

# 國立交通大學

## 多媒體工程研究所

### 碩士論文



光束構成法之腦部活動相關性時空造影  
Beamformer-based Spatiotemporal Imaging of Correlated  
Brain Activities

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中華民國九十八年六月

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A Thesis

Submitted to Institute of Multimedia Engineering

College of Computer Science

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for the Degree of

Master

in

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I-Tzu Chen



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## 中文摘要

大部分的研究都同意腦部的神經元會集體有著同步的活動特徵。過去的研究指出時序上的相關性與腦部區域間的溝通息息相關。在腦磁圖儀與腦電圖儀的研究中，一般會透過神經活動的振盪訊號來研究區域間的功能關聯性。然而，神經活動的時序訊號一般都是包含跨頻帶的資訊，所以從一般性的同步來研究區域間的功能相關性是很重要的。

在這篇論文中，我們提出了一個以光束構成法為基礎的方法來估算腦部活動相關性。透過我們的方法，可以揭露神經互聯網的活動情形。神經互聯網間是利用類似的時序特徵訊號來交換資訊。一旦使用者指定了一個區域，我們便可分析該區域中最具代表性的特徵訊號，並找出具有相似特性的區域的分布情況。原則上，將腦中的位置兩兩用我們的方法計算，就可以找出所有可能的神經互聯網。

我們的方法利用最大相關性準則來最大化參考區域和全腦的其他區域的活動相關性。透過這個準則，我們可以用閉形式解的方式正確地解析出訊號源電偶極方向，進而有效的決定對應各個位置的空間濾波器。我們的方法可以計算出相關性分布圖，從這個圖可以看出與參考區域有顯著相關性的腦部區域。

實驗證明了我們的方法確實可以正確的計算出腦部中有相關活動的區域。與過去傳統的腦部定位方法不同的是，我們專注在找出有著與參考訊號類似的時序訊號特徵的腦部皮質區域。除此之外，我們也將方法應用到實際由人腦量測的實驗證明我們方法的可行性。在鏡像神經元實驗中，大多我們找出有相關性的區域都曾在之前情緒處理、臉部感知和鏡像神經原系統的研究中發現。除此之外，我們還可以提供這些與神經互聯網相關的區域在時間上的資訊。

簡言之，我們提出的方法是利用腦磁波來研究腦部活動間的相關性。並建立一個腦部活動動態的時空造影與顯示系統。使用者給定一個神經網路中的區域來當作參考的區域，我們的方法可以推估在每個時間點與參考的區域相關的區域分布情形，進而揭露出這個時間網路的活動情況。

## Abstract

It has been widely accepted that neurons in the human brain collectively have synchronous patterns of activities. The past findings have suggested that temporal correlation may relate to the communications between the distributed areas. There are some studies in magnetoencephalography and electroencephalography that analyze the functional connectivity between cortical areas using the oscillatory features of neuronal activity. However, temporal dynamics of neuronal activities is generally consisted of cross-frequency components. Therefore, it is also important to directly investigate the functional connectivity as well as general synchronization.

In this thesis, we have proposed a beamformer-based imaging method of correlated brain activities that can reveal the neural network with similar temporal patterns for information exchange. The method can identify the correlation distribution referred to a specified position, called the reference region. In principle, we can apply our method on all pairs of grid points to identify all possible neural networks of correlated activities.

Our method exploits a maximum-correlation criterion that maximizes the significant level of correlation between the reference region and the entire brain volume. The maximum correlation criterion helps to analytically and accurately determine the dipole orientation in a closed-form manner and thus determine the spatial filter very efficiently for each position. The correlation map can be calculated to reveal cortical regions with significant similarity to the reference position in the brain.

The experiments with simulation data demonstrated that our method can accurately determine the correlated regions. Different from the conventional source localization method, we focus on the areas which have the similar temporal patterns with the reference signal. We demonstrated the applicability of the proposed method on real data. In the mirror neuron experiment, most of the regions we revealed are reported by the previous findings of emotional processing, face perception and the mirror neuron system. Moreover, we can provide the time information about when these regions are correlated to the neural network.

In summary, the proposed method can be used to directly study dynamics of correlation brain areas based on electromagnetic recordings of brain activities. Given the reference region as one of the areas in the neural network, our method can estimate the correlated regions at each time point and thus reveal the dynamic behavior of the neural network.

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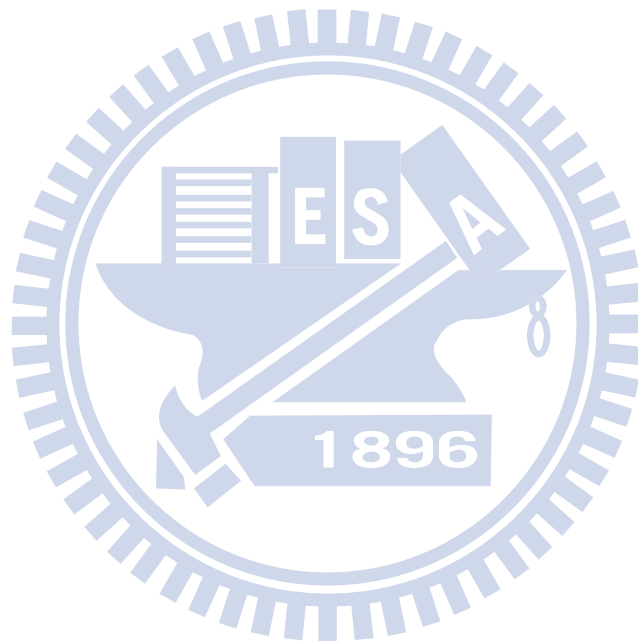




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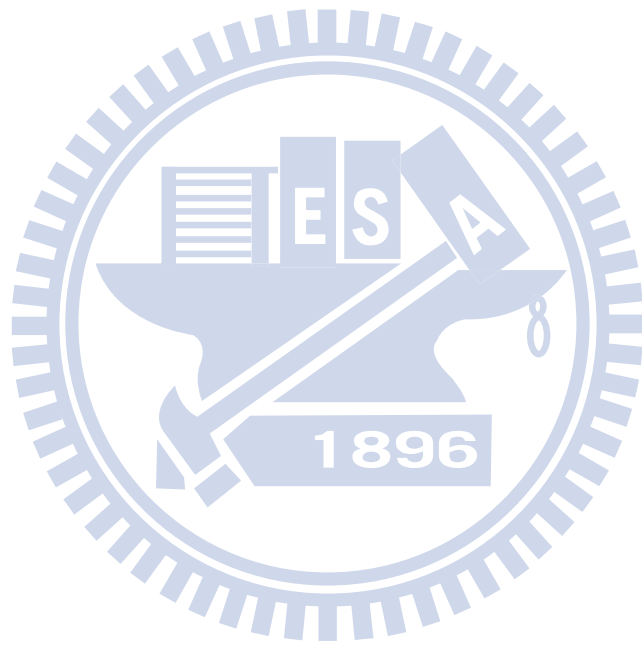
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# **Chapter 1**

## **Introduction**



## 1.1 Correlated Brain Activities

The brain is the most important component of human to coordinate the other parts of human body, and it is the center of the human nervous system and is the most complex organ in any creature on earth. The human brain has been estimated to contain  $10^{12}$  neurons, of which about  $10^{11}$  are cortical pyramidal cells. These cells pass signals to each other via around  $10^{15}$  synaptic connections [1]. Human brain is often analogized with the most powerful computer, which is compared as ‘computer’ capable of processing  $10^{12}$  Gigabits of ‘information’ per second [2]. At the end of the 18th century, the electric brain signal was found. When we perform a task, the neurons at corresponding cortex activate. The entire excited neuron can be thought of as a battery, and the potential difference causes a current flow, therefore the information interchange between the neurons. As neurons become active, they induce changes in blood flow and oxygenation levels.

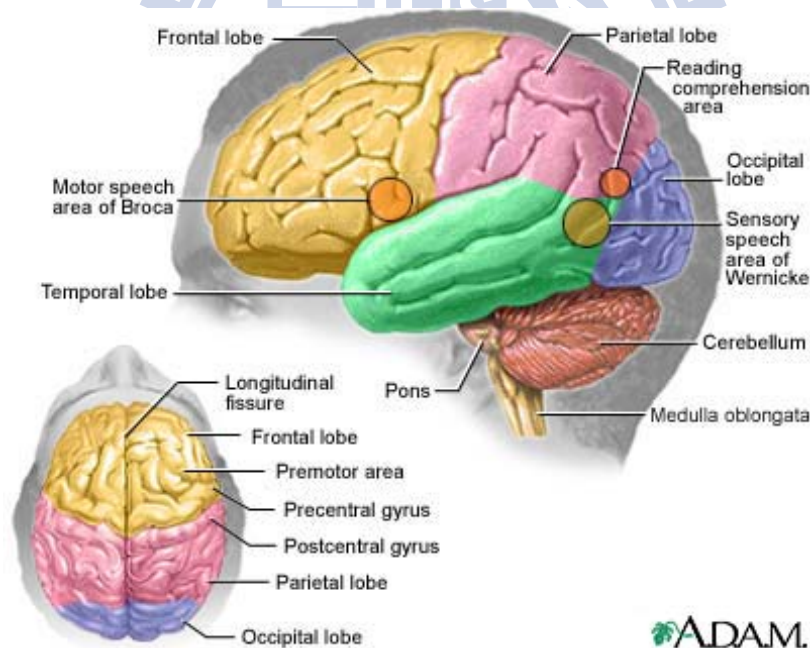


Figure 1.1: The major areas of the human brain - frontal lobe, partial lobe, occipital lobe and temporal lobe.

Our brain can be separate to several parts according to their anatomical structure or the

function which were suggested by past findings. It can be separated to four major area which have one or more specific functions. The major separation is frontal lobe, parietal lobe, occipital lobe and temporal lobe as Figure 1.1. The function of the frontal lobe is mainly about thinking, planning, and central executive function, motor execution. Then the function about parietal lobe is known as a somatosensory perception, integration of visual and somatospatial information. And the temporal lobe is charged about the language function, auditory perception and is involved in long term memory and emotion. The last, the occipital lobe work for visual perception and processing.

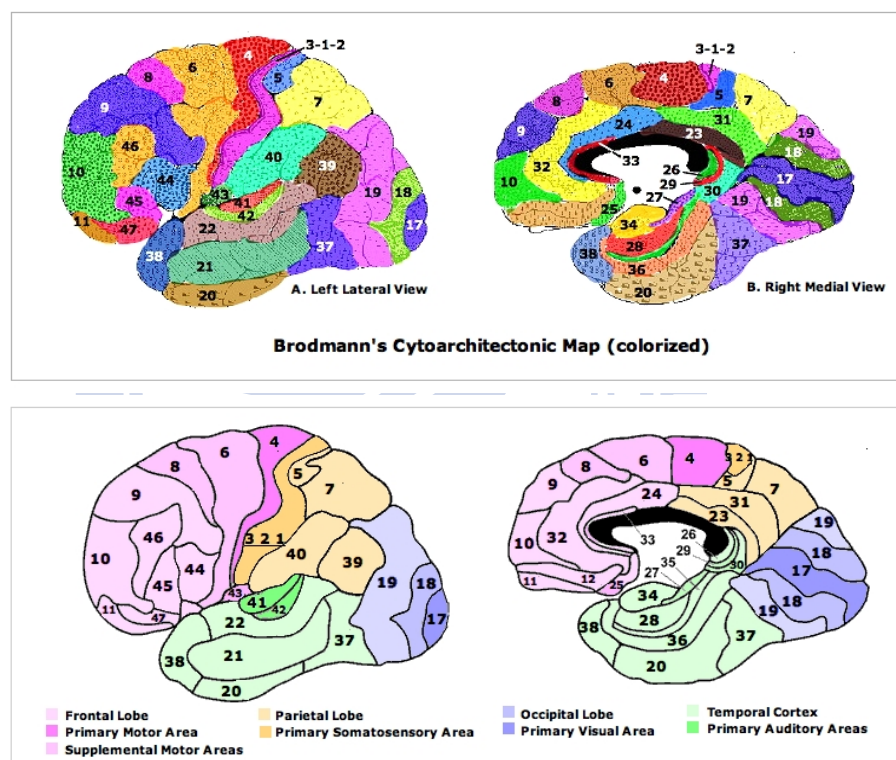


Figure 1.2: The broadmann areas of the lateral and medial side of human brain.

Those major areas introduced above are separated in rough. One of the most common separation is brodmann area as Figure 1.2. It was defined by Korbinian Brodmann. The human brain is separated to 47 areas according to the organization of neurons. However many studies analyze the function of each partition. For example, the brodmann area 45 is well-known broca area which is responsible for speech production.

Even many studies have revealed the functions of the partitions of brain, and traditional research has focused on how neurons represent and the mechanisms. However, human's activities can't accomplish by only activate dependently at just one, two specific areas with one or two times can accomplish the activities. It need the communication between neurons, no matter local communication or long-rance communication, to accomplish a task, even the simple task in our opinion like lifting our finger. The precise coordination of many brain areas is one of the important reasons why our brain own such amazing processing capabilities.



Figure 1.3: Different features are processed by deferent location of the brain, then the brain combine the information to a perception.

For example, the past finding has suggested a so-called "binding problem" that is the problem of combining different features of an object, which are represented in different location in the brain as the Figure 1.3. For multiple objects, it is a particularly complex problem for binding the right features of each object to a representation [3–5]. On the other word, the binding problem is about feature integration, perceptual segmentation, attention, memory, motor control, sensorimotor integration, language processing and logical inference [6]. To handle a cognitive function or perception of and action in a complex environment require the parallel processing of information related to different objects or events. Therefore, neural communication is exiting and important [7].

However, what is the mechanism of the binding problem, or how neuron communicate? Given that the activity evoked by the features comprising an object is distributed,

some mechanism is necessary to identify the members of a representation as belonging together and to distinguish them from other representations that may be present at the same time. What is the mechanism of the binding problem, or how neurons communicate would distinguish it from all other neuronal activity present simultaneously in the cortical network?

The past findings have suggested that temporal correlation may relate the communications and the information flow between the distributed areas [8]. The temporal correlation hypothesis proposes that neural assemblies consist of active neural units that are grouped together based on temporal correlation [9–11]. The temporal binding is that signals of neurons that are to be grouped together are correlated in times. It has been suggested that the binding problem may be solved by a mechanism which exploits the temporal aspects of neuronal activity [9]. The synchronization phenomena predicted by temporal binding hypothesis have been documented for several years [6, 11]. In both cortical and subcortical centers, neurons can synchronize their discharge with a precision in the millisecond range [6, 11–13] in sensory-motor system and perceptual and cognitive functions.

Synchronization includes oscillation, phase synchronization and general synchronization where general synchronization is a broad synchronization. Oscillation is a common approach toward modeling such temporal binding to group the neural assemblies. The dynamical linking of different neural structures via oscillatory coupling was demonstrated first by animal experiments [13]. It has also been noticed that responses often exhibit an oscillatory patterning which is best revealed by recording jointly the activity of several adjacent cells [14].

Recording the activity of neurons, it requires electrodes to be inserted through the skull into the brain. Such electrodes can record extracellular single-neuron activity, multi-unit activity and local field potential (LFP). Single- and multi-unit activity reflects the action potentials. LFPs represent the aggregate activity of a population of neurons located close to the electrode (spatial average across many neurons) as shown in Figure 1.4, consistent effects across a local population of neurons are enhanced [7, 15, 16]. For several years, many animal studies report the synchronization phenomena at single neural or LFP levels [6].

On the contrast to invasive modalities, there are several ways to study on brain, through noninvasive imaging of the electrophysiological, hemodynamic, metabolic, and neuro-

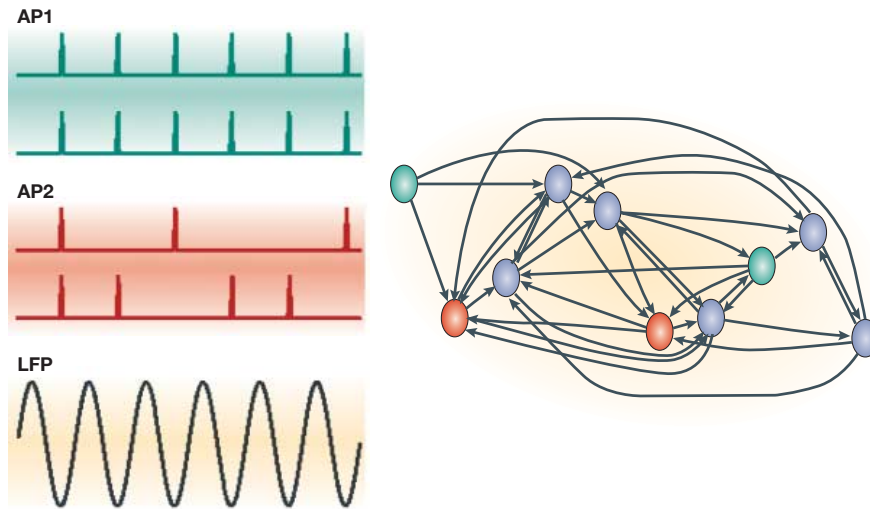


Figure 1.4: Action potentials are AP1 and AP2, and local field potentials (LFPs) are LFP which represent the spatial average of a populations of neurons (right panel) [15].

chemical processes, instead of anatomizing. ‘Noninvasive’ means without physical harm. There are four major non-invasive modalities, which are Magnetoencephalography (MEG), Electroencephalography (EEG), functional Magnetic Resonance Imaging (fMRI) and Near-Infrared Reflectance Spectroscopy (NIRS). These techniques record a spatial summation of LFPs [15].

The functional magnetic resonance imaging (fMRI), measures blood oxygen level dependent (BOLD) component of the hemodynamic response that is associated with local neural activity with spatial resolution as high as 1-3 mm. Several studies shows some evidence the correlation between LFP and BOLD, and this evidence indicates that the firing activity of a neuronal population will, in general, be proportional to the BOLD response [16]. Therefore, functional magnetic resonance imaging (fMRI) measure the spatial summation of LFPs. Even though it is a very promising approach to investigate the neural activity and the cortico-cortical correlation. However, the temporal resolution is insufficient to observe the details of the communications while the temporal resolution is limited by the relatively slow hemodynamic response, approximately 1s [17].

Another popular non-invasive technique, the scalp MEG/EEG/event-related potential



(ERP), is also thought to reflect the summed electrical effects of excitatory synaptic neurotransmission in large populations of neurons. MEG and EEG are two complementary techniques that measure the magnetic induction outside the head and the scalp electric potential those produced by the neuron activities inside the brain. Therefore, the character of higher temporal resolution compared to fMRI allows the studies of the dynamics of neuron network on the order of tens of milliseconds. These techniques non-invasively record the neural activity at high temporal resolution; Therefore, they are a proper modality to analyze the neural communication at cortical level.

However, the analysis of neural communication at cortical level based on non-invasive MEG/EEG need some steps. We introduce the background knowledge in later section 1.2 and then introduce how to estimate the cortical neural activity.

## 1.2 Magnetoencephalography

### 1.2.1 Background

At the end of the 18th century, the electric brain signal was found. When we perform a task, the neurons at corresponding cortex activate. The entire excited neuron can be thought of as a battery, and the potential difference causes a current flow, therefore the information interchange between the neurons. As neurons become active, they induce changes in blood flow and oxygenation levels, which is imaged by fMRI. fMRI can monitor the hemodynamic changes with spatial resolution as high as 1-3 mm; however temporal resolution is limited by slow hemodynamic changes. Therefore, fMRI has poor temporal resolution compared with MEG and EEG.

MEG and EEG are two complementary techniques that measure the magnetic induction outside the head and the scalp electric potential those produced by the neuron activities inside the brain. Therefore, the character of higher temporal resolution compared to fMRI allows the studies of the dynamics of neuron network on the order of tens of milliseconds.

Nevertheless, low signal to noise ratio (SNR), and inherent ill-posed problem are two major difficulties in the studies of brain functionality by using modality of MEG and EEG. First, electrical brain signal is very tiny compared to the environmental noise. Typical EEG

scalp voltages are on the order of tens of microvolts, and characteristic magnetic induction produced by neural currents is extraordinarily weak, on the order of several tens of femtoTeslas. Therefore, MEG measure induced magnetic field via superconducting quantum interference devices (SQUIDs), a highly sensitive amplifier, inside a magnetically shielded room. So, compared to EEG, MEG has higher signal to noise ratio (SNR). Second, the recording of MEG and EEG are induced by sources distributed the whole head. Even with infinite MEG/EEG sensors, a non-ambiguous solution to source localization of the neuronal activities inside the brain would be possible, let alone the number of electrodes of MEG and EEG sensors usually ten or a few hundreds.

Given the recording of MEG/EEG, the inverse problem involves estimation of the properties of the current sources within the brain that produced these signals. We can acquire the concept of inverse problem from the Bayesian statistic framework.

$$P(x|y) = \frac{P(x)P(y|x)}{P(y)} \quad (1.1)$$

$P(x|y)$  denotes the conditional probability of  $x$  given  $y$ , also called the posterior probability because it is derived from or depends upon the specified value of  $y$ .  $P(y|x)$  is the conditional probability of  $y$  given  $x$ .  $P(y)$  is the prior or marginal probability of  $y$ , and acts as a normalizing constant.  $P(x)$  is the prior probability or marginal probability of  $x$ . It is 'prior' in the sense that it does not take into account any information about  $y$ . Apply to the MEG inverse problem and let  $x$  represent the distribution of the sources inside the brain and  $y$  represent the recordings from the MEG/EEG sensors.  $P(x|y)$  can describe the inverse problem that to get the distribution of the sources while given MEG recordings. From the Bayesian equation, we can simplify the inverse problem as the form of the right side of the equal sign if we want to know parameters of the source distribution from the recordings. Therefore,  $P(y|x)$  is the key to the solution.  $P(y|x)$  describes the probability of the recordings when given parameters of the source distribution and that is the forward problem [18, 19].

The inverse problem is to estimate the neuronal activities in the brain based on MEG/EEG recordings [17]. As mention above, involving estimation of the properties of the signal induced by the current source inside the brain help to solve inverse problem. Before we can make such an estimate, we must first understand and solve the forward problem, in

which we compute the scalp potentials and external fields for a specific set of neural current sources. Therefore, the inverse problem can be transformed to the form Eq 1.1. But the inverse problem is an inherent ill-posed problem which has infinite solutions. Lots of algorithms with difference constraint had been proposed to solve the inverse problem.

### 1.2.2 Related work of the source activities at cortical level

Approximations such as the equivalent current dipole (ECD) model [17, 18, 20, 21], assumptions such as a fixed number of dipoles within an epoch is obtained by the least squares source estimation which is one of the most widely-used methods. It finds out the best solution by nonlinear search to minimize error between the induced electromagnetic field by ECDs and the MEG/EEG recordings. However, it is difficult to decide the prior number of the sources and it may trap in local minimum. Multiple Signal Classification (MUSIC) [22–24] is another kind of method which can avoid trapping in local minimum through scanning the region of interest and determining the locations with peak projections of forward models in the signal subspace. Minimum Norm Estimation (MNE) [25–27] will estimate the brain activities on the cortical surface, so it sets dipole orientation either to be on the tangential plane or normal to the local cortical surface. But the major problem is that because of the minimum norm constraint, the result will tend to emphasize the cortical regions closer to the MEG sensors [28].

Recently, beamformer is one of the most promising solutions to the inverse problem. [29]. Beamformer performs a spatial filter on recordings of MEG/EEG to filter out the signal at the targeted location, acting as a virtual sensor to measure the signal with a specific orientation. Beamformer can obtain the activities of the targeted location and suppress the influence contributed from other sources by imposing the unit-gain constraint and minimum variance criterion. Given a unit dipole with specified position and orientation, we can calculate a spatial filter from the data covariance matrix and the lead field of the dipole. The neuronal activity of the dipole at the specified position can be obtained by applying this spatial filter on the recordings of MEG/EEG. By repeating the procedure for each position inside the brain, we can obtain the neuronal activities of the whole brain.

Two kinds of beamformer, vector-type beamformer [30] and scalar-type beamformer,

have been studied. [31, 32]. The vector-type beamformer decomposes the dipole orientation into three orthogonal components, each one with a fixed orientation. Every component has its own spatial filter calculated individually. Linearly constrained minimum variance (LCMV) [30] is one of the vector beamformers and it sums the results probed on three directions. Only one spatial filter is used for each specific position in scalar-type beamformer. Scalar-type beamformer determines the direction by maximizing the pseudo Z value. Compared to vector-type beamformer, the major advantage of scalar-type beamformer is that the activity distribution is more focal and higher signal-to-noise ratio [32,33]. But using vector-type beamformer is more efficient to calculate the spatial filter because all the procedures involved are deterministic.

In the scalar-type beamformer, only when the dipole orientation is accurate, the effective spatial filter can be calculated. Therefore, it is essential to accurately determine the dipole orientation [33,34]. One way to determine the dipole orientation is to use the normal of cortical surface [34]. But the surface reconstructed very difficultly and the reconstruction deviation will decrease the accuracy of dipole orientation. Only when the estimation error is smaller than ten degrees, the spatial filter determined by the cortical surface normal is feasible [34]. Another way to determine the dipole orientation is to maximize the pseudo Z in the synthetic aperture magnetometry (SAM) method [31] by exhaustively evaluating all the possible candidates. Nonlinear optimization method is more efficient but only can guarantee the suboptimal solution.

Recently, a novel spatial filtering technique, called the maximum contrast beamformer (MCB), was proposed by Chen et al [35]. This MCB method has the advantages of good output SNR and focal activity distribution as in scalar beamformers, while the dipole orientation is determined accurately and efficiently in a close-form solution. The method exploits a maximum-contrast criterion that maximizes the ratio of the reconstructed neuronal activities in the active state to those in the control state and helps to analytically and accurately determine the dipole orientation in a closed-form manner.

The below is the result of MCB algorithm. There are three simulated sources and their strength and frequency are shown as Figure 1.5 (b), three different sinusoidal signals. Their locations in the cortical area are shown as Figure 1.5 (a). The electromagnetic mapping of brain activities calculated by MCB is shown as Figure 1.5 (c). It can be demonstrated that

the three sources are correctly displayed by comparing Figure 1.5 (a) to Figure 1.5 (c).

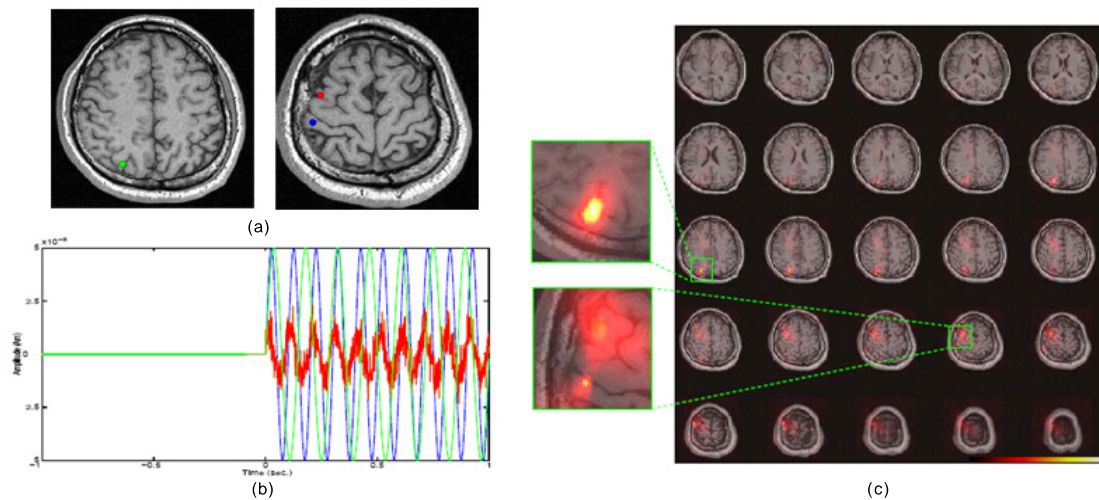


Figure 1.5: This figure shows the MCB result of the simulated data. (a) is the ground truth of this simulated data. (b) is their waveforms. And (c) is the solution to inverse problem calculated by MCB algorithm. [35]

### 1.3 The synchronization phenomena in MEG

As mention in section 1.1, MEG and EEG are non-invasively record a spatial summation of local field potentials with a temporal resolution of millisecond. For several years, most MEG/EEG studies about oscillation for the binding problem analyze at sensor level [36–44]. For example, sleep is conventionally divided into several distinct phases on the basis of the EEG. During slow-wave sleep (SWS), dreaming typically does not occur and the scalp EEG is dominated by high-amplitude, low-frequency oscillations. Most vivid visual dreams take place during the rapid eye movement (REM) phase of sleep, when the scalp EEG shows similar patterns of activity to the waking state, being characterized by high-frequency, low-amplitude signals [45].

Some studies in Magnetoencephalography (MEG) and electroencephalography (EEG) have analyzed the functional connectivity between cortical areas with the oscillatory feature

of neuronal activity using the analysis tool, DICS [15]. In 2001 Gross et al. proposed "dynamic imaging of coherent sources (DICS)" method [46] which image the coherent brain areas using a frequency domain implementation of beamformer inverse algorithm. It can be used for imaging the spatial distribution of power and coherence to a reference signal in a narrow and chosen frequency bands. And the method determines the source orientation by the eigenvector of cross spectral density. The reference signal can be electroencephalographic recording of muscle activities or the activities at a reference area in the brain. And through the phase synchronization analysis can provide the latency information.

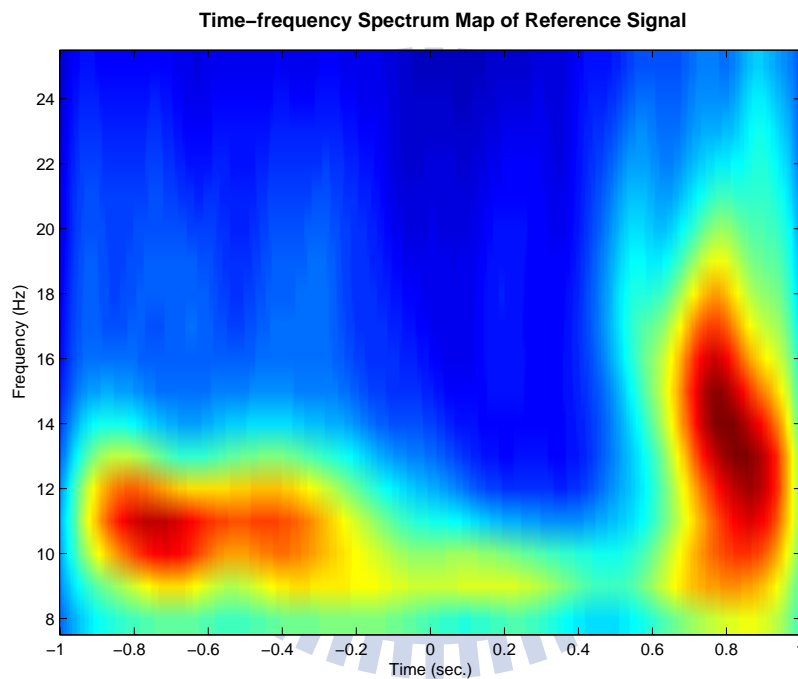


Figure 1.6: The time-frequency map of the estimated sources by maximum contrast beamformer in the experiment of lifting left index finger [35]

However, the method DICS calculate the coherent map in a narrow frequency band. Some tasks may activate on specific frequency band like slow-wave sleep stage, but still some tasks would activate on different frequency band as Figure 1.6. The Figure 1.6 is the time-frequency map of the signal at the significant position calculated by maximum contrast beamformer [35]. Naturally, the neural communication might include multi-frequency

information. It is necessary to develop a new analysis tool to investigate the general synchronization between the cortices directly.

Besides, the dipole orientation estimation is a crucial issue in scalar-type beamformer method [32,33,35]. The spatial filter with an inaccurate orientation fails to correctly estimate the neuronal activities (see the [35] for the theory and the experiment). Therefore, the accurate dipole orientation of the spatial filter to image the cortico-cortical interaction in the brain is necessary. In summary, to study the functional connectivities network which communicate with temporal dynamics needs a new, accurate and effective tool.

## 1.4 Thesis scope

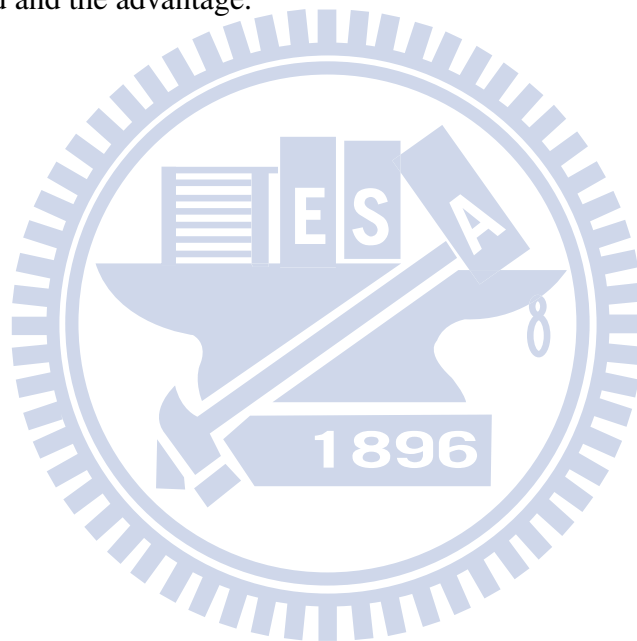
In this thesis, we propose a beamformer-based imaging method of correlated brain activities that can study the studies of the temporal interaction between different brain cortices by imaging correlation and can reveal the similarity signal pattern. The method can identify the correlation regions to a specific brain region, called reference region. In principle, we can obtain the neural network to apply the method on all pairs of grid points for significant correlation for identifying the neural network of correlated brain region.

Our method exploits a maximum-correlation criterion that maximizes the significant level of correlation between the reference region and other regions inside the brain. Then, the output is the imaging of the brain activities correlated to the reference region. Our method can analytically and accurately determine the dipole orientation in a close-from manner and thus determine the spatial filter efficiently for each position. The correlation map can be calculated to reveal cortical regions with significant similarity to the reference position in the brain.

## 1.5 Thesis organization

In Chapter 1, we introduced the neural communication phenomena in our brain, the background knowledge of MEG/EEG, the source localization method and the coherence source localization. In later chapter, the method detail would be describe including the

algorithm of beamformer method and the output of our method and the optimal solution of the dipole orientation. In Chapter 3 we showed the experiment setting, preprocessing, and results. In Chapter 3.1, the experiment material, the method of generating simulation data, the paradigm of mirror neuron experiment would be describe. In Chapter 3.2, the process of data preprocessing would be depicted. Then, the experiment results of the simulation data and real data from the mirror neuron experiment are in Chapter 3.3. In Chapter 4, we discussed the results in previous chapter. In Chapter 4.1, we discussed the results of the simulation data and the merit of proposed method. Then the results of the real data from mirror neuron experiment would be discussed in Chapter 4.2. In the last Chapter 5, we concludes our method and the advantage.





## **Chapter 2**

### **Method**



## 2.1 Scalar beamformer

The Sarvas forward model estimate the recordings when given some dipoles in the brain. If there are  $k$  dipoles in the brain, at a certain instance, the estimated recordings  $\mathbf{m}$  at time point  $t$  equals the summation of the productions of each gain matrix and its corresponding dipole moment at time point  $t$ :

$$\mathbf{m} = \sum_{r=1}^k \mathbf{L}_r \mathbf{d}_r \quad (2.1)$$

where  $\mathbf{d}_r$  locating at  $\mathbf{r}$  is the dipole moment and  $\mathbf{L}_r$  is the corresponding gain matrix which can be derived from the forward model. Then,  $\mathbf{m}$  is the summation of the effects by every source dipoles in the brain. Without of losing generality, we represent the source dipole in the Cartesian coordinate system such that  $\mathbf{d}_r$  is a  $3 \times 1$  vector and its elements represent  $x$ ,  $y$ ,  $z$  components of  $\mathbf{d}_r$  respectively:

$$\mathbf{d}_r = \begin{pmatrix} d_{rx} \\ d_{ry} \\ d_{rz} \end{pmatrix}$$

and therefore,  $\mathbf{L}_r$  is a  $N \times 3$  matrix.

Then, we separate the dipole moment  $\mathbf{d}_r$  into orientation  $\mathbf{q} = \mathbf{d}_r / \|\mathbf{d}_r\|$  and magnitude parts  $s = \|\mathbf{d}_r\|$ . The Equation 2.1 derive to

$$\mathbf{m} = \sum_{r=1}^k \mathbf{L}_r \mathbf{d}_r \quad (2.2)$$

$$= \sum_{r=1}^k \mathbf{G}_r(\mathbf{d}_r / \|\mathbf{d}_r\|) \|\mathbf{d}_r\| \quad (2.3)$$

$$= \sum_{i=1}^k \mathbf{L}_r \mathbf{q} s. \quad (2.4)$$

Therefore, we define a unit dipole with parameter  $\theta = \{\mathbf{r}, \mathbf{q}\}$ , where  $\mathbf{r}$  is the dipole location and  $\mathbf{q}$  is the dipole orientation, and  $\mathbf{l}_\theta$  is the lead field vector of the unit dipole. The lead field vector is the predicted measurement of  $N$  MEG sensor with the unit dipole with  $\mathbf{q}$  orientation.  $\mathbf{l}_\theta$  is calculated by

$$\mathbf{l}_\theta = \mathbf{L}_r \mathbf{q} \quad (2.5)$$

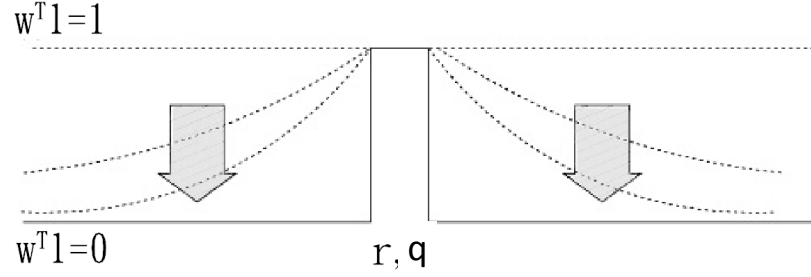


Figure 2.1: With unit-gain constraint, the spatial filter at the location of the target source  $(\mathbf{r}, \mathbf{q})$  will preserve the most strength and impress the contribution from other sources by minimum variance constraint.

The MEG recordings  $\mathbf{m}(t)$  is decomposed into three components

$$\begin{aligned}\mathbf{m}(t) &= \mathbf{m}_\theta(t) + \mathbf{m}_\delta(t) + \mathbf{n}(t) \\ &= \mathbf{m}_\theta(t) + \mathbf{m}_n(t)\end{aligned}\quad (2.6)$$

where  $\mathbf{m}(t) = \mathbf{l}_\theta s_\theta(t)$  denotes the magnetic field originated from the source with parameter  $\theta$ ,  $\mathbf{m}_\delta(t)$  denotes the magnetic field originated from all other sources,  $\mathbf{n}(t)$  is the noise, and  $\mathbf{m}_n(t)$  denotes the combination of the noise and the magnetic recordings originated from all other sources.

Scalar MEG beamformer performs spatial filtering on recordings to set apart the signals of the location of interest and the others. For a dipole source with parameter  $\theta$ , the output signal of the beamformer  $y(t)$  is acquired by

$$y(t) = \mathbf{w}_\theta^t \mathbf{m}(t) \quad (2.7)$$

which approximates the source signal  $s_\theta(t)$  of the dipole. To achieve this goal, the spatial filter  $\mathbf{w}_\theta$ , a  $N \times 1$  column vector, can be decided by the unit-gain constraint and minimum variance. With these constraints, the strength of output signal  $y(t)$  can be identical with the source strength  $s_\theta(t)$  while nulling the contribution of the other sources. We can get the concept about unit-gain and minimum variance constraints from Figure 2.1.

As the following equation,

$$\begin{aligned}
y(t) &= \mathbf{w}_\theta^t \mathbf{m}(t) \\
&= \mathbf{w}_\theta^t \mathbf{m}_\theta(t) + \mathbf{w}_\theta^t \mathbf{m}_n(t) \\
&= s_\theta(t) \mathbf{w}_\theta^t \mathbf{l}_\theta + \mathbf{w}_\theta^t \mathbf{m}_n(t) \\
&= s_\theta(t) + \mathbf{w}_\theta^t \mathbf{m}_n(t)
\end{aligned} \tag{2.8}$$

the source signal  $s_\theta(t)$  can retrieve by applying unit-gain constrain,  $\mathbf{w}_\theta^t \mathbf{l}_\theta = 1$ , and we still have to reduce the leakage of all other sources,  $\mathbf{w}_\theta^t \mathbf{m}_n(t)$ . This is equivalent to minimize the variance of  $y(t)$ . Therefore, the optimal spatial filter  $\hat{\mathbf{w}}_\theta$  can be calculated by

$$\hat{\mathbf{w}}_\theta = \arg \min_{\mathbf{w}_\theta} E\{|y(t) - E\{y(t)\}|^2\} + \alpha \|\mathbf{w}_\theta\|^2 \quad \text{subject to} \quad \mathbf{w}_\theta^t \mathbf{l}_\theta = 1 \tag{2.9}$$

where  $E$  represents the expectation value and  $\alpha$  represents the parameter of Tikhonov regularization. Here  $\alpha$  is a parameter to restrict the norm of  $\hat{\mathbf{w}}_\theta$ , corresponding to the shape of beamformer spatial filter. Substituting the Equation (2.8) into Equation (2.9), we can solve the equation by Lagrange multipliers and obtain the optimal solution of  $\hat{\mathbf{w}}_\theta$

$$\begin{aligned}
\hat{\mathbf{w}}_\theta &= \arg \min_{\mathbf{w}_\theta} \mathbf{w}_\theta^t (\mathbf{C} + \alpha \mathbf{I}) \mathbf{w}_\theta \quad \text{subject to} \quad \mathbf{w}_\theta^t \mathbf{l}_\theta = 1 \\
&= \frac{(\mathbf{C} + \alpha \mathbf{I})^{-1} \mathbf{l}_\theta}{\mathbf{l}_\theta^t (\mathbf{C} + \alpha \mathbf{I})^{-1} \mathbf{l}_\theta}
\end{aligned} \tag{2.10}$$

where  $\mathbf{C}$  is the  $N \times N$  covariance matrix of the MEG recordings  $m(t)$  and  $\mathbf{I}$  is the  $N \times N$  identity matrix.

## 2.2 Imaging of the brain activities correlated to the reference signals

For each dipole source in location  $\mathbf{r}$  with fixed orientation  $\mathbf{q}$ , we can use equation Equation 2.10 to obtain the spatial filter, and further compute the dipole activities by using equation Equation 2.7. Once we apply the procedure mentioned above individually to each position of head region, we can acquire the activities of whole head.

Although there are many kinds of activities in brain, we are only interested in the brain activities which correlating to the source signals at reference region. But through the spatial filter calculated from Equation 2.10 we may obtain strong non-interested activities in the filtered outputs. What we focus on is the correlation level to the reference signal. Therefore, we proposed a method to calculate the imaging of the brain activities correlated to the targeted signals. In contrast to the conventional Beamforming methods which provide statistical maps to reveal the regions having significant neuronal activities, we calculated the correlation between source signal and reference signal.

$$\begin{aligned}
 R_\theta &= \frac{E\{|\mathbf{w}_\theta^t \mathbf{m}_c(t) \mathbf{a}(t)|\}}{E\{|\mathbf{w}_\theta^t \mathbf{m}_c(t)|^2\}^{\frac{1}{2}} E\{|\mathbf{a}(t)|^2\}^{\frac{1}{2}}} \\
 &= \frac{\{\mathbf{w}_\theta^t E\{|\mathbf{m}_c(t) \mathbf{a}(t)|^2\} \mathbf{w}_\theta\}^{\frac{1}{2}}}{\{\mathbf{w}_\theta^t \mathbf{C}_m \mathbf{w}_\theta\}^{\frac{1}{2}} E\{|\mathbf{a}(t)|^2\}^{\frac{1}{2}}} \\
 &= \frac{\{\mathbf{w}_\theta^t \mathbf{C}_{am} \mathbf{C}_{am}^t \mathbf{w}_\theta\}^{\frac{1}{2}}}{\{\mathbf{w}_\theta^t \mathbf{C}_m \mathbf{w}_\theta\}^{\frac{1}{2}} E\{|\mathbf{a}(t)|^2\}^{\frac{1}{2}}} \tag{2.11}
 \end{aligned}$$

$\mathbf{a}(t)$  is the reference signal at the reference region which is chosen by users. Appropriate strategies for the selection of the reference region are introduced and illustrated in Chapter 2.4. The  $\mathbf{C}_{am}$  is the  $N \times 1$  cross-covariance matrix between MEG recording  $\mathbf{m}(t)$  and reference signal  $\mathbf{a}(t)$ . And  $\mathbf{C}_m$  is the  $N \times N$  covariance matrix. Therefore, the value of  $R_\theta$  indicates the significant level of similarity between the dipole activities with parameter  $\theta$  and the reference region at the targeted position  $\mathbf{r}$  with dipole orientation  $\mathbf{q}$ .

There are three covariance matrix involved in the beamformer-based process, that is  $\mathbf{C}$ ,  $\mathbf{C}_{am}$  and  $\mathbf{C}_m$ . The matrix  $\mathbf{C}$  is used to calculate the spatial filter and the time interval of  $\mathbf{m}(t)$  should be large enough to obtain a reliable result. The matrix  $\mathbf{C}_{am}$  is used to calculate the correlation value between the interval of  $\mathbf{m}_c(t)$  and the interval of the reference signal  $\mathbf{a}(t)$ .

## 2.3 Maximum correlation beamformer

The solution of  $\hat{\mathbf{w}}_\theta$  is derived with parameter  $\theta = \{\mathbf{r}, \mathbf{q}\}$ . Because we calculate the activities of whole head by scanning all of the position in the brain, the position parameter

$\mathbf{r}$  is set to be each position. Then we can obtain the correlation level to the reference region in the entire brain.

However, the orientation parameter  $\mathbf{q}$  is difficult to determine. As Chapter 1.3 describe, the accurate dipole orientation  $\mathbf{q}$  of the spatial filter extremely influence the accuracy of the spatial filter. Therefore, instead of exhaustive search, we propose a optimal closed-form solution to decide the dipole orientation. By substituting Equation 2.5 to Equation 2.10, we can separate parameter  $\mathbf{q}$ .

$$\begin{aligned}\hat{\mathbf{w}}_\theta &= \frac{(\mathbf{C} + \alpha\mathbf{I})^{-1}\mathbf{L}_r\mathbf{q}}{\mathbf{q}^t\mathbf{L}_r^t(\mathbf{C} + \alpha\mathbf{I})^{-1}\mathbf{L}_r\mathbf{q}} \\ &= \frac{\mathbf{A}_r\mathbf{q}}{\mathbf{q}^t\mathbf{B}_r\mathbf{q}}\end{aligned}$$

where  $\mathbf{A}_r = (\mathbf{C} + \alpha\mathbf{I})^{-1}\mathbf{L}_r$  and  $\mathbf{B}_r = \mathbf{L}_r^t\mathbf{A}_r$  (2.12)

$\mathbf{A}_r$  and  $\mathbf{B}_r$  are depend only on the parameter position  $\mathbf{r}$ , We determine the optimal dipole orientation  $\hat{\mathbf{q}}$  which can maximize the correlation between the source signal  $s_\theta$  and the reference signal. By substitute Equation 2.12 into Equation 2.11 and maximin the correlation value, we obtain the optimal  $\hat{\mathbf{q}}$ :

$$\begin{aligned}\hat{\mathbf{q}} &= \arg \max_{\mathbf{q}} \left( \frac{(\mathbf{w}_\theta^t \mathbf{C}_{am} \mathbf{C}_{am}^t \mathbf{w}_\theta)^{\frac{1}{2}}}{(\mathbf{w}_\theta^t \mathbf{C}_m \mathbf{w}_\theta)^{\frac{1}{2}} E\{|\mathbf{a}(t)|^2\}^{\frac{1}{2}}} \right)^2 \\ &= \arg \max_{\mathbf{q}} \frac{\mathbf{q}^t \mathbf{A}_r^t \mathbf{C}_{am} \mathbf{C}_{am}^t \mathbf{A}_r \mathbf{q}}{\mathbf{q}^t \mathbf{A}_r^t \mathbf{C}_m \mathbf{A}_r \mathbf{q}} \\ &= \arg \max_{\mathbf{q}} \frac{\mathbf{q}^t \mathbf{P}_r \mathbf{q}}{\mathbf{q}^t \mathbf{Q}_r \mathbf{q}},\end{aligned}$$

(2.13)

in which the term  $E\{|\mathbf{a}(t)|^2\}^{\frac{1}{2}}$  is a scalar so it can eliminated.  $\mathbf{P}_r = \mathbf{A}_r^t \mathbf{C}_{am} \mathbf{C}_{am}^t \mathbf{A}_r$  and  $\mathbf{Q}_r = \mathbf{A}_r^t \mathbf{C}_m \mathbf{A}_r$  are  $3 \times 3$  matrix. The solution of Equation 2.13 is the eigenvector corresponding to the maximum eigenvalue of the matrix eigenvalue of the matrix  $\mathbf{Q}_r^{-1}\mathbf{P}_r$ . Because these two matrices,  $\mathbf{Q}_r$  and  $\mathbf{Q}_r^{-1}\mathbf{P}_r$  are both  $3 \times 3$  matrix, we can solve the matrix inverse problem and the eigne problem in a closed-form manner.

## 2.4 Reference region

In principle, applying the method as above on all pairs of grid points for significant correlation can identify the neural network of correlated brain region; However, it requires large amount of computation. The work can be reduced if we can pick at least one member of the neural network. Picking a suitable reference region is a important issue in our method. Four strategy for selecting the reference regions were listed.

### I. The prior information of physiological

A reference region is defined by prior knowledge from the results of others functional imaging studies or anatomical structures or neural pathways.

### II. The region of significant activities

A reference region is defined from the source area of strongest activities. For example, the peak in the F-value map of maximum contrast beamformer.

### III. The specific signal pattern - independent component

A reference region is defined from the mixing matrix of independent component analysis (ICA). ICA is proposed to solve the problem of blind source separation. It can decompose the input into several independent components, as  $\mathbf{X} = \mathbf{MS}$ . Given input  $\mathbf{X}$ , it can calculate  $\mathbf{S}$ , which contains independent components, under the assumption that the estimated sources  $\mathbf{S}$  are as statistically independent as possible.  $\mathbf{M}$  is the mixing matrix.

Applying ICA on MEG recordings, it will decompose some independent component. Each column of the mixing matrix is the topography of the respective independent component. We can choose the independent component as reference signal according to the topography, and calculate the cortico-sensor correlation.

## 2.5 Studying the interactions

We can calculate for significant correlation between other brain areas and the reference region through the introduced analyze method which derive the spatial filter as Equation 2.12, calculate the correlation map through Equation 2.11, and obtain the optimal dipole orientation through the maximum criterion as Equation 2.13.

If we want to analyze the dynamic correlation map of the neural network, we can just choose a short time interval of the reference signal for calculating because the reference region may involve in the neural network just a short time. Besides, the reference signal  $\mathbf{a}(t)$  and part of the MEG measurement  $\mathbf{m}_c(t)$  can choose different time interval to calculate. For example, we choose 100 to 200 ms of the source signal as the reference signal and then choose 0 to 100 ms of the MEG measurement  $\mathbf{m}(t)$  as the  $\mathbf{m}_c(t)$  to calculate the correlation map. Therefore, we can calculate the significant correlation between a time interval of the reference region and different time intervals of the other brain areas. Furthermore, we can obtain the sequential correlation map to the reference region through the successive measurement segment which are overlapping by the user define length.

In summary, to analyze the functional connectivity between the cortices, we can follow the progress as shown in Figure 2.2. At first, user has to choose a reference region which can refer our advise in Chapter 2.4. Second, user can use source localization tool to calculate the source signal of the reference region or use the ICA component, and define a time interval as the reference signal. Third, user apply our method to a segment of MEG measurers calculate the correlation distribution to the reference signal in the entire brain. Then user repeat the third step until all the segments of data have calculated so that user can have the dynamic correlation map to the reference region.



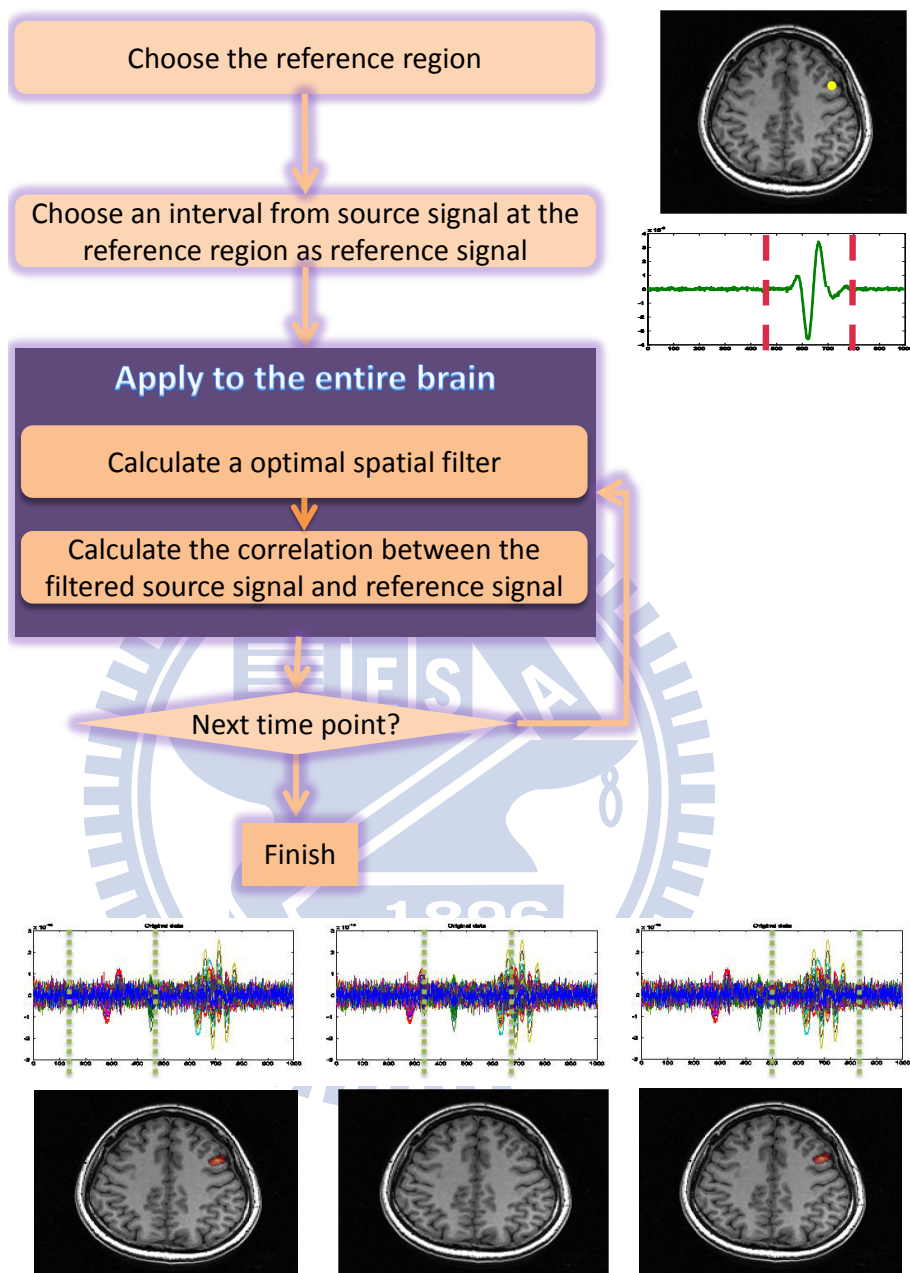


Figure 2.2: First step, user has to choose a reference region. Second step, user can use source localization tool to calculate the source signal of the reference region or use the ICA component, and define a time interval as the reference signal. Third step, user apply our method to a segment of MEG measurers calculate the correlation distribution to the reference signal. Then user repeat the third step until all the segments of data have calculated so that user can have the dynamic correlation map to the reference region.



## **Chapter 3**

### **Experiment Results**



## 3.1 Material

To verify the proposed method in Chapter 2, we need the information of the Anatomical Data and the MEG recordings of the magnitude field. There are two kinds of MEG data, including simulation and the real MEG measurement from the experiment of the happy mirror neuron. We will describe some information of these data in the below statements.

### 3.1.1 Anatomical Data

The Magnetic Resonance Imaging (MRI) images were from the 1.5T GE scanner at the Taipei Veterans General Hospital with  $TR = 8.672$  ms,  $TE = 1.86$  ms,  $FOV = 26 \times 26 \times 10 \text{ cm}^3$ , matrix size =  $256 \times 256$ , slices = 128, voxel size =  $1.02 \times 1.02 \times 1.5 \text{ mm}^3$ .

### 3.1.2 MEG Data

#### Simulations

We simulate the MEG recordings by the forward model in Equation.2.6 with given sources as ground truth and add some dipoles acting as noises. There are two kind of noises, background sources and sensor noises. We simulate background sources as random dipoles with zero-mean Gaussian strength and uniformly distributed in the putative sphere of head model. The variances of sensor noises are estimated from the empty room recordings of the MEG system. We also use 1 kHz sampling rate as sampling frequency of the simulated recordings. Before data analysis, we do preprocessing depicted later in Section 3.2

#### Real MEG measurement

A whole head MEG system at the Taipei Veterans General Hospital (Neuromag Vectorview 306, Neuromag Ltd., Helsinki, Finland) is used for recording of the minute magnetic field generated by electrical activities within the living human brain. The MEG system is placed in a magnetically shielded room and has capability of 306 channels simultaneous

recording at 102 distinct sites, 24 bits analog to digital conversion, and up-to-8 kHz sampling rate which is sufficient to probe the fast dynamic changes inside human brains.

**Experiment paradigm of happy mirror neuron** The study focused on the the roles of mirror neuron system for position emotion. Three condition, observation, imitation and execution, were studied. The stimuli were randomized grayscale photographs of faces, depicting neutral and smile, from Taiwanese facial expression image database (<http://bml.ym.edu.tw/download/html/news.htm>). The experiment paradigm was shown in Figure3.1. In observation condition stimuli had presented for 700 ms with an inter-stimulus interval (ISI) 1300 ms; Imitation and execution condition with ISI 1500 ms, the stimuli had presented for 2000 ms after a rest block consisting of a fixed cross at the center of the screen. However the stimuli in execution condition were neutral face and neutral face with a fixed cross upon the nose.

Twenty four subjects with no neurological and psychiatric disorder participated in the study. The subjects were introduced to observe the face in observation condition. In imitation condition they were asked to follow the facial motion of the stimuli. In execution condition, they had to smile when the stimuli with the fixed cross upon the nose was showed.

The experiment was performed by Hung-Che in brain mapping laboratory of institute of brain science in national yang-ming university.

## 3.2 Data Preprocessing

The brain signal is comparatively small than the environmental noises. Preprocessing for the recordings to enhance the signal to noise ratio (SNR) is necessary so that further processing would be more smooth going [47]. Generally the experiment will be repeated several times to obtain sufficient amount of recordings. we call the recordings at each time as “trial”. The preprocessing steps we use for MEG recording are stated as below. The first step is to find out the abnormal scale recordings and cut them. Because artifacts, body action and eye blinking produce significant noises, compared to the measurement induced by the electric brain signal while experiment. Hence, we can find out the unusual scale recording to reduce artifact noise on MEG/EEG sensor and electric ocular graph (EOG) channels. The second step is to eliminate the sensor noise. By using signal space projection

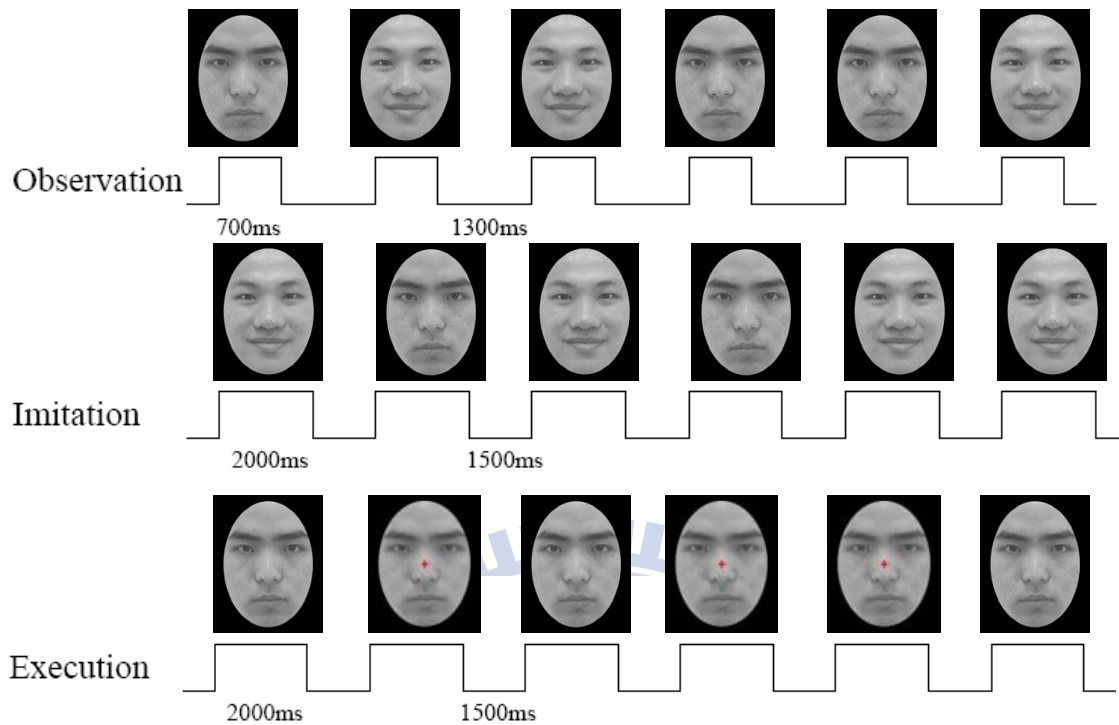


Figure 3.1: The figure was shown the paradigm of happy mirror neuron experiment. The stimuli were face image with random emotion, neutral and happy, on observation and imitation conditions; However, on execution condition, the stimuli were neutral face image as observation and imitation condition and neutral face image with fixed cross upon the nose.

(SSP) [48] we remove the recording those were projected to the individual basis vector of the noise subspace and eliminate from the MEG/EEG measurement. We can obtain the signal space through the noise space which is calculated from emptyroom. By this method, we can transform the measurement to the signal space and reserve them [49]. The third step is to remove unavoidable artifacts such as heartbeat, breath and power line noises. We use bandpass filter to cut them because the artifact of heartbeat and breath is 1 Hz signal, and power line is 60 Hz and its harmonic. The fourth step is to cut down the drift of recordings along with time on each sensor because of the device. By conducting baseline correction, we subtract a baseline estimated by the mean of the recordings at the period which is unaffected by the stimulus, in order to decrease the influence of the noise in the baseline. The preprocessing steps are shown in Figure 3.2

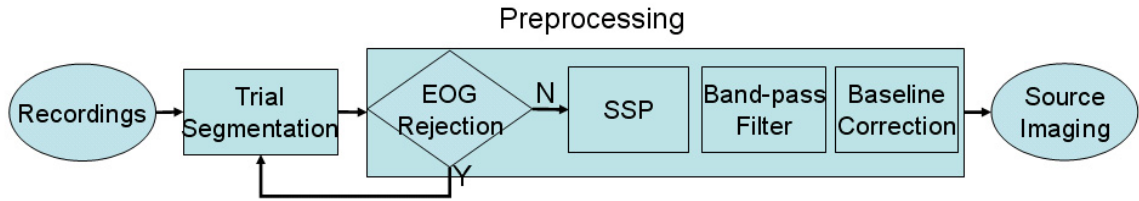


Figure 3.2: This graph shows the all preprocessing steps for MEG recordings. For strengthening SNR, preprocessing for the recordings is necessary. The first step is removing artifacts by finding out the abnormal scale of MEG/EEG recording and EOG channels called artifact rejection. The second step is to eliminate the sensor noise by applying SSP. The next step is applying bandpass filter to cut out the other artifacts which are in specific band like heartbeat and breath and some environmental noises like power line noises. The final step is to conduct the baseline correction to eliminate the drift of recordings. After preprocessing, we can obtain the MEG/EEG recording with higher SNR..

### 3.3 Experiments

We conduct the simulation to validate our method. Each simulation is added background sources with 3000 random dipoles with the standard deviation of 10 nAm. The variance of sensor noises are estimated form the emptyroom recording of the MEG system.

#### 3.3.1 Simulation data 1

In this simulation, we put a 15 Hz sine wave on the ground truth position (as Figure 3.5). Applying the 15 Hz signal sine wave as the targeted signal, the result of our method is shown in Figure 3.4. The correlation map of the estimated source is focal and significant. The peak exactly locate on the location as the ground truth.

#### 3.3.2 Simulation data 2

Four dipole sources with temporal profiles of sinusoidal were located in three position inside the brain, as shown in Figure 3.5. Strengths of the red, green, and blue profiles

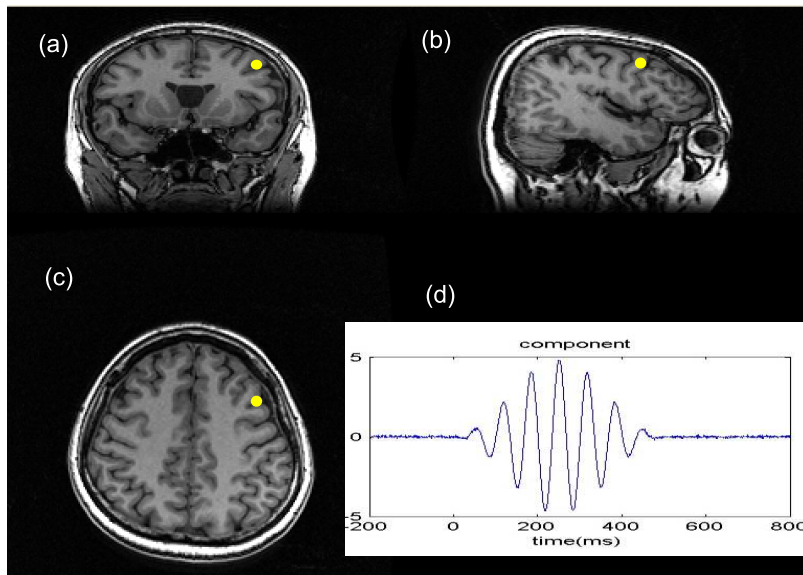


Figure 3.3: (a) the ground truth location in anatomical image of the simulated recordings by coronal view (b) the ground truth location in anatomical image of the simulated recordings by sagittal view (c) the ground truth location in anatomical image of the simulated recordings by transverse view (d) the 15 Hz sine wave temporal profiles

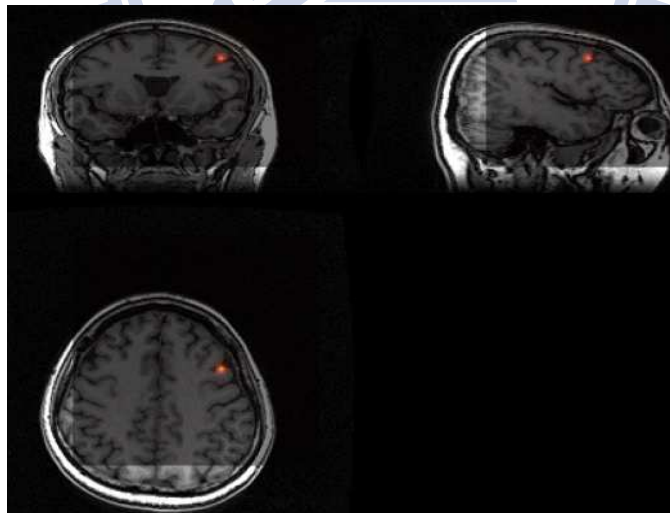


Figure 3.4: Correlation map of the estimated source by our method with the recordings of simulation 1. The significant source are viewed by sagittal, coronal and transverse view.



are all 40 nAm. The profile in the green position is as the red profile at yellow position with 350 ms delay. The orientation of each of the four dipoles was arbitrarily set on the plane tangential to the head sphere. We used (2.6) to compute the simulated MEG signals induced from the four dipole sources, as well as additive background noises from 3000 random dipoles with the standard deviation of 25 nAm.

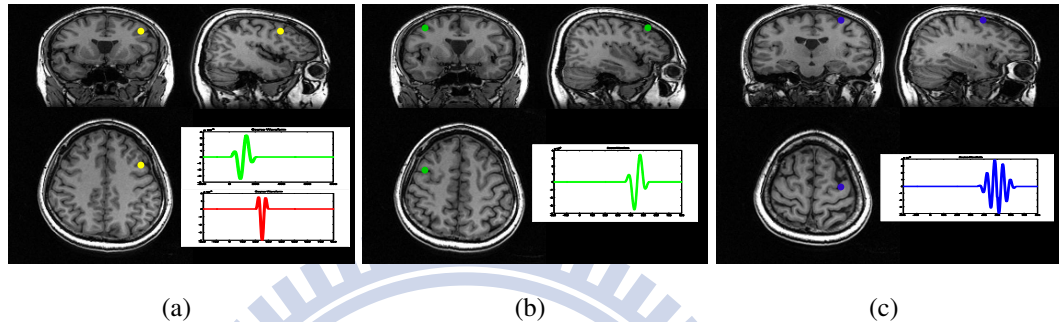


Figure 3.5: Dipole sources of simulation data contain (a) the first two sources at yellow location with different temporal activities (in red and green), (b) another source at green location with the same temporal activities as the green one at (a), and (c) the last source at the blue location with the temporal activities in blue.

We applied independent component analysis on the simulated measurements to extract components (Figure 3.6) and manually selected four components C1, C2, C3, and C4. Then we calculated and imaged the correlation distribution between each of the selected component and brain activities by (2.11) as shown in Figure 3.7. The correlation map of the estimated source is focal and significant, and the source localization error is 0 mm for all chosen components.

We applied MCB on the simulated recordings to calculate the F-statistic maps which reveal cortical regions with significant difference of activities between the active and control states. Then we chose the filtered signal at the highest F value position from 350 to 550 ms interval as the reference signal. Then we calculated the correlation map between the reference signal and brain activities at different time interval. Figure 3.8(a) shows the correlation map from 0 to 200 ms, and Figure 3.8(b) shows the map from 350 to 550 ms. It is obviously that both maps match the dipole locations at the corresponding time interval.

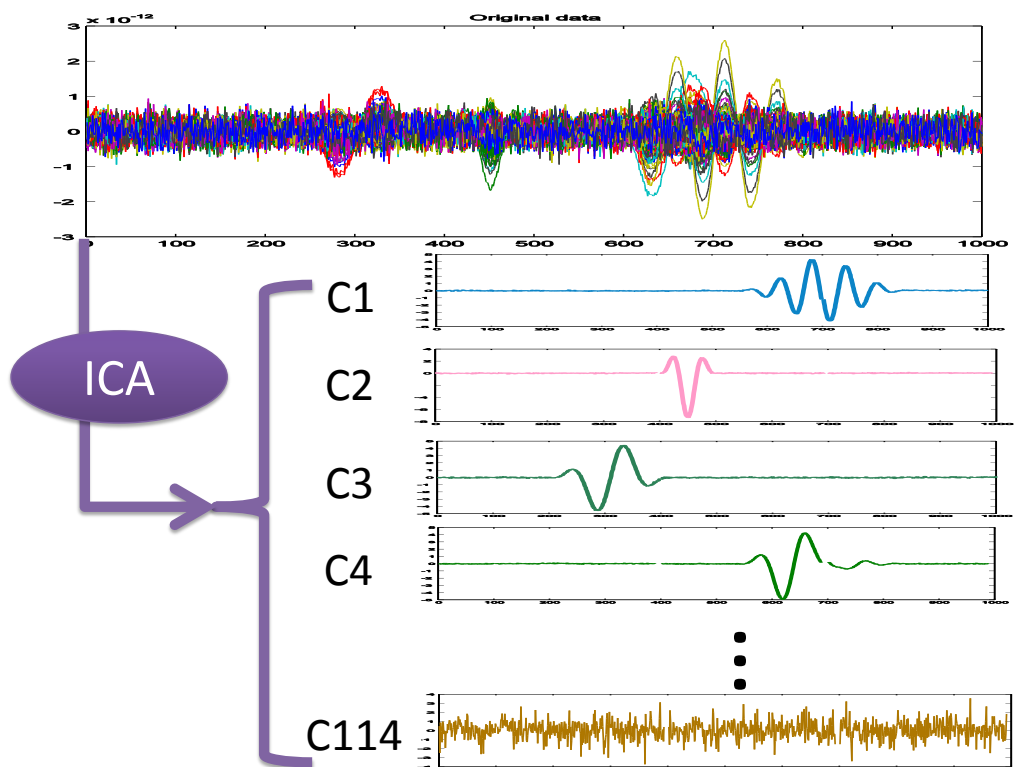


Figure 3.6: The simulated data was decomposed by ICA into 114 components.

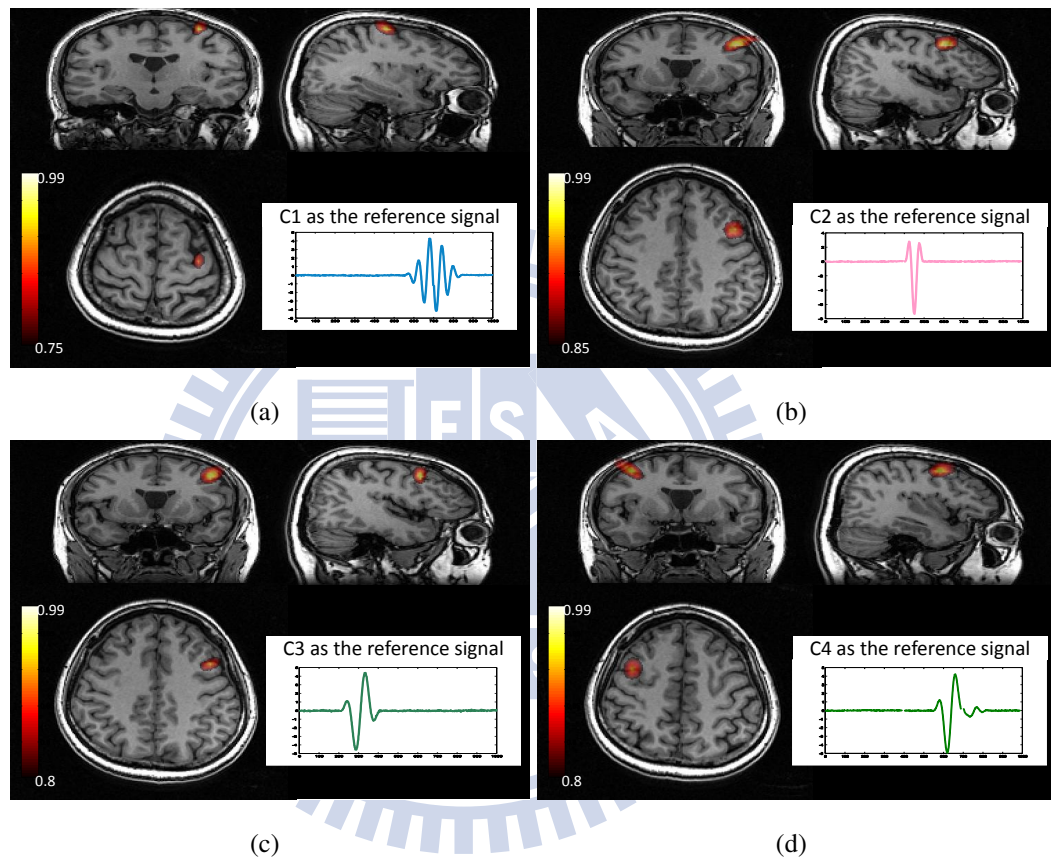


Figure 3.7: The correlation map calculated with the reference signal (a) C1, (b) C2, (c) C3, and (d) C4.

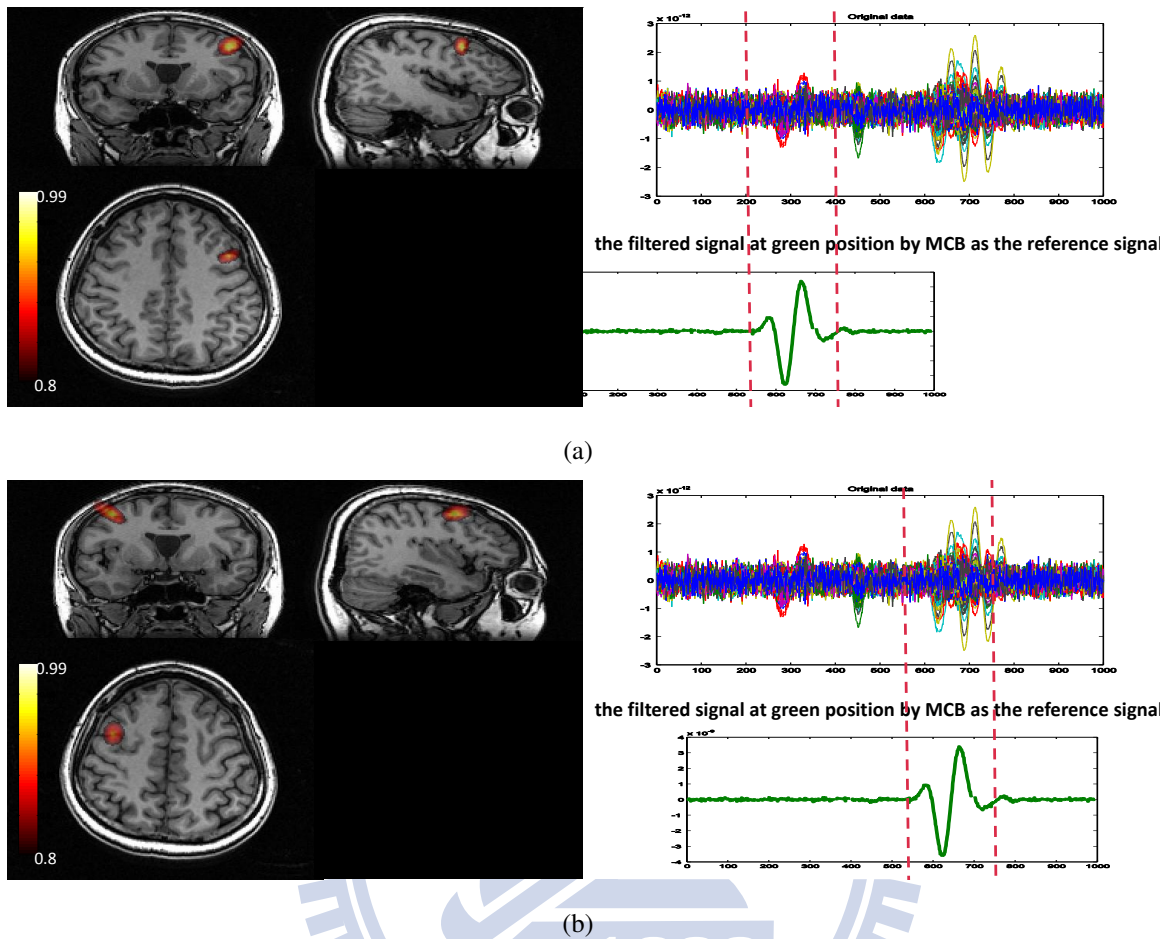


Figure 3.8: The correlation maps calculated with the reference signal filtered by MCB at different time intervals within (a)  $[0, 200]$  ms and (b)  $[350, 550]$  ms.

### 3.3.3 Real data - happy mirror neuron

In this experiment, we applied our method on the measurement of two subject with three conditions. We chose seven reference brain regions as reference to find out the highly correlated brain regions and the time between the reference. The seven reference regions were right insula, left inferior frontal gyrus, right inferior frontal gyrus, left amygdala, right amygdala, inferior occipital gyrus and the v1. Those region were suggested highly correlated with mirror neuron system, emotion processing and face perception. That is why we chose them as our reference region. The source signal of those regions were calculated

Table 3.1: The parameters of maximum contrast beamformer on the happy mirror neuron experiment.

the parameter information of MCB	
artifact threshold	6000 fT
electrooculography rejection	0.0002 V
bandpass	2 to 30 Hz
baseline	-200 to 0 ms
tradeoff	0.03
window interval	-50 to 850 ms
control interval	-200 to -100 ms

by MCB, and the time interval of the source signal chosen as the reference signal depended on each reference region and the pattern of the source signal. The parameters of MCB was listed at Table 3.1.

### Left inferior frontal gyrus

#### Subject A

The anatomical position of left inferior frontal gyrus was shown in the first row of the Table 3.3. The axis of the volume was at (56,152,76) voxel. The source signals at the left inferior frontal gyrus of three conditions calculated by MCB was shown in the next row of the Table 3.3. We chose a time interval as reference signal of each condition as shown in Table 3.2; In this reference position, 100 to 200 ms were chosen as reference signal on imitation and observation conditions, and 180 to 280 ms was chosen as reference signal on execution condition.

**Imitation condition** The results were shown in Table 3.4. We can observe that at

Table 3.2: The referenced time interval of each source signal

	imitate	observation	execution
Right insula	100 to 200 ms	100 to 200 ms	100 to 200 ms
Left inferior frontal gyrus	100 to 200 ms	100 to 200 ms	180 to 280 ms
Right inferior frontal gyrus	50 to 150 ms 50 to 250 ms	140 to 280 ms	120 to 220 ms
Left amygdala	100 to 200 ms	100 to 200 ms	140 to 250 ms
Right amygdala	100 to 200 ms	100 to 160 ms 130 to 280 ms	150 to 250 ms

Table 3.3: The source signal of the left inferior frontal gyrus as reference signal which were calculated by MCB. The first row shows the position of the left inferior frontal gyrus. The next is the source signal of three condition - imitate, observation and execution.

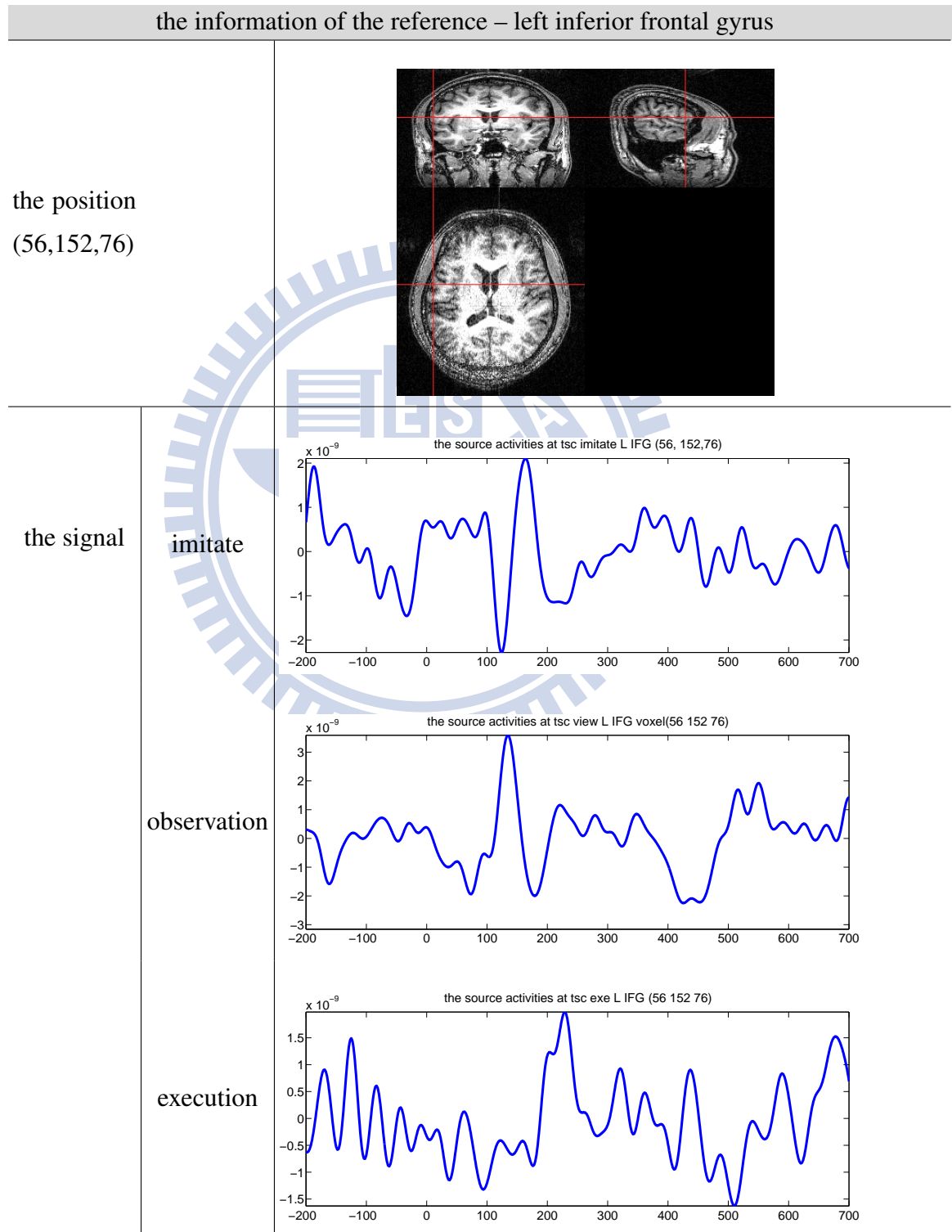
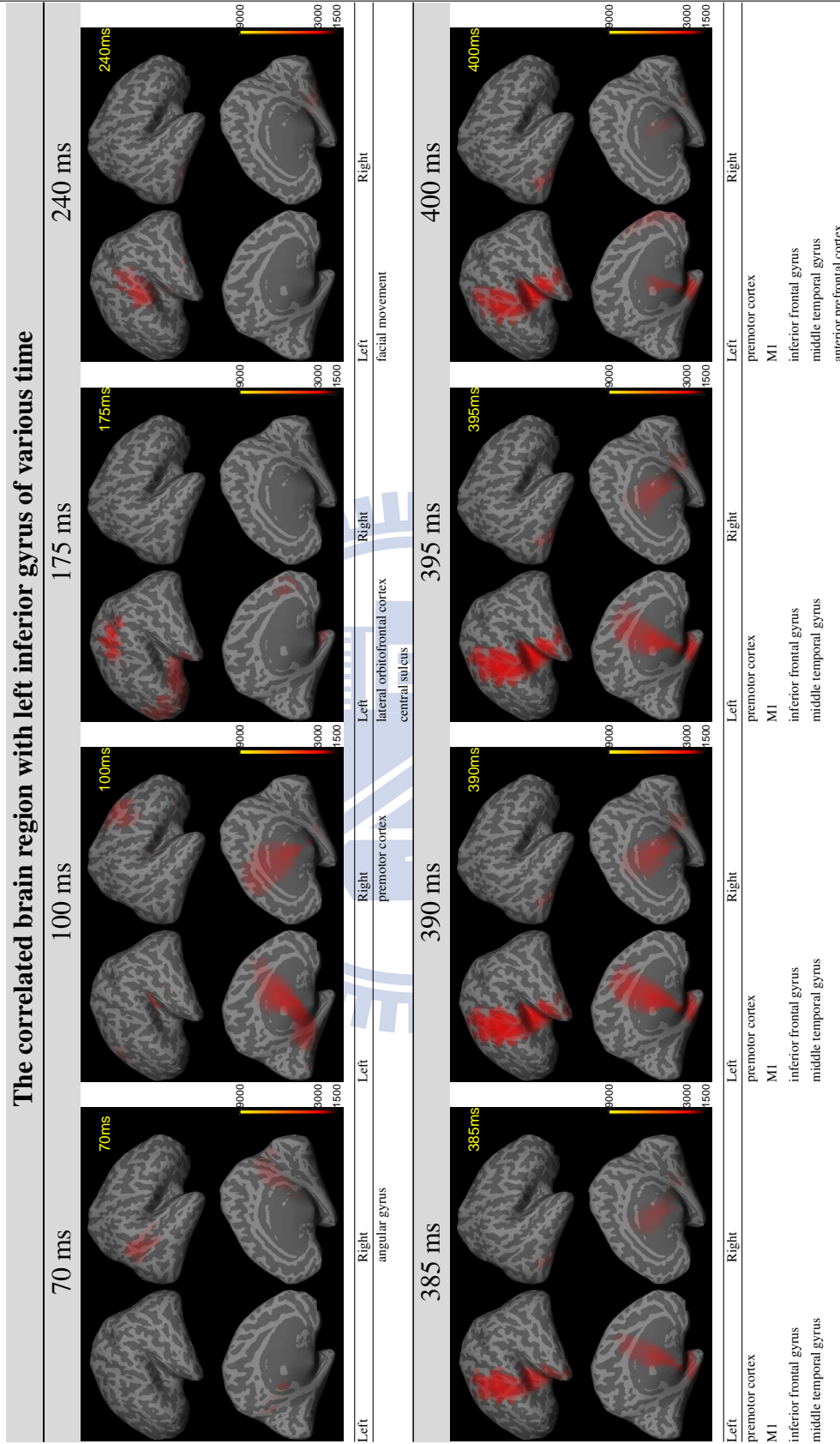
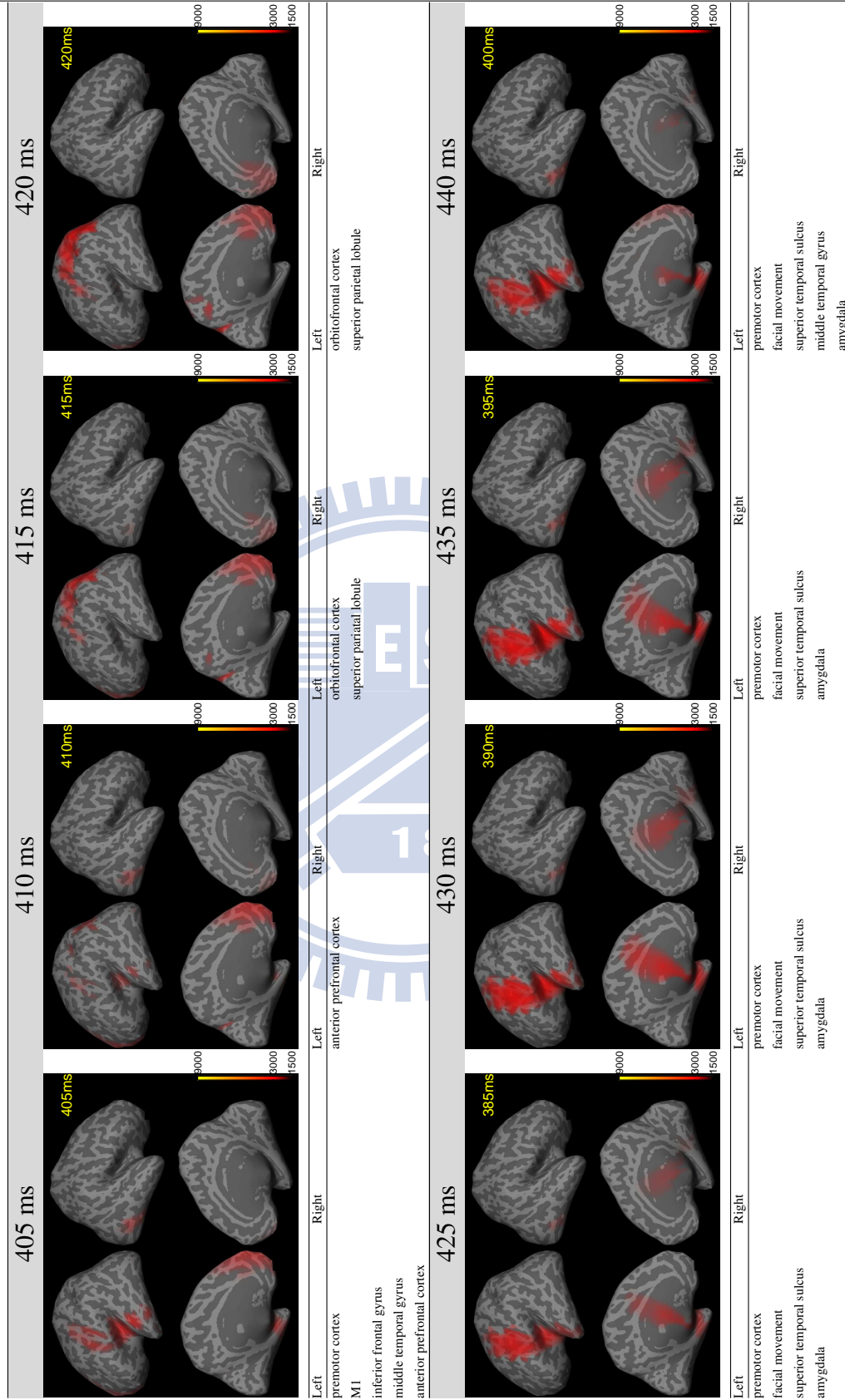
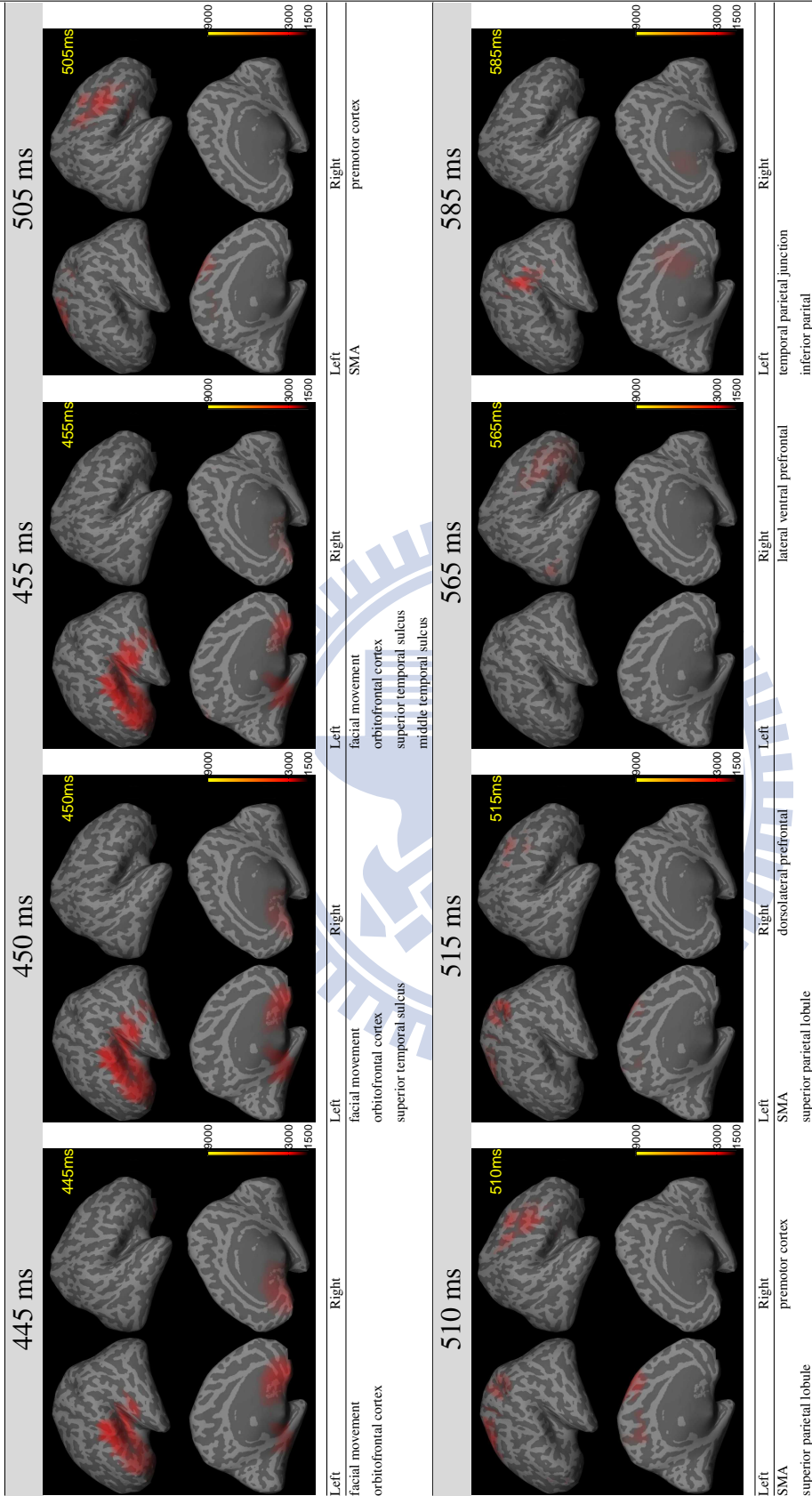


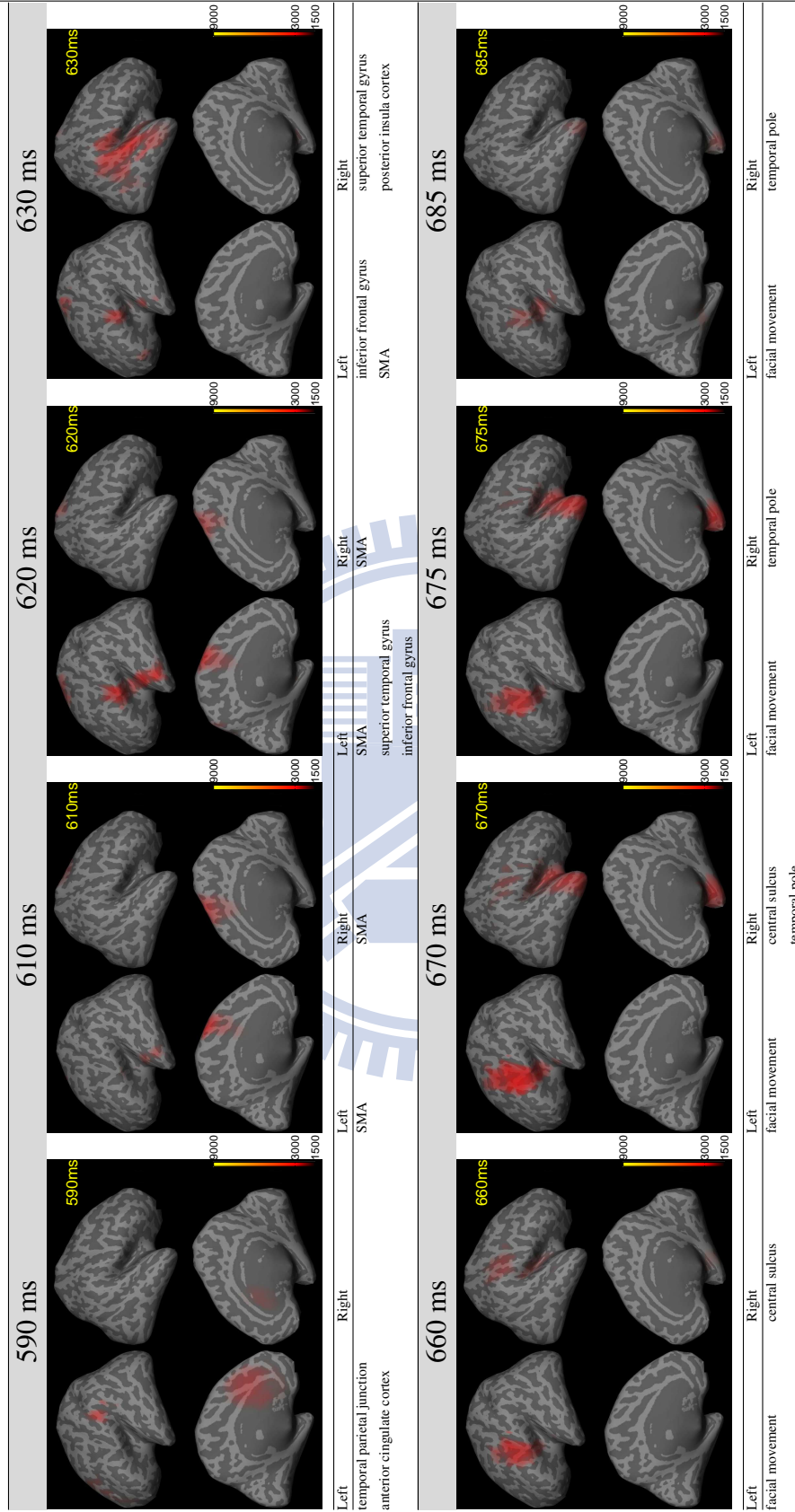
Table 3.4: The correlation map and the significant correlation regions of the reference region at left inferior frontal gyrus on imitation condition at different time interval.

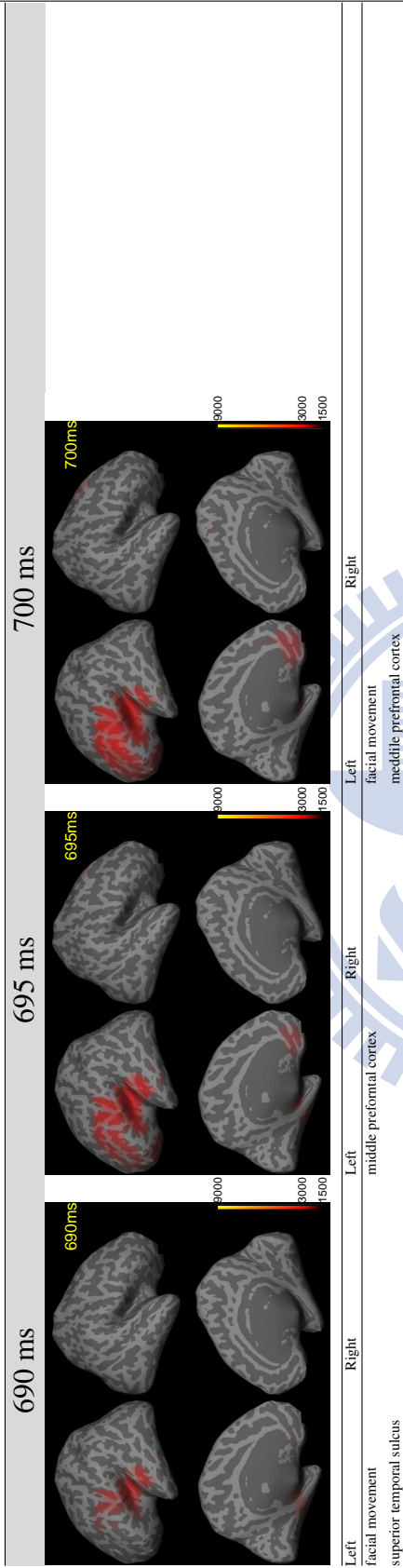












**Observation condition** The results were shown in Table 3.5.

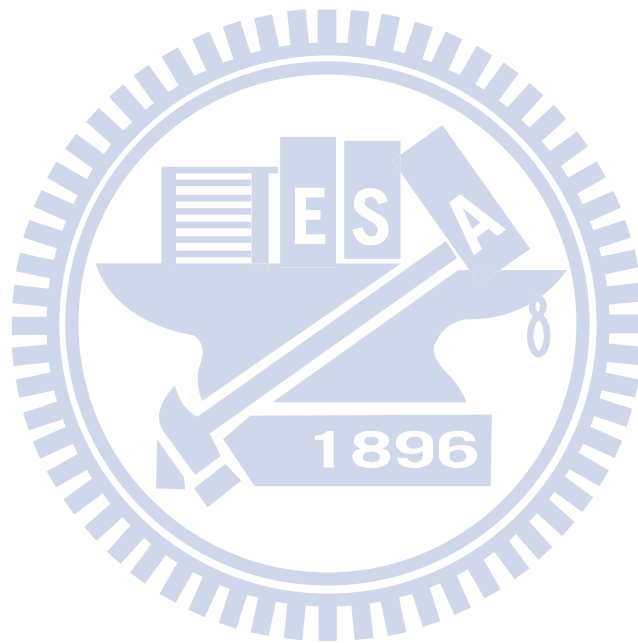
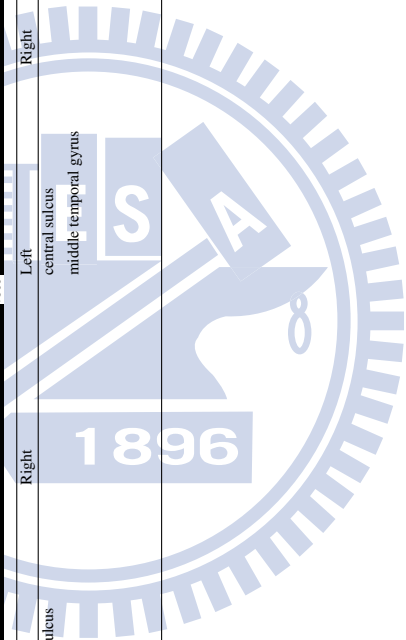
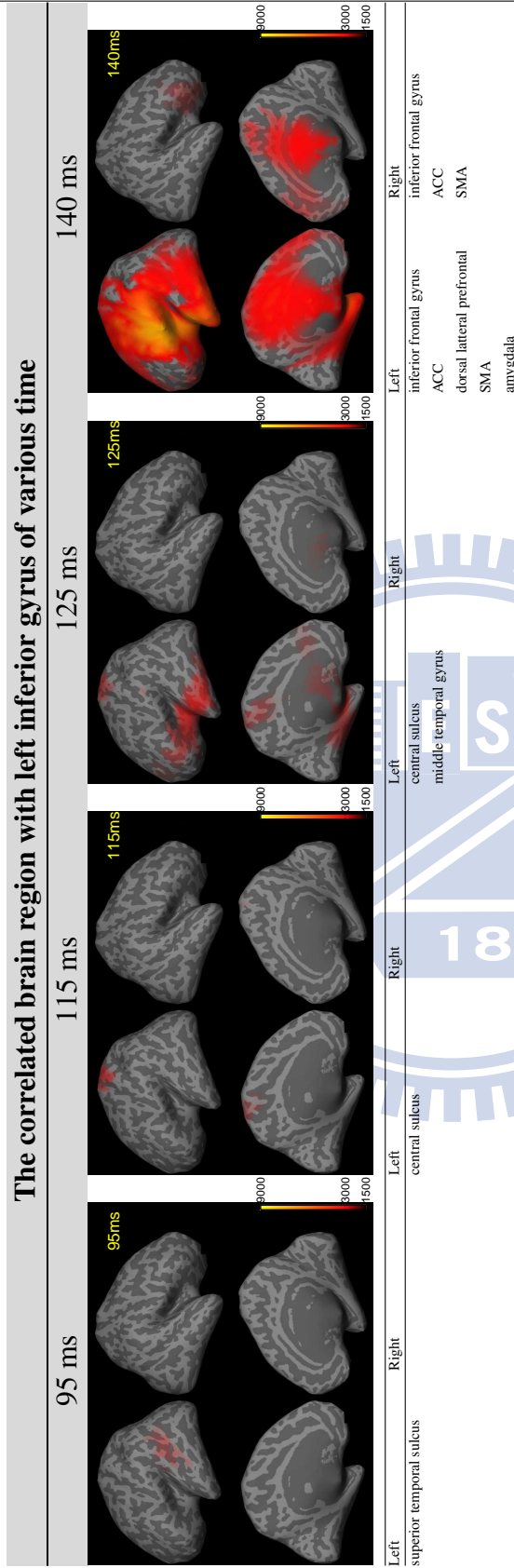
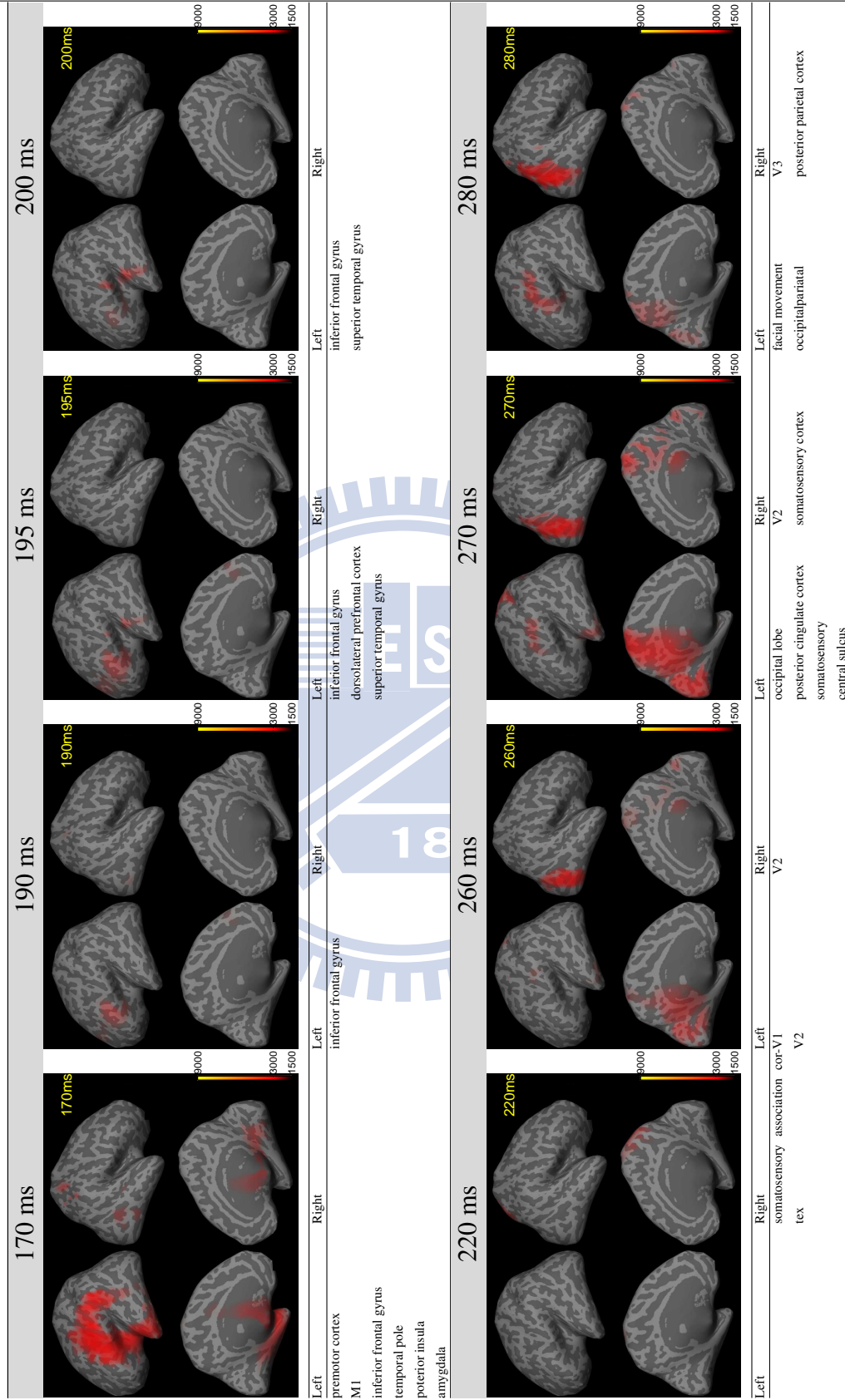
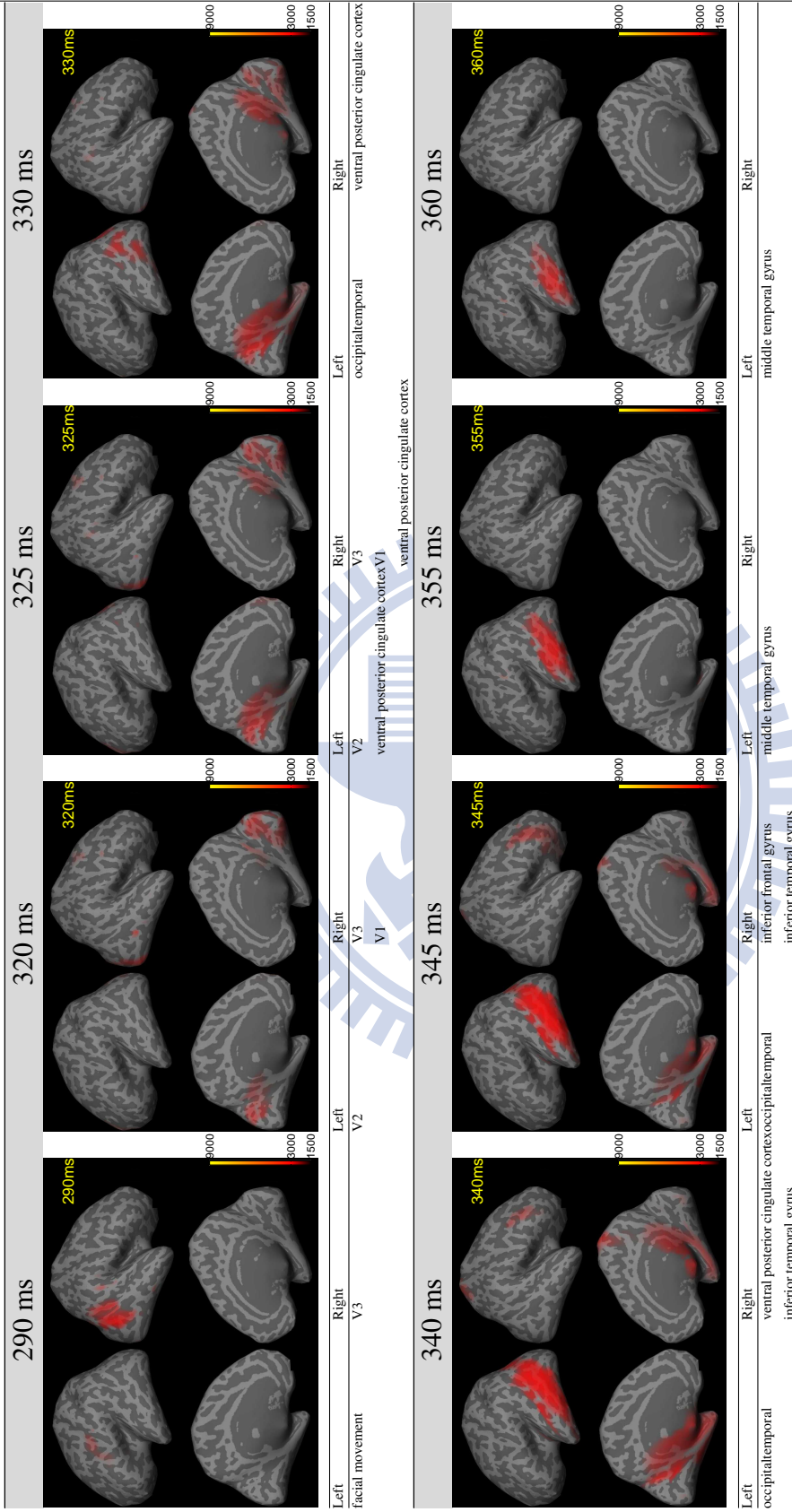


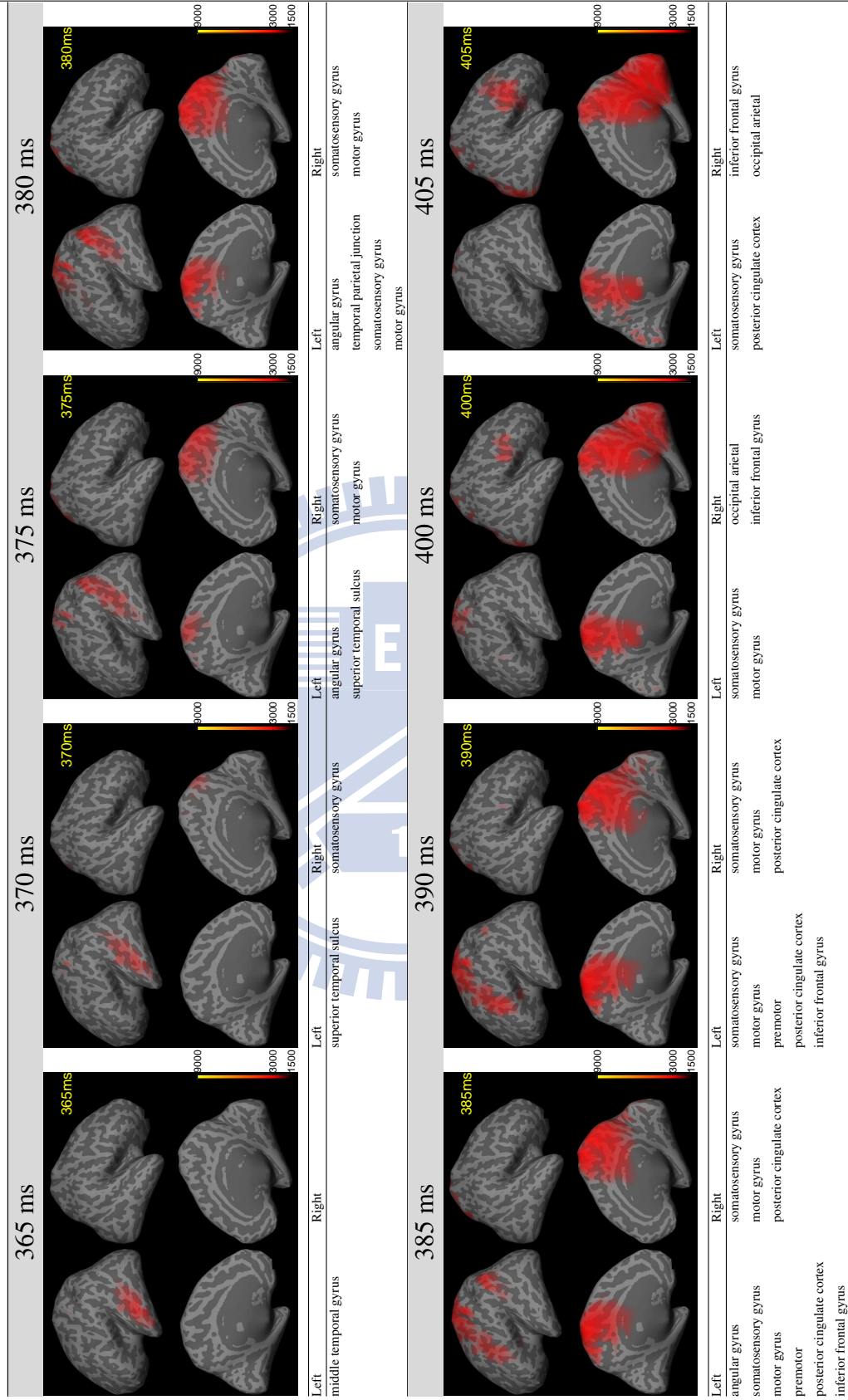
Table 3.5: The correlation map and the significant correlation regions of the reference region at left inferior frontal gyrus on observation condition at different time interval.

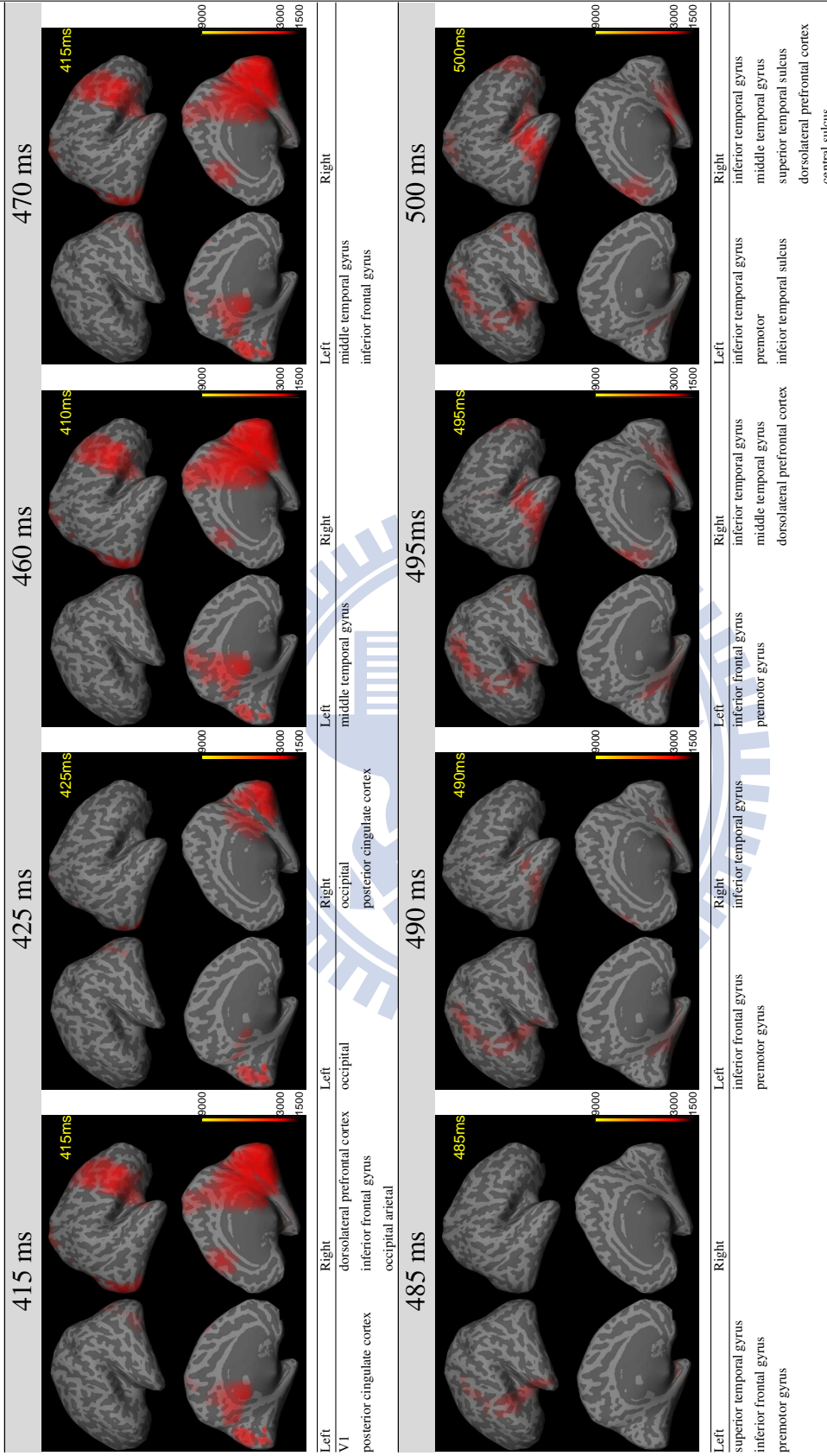


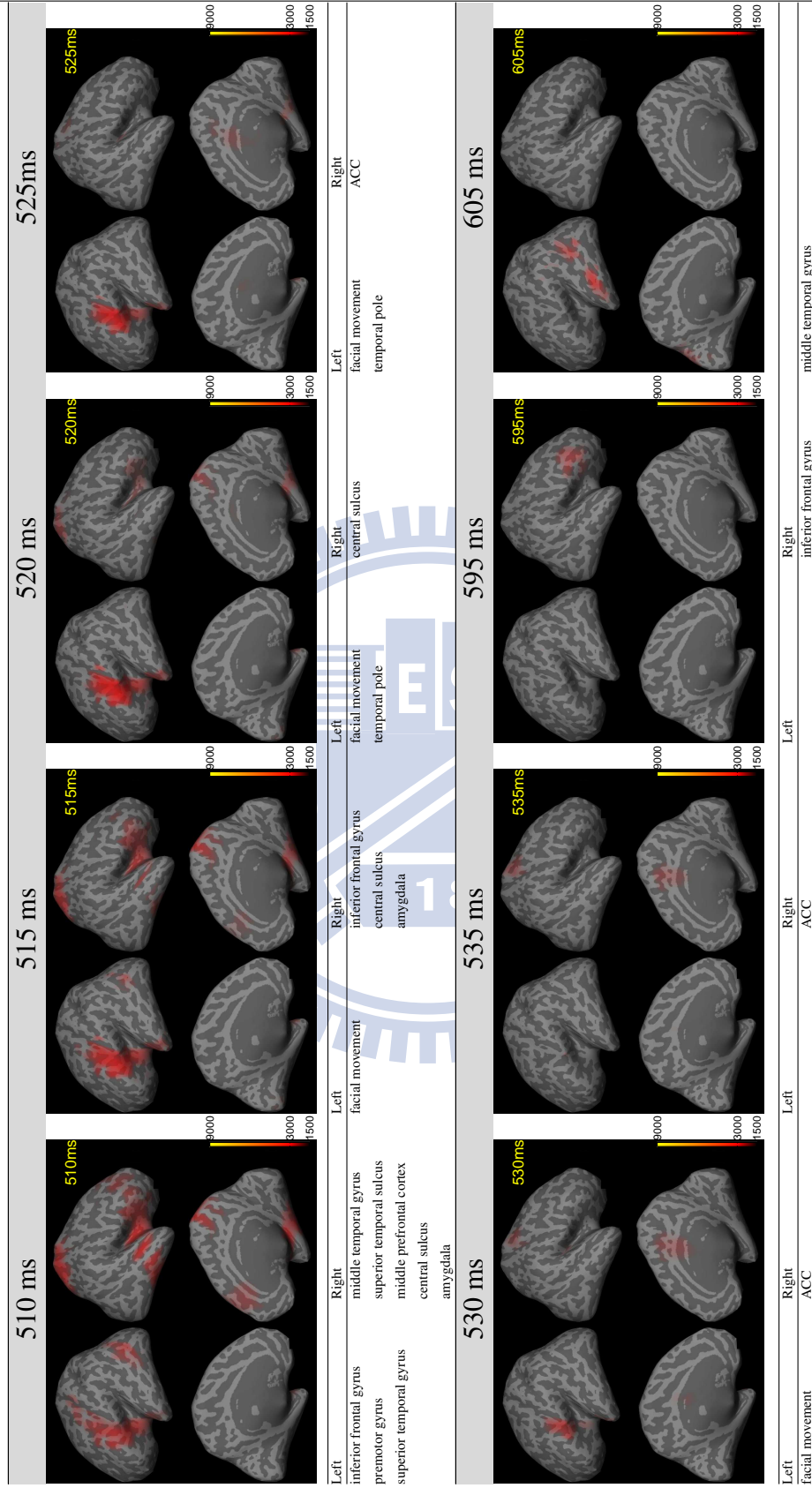


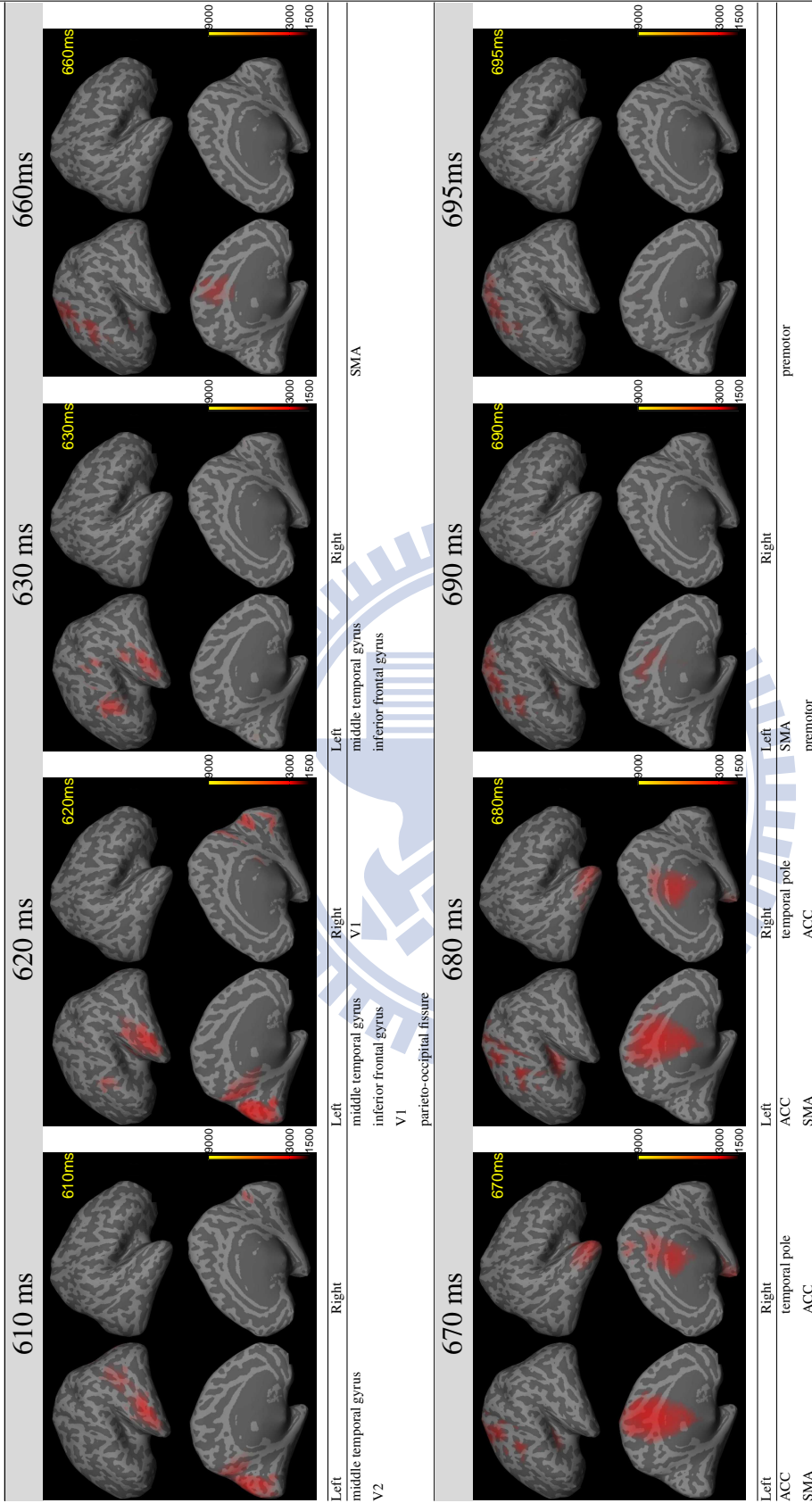












**Execution condition** The results were shown in Table 3.6.

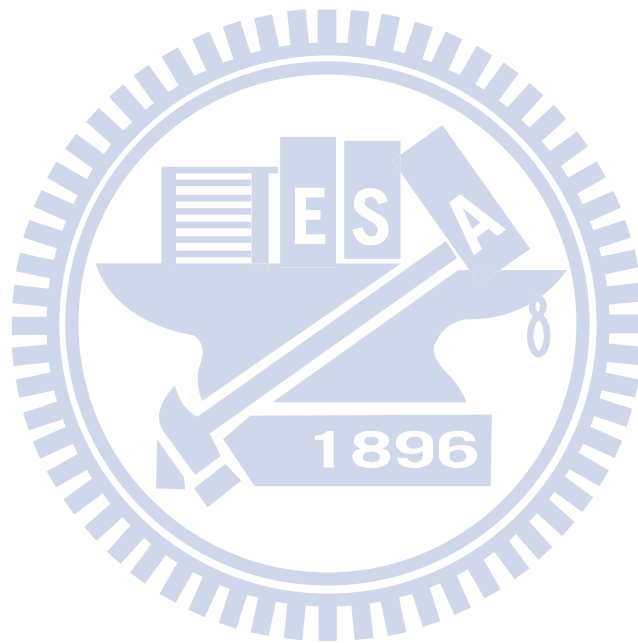
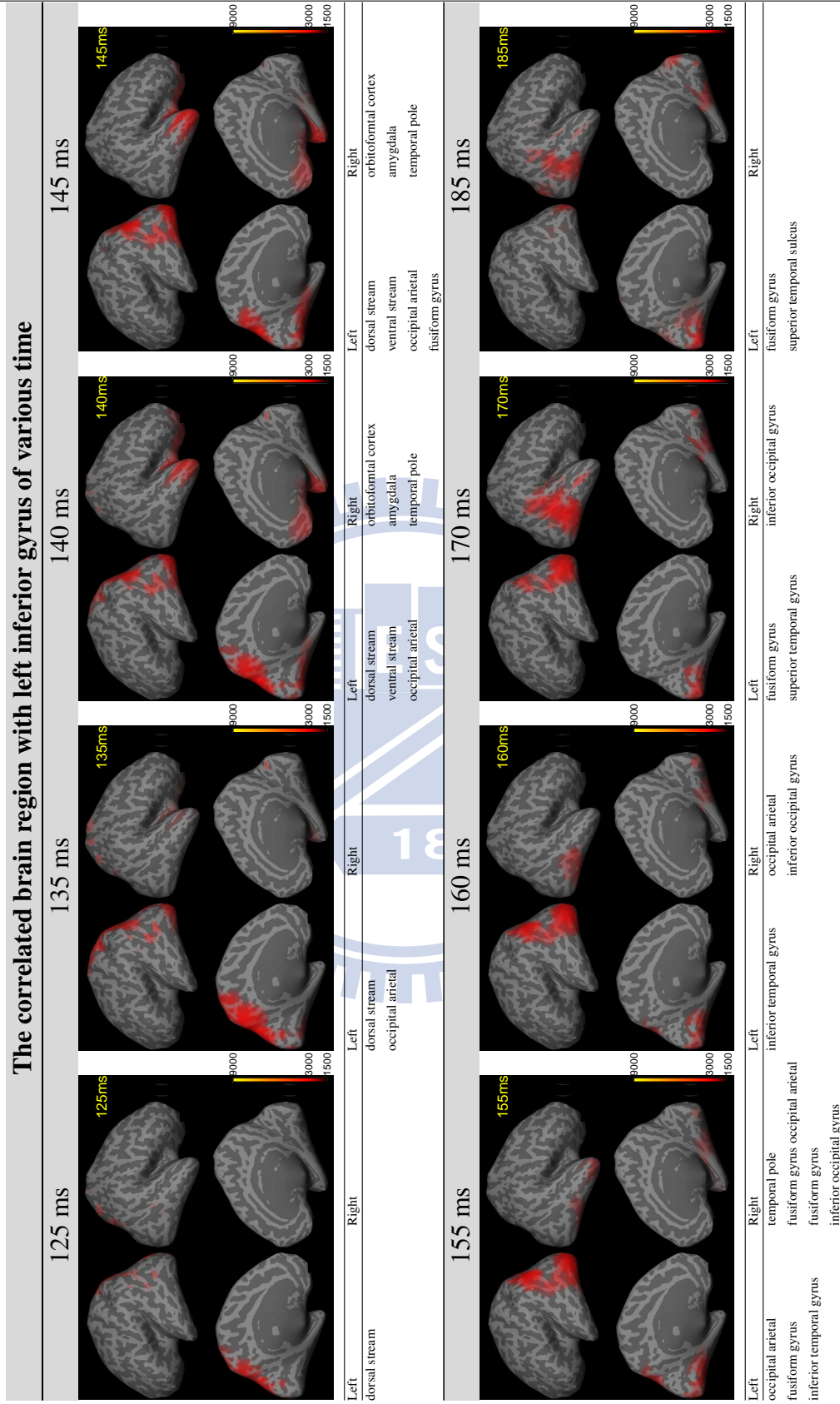
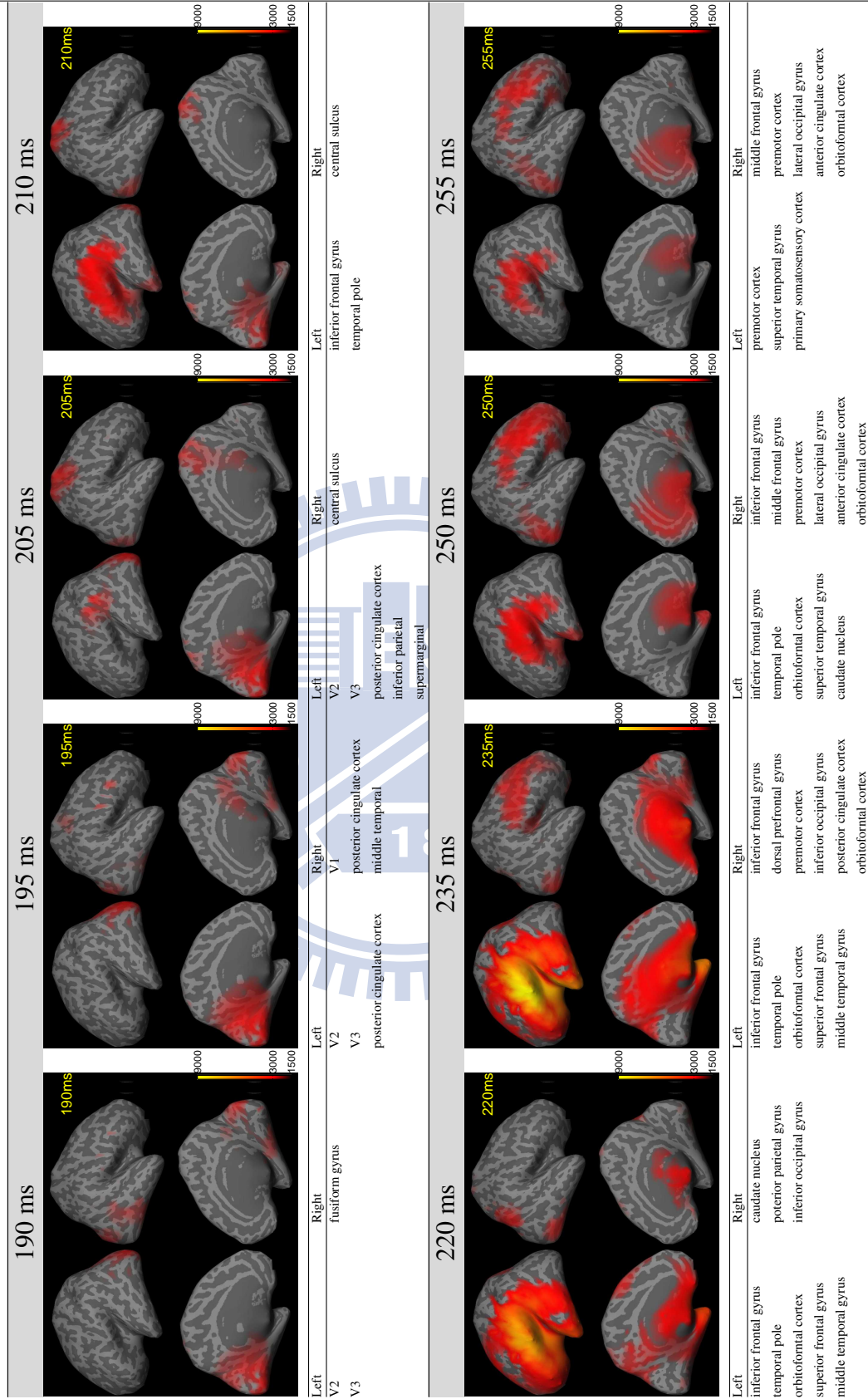
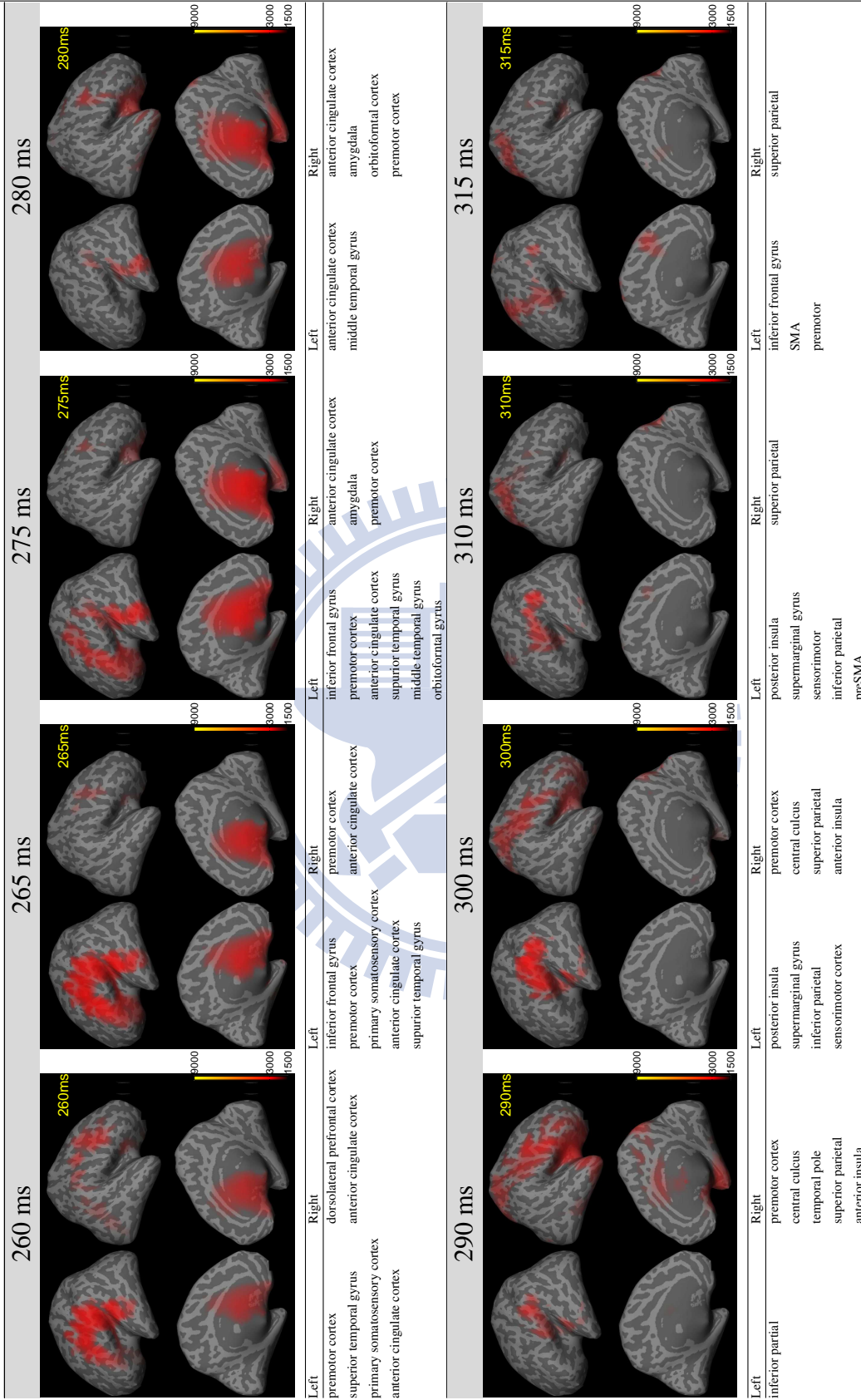


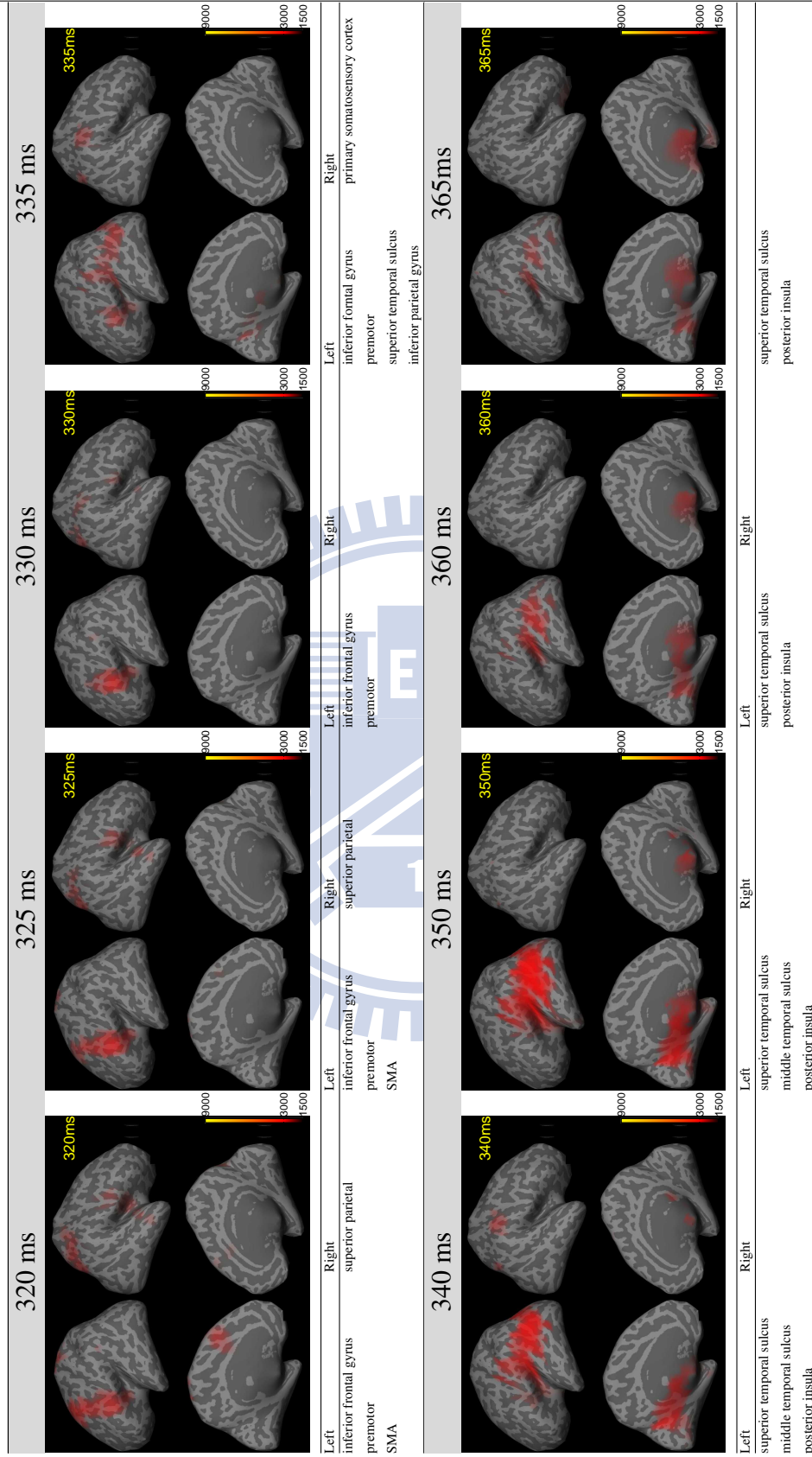
Table 3.6: The correlation map and the significant correlation regions of the reference region at left inferior frontal gyrus on execution condition at different time interval.

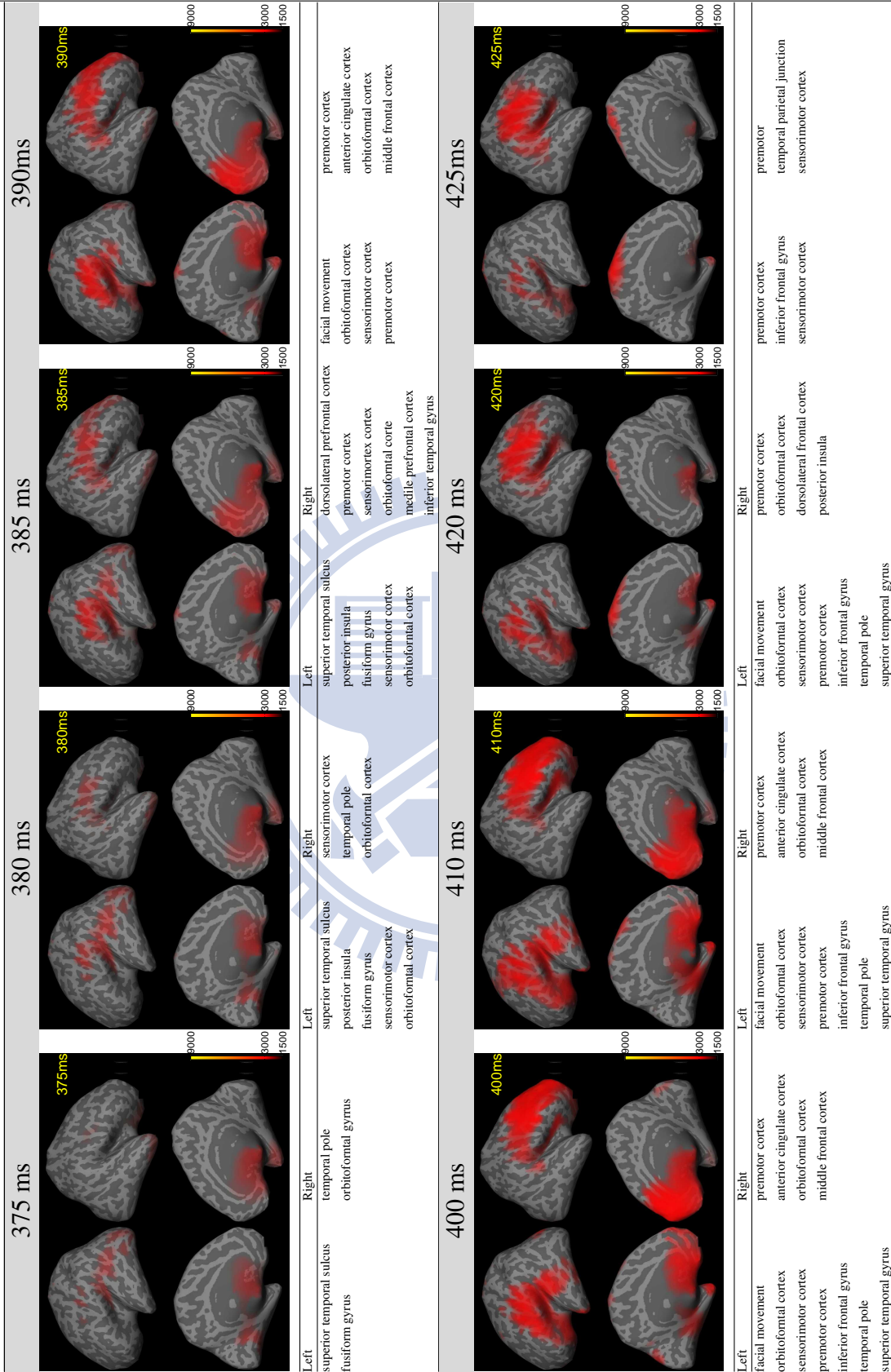


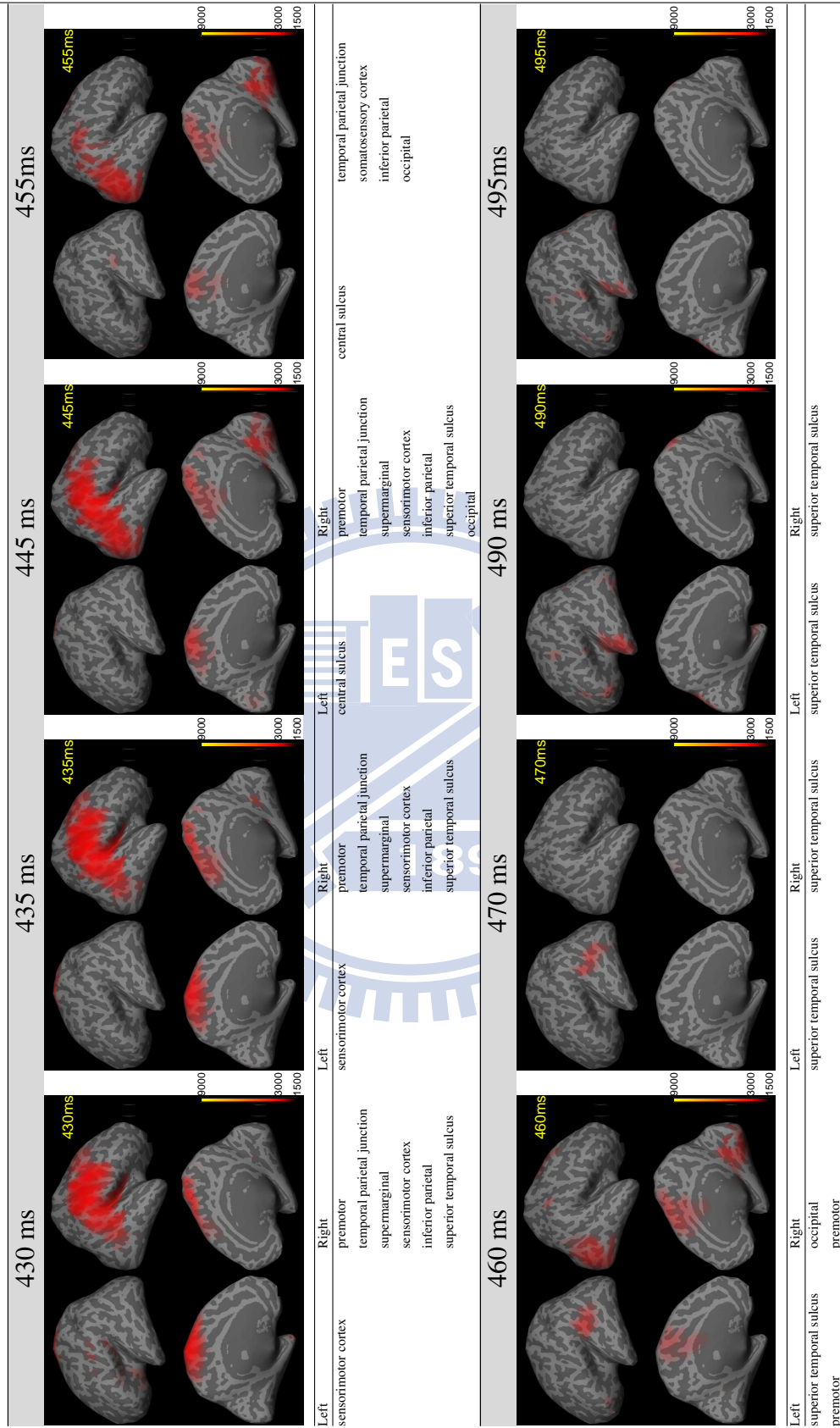


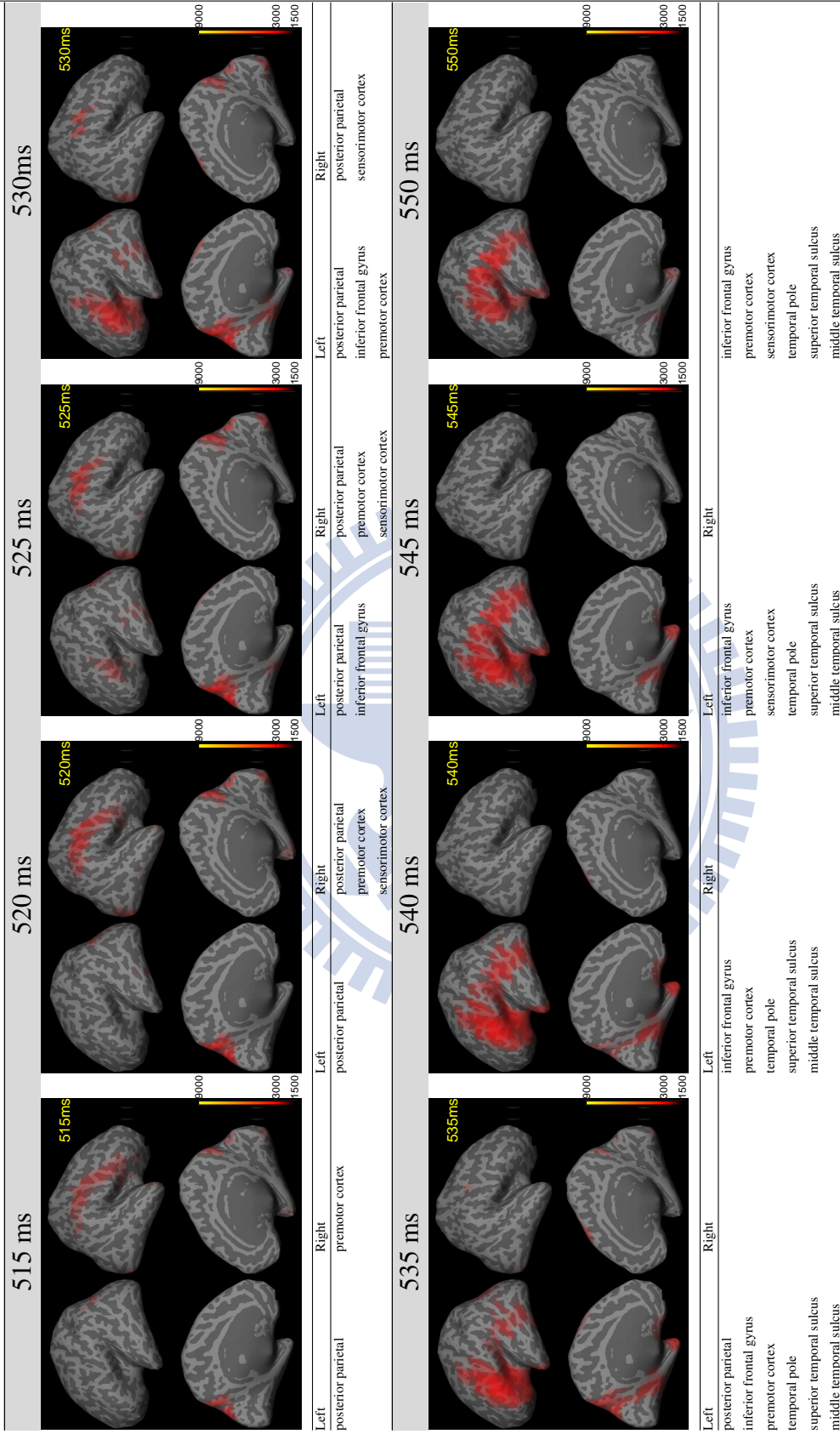


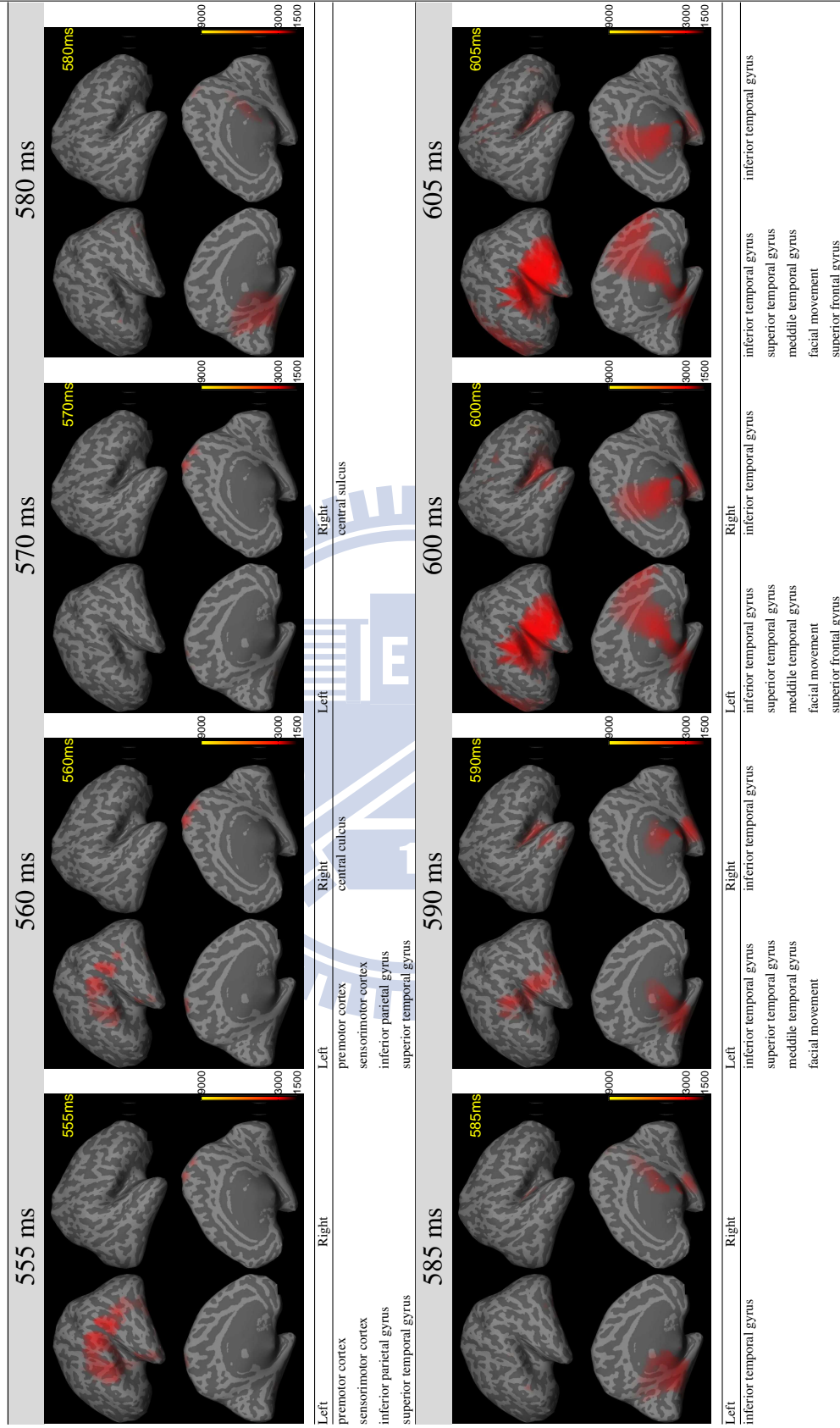


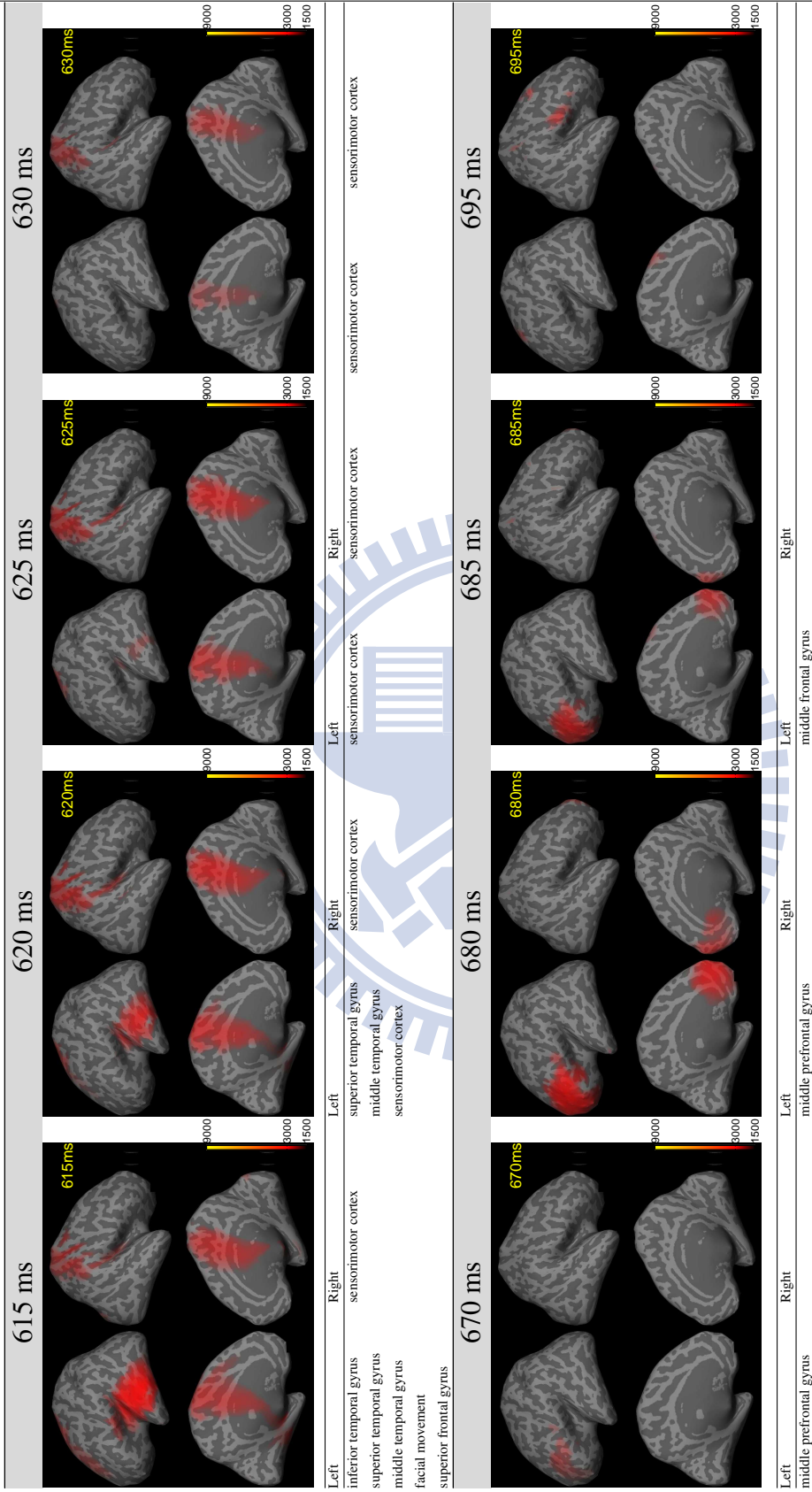












**Subject B**

The anatomical position of left inferior frontal gyrus was shown in the first row of the Table 3.7. The axis of the volume was at (68,160,68) voxel. The source signals at the left inferior frontal gyrus of three conditions calculated by MCB was shown in the next row of the Table 3.7. In this reference position, We chose 120 to 220 ms were chosen as reference signal on imitation and observation conditions, and 180 to 220 ms was chosen as reference signal on execution condition.

**Imitation condition** The results were shown in Table 3.8. In addition, the result with different threshold were shown in Table 3.9 which included 400 ms to 670 ms. We can observe that at

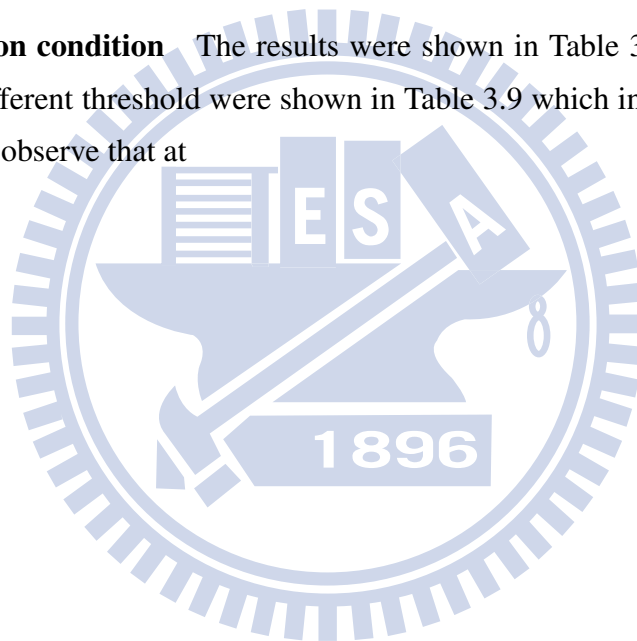


Table 3.7: The source signal of the left inferior frontal gyrus as reference signal which were calculated by MCB. The first row shows the position of the left inferior frontal gyrus. The next is the source signal of three condition - imitate, observation and execution.

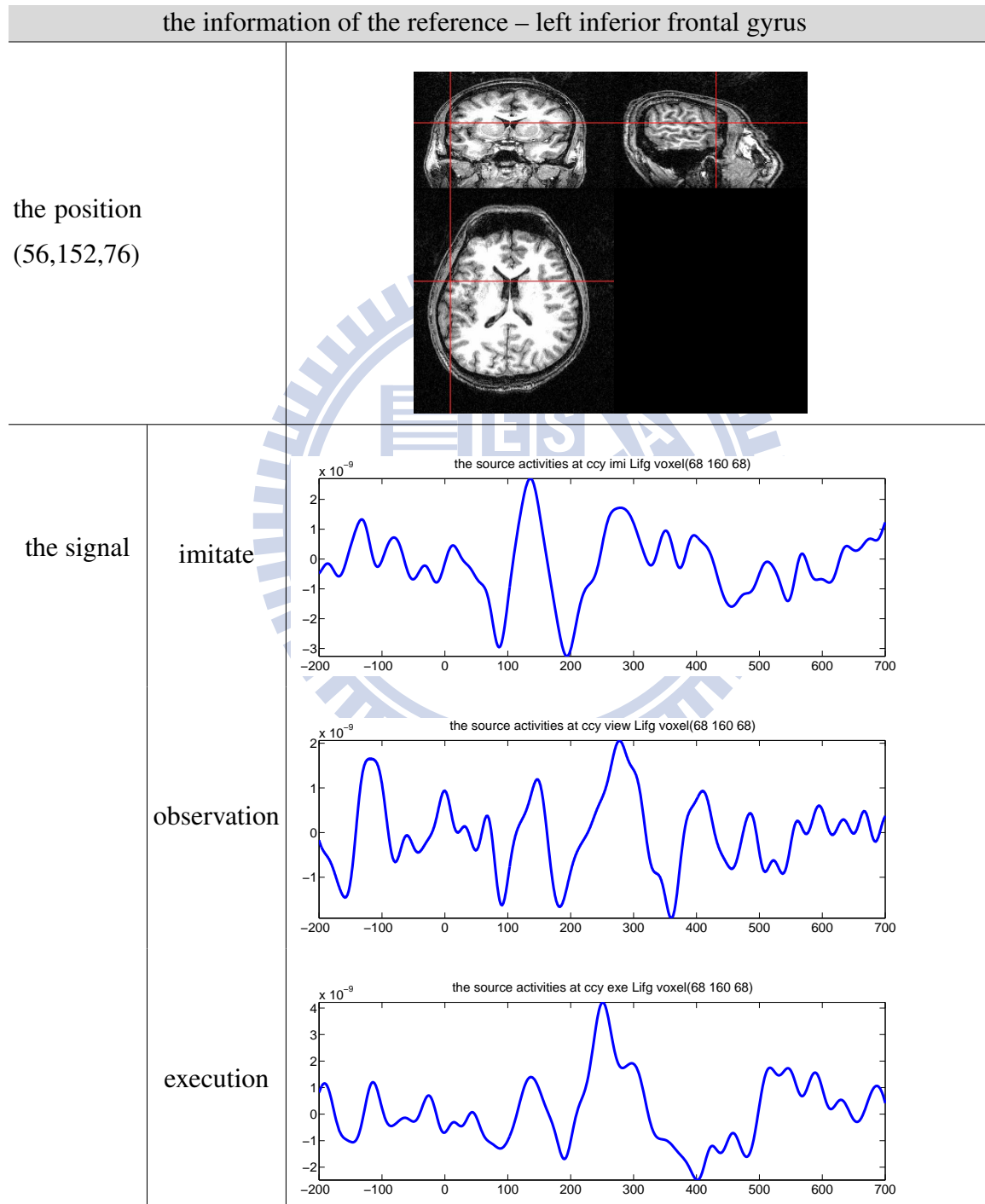
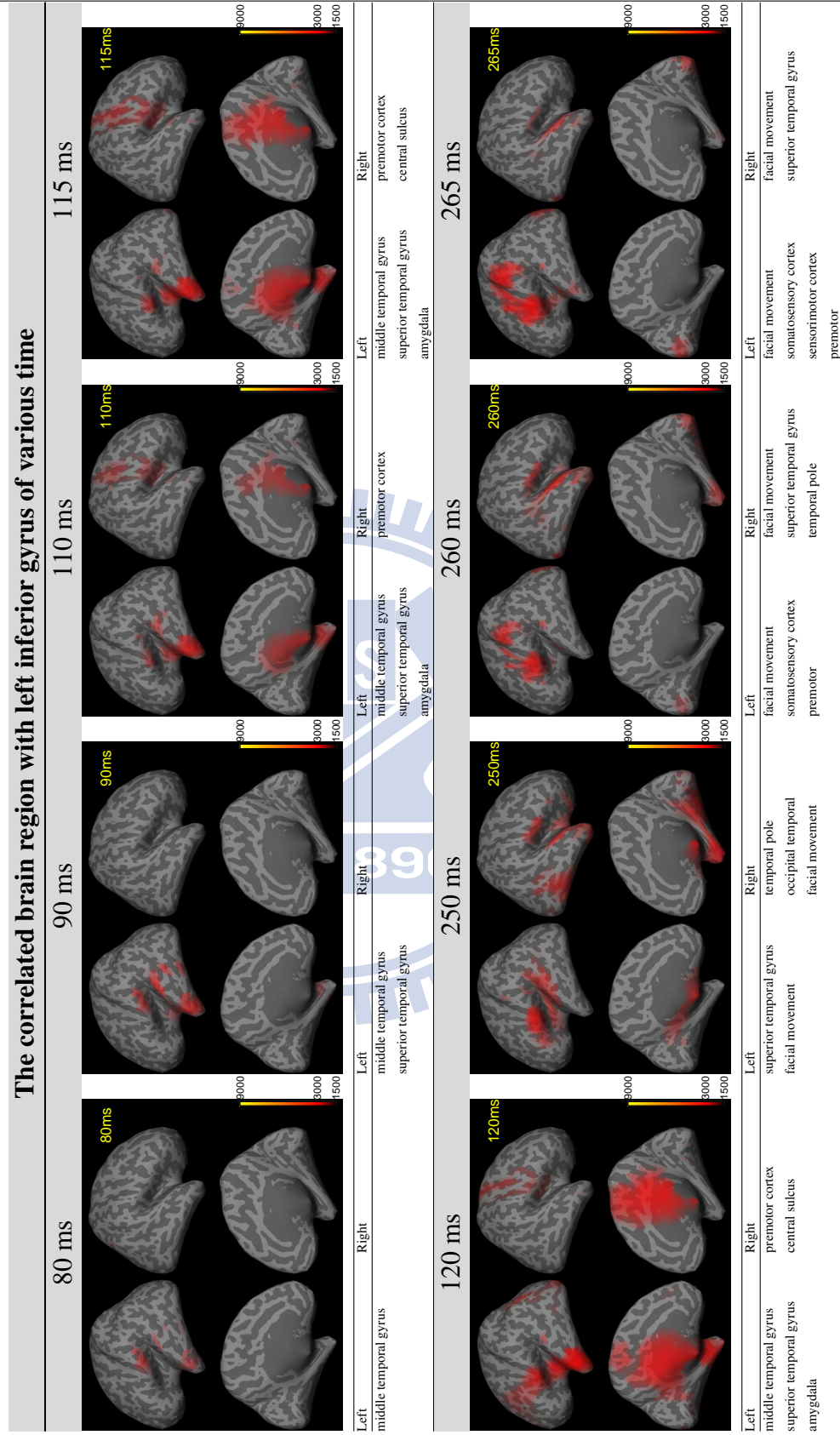
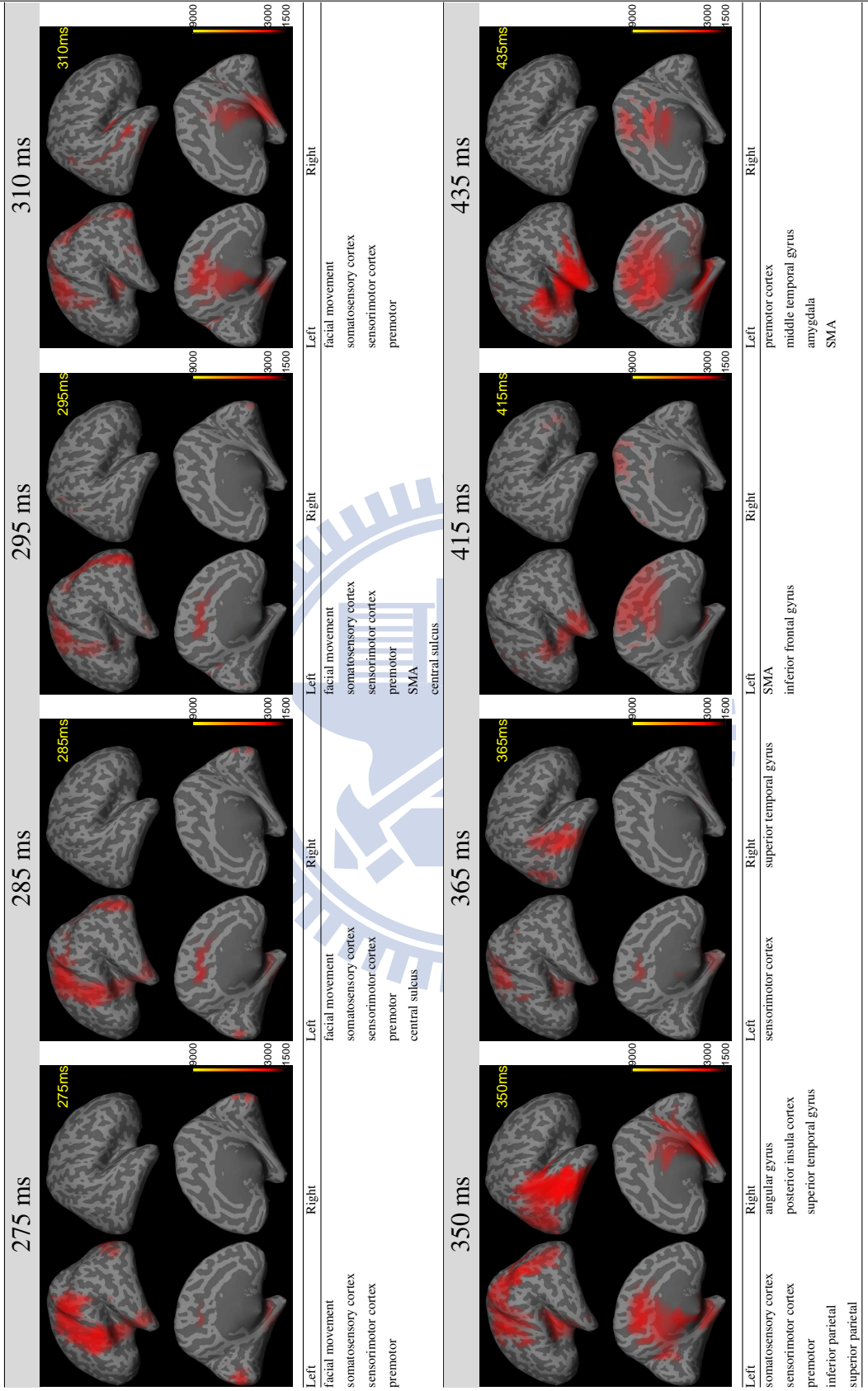
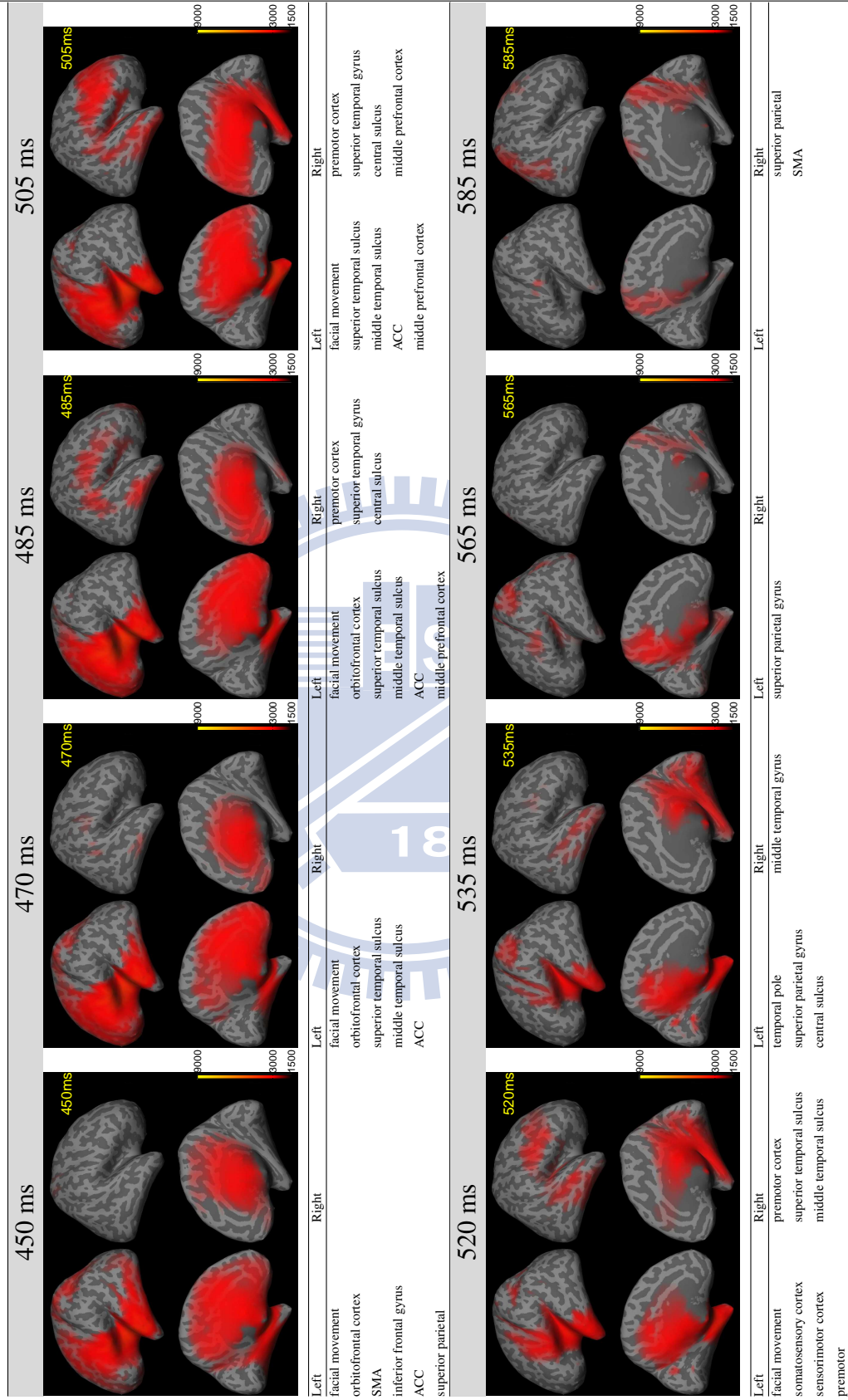




Table 3.8: The correlation map and the significant correlation regions of the reference region at left inferior frontal gyrus on imitation condition at different time interval.







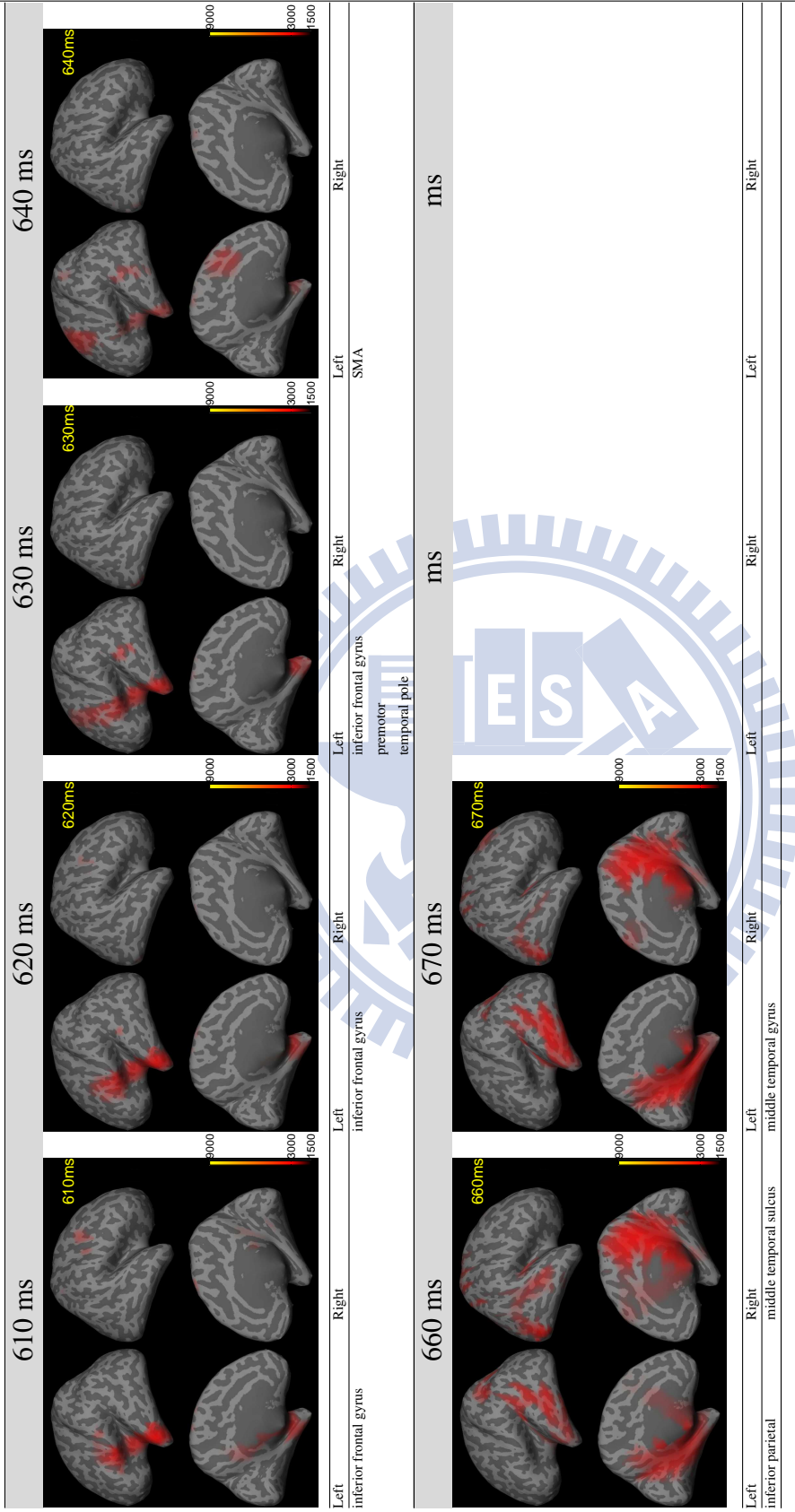
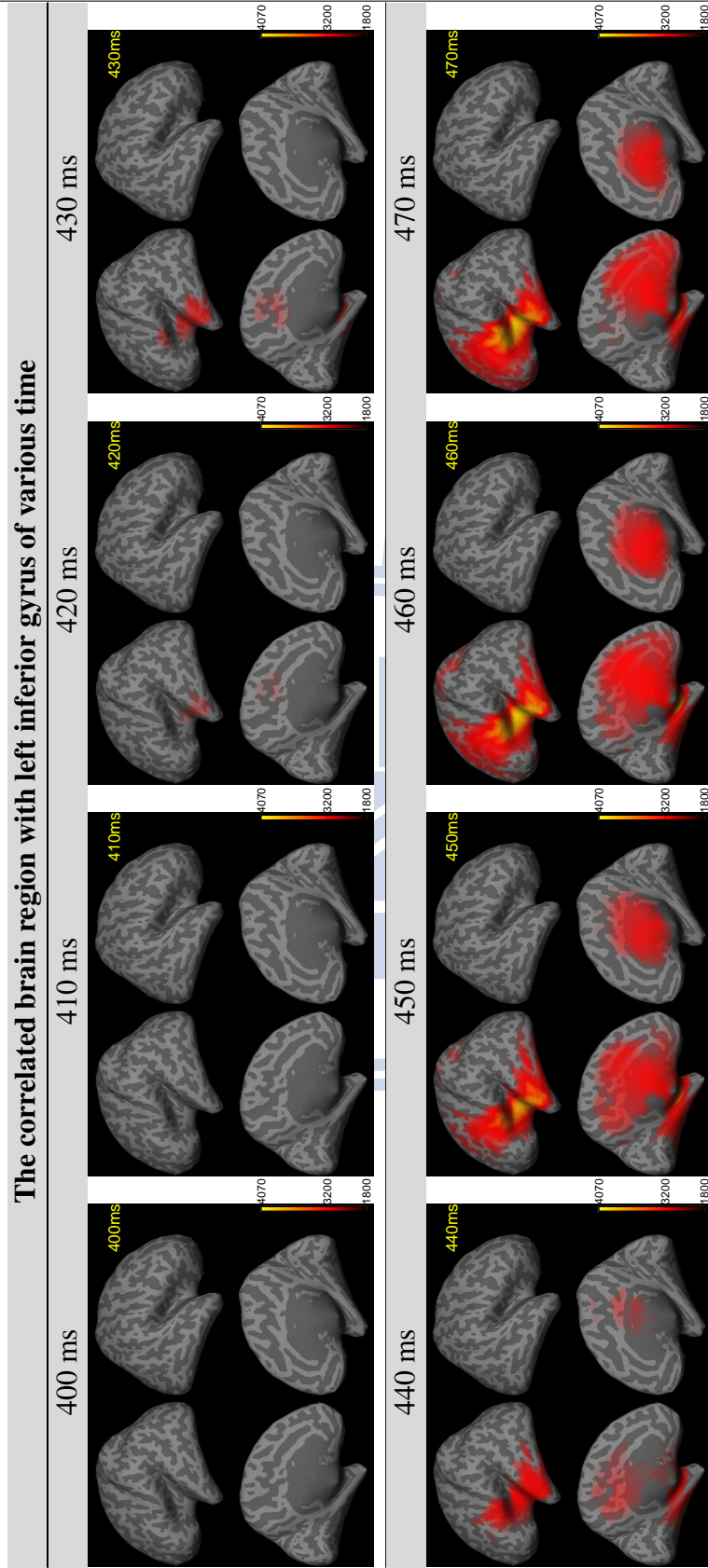
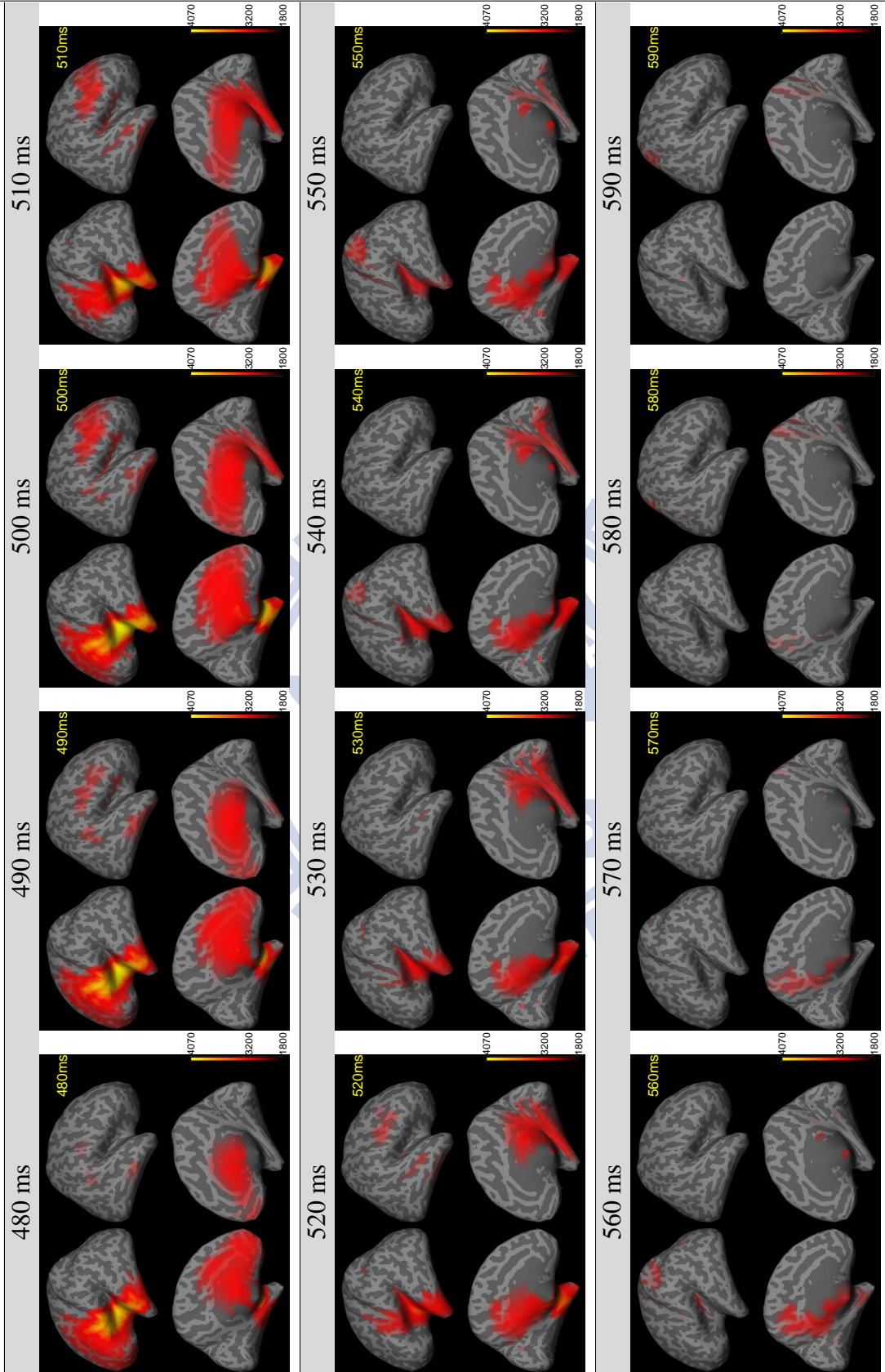
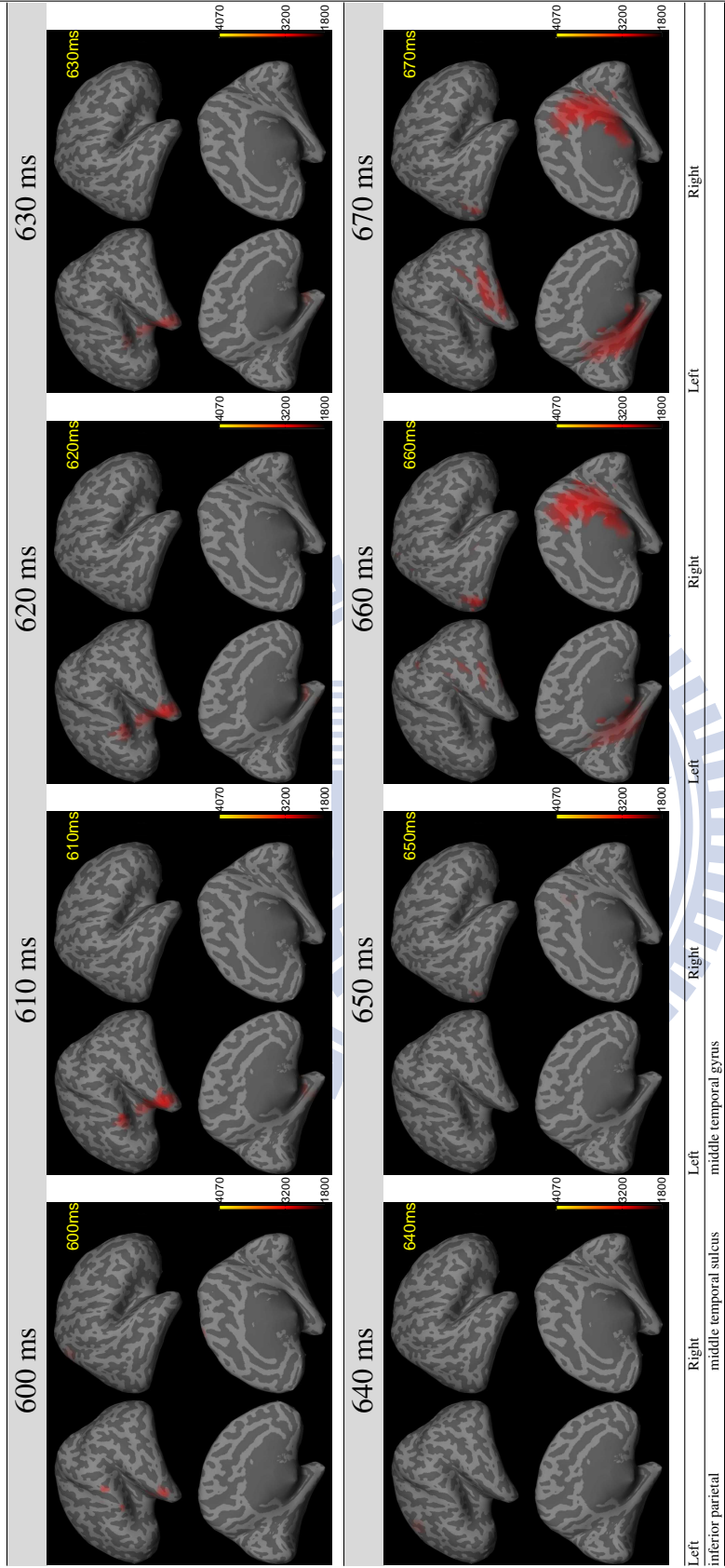


Table 3.9: The correlation map with threshold [1800 - 3200 - 4070] and the significant correlation regions of the reference region at left inferior frontal gyrus on imitation condition at different time interval.





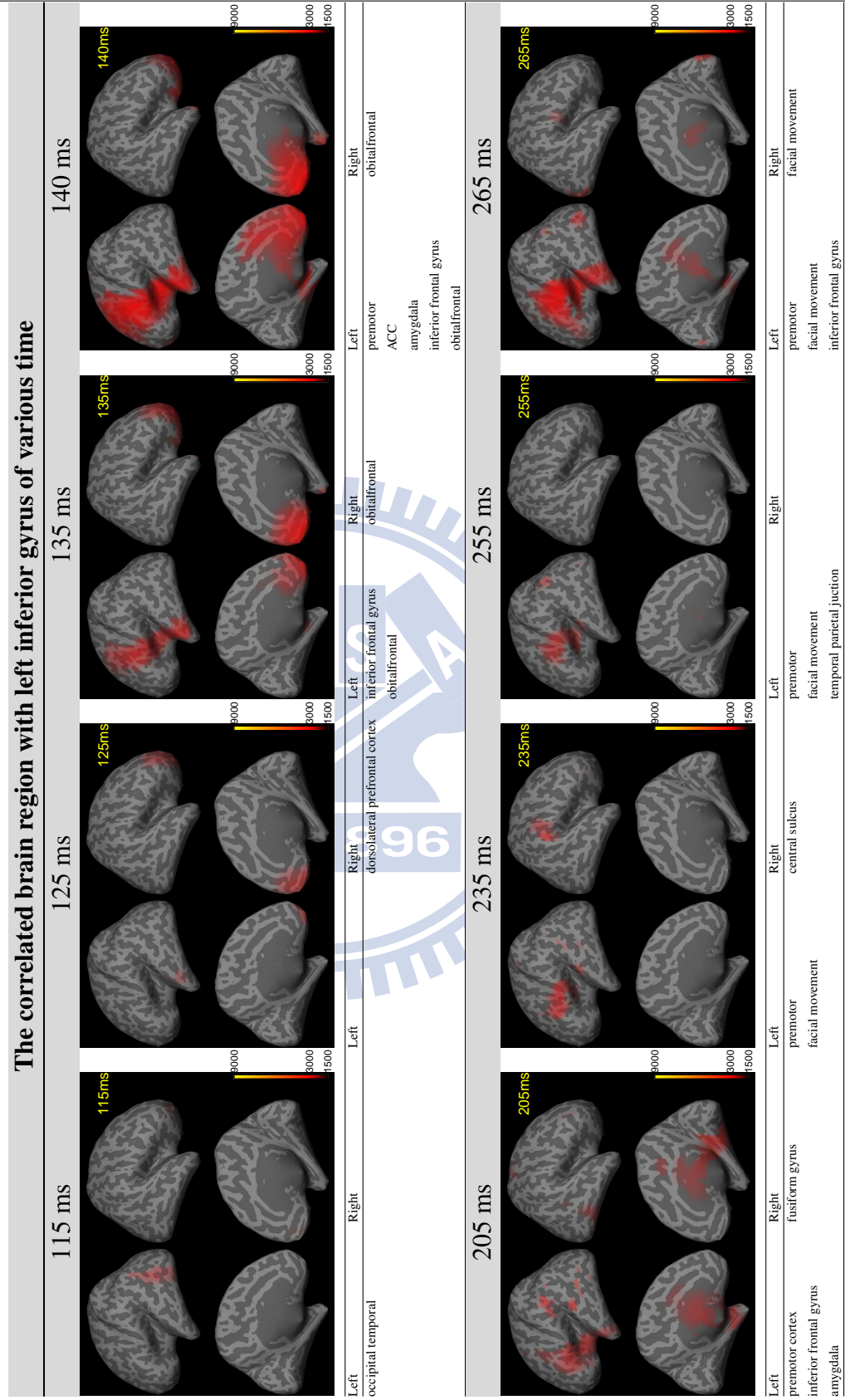


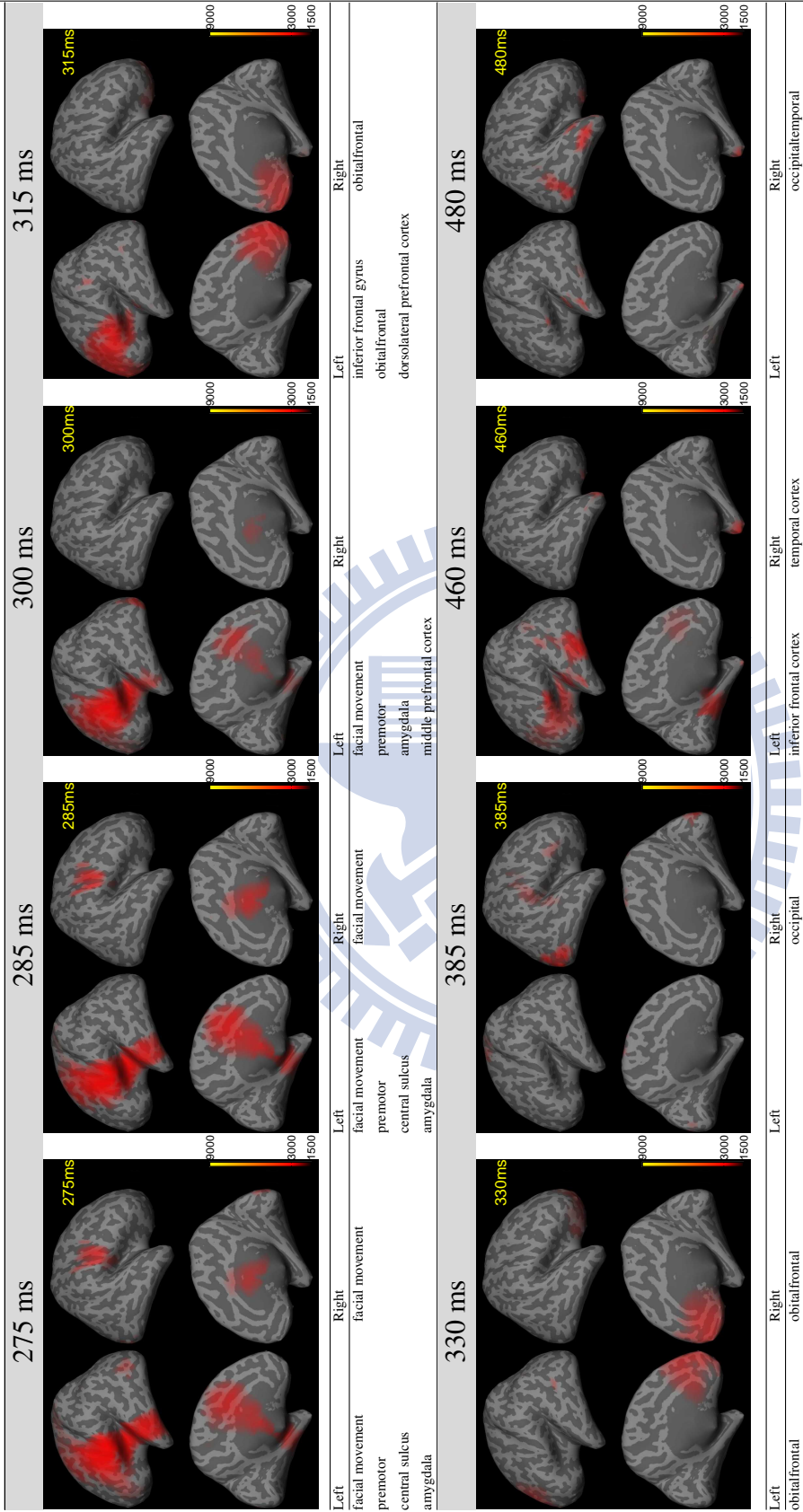
**Observation condition** The results were shown in Table 3.10.

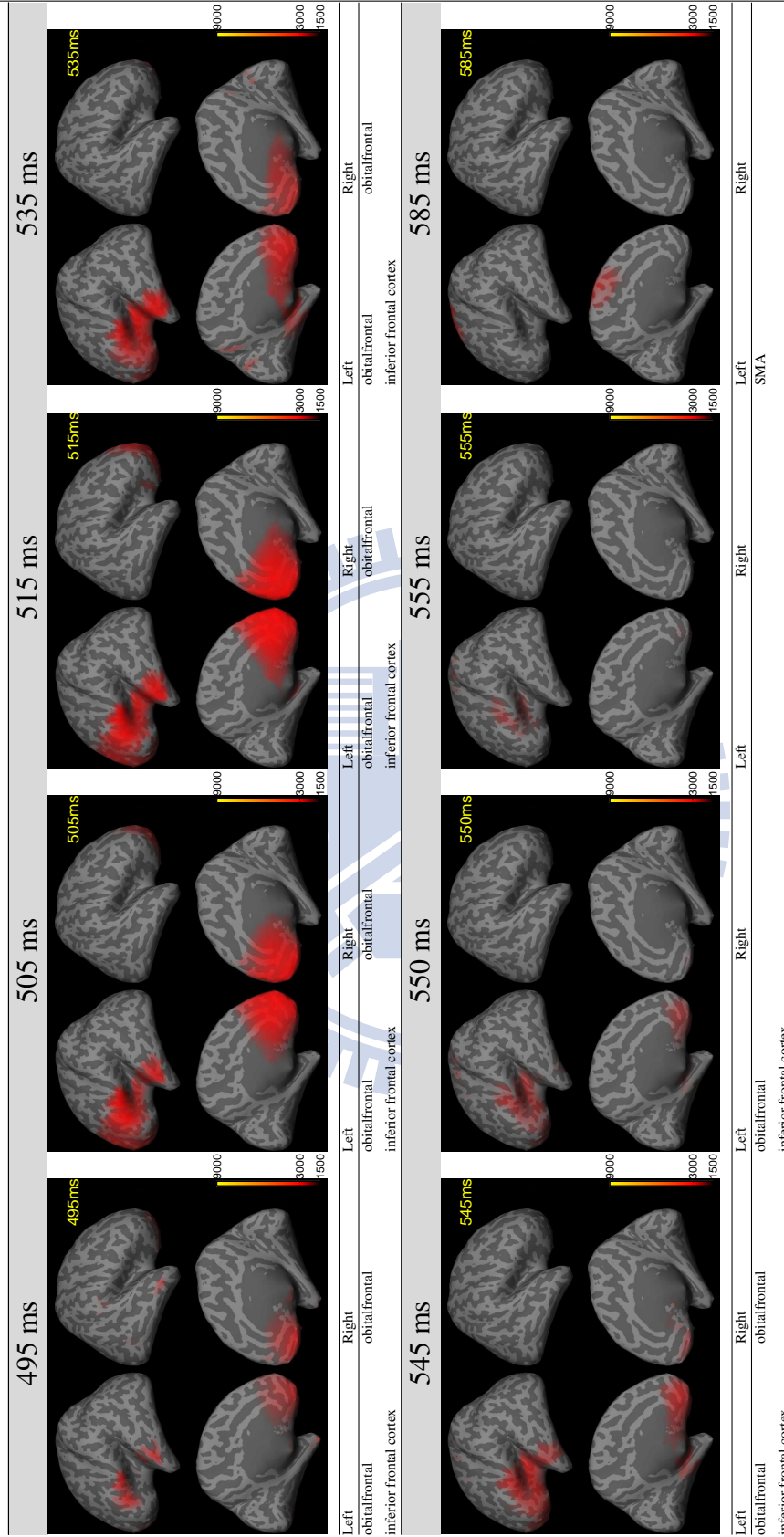


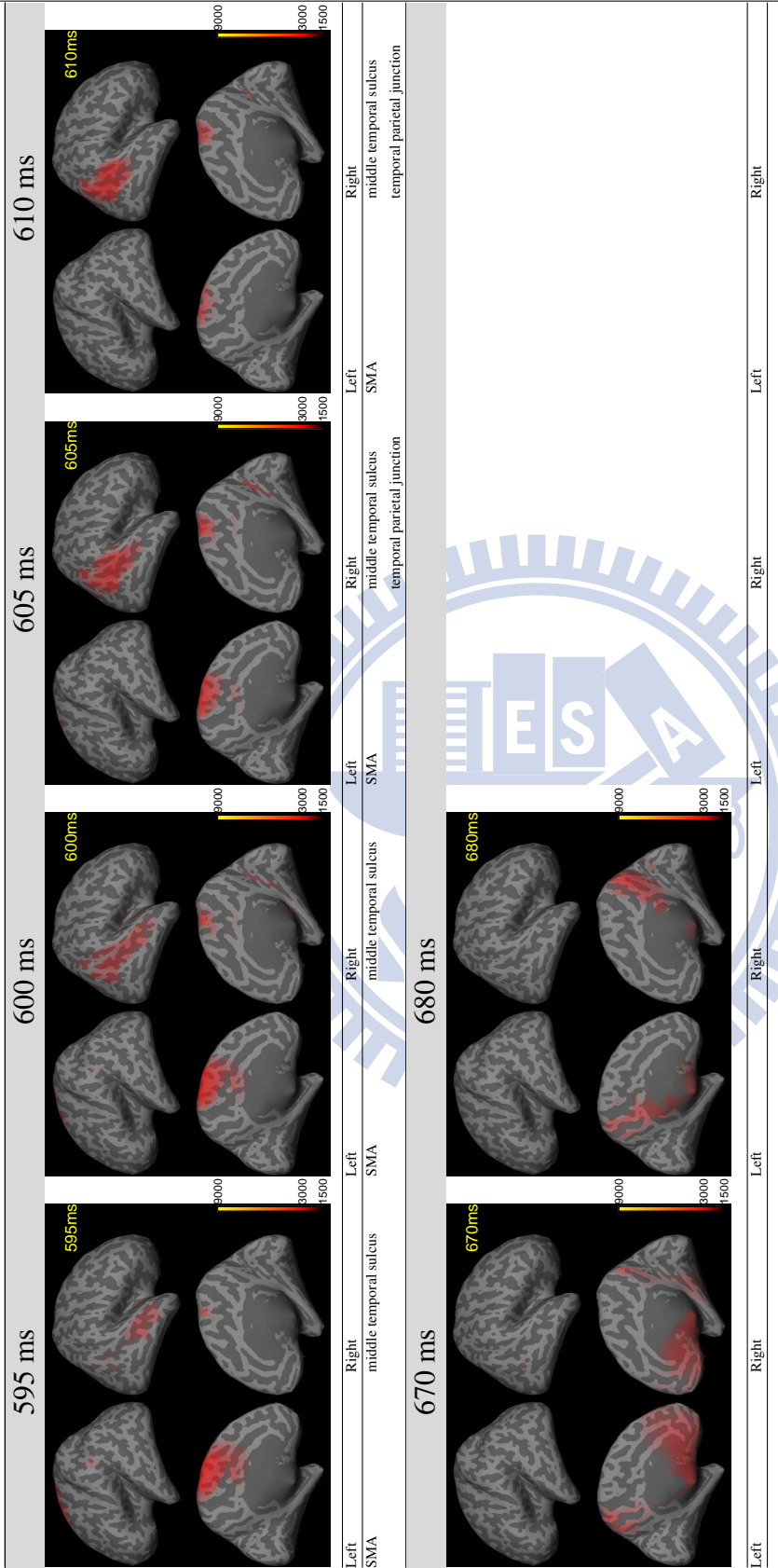


Table 3.10: The correlation map and the significant correlation regions of the reference region at left inferior frontal gyrus on observation condition at different time interval.









**Execution condition** The results were shown in Table 3.11.

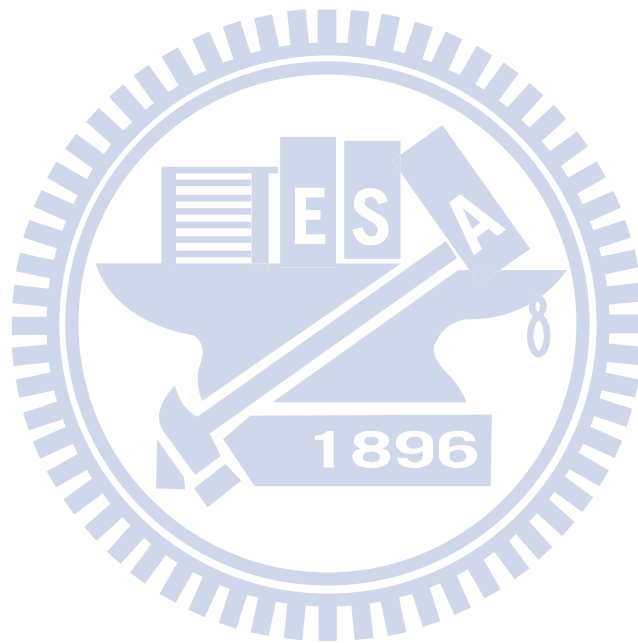
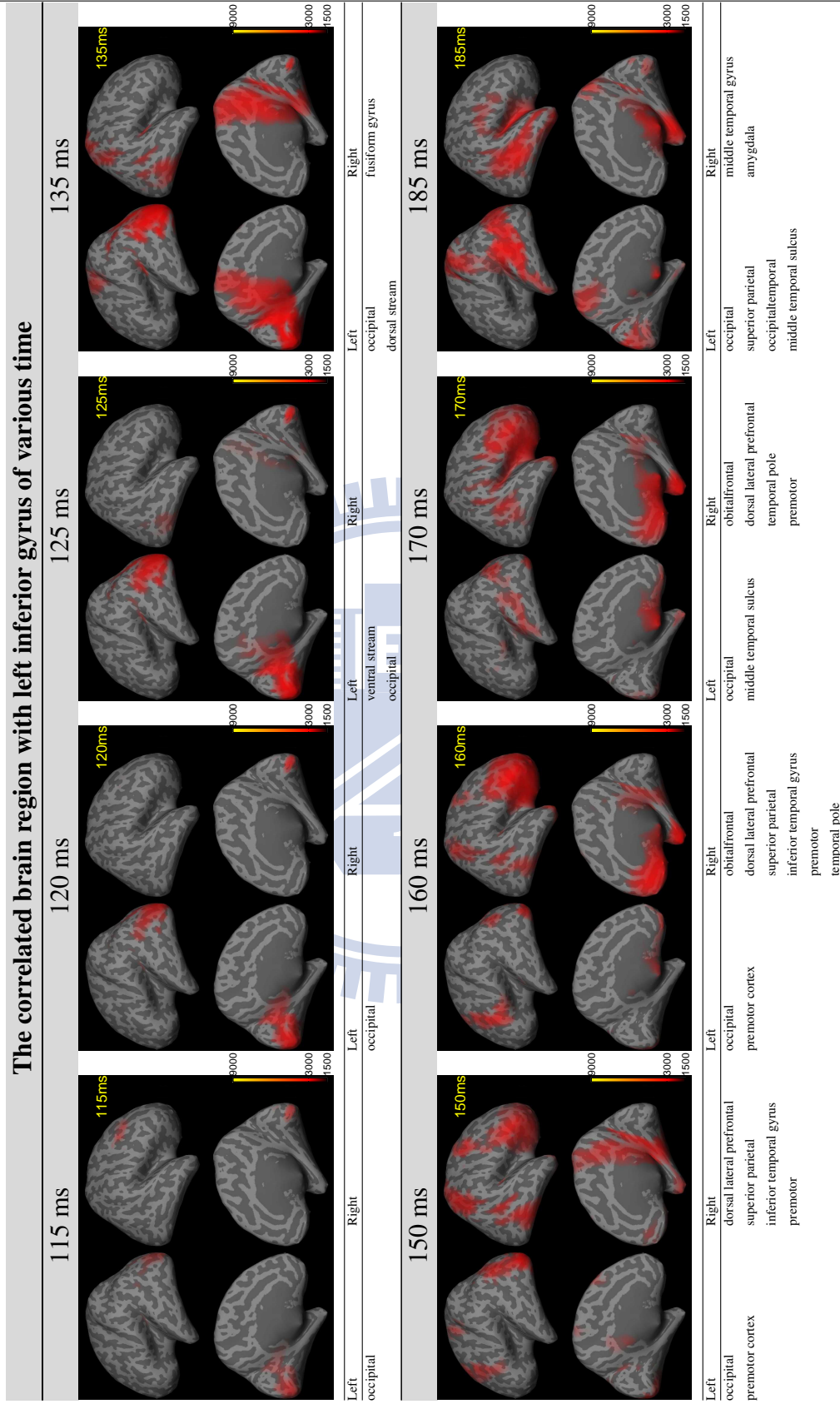
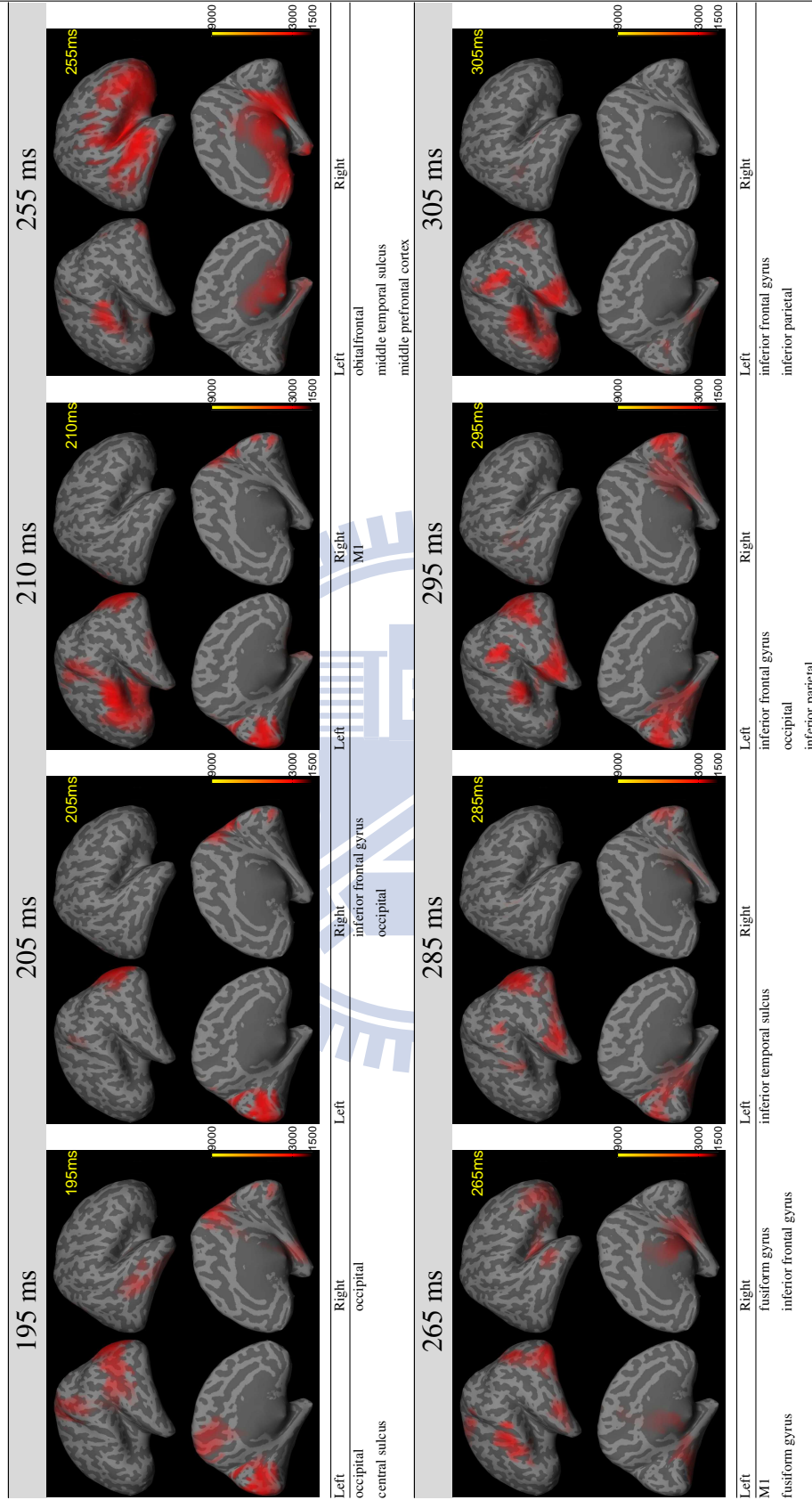
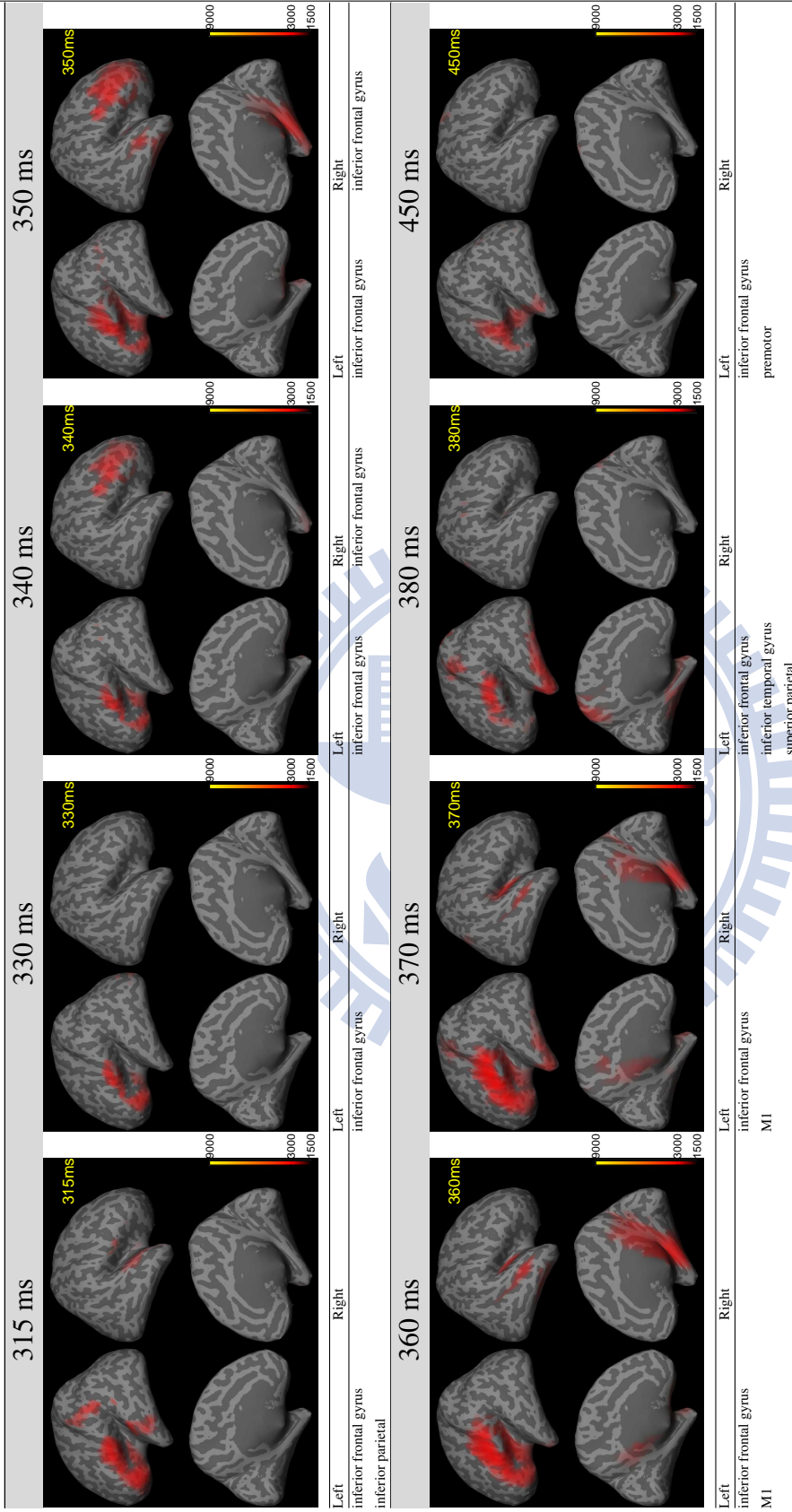


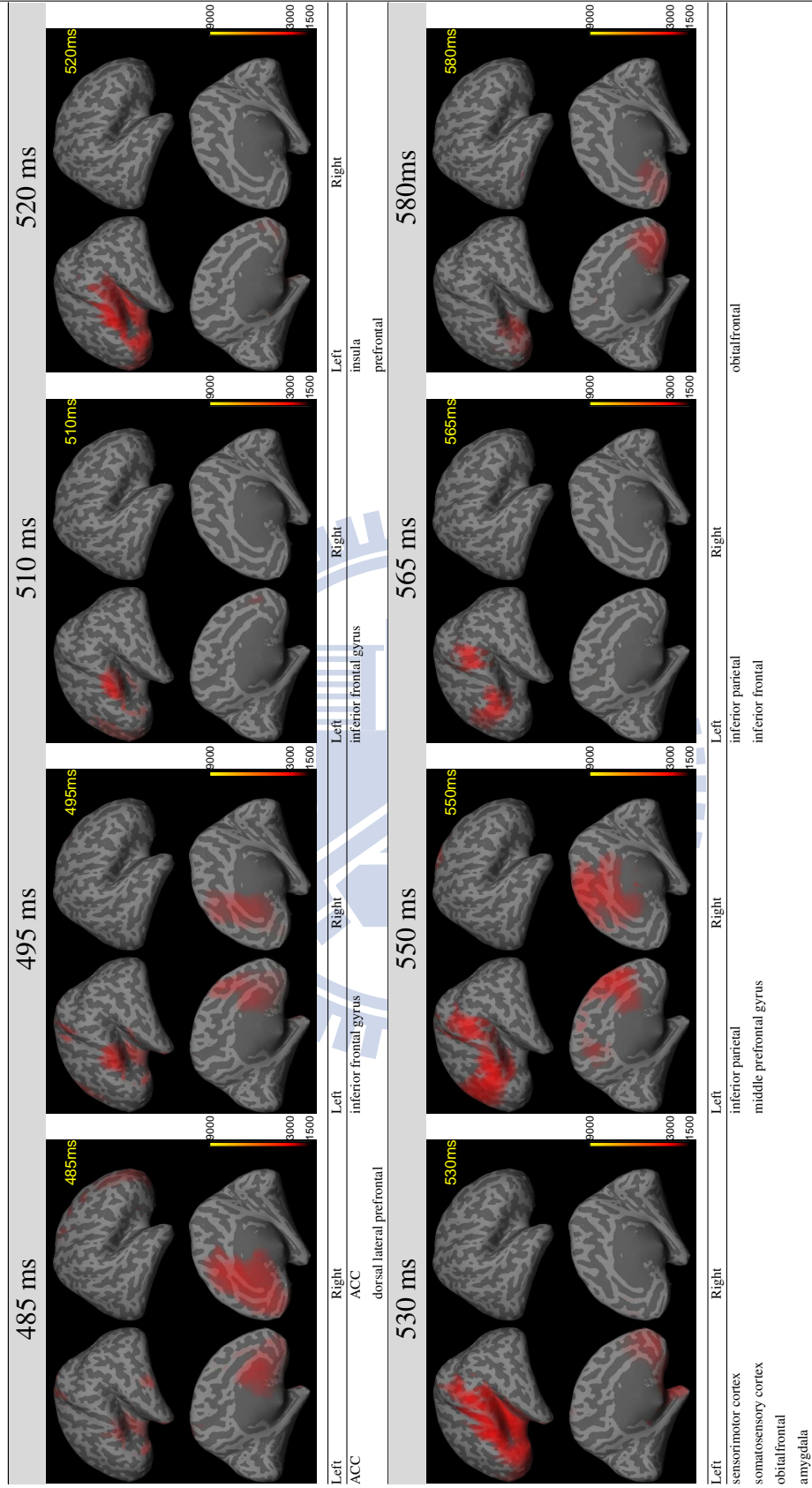
Table 3.11: The correlation map and the significant correlation regions of the reference region at left inferior frontal gyrus on execution condition at different time interval.

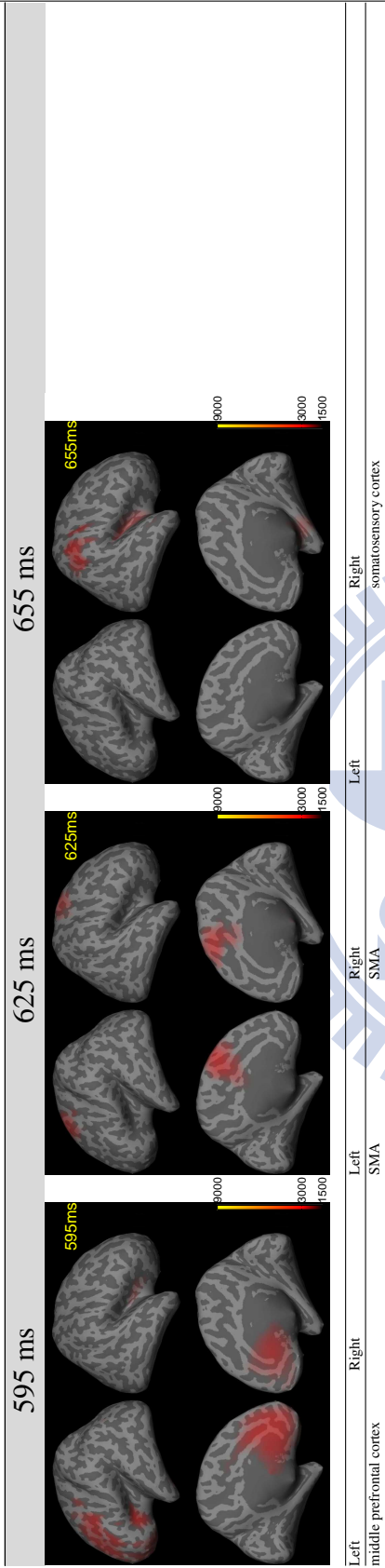












# Chapter 4

## Discussion



## 4.1 Simulation data

We apply our method to the simulation data in Chapter 3.3.1 and Chapter 3.3.2, and the result is accurate. The correlation source localization error is zero mm. It can prove our method can correctly image the distribution.

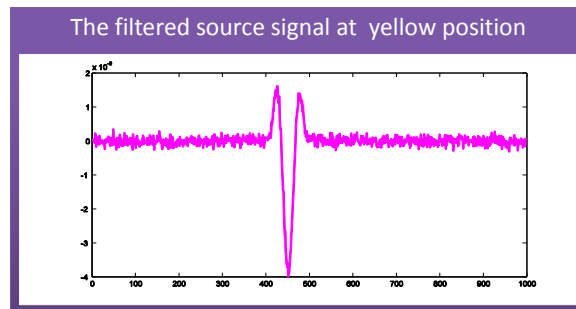
Furthermore, The result in Figure 4.1(a) is the reconstructed signal at the highest correlation position when we used C2 as the reference signal. The filtered signal is similar to reference signal even there are two source signals at the position. When we used the conventional source localization technique, we can reconstruct the signal containing two sources. The Figure 4.1(b) is the result calculated by MCB. The reconstructed signal is not similar to what we focus on, that is why we need to develop the proposed method to reveal the correlated level according to a specified reference. The reference can be a component decomposed by ICA, a cortical activities inside the brain, or the peripheral signal such as EMG measurement.

## 4.2 Real data - happy mirror neuron

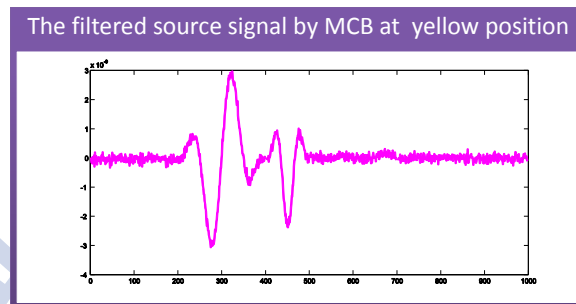
In the section 3.3.3, those highly correlation region are important in the emotional face perception, mirror neuron system. The related emotional face perception regions which have suggested by the past studies are shown as Figure 4.2; And the related mirror neuron regions are shown as Figure 4.3

In Figure 4.2, the area in yellow represent regions about the processing identity and associated semantic information, the area in red represent region involved in emotion analysis, and those in blue represent regions involved in spatial attention. The solid lines mean cortical pathway and dashed lines represent the subcortical route for rapid processing.

At beginning, mirror neuron system is originally discovered in area F5 of the monkey premotor cortex, that discharge both when the monkey does a particular action and when it observes another individual. Later, some evidences show the mirror neuron system is also exist in humans. A large number of studies showed that the observation of actions done by another individual activates a neural network formed by occipital, temporal, parietal and rostral part of inferior parietal lobe and inferior frontal gyrus. These region form the core



(a)



(b)

Figure 4.1: (a) The filtered signal at the yellow position obtained by our method (b) The filtered signal in the yellow position obtained by MCB.

of human mirror neuron system.

If the subject is asked to follow the action of what they see (imitation), some areas would activate more strong, such as left IFG, the right anterior parietal region, the right parietal operculum, and right STS. A study show superior parietal is not present when the subject just instruct to observe.

In Figure 4.3, it represents an extended mirror neuron system was proposed by Pineda [51]. The extended mirror neuron system include insula, middle temporal gyrus and somatosensory cortex. In general, the STS and parietal operculum are not thought as mirror neuron area. However, at the level of transformation performed on the data would make them important. Therefore they are included into extended mirror neuron system.

We collected the significant correlation regions from Table 3.4, Table 3.5 and Table 3.6 and listed them in Table 4.1. These regions are correlated to left inferior frontal gyrus

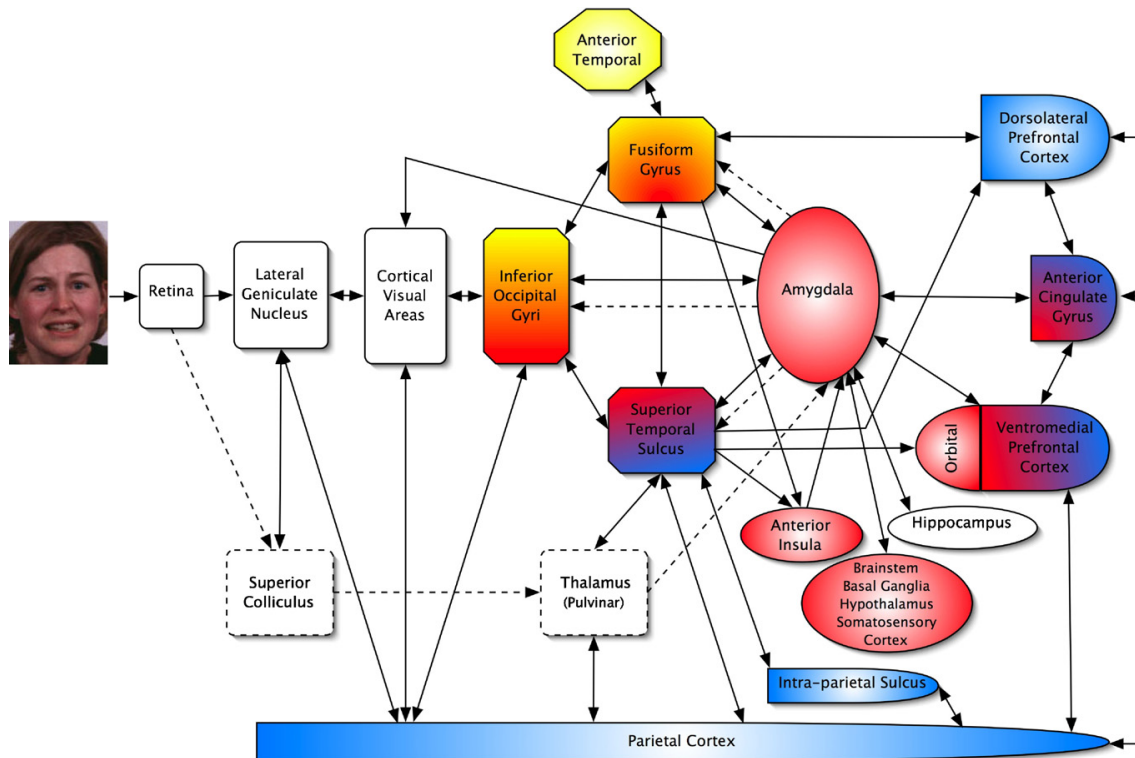


Figure 4.2: Anatomical view of a human brains showing areas involved with the mirror neuron system [50].

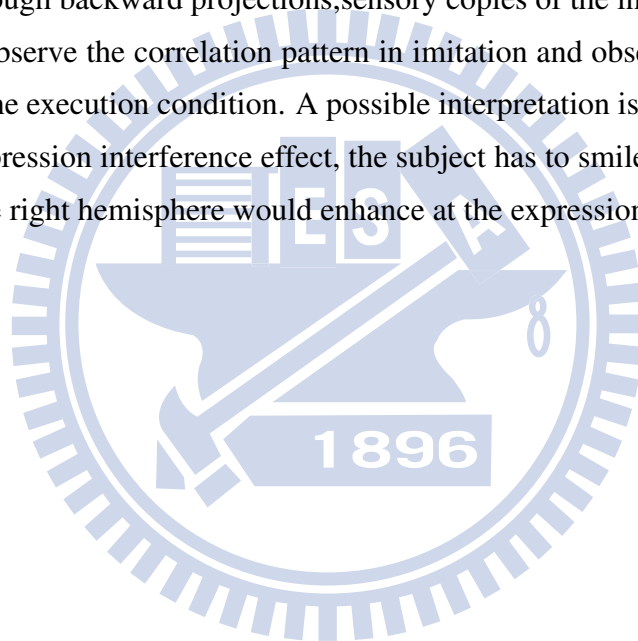
on corresponding condition. There correlation regions are highly coherent with previous finding of emotion processing, face perception and the mirror neuron task. The areas correlated the emotion processing and face are amygdala, dorsolateral prefrontal cortex, ACC, orbitofrontal cortex, fusiform gyrus, anterior temporal, superior temporal sulcus, occipital and parietal cortex [50, 52–56]. The areas correlated the mirror neuron system are inferior frontal gyrus [51, 57–62], fronto-parietal [63], superior temporal sulcus [51, 59, 60, 64, 65], meddle temporal gyrus [60, 66], insula [51, 56, 60, 66, 67], superior parietal [66], inferior parital [51, 59, 65, 66, 68], SMA [51, 66], sensorimotor cortex [51], premotor cortex [51, 69].

Besides, in imitation and observation condition, we can reveal the automatic smiling at 240 ms and 275 ms respectively as suggested in a previous study suggested [60]. We also find the highly correlation between the left inferior frontal gyrus and the facial movement at 435 ms in the imitation condition, and it is the voluntary smiling. Furthermore,

in observation condition, the facial movement is also highly correlated with the left inferior frontal gyrus at 520 ms. This phenomenon matches the theory of the mirror neuron system [51, 57–59, 61].

Furthermore, a previous finding [70] pointed out the superior parietal lobe is typically not present when subjects are instructed to observe actions without the instruction to imitate them. In our study, we have the same finding. In imitation condition, the left superior parietal is highly correlated to left inferior frontal gyrus at 420 ms. And in execution condition the right superior parietal is highly correlated to the left inferior frontal gyrus at 310 ms. The impossible interpretation of this activation is that the request to imitate produces, through backward projections, sensory copies of the intended actions.

We also observe the correlation pattern in imitation and observation condition is more similar than the execution condition. A possible interpretation is the execution condition is a emotion expression interference effect, the subject has to smile at a neutral face. As [60] suggested, the right hemisphere would enhance at the expression interference effect.



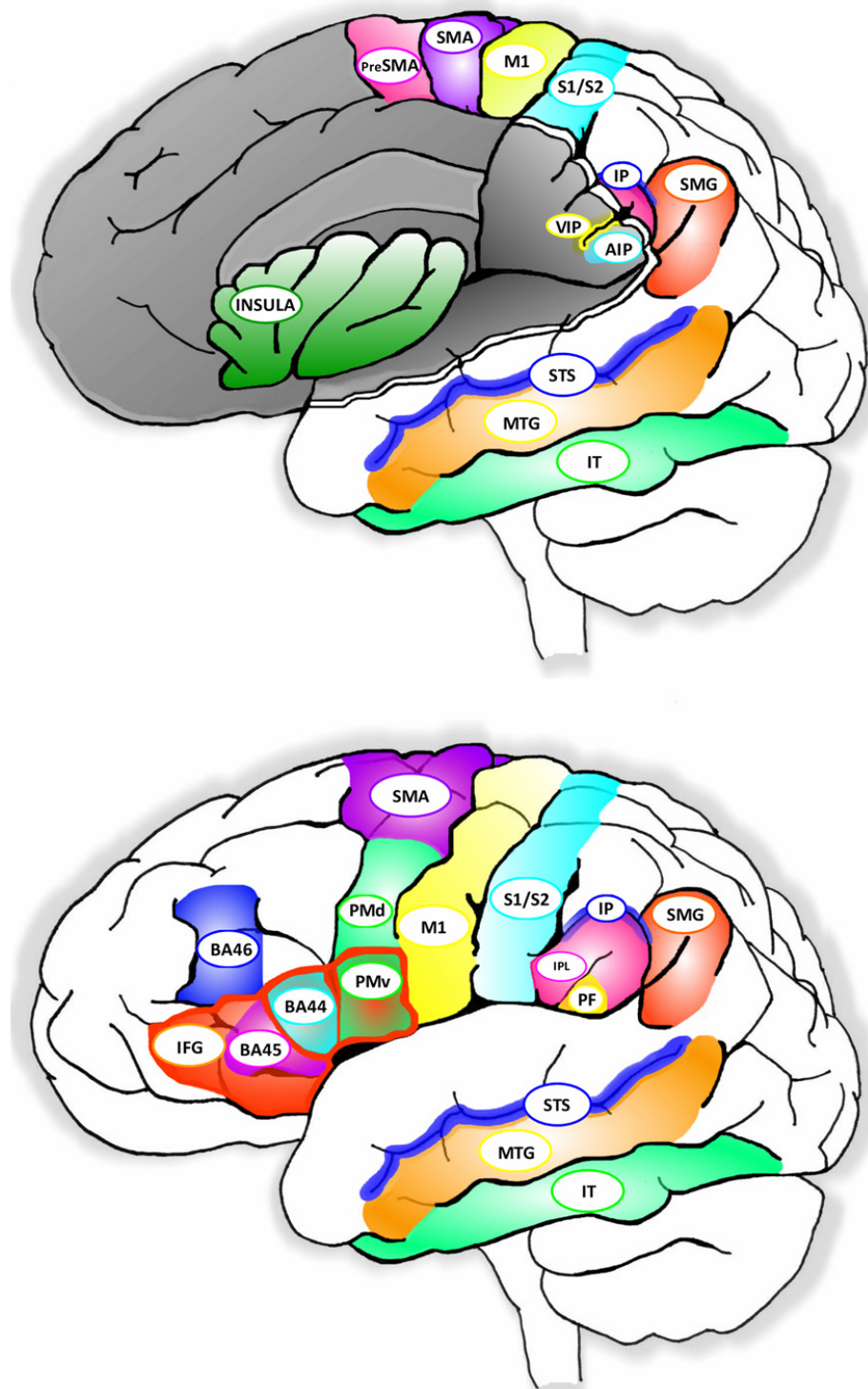


Figure 4.3: Anatomical view of a human brains showing areas involved with the mirror neuron system [51].

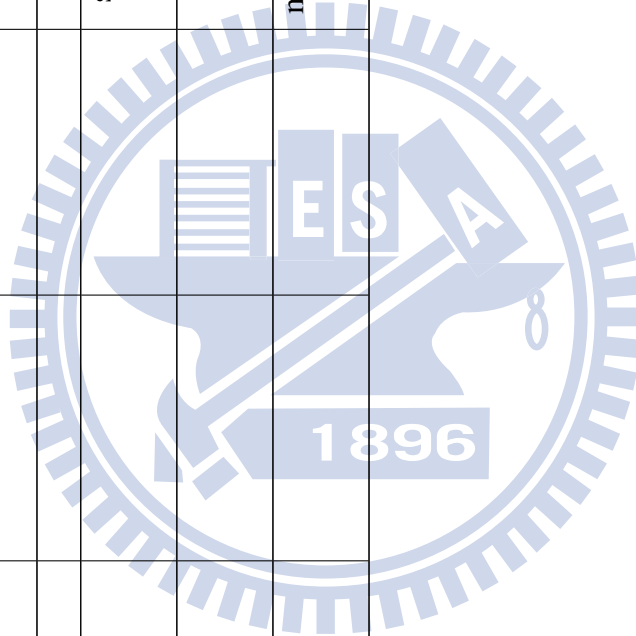


Table 4.1: The significant correlation regions of the reference region at left inferior frontal gyrus on imitation, observation and execution condition. If the region have exist at any time, it will be collected in the table.

imitation		observation		execution	
left	right	left	right	left	right
central sulcus	central sulcus	central sulcus	central sulcus	central sulcus	central sulcus
premotor cortex	premotor cortex	premotor cortex	premotor cortex	premotor cortex	premotor cortex
SMA	SMA	SMA	SMA	SMA	
middle prefrontal cortex	middle prefrontal cortex		middle prefrontal cortex	middle prefrontal cortex	middle prefrontal cortex
sensorimotor cortex		sensorimotor cortex	sensorimotor cortex	sensorimotor cortex	sensorimotor cortex
inferior frontal gyrus		inferior frontal gyrus	inferior frontal gyrus	inferior frontal gyrus	inferior frontal gyrus
middle temporal gyrus		middle temporal gyrus	middle temporal gyrus	middle temporal gyrus	middle temporal gyrus
somatosensory cortex		somatosensory cortex	somatosensory cortex	somatosensory cortex	somatosensory cortex
superior temporal sulcus		superior temporal sulcus	superior temporal sulcus	superior temporal sulcus	superior temporal sulcus
ACC		ACC	ACC	ACC	ACC
dorsolateral prefrontal cortex		dorsolateral prefrontal cortex	dorsolateral prefrontal cortex		dorsolateral prefrontal cortex
amygdala		amygdala	amygdala		amygdala
facial movement		facial movement		facial movement	

imitation		observation		execution	
left	right	left	right	left	right
temporal parietal junction		temporal parietal junction			temporal parietal junction
inferior parietal orbitofrontal cortex		inferior parietal orbitofrontal cortex		inferior parietal orbitofrontal cortex	inferior parietal orbitofrontal cortex
superior parietal				superior parietal	superior parietal
	superior temporal gyrus	superior temporal gyrus	superior temporal gyrus	superior temporal gyrus	
	temporal pole	temporal pole	temporal pole	temporal pole	temporal pole
	angular gyrus	angular gyrus			
	posterior insula cortex			posterior insula	posterior insula
		occipital	occipital	occipital	occipital
		posterior cingulate cortex	posterior cingulate cortex	posterior cingulate cortex	posterior cingulate cortex
			posterior parietal cortex	posterior parietal	posterior parietal
		occipital temporal	occipital temporal		
		occipital parietal	occipital parietal	occipital parietal	occipital parietal
		parieto-occipital fissure			
			inferior temporal gyrus	inferior temporal gyrus	inferior temporal gyrus

imitation		observation		execution	
left	right	left	right	left	right
			posterior insula		
				dorsal stream	
				ventral stream	
				supermarginal	
				superior frontal	
				gyrus	
				supermarginal	
				gyrus	
				medial prefrontal	
				cortex	





## **Chapter 5**

## **Conclusion**



In this thesis, we have proposed a beamformer-based imaging method of correlated brain activities that can reveal the neural network with similar temporal patterns for information exchange. The method can identify the regions correlated to a specified brain region, called the reference region. In principle, we can apply our method on all pairs of grid points to identify all possible the neural networks of correlated activities.

Our method exploits a maximum-correlation criterion that maximizes the significant level of correlation between the reference region and other regions inside the brain. The maximum correlation criterion helps to analytically and accurately determine the dipole orientation in a closed-form manner and thus determine the spatial filter very efficiently for each position. The correlation map can be calculated to reveal cortical regions with significant similarity to the reference position in the brain.

The experiments with simulation data demonstrated that our method can accurately determine the correlated region. Different from the conventional source localization method, we focus on the areas which have the similar temporal patterns with the reference signal. In the mirror neuron experiment, most of the regions we revealed are reported by the previous finding of emotional processing, face perception and the mirror neuron system. Moreover, we can provide the time information about when these regions are correlated to the neural network.

In summary, the proposed method can be used to directly study dynamic of correlation brain areas based on electromagnetic recordings of brain activities. Given the reference region as one of the areas in the neural network, our method can estimate the the correlated regions at each time point and thus reveal the dynamic behavior of the neural network.

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