortical regions during post-perception stage.

Discussion

Fuzzy clustering analysis provides a set of ideal descriptive index to comprehend parallel distributed processes. Under the hypothesis of serial processing, only those spatial patterns that occur at the same time relative to the onset of stimulus (behavior) are comparable. Such constraint may be inappropriate as the duration of each processing stage is not stable and actually varies with different conditions. In consideration of parallel microstates and their memberships, two comparable spatial patterns may occur at different times. Those fuzzy indices suggest windows for further measures and analysis and give us evidence and confidence of alternative selection beyond time-index. The limit of serial processing does not exist under such choice.

Not confined to "P1 reprise" reported in a semantic processing task (Curran et al. 1993), we observed a whole pattern reappearing during the stimulus evaluation stage. This reprise phenomenon may be an evidence of "time-locked multiregional retroactivation" proposed by Damasio (1989), which would not only be the neural substrates of recall and recognition but also perception. Its neural mechanism still needs clarification.

Space-oriented segmenting points give a set of mental chronmetric indices different from the classic measurements based on peaks and toughs of components. The results suggested the optimal boundary between perception and post-perception would be at interval of 270 ~ 280 ms. SPM(F) had also indicated the same key translation period from perception to behavioral response. Significant task effect in the post-perception stage starting at about 280 ms supports the idea that the feelings of conflict and effort and longer RT must arise more from the conflicting response tendencies.

Significant stimulus effect in the early perception stage might reflect top-down attentional regulation (Desimone and Duncan 1995). Those visual regions showing feature selective modulations not only fit well with PET studies (Corbetta 1998) but also reveal temporal order.

FCMA as a universal method can be employed to other spatial patterns generated by features of transformed domains (power spectrum, coherence, wavelet, nonlinear indices etc.) and neuroimaging data. Such compressed dynamic information may be useful in pattern recognition and other aspects.

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