Decoding Subjective Simultaneity from Neuromagnetic Signals

K. Takahashi[1 2], S. Hidaka[3] and K. Watanabe[1 4 5]

[1] Research Center for Advanced Science and Technology, The University of Tokyo, Tokyo, Japan
[2] Japan Society for the Promotion of Science, Tokyo, Japan
[3] Department of Psychological and Brain Sciences, Indiana University, USA
[4] Japan Science and Technology Agency, Saitama, Japan
[5] National Institute of Advanced Industrial Science and Technology, Ibaraki, Japan

Abstract— **The present study examined the neural correlate of subjective simultaneity by using whole-head magnetoencephalography. Observers were asked to judge whether the visual and auditory stimuli occurred simultaneously. The auditory and visual stimuli were presented with temporal asynchrony. The subjective judgment of simultaneity for 90-ms-asynchrony showed trial-by-trial variation, and we successfully classified subjective simultaneity using neuromagnetic signals. We submitted raw MEG signals, a wavelet transform, and nonlinear dynamics to a naive Bayes classifier. In the case of raw signals and nonlinear dynamics, the classifier trained with the VA (where the visual stimulus was given first) or AV (where the visual stimulus was given second) data could predict the subjective simultaneity of the other VA (or AV) data at a rate better than chance. The classification rate using nonlinear dynamics was comparable to that using raw signals, despite the fact that the dimension was considerably low (101 vs. 88,000 dimensions). In the case of the wavelet transform, the classifier trained with the VA data was able to decode the AV data, and vice versa. These results suggest that (1) subjective simultaneity can be decoded using MEG signals, (2) low-dimensional nonlinear dynamics may encode simultaneity specific to the order of the audiovisual inputs, (3) the time-frequency characteristics of neural activity may predict subjective simultaneity independently of the physical order of the audiovisual inputs, and (4) the neural activity (time-frequency characteristics) reflecting subjective simultaneity may share a common mechanism among different sensory modalities.**

Keywords— **magnetoencephalography (MEG), decoding, time perception, subjective simultaneity**

I. Introduction

The temporal interval between two events is a key aspect of integrating multisensory inputs. A smaller interval leads to a feeling of subjective simultaneity. Several studies have found that neural activity is relevant to subjective time perception [1] through the use of electroencephalograms (EEG) and magnetoencephalograms (MEG). Most of these studies examined neural correlation of biased simultaneity (or temporal order) by presenting additional stimuli

However, time perception in humans is inherently variable; even if the temporal intervals of two events are kept constant, observers show trial-by-trial variation with regard to subjective simultaneity. In the present study, we examined the neural mechanisms underlying subjective simultaneity independent of stimulation by using a decoding approach [2]. If the classifier successfully predicts trial-by-trial subjective simultaneity in cases where the stimuli are completely identical, this implies that subjective simultaneity is encoded in the neural activity, independent of the stimulus.

Observers performed an audiovisual simultaneity judgment task in an MEG scanner. We presented visual and auditory stimuli with small temporal asynchrony. We first tested whether the ERP in trials where the observers judged “simultaneous” and “non-simultaneous” would differ in peak amplitudes and latencies [3, 4]. Further, we performed a classification analysis using a wavelet transform and the nonlinear dynamics of neuromagnetic signals to examine whether subjective simultaneity can be decoded.

II. Methods

Neuromagnetic responses were measured using a 160-channel whole-scalp MEG system (Yokogawa PQ1160C) in a magnetically shielded room. The magnetic signals were low-pass filtered at 500 Hz, digitized at 1000 Hz, and stored for off-line analysis. Visual stimuli were presented on a screen in the MEG scanner using a high luminance LCD projector, and auditory stimuli were presented to the right ear using a magnetic-free earphone. The visual stimulus was a white square presented in the center of the screen for 50 ms, and the auditory stimulus was a 50 ms beep sound.

Nine observers performed an audiovisual simultaneity judgment task in the MEG scanner. In each trial, one visual stimulus and one auditory stimulus were presented in temporal asynchrony. The asynchrony was randomly chosen from five stimulus onset asynchronies (SOA; 0, ±90, ±180 ms). The observers were asked to report whether the auditory and visual stimuli occurred simultaneously, by pressing the left or right button. The 0-ms- and ±180-ms SOAs were repeated 60 times and the ±90-ms-SOAs were repeated 120 times.

III. Results and discussions

A. Behavioral data

Table 1 Percentages of "simultaneous" judgments for each SOA.

SOA (ms)	–180	–90	0	+90	+180
% Simultaneous	26.9	58.8	85.6	65.6	26.5

Table 1 shows the percentage of "simultaneous" responses that were prompted for each SOA. The observers judged that most of the ±180-ms-SOA trials were "non-simultaneous" and most of the 0-ms-SOA trials were "simultaneous." The subjective simultaneity judgments for the ±90-ms-SOA were highly variable. In the following MEG analyses, we used a –90-ms-SOA condition (i.e., the visual stimulus was presented 90 ms before the auditory stimulus—a VA condition) and a +90-ms-SOA condition (i.e., the visual stimulus was presented 90 ms after the auditory stimulus—an AV condition).

B. Event related potentials

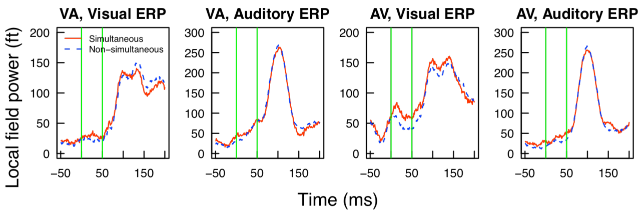

Fig. 1 The local field power of event related potentials. The red and blue lines indicate the ERP in "simultaneous" and "non-simultaneous" responses, respectively. The green lines indicate the onset and offset of the stimuli (a flash for the visual ERP and a sound for the auditory ERP).

Subjective simultaneity may be determined by external noise (e.g., the fluctuation of light and sound stimulation) and/or internal noise (e.g., the fluctuation of neural transmission). If this is the case, we should find difference in the latency or amplitude of event-related potentials (ERPs), depending on the subjective simultaneity judgment. To test the difference between ERPs, we picked six visual and six auditory channels that were strongly responsive to the stimuli. Figure 1 shows the ERPs at visual and auditory channels (the mean of the RMS of the six channels). Visual inspection showed that both visual and auditory ERPs appeared approximately 90 ms after stimulus onset. In the quantitative comparison between the ERP in the trials of "simultaneous" responses and those of "non-simultaneous" responses, we did not find any significant difference in the latencies and amplitudes (Table 2, all *ps* > .10). Thus, the ERP did not represent subjective simultaneity in the present task. The peak amplitudes [3] and the latencies [4] of ERP are known to correlate with subjective temporal order of two events. The absence of neural correlation here may imply that the neural mechanisms underlying simultaneity and temporal order judgments are different.

Table 2 Latencies and amplitudes of the peaks of ERP. The S and NS indicate "simultaneous" and "non-simultaneous" responses, respectively.

Condition		VA		AV	
Channel		Visual	Auditory	Visual	Auditory
Latency (ms)	S	120	100	112	101
	NS	112	101	104	99
Amplitude (fT)	S	158.8	287.6	179.1	279.4
	NS	161.8	287.3	192.9	278.8

C. Classification analyses

Treating neuromagnetic responses as high-dimensional signals, we tried to "decode" subjective simultaneity. As part of the decoding approach [2], we trained a naive Bayes classifier [5] using the neuromagnetic signals from some of the trials (the training dataset), and performed a validation test using the other trials (the test dataset), to assess whether the classifier successfully discriminates between "simultaneous" and "non-simultaneous" classes. If the discrimination rate was above chance (0.5 in the case of two classes), this would imply that the classifier could "decode" subjective simultaneity from neuromagnetic signals. We performed a separate classification analysis for each observer.

With regard to the pairs of training and test datasets, we conducted four types of cross-validation test: first, where both training and test datasets were a VA condition (VA→VA); second, where both datasets were an AV condition (AV→AV); third, where the training dataset was a VA condition and the test dataset was an AV condition (VA→AV); and fourth, where the training dataset was an AV condition and the test dataset was a VA condition (AV→VA). Note that VA→VA and AV→AV were within-condition validation, and VA→AV and AV→VA were between-condition validation. We randomly chose the training and test trials without overlap, and the numbers of "simultaneous" and "non-simultaneous" trials were made equal in order to avoid the bias caused by the different prior probabilities.

We tested three different types of the feature-dimensions that were submitted to the classifier: the raw neuromagnetic signals of all channels, the time-frequency characteristics of visual and auditory channels, and the non-linear dynamics of all channels.

a) Decoding using raw neuromagnetic signals

Table 3 Percentages of correct classification of subjective simultaneity. * significantly ($p < 0.05$) higher than chance (0.5) in the validation test.

	VA→VA	AV→AV	VA→AV	AV→VA
Raw signal				
Training	89.1	92.4	88.7	92.1
Test	54.6 *	58.0 *	51.2	49.4
Wavelet transform				
Training	80.2	87.1	79.1	86.3
Test	50.9	52.8	55.1 *	53.1 *
Nonlinear dynamics				
Training	85.9	90.0	86.0	90.0
Test	53.3 *	56.1 *	51.2	51.2

We submitted the raw neuromagnetic signals of all channels and samples (ranging from –50 to 499 ms after the onset of the stimulus at 1 ms intervals) to the classifier (i.e., 160 channels × 550 samples = 88,000 dimensions). Table 3 shows the correct classification rates. The classifier worked well for the training dataset; the correct rates were significantly high but not perfect, indicating that over-fitting did not take place. For the test dataset of within-condition validation (VA→VA, AV→AV), the classifier was able to predict subjective simultaneity at a rate better than chance. In contrast, the same classifier failed to predict subjective simultaneity in between-condition validation; that is, the classifier that was trained with the VA data could not decode subjective simultaneity of the AV data, and vice versa.

b) Decoding using time-frequency characteristics

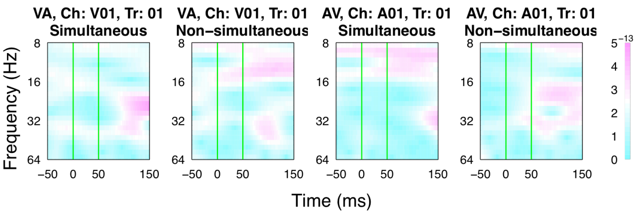

Fig. 2 Representative scalograms of the wavelet transform. The horizontal axis indicates the time from the onset of the stimulus. The green lines indicate the onset and offset of the stimulus (a flash for the VA and a sound for the AV condition).

Neural oscillations are known to be relevant to a wide range of cognitive functions [6], including time perception (e.g., gamma-band oscillation [1]). Therefore, we tried to decode subjective simultaneity using the time-frequency characteristics of neuromagnetic signals. We performed the Morlet wavelet transform on the raw neuromagnetic signals. We chose a different set of six channels for the VA and AV conditions, on the basis of the strength of the ERP. The sampled time range was –50-149 ms with a 1 ms interval, after the onset of the stimulus. The range of frequency was 24 bins of 8-64 Hz. Figure 2 shows the representative scalogram of the wavelet transform. We then submitted the power of time-frequency (the modulus of the wavelet transform) to the classifier (6 channels × 200 samples × 24 frequencies = 28,800 dimensions). The classifier also worked well for the training dataset, without over-fitting (Table 3). In the cross-validation test, in contrast to the raw neuromagnetic signals, the classifier could predict subjective simultaneity in between-condition validation but not in within-condition validation.

The fact that the classifier worked better in between-condition validation was surprising, since the order of visual and auditory stimuli was reversed between conditions and we picked a different set of channels for the VA and AV conditions. Although the reason why the classifier failed to pass the within-condition validation is unclear, these results still imply that subjective simultaneity can be decoded, independent of the stimulus condition. The classifier could predict subjective simultaneity using the signals of sensory-specific channels and only the early response (<150 ms) to the first stimulus. Hence, the time-frequency characteristics of the sensory area related to the first stimulus, independent of the sensory modality, may influence the stochastic process that determines subjective simultaneity.

c) Decoding using nonlinear dynamics

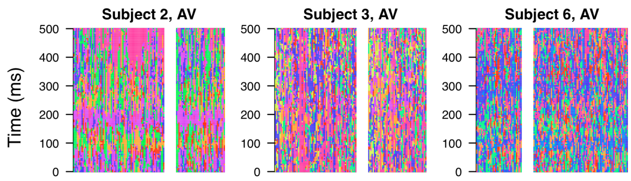

Fig. 3 Representative symbol sequence estimated based on the nonlinear dynamics of neuromagnetic signals. The vertical axis indicates the time from the onset of the stimulus. Each column shows a symbol sequence for each trial. Each color indicates the estimated symbol. The trials of "non-simultaneity" response are shown on the left panel and those of "simultaneous" response are on the right panel.

The two decoding methods above used only the linear characteristics of neuromagnetic signals. However, the nonlinear dynamics of neuromagnetic signals may include crucial information that can be used to discriminate observers' subjective state [7]. To test this possibility, we estimated a generating partition on neuromagnetic signals, wherein the continuous time series was discretized into a given number of symbols. We sampled 101 points (ranging from 0 to 500 ms after the stimulus onset at 5 ms intervals) from the raw signals of 160 channels. The 160 dimensions of the channels were reduced to 70-90 dimensions (different for each observer) using a principal component analysis (PCA). We then estimated the generating partition (10 symbols or less) on the reduced matrix (101 × 70-90 dimensions) using the Symbol False Nearest Neighbor (SFNN) method [8, 9]. Thus, we obtained the estimated symbol sequence of 101 dimensions for each trial (Figure 3) Finally, we submitted the symbol sequence (101 dimensions) to the classifier. The results showed that the classification rates were comparable to those using the raw signals (Table 3): in within-condition test, the classifier could predict subjective simultaneity at a rate better than chance. Note that the dimensions of data submitted to the classifier were 88,000 in the raw signal and only 101 in the nonlinear dynamics. Thus, we successfully extracted the nonlinear neural dynamics correlated with subjective simultaneity as the discrete symbol sequence.

d) Comparison among decoding methods

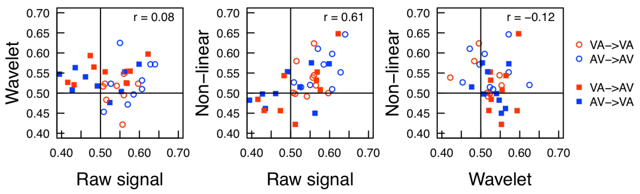

Fig. 4 Within-subject correlation among the three types of decoding methods. Each point represents the individuals' data. Red and blue symbols indicate that the training dataset were VA and AV conditions, respectively. Open circles and filled squares indicate within-condition and between-condition classification, respectively.

As we submitted different features to the classifier, we analyzed within-subject correlation among three decoding methods (Figure 4). We found significant positive correlation in the classification rate between the raw signals and the nonlinear decoding (Figure 4, middle panel). Together with the comparable classification rate and the failure of between-condition validation, these two methods focus on the similar features of neuromagnetic signals. The subjective simultaneity may be encoded as low-dimensional nonlinear dynamics in a form that is sensitive to the order of visual and auditory stimulus.

On the other hand, the classification rate in the wavelet transform correlated to neither the raw signals nor the nonlinear decoding. In addition, the classifier with the wavelet transform passed the between-condition validation, i.e., it was insensitive to the order of the visual and auditory stimuli. Therefore, it seems clear that the wavelet method emphasizes different features from the other methods. Although the sample included only a small number of channels showing ERP, and also small time range (<150 ms) in comparison with the other two methods, we suggest that extracting time-frequency characteristics (e.g., gamma-band oscillation [1, 6]) enables to pass the between-condition validation. Further research that applies the wavelet transform to all channels and that uses a long time range will clarify those features that are crucial for decoding subjective simultaneity insensitive to the stimulus order.

IV. Conclusion

The naive Bayes classifier successfully decoded subjective simultaneity independent of the stimulus condition, using high-dimensional neuromagnetic signals. The dissociation of the results of decoding using nonlinear dynamics and time-frequency characteristics may imply that different types of neural dynamics are relevant to subjective simultaneity. This study will provide a useful foundation for further research aimed at revealing the underling neural mechanisms of subjective time perception.

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