An AdaBoost-Based Weighting Method for Localizing Human Brain Magnetic Activity *

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1 Introduction

Non-invasive measurements using magnetoencephalography (MEG) have recently been used to study how stimulus features are processed in the human brain. In particular, because neural electric activity of the brain associated with speech and language stimuli happens in a time frame of milliseconds, the high temporal resolution of MEG is required for measuring rapid changes in brain activity during speech perception. Research carried out with MEG has reported left hemisphere dominance for processing of vowels in right-handed subjects [1], and the prominent N1m wave of the auditory-evoked field has been shown to exhibit sensitivity to a variety of acoustic attributes of the speech signal [2], as well.

Recently, application of pattern recognition methods to neuromagnetic responses has created much interest, and progress has been made through the use of machine learning, such as support vector machines (SVMs) [3, 4]. SVMs are efficient tools for automatic recognition, but neuroscience research requires not only classification tools (that have high accuracy) but also analysis tools that can locate both the dominant area of the brain, showing strong activity related to speech and language, and the significant time frame, exhibiting this increased brain activity.

In this paper, we present a new weighting method for the AdaBoost algorithm, where the weight is associated with each MEG sensor. In our approach, AdaBoost was applied to MEG responses or amplitudes, to localize brain areas that contribute to the accurate decoding of vowels. Sixty-one MEG amplitudes, each calculated from each of 61 pairs of MEG sensors (in total 122 MEG sensors), constituting a 61-dimensional feature vector, are separately weighted; each weight value calculated by AdaBoost indicates how useful each MEG sensor pair is for classifying the MEG responses to vowel recognition. To identify the MEG sensors or brain areas important for vowel recognition, the weights were averaged across subjects.

2 Recording of MEG Responses to Vowels

Four right-handed volunteers were recruited as subjects after obtaining consent forms from them. All were native Japanese speakers with normal hearing. We used two speech sounds (Japanese vowels), /a/ and /o/, to explore subject's vowel recognition process in the brain. These 200-ms auditory stimuli were delivered to the subject's right ear through a plastic tube with a random interstimulus interval between 1,300 and 1,500 ms. The subject's task was to press a reaction key with the index finger when the subject identified the stimulus /a/ and another reaction key with the middle finger when the subject identified the stimulus /o/.

Neuromagnetic data were recorded by a 122-channel whole-scalp Neuromag MEG system in a magnetically shielded room. The MEG signal was sampled at 497 Hz for 1,200 ms including a 100-ms pre-stimulus baseline; more than 80 epochs were averaged to increase the S/N ratio. A low-pass filter with a cutoff frequency of 40 Hz was used in calculating the feature vector. Epochs in which the magnetic signal exceeded an absolute amplitude variation of 3,000 fT/cm were discarded. Eye-movement artifacts were also automatically removed (threshold = 150 μV).

Feature extraction was applied to a 996-ms MEG signal. Since the mean reaction times, however, for /a/ and /o/ were 495.1 ms (SD = 51.7) and 497.3 ms (SD = 46.8), respectively. The MEG feature vectors up to 450 ms were used to analyze the MEG response pattern to localize the brain activation during recognizing vowels.

3 Feature extraction

The signal obtained by averaging over 80 MEG epochs was converted (using a feature extraction transformation) into a normalized magnitude feature. The MEG signal at time t is represented by

$$\mathbf{x}(t) = [x_1(t), \cdots, x_m(t), \cdots, x_M(t)]^T \tag{1}$$

where $x_m(t)$ denotes the observation at the m-th sensor, and the symbol M denotes the total number of MEG sensors. The MEG magnitude was first calculated by the following Eq. (2), which is a vector magnitude of paired vertical and horizontal sensors.

$$y_j(t) = \sqrt{x_i^2(t) + x_{i+1}^2(t)} \tag{2}$$

where $y_j(t)$ $(1 \leq j \leq M/2)$ is the magnitude feature. Then, the magnitude feature is normalized to have zero mean and unit variance.

The normalized MEG magnitude feature at each MEG sensor constituted 61-dimensional MEG-magnitude feature vector, as shown in Eq. (3), for further analysis or classification using an AdaBoost algorithm.

$$\hat{\mathbf{y}}(t) = [\hat{y}_1(t), \cdots, \hat{y}_{M'}(t)]^T,\ M' = M/2 \tag{3}$$

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4 MEG-Sensor Weighting Based on AdaBoost

"Boosting" is a technique in which a set of weak classifiers is combined to form one high-performance prediction rule, and AdaBoost [5] serves as an adaptive boosting algorithm in which the rule for combining the weak classifiers adapts to the problem and is able to yield extremely efficient classifiers.

In this paper, AdaBoost was developed to localize brain areas associated with the subject's task, namely the accurate decoding of vowels, by assigning independent weights to each MEG sensor, where the larger the MEG-sensor weight is, the more important role the brain activity underneath the MEG-sensor plays.

The AdaBoost algorithm uses a set of training data, $\{(\hat{\mathbf{y}}(1), c(1)), \ldots, (\hat{\mathbf{y}}(T), c(T))\}$, where $\hat{\mathbf{y}}(t)$ is the t-th feature vector of the observed signal, and c is a set of possible labels. For our task, we consider just two possible labels, c = {-1, 1}, where the label, 1, means a stimulus /a/, and the label, -1, means a stimulus /o/. Next, the training data weight for the t-th training data is initialized to $d_1(t) = 1/(2p)$ for $c(t) = 1$ and $1/(2q)$ for $c(t) = -1$. Here p is the total frame number for the stimulus /a/, and q is the total frame number for the stimulus /o/.

The weak learner generates a hypothesis h_n: $\hat{\mathbf{y}}(t) \rightarrow$ {-1, 1} that has a small error. In this paper, single-level decision trees (also known as decision stumps) are used as the base classifiers. After training the weak learner on n-th iteration, the error of h_n is calculated by

$$e_n = \textstyle\sum_{t:h_n(y(t)) \neq c(t)} d_n(t) \qquad (4)$$

Next, AdaBoost sets a parameter $\alpha_n = 1/2 \cdot \log[(1 - e_n)/e_n]$. Intuitively, α_n measures the importance that is assigned to h_n. Then the training data weight d_n is updated.

$$d_{n+1}(t) = \frac{d_n(t) \exp\{-\alpha_n \cdot c(t) \cdot h_n(\hat{\mathbf{y}}(t))\}}{\sum_{t=1}^{T} d_n(t) \exp\{-\alpha_n \cdot c(t) \cdot h_n(\hat{\mathbf{y}}(t))\}} \qquad (5)$$

The equation (5) leads to the increase of the training data weight for the data misclassified by h_n. Then, the weight for the feature (MEG-sensor weight) is calculated using

$$w_j = \textstyle\sum_n \alpha_n \delta_{j_n, j} \qquad (6)$$

where $\delta_{j_n,j}$ is the Kronecker's delta, which has the value 1 if j_n is j, and 0 otherwise.

5 Analysis Results

To localize MEG sensor important for MEG activity pattern classification using AdaBoost, which were considered to have contributed to the processing of vowel recognition, the MEG sensor weights obtained from the AdaBoost method are displayed on a topological plot of the scalp in Figure 1. Figure 1 shows color-coded average weights for each MEG sensor in each latency range; more important or more highly weighted MEG sensors for classifying neuromagnetic responses are shown in darker colors; the black areas indicate that this area of the brain played an important role in classification of neuromagnetic responses to vowel recognition. The larger weights in the latency range, between 50 and 150 ms, between 100 and 200 ms, and between 150 and 250 ms, are seen to be in the left language area.

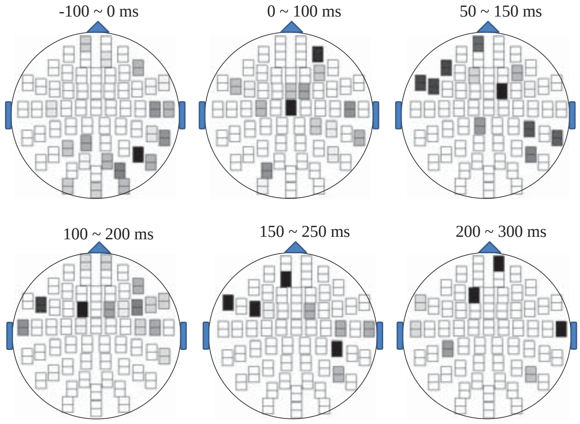

Fig. 1 MEG-sensor weighting based on AdaBoost. There are 6 top-view circle heads with nose upward.

6 Conclusion

We presented a new MEG-sensor weighting method using an AdaBoost algorithm for analyzing areas of the brain that contributed to the accurate decoding of two vowels. The brain area covered by the MEG sensors with the larger weight obtained by our AdaBoost method corresponded to the language area of the left hemisphere. As the magnetic fields generated by brain activity are extremely weak and usually largely contaminated by external magnetic noises, we will have to develop a noise-robust feature extraction method.

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