Investigation of speech-planning mechanism based on eye movement and EEG

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***Abstract*—A major concern in the speech production research is how speakers make a plan for speech articulation, in which the latent time is an important index for evaluating the planning process. Previous researches on this topic using either isolated words or phrases found that the word length and familiarity could affect the latent time of speech planning. However, in continuous sentence processing, semantic prediction was found to be more influential from our previous eye movement investigation. To probe further into the underlying neural causes, this study combined eye movement and EEG techniques to analyze the behavior-locked brain activities during the speech planning process in a sentence reading task. The results showed that the latent time decreases gradually with ongoing reading process as the context information got richer. And the subjects tend to look ahead prior to the articulation of the current word. Functional network analyses for the visual and semantic processing were consistent with the behavior results and suggested that the look-ahead phenomenon is a companying effect of speech coarticulation, and as speech prediction becomes easier, the latent time for speech planning tend to be shortened.**

***Index Terms*—Speech planning, Latent time, Eye movement, EEG, Functional network analyses, look-ahead phenomenon.**

I. Introduction

Major concerns in speech production research include how speakers perform speech-planning, and what are the major factors that affect the planning process. In the case of oral reading, speakers first obtain text information via visual perception, and transform the visual information into lexical information. During this process, semantic and phonological processes might be also involved. Then, motor commands were executed for articulation, and thus speech sounds are finally generated [1]. From the physical and physiological aspects, we should consider at least three factors in abovementioned speech planning stages, namely the latent time, anticipation effect and carryover effect. The latent time is the period of speech planning process, which is defined as the time from the gaze onset of the reading text to the onset of the speech output in oral reading. The anticipation effect describes the phenomenon that speakers look ahead a number of words for the integrated processing of the current words when the coarticulatory effect was taken into account. The carryover effect is another expression of the coarticulatory effects, which reflects the movement and deformation of the speech organs in preceding words. The anticipatory coarticulation reflects high-level phonological-phonetic processing, which occurs only if the speaker can look ahead in context and anticipate oncoming sounds [2]. The benefits of planning ahead include avoiding mistakes and avoid becoming tongue-tied. To describe this process, Henke proposed a phonemic-segment model, called the look-ahead model [3]. It hypothesized that for the production system to perform fluently, the speakers need to scan ahead to find out which sounds are to be produced next. If the specification of a sound permits (i.e. if with semantic coherence), the articulators are brought into the position necessary for the particular sound that is yet to come. That is, speech planning does not proceed in a word-by-word fashion.

Previous studies on speech planning were mostly conducted on isolated words by eye movement and speech information, in which the planning period was measured from the onset of the word presentation to the onset of the uttering [4]–[7]. Studies using this methodology have shown a tight link between the onset of participants fixation of a word and the onset of uttering the fixated word. It is found that the length [8]–[10] and the familiarity [11]–[13] of words would significantly affect the mean latent time for speech planning. However, with only isolated words investigated, this approach is not able to reflect some intrinsic factors such as the anticipation effects in continuous speech processing. In recent years, researchers started to adopt phrase and sentence reading tasks to explore such effects. In the case of producing a noun phrase, Smith and Wheeldon [14] found significantly longer onset latencies when producing a complex noun phrase than a simple noun phrase. Damian and Dumay [15] showed that (in English) the onset latencies for phrases consisting of an adjective and noun beginning with the same phoneme (e.g., blue bell) were faster than for those began with different phonemes (e.g., white bell). These results implied that the speakers access the latter lexical representations and phonological information prior to the speech onset of the phrase. In that case by delaying production of the first word in the utterance until they had some sense of the availability of the phonological form of the upcoming word [9]. These results implies that the latent time of speech planning is affected by the anticipation and carryover effects. In our previous study, we used eye movement to measure the latent time in oral reading of continuous sentences, and found that latent time is heavily dependent on the word location in the sentences, where the latent time reduced along with the sentence monotonically [16]. The location effect in continuous speech is more significant than the word length, which is inconsistent from previous studies.

So far, the above-mentioned studies mainly adopted behavioral analysis to explore the latent time of speech planning. The limitation of this line of investigation lies in that lack of explanation of the brain activation during the latent time it could make. To shed light on the black box, neural investigation is necessary to combine with behavior ones to for a comprehensive exploration. For this reason, this study investigated the speech planning process from the human behavioral and neurological aspects by combining electroencephalography (EEG), eye-tracking and speech data during oral reading of continuous sentences. This multimodal data analysis method is promising to uncover the causes of the difference between our results and previous ones and clarify the mechanism of speech planning.

In general, the brain activation obtained during articulation movement is easily buried in muscle activity artifacts and disturb further analyses. Fortunately, with recent advances in the neurophysiological techniques represented by Electroencephalography (EEG), it is possible to reduce artifact interferences using blind source reconstruction methods [17]. and investigate the brain dynamics at the millisecond level [16]. Besides, the latest advent of the Granger causal analysis [18] and multivariate autoregressive (MVAR) modeling [19] along with the source information toolbox (SIFT) [20] provided a novel framework to estimate and visualize the information flow within distributed brain networks based on time-frequency information [18]. On the other hand, neuroimaging techniques, such as fMRI, possess high spatial resolution in characterizing regional dynamics. In this study, we use fMRI-based brain network from previous studies as constraint on EEG signal processing to examine the spatial network dynamics of our EEG-constructed network sequences.

II. Method

A. Experimental design

In this experiment, 180 sentences with unified structures (US) were used as the oral reading text, where the experiment is separated as three blocks with 60 sentences, each trial has one sentence. Each of the sentences is composed of 8 two-character Chinese words (16 characters/syllables per sentence). For each trial, once the sentence was presented on the screen along a horizontal line, the subject was asked to utter the sentence at a natural speech rate, as soon as possible. When the subjects gazing point fell in either one of the 16-character fields, a trigger with the corresponding number would be marked on EEG signals, where EEG, eye movement and speech data are recorded simultaneously. The trial ends with an ESC key press. There is a 2000-ms resting period after the preceding trail, and then a fixation cross appears in the center of the screen for 1000ms, followed by the presentation of a randomly selected sentence. The whole experiments lasted around 52 to 88 minutes.

Totally, 16 Mandarin speakers from Tianjin University (8 male and 8 female, 20-26 years, mean age 22.8 years, Std=1.6) participated in this study. All the subjects reported normal or corrected-to-normal vision, right-handed [21], and with normal hearing and speaking abilities. The ethical approval for this experiment was obtained from the Tianjin University Research Ethics Committee and JAIST Research Ethics Committee.

B. Equipment and data acquisition

During the experiment, participants were seating in a comfortable armchair in an acoustically shielded room and facing a computer screen that was 1 m away. In order to minimize the possibility of EEG artifacts associated with large movement, their foreheads were asked to place against a rest. The experiment started with a practice session with a number of sample trials for familiarization. EEG data were acquired with a SynAmps RT amplifier (Neuroscan, USA) with 128 electrodes mounted on the scalp by the standard of the105 system [22]. Six EOG electrodes were affixed to the left and right outer eye canthi and above and below both eyes. EEG data were referenced to the FCz electrode during acquisition and sampled at 1000 Hz. The impedance for each electrode was maintained below 5 k. Eye movement was recorded at 100Hz via a monocular pupil tracking system (Eyelink 1000, SR Research Ltd., Canada). A three-point (horizontally distributed) calibration was adopted when the eye-tracking failed or shifted (Gaze accuracy deviation <0.50). Meanwhile, Speech was recorded using a microphone (SONY ECM MS957) at 44100 Hz.

III. Data processing and analysis

A. Behaviors data analysis

The locations and durations of eye movement were analyzed in MATLAB (MathWorks) for detecting the onset and offset of eye gazing of each word in the sentence. The speech was segmented and aligned using SPPAS software [23] for detecting the onset and offset of the pronunciation of each word. The time from each eye onset to eye offset is defined as the visual processing period, and the time from eye onset to speech onset of a word is regarded as speech planning of the word. Semantic processing may happen somewhere within the whole process. Fig.2(a) listed the averaged latent time of speech planning for each of the eight words over ten subjects.

B. Preprocessing and analysis of EEG

Pre-processing was performed by using the EEGLAB toolbox [24]. Firstly, the EEG signals passed through a high-pass filter with cutoff frequency of 1Hz after down-sampled to 250Hz. In order to preserve the active component of speech perception (a part of gamma band: 30Hz - 60Hz), we applied a 60Hz low-pass filter on the data, where the line noise was filtered out by a band stop filter from 49.5Hz to 50.5Hz [25].

Bad channels with over 10 of abnormal fluctuations were removed before re-referencing the data to average. Then the continuously recorded data were segmented into 180 epochs ranging from -1000 ms to the end of each trial, where the presentation timing of each sentence is defined as 0 ms, and the segment from -1000 ms to 0 ms was used as the baseline. Following the preprocessing, we applied the adaptive mixture independent component analysis algorithm (AMICA) to transform the scalp-EEG data from a channel basis to a component basis [17], and separated out those maximally independent cortical sources from biological artifacts (such as the eyes, muscles, and heart) and noise components [25]. After the reject noise AIMCA components, an equivalent current dipole (ECD) model of each brain component was computed using the standard boundary element method (BEM) head model included in the EEGLAB DIPFIT plug-in to localize dipoles on the cortex http://sccn.ucsd.edu/wiki/A08:_DIPFIT. Based on the dipole features, those physiologically plausible dipoles were selected and clustered across subjects to define the regions of interest (ROIs). In the EEGLAB, the ROIs is defined as 76 cerebral cortical areas.

C. Constructing Time-Frequency Brain Networks

Once activity in specific brain areas have been identified using source separation with AMICA and localized using DIPFIT, it is possible to look for transient changes in the independence of these different brain source processes. In this paper, we applied routines from a source information flow toolbox (SIFT) for modeling ongoing or event-related effective connectivity between these ROI time-series [20]. In the processing, a linear vector adaptive multivariate auto-regressive (AMVAR) model [28] of order 10 was then fitted to the multi-trial ensemble with 500 ms sliding window and a step size of 25 ms, using the Vieira-Morf lattice algorithm. Following the model fitting and tests of stability and residual white-ness, the Direct Directed Transfer Function (dDTF) was estimated from the AMVAR coefficients to quantify time-varying connectivity [26]. In paper, 13 subjects out of 16 participants were used for the statistical analysis by means of the group level SIFT to analysis the spatiotemporal brain dynamics.

D. Spatial Correlation Analysis of brain functions

In order to assess the change in brain activity related to the reading sentence, we focus on five brain functions in speech planning. To take the high spatial resolution of the fMRI into our EEG analysis, we employed the existing fMRI achievement of the brain networks as an initial value and constraint in our EEG analysis. In this study, we used the fMRI database of Morphological and Connectomic Atlas of Human Brain Functions (Connectopedia Knowledge Database, a freely available database at http://www.fmritools.com/kdb/morphological-and-connectom/index.html) to construct functional adjacency matrices from the brain functions of the visual, phonological, semantic, speech motor programming and speech perception. We calculated the similarities for each

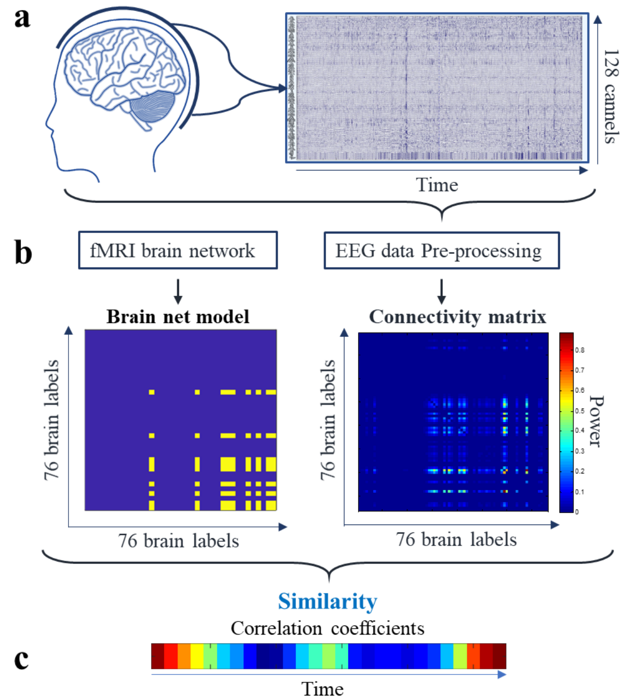

Fig. 1. Brain stages of Spatial Correlation Analysis (SCA). (a) the EEG data Pre-processing from EEGLAB. (b) The functional networks matrix from Connectopedia Knowledge Database and effective connection matrix from Group-SIFT toolbox. (c) Correlation coefficients for functional networks.

function using the fMRI-based functional adjacency matrices (FAM) and the EEG-based FAM along with time by means of Pearson correlation coefficient. Using the approach shown in Fig.1, we calculated the correlation between the fMRI-based FAM and the time-varying FAM obtained from our EEG experiment. Thus, a time-varying correlation coefficient is obtained for each brain network. The higher the coefficient in a certain period, the higher activation the brain network in that time. In Fig.1(c), the red color shows the high correlation coefficient, and indicates that the brain network is activated highly.

IV. Results

A. Behaviors results

Fig.2(a) shows the averaged latent time distribution for the sentence with 8 disyllable words over all of the 180 sentences from 13 subjects. The horizontal axis indicates the word order of the sentence, and the vertical axes show the latent time (LT) of words. In this figure, the thick blue line is the averaged LT of each word. The light dark region and pale region surround the middle line represents the LT distribution with a 25%-75% and 9%-91% difference area, respectively. Finally, the maximum and minimum LT was showing as the most outside light blue line. In addition, the exact LT of each word was shown in a table besides the plot. Fig.2(b) shows the averaged gaze onset (GO) (red dotted line) and speech onset (SO) (blue

TABLE I
AVERAGED OVERLAP (MS) OF THE GAZING/SPEECH ONSET /OFFSET FOR 8 WORDS.

Word number	GO	GF	SO	SF	Overlap
Initial	347 (77)	939 (232)	1041 (192)	1569 (234)	
2	939 (232)	1540 (284)	1569 (234)	1996 (265)	101
3	1540 (284)	2014 (309)	1996 (265)	2473 (306)	29
4	2014 (309)	2459 (373)	2473 (306)	2959 (365)	-18
5	2459 (373)	2963 (423)	2959 (365)	3472 (402)	13
6	2963 (423)	3505 (443)	3472 (402)	3995 (402)	-4
7	3505 (443)	4058 (482)	3995 (461)	4497 (526)	-33
Last	4058 (482)	4588 (507)	4497 (526)	4988 (565)	-63

dotted line) as reading the sentence. The latency of each word is indicated by a solid gray line, and the overlap between the words before and after is marked with a solid green line. The detailed values and standard deviation are shown in Table 1.

As shown in Fig.2(a), the latent time of the initial word is 694 ms (Std=210) and decreases gradually to 438 ms (Std=133) for the last word. As one can see, these is a significant difference (F(1,25)=12.6, p=0.0016) in the latent time between the initial word and the last word have although they are equal in lengths. On average, the latent time of the last word is 37% shorter (256 ms) than that of the initial one. It indicates that the latent time of speech planning changes with the location of the words in continuous speech.

Comparing the gaze onset (GO) and speech onset (SO) in Fig.2(b), speaker starts to utter the first word after they looked at the second word. That is, looks ahead one more word. In the middle portion of the sentence, the SO starts almost at the same time as GO moves on the following word. In this case, the split light of the speakers eyes possibly get some information of the following word. In the posterior part, especially for the last two words, speaker utters the word without look ahead. When randomizing the words for the same sentence, the latent time of a word does not change with its location [30]. This indicates that the context in the posterior part of the sentence can provide sufficient information for making the speech planning, so that it does not require the look ahead action for the anticipation. To clarify the relation of the look ahead action and comprehension in the brain, we conduct the following EEG analysis.

B. EEG results

Fig.3 illustrates the brain connectivity structure of the two selected fMRI functional networks (the visual processing and semantic processing) and their representational similarity with our EEG dynamic network series, shown as the color bar where warm color indicates high similarity (strong functional activity) and cold color indicates little similarity (no significant functional activity). In addition, the brain dynamics corresponding to the high-similarity moments are given below, with the nodes of the regions of interest (ROIs) and their interconnections during the whole range and across all the subjects. The size of the node indicates the activeness of the corresponding region and the link is the connectivity with other nodes. The active areas are listed in the bottom of the figure. The ROIs are consistent with those of previous research.

From the results of the first word, visual processing network initiated from the start (0 ms) and lasted until 144 ms. The gaze point has moved to the second word at 592 ms before starting utterance of the first word at 694 ms. Visual processing network is also activated again at 552 ms when looking at the the second word and continues until the end of 600 ms. This is basically consistent with above behavior results. Note that the semantic processing network is working when the gaze point moving to the second word. This indicates that for the first few words the semantic processing needs more contextual information via the lookahead actions.

For the results of the last word, visual processing network were significantly activated at the onset of the gaze and lasted until 72 ms, which is about the half of the time used in the first word. It can be observed that the activation pattern of the brain network becomes complicated (network has more activation area) due to the superposition of the effect of previous words. The semantic processing network is activated at the near the ending of the latent period (360 ms - 438 ms). The interval between the peaks of visual processing and sematic processing is 520 ms for the first word and 350 ms, the difference is 170 cm. Both the time of visual processing and semantic processing of the final word were about the half of that for the first word. The reduction of the intervals and processing times is plausibly caused by the factor that the final word has richer contextual information than the first word.

V. DISCUSSION

In this study, we measured the behavioral (eye movement and speech) and neurophysiological data (EEG) during oral reading of continuous sentences to clarify the mechanism of speech planning. To remedy the spatial limitation of EEG, we introduced fMRI-based functional network database as a constraint to examine the functional significance of the brain networks over time. From our behavioral results, the lookahead action was clearly observed in the anterior part of the sentence, but was not obvious in the posterior part. The neurological results showed that the semantic processing is synchronized with the lookahead actions. In other words, looking ahead is required for anticipation of the following words during the semantic processing. It was also found that the interval between the peaks of visual processing and semantic processing was reduced approaching to the final word, and the duration of visual processing and semantic processing of the final word decreases by half compared to the first word. The reduction of the intervals and processing times is plausibly caused by the factor that the final word has richer contextual information than the first word.

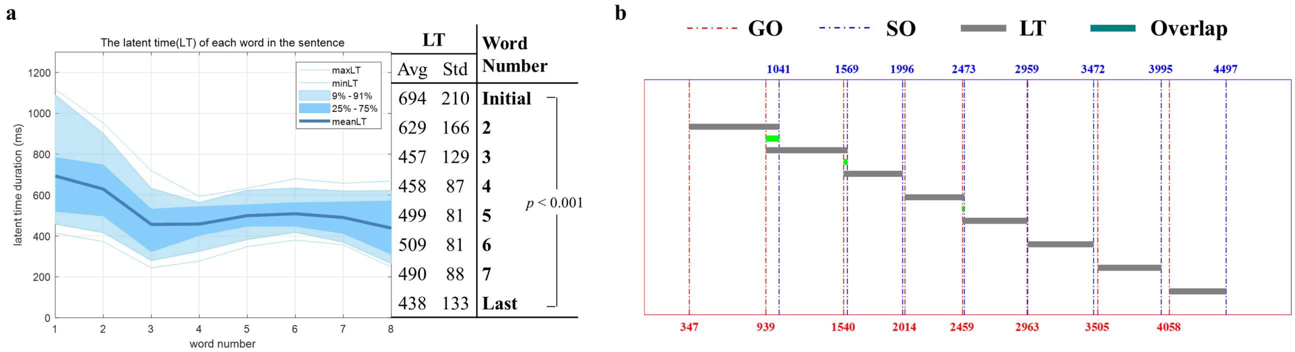

Fig. 2. (a) The averaged latent time distribution for each of the 8 disyllable words. (b) The latent time and the overlap.

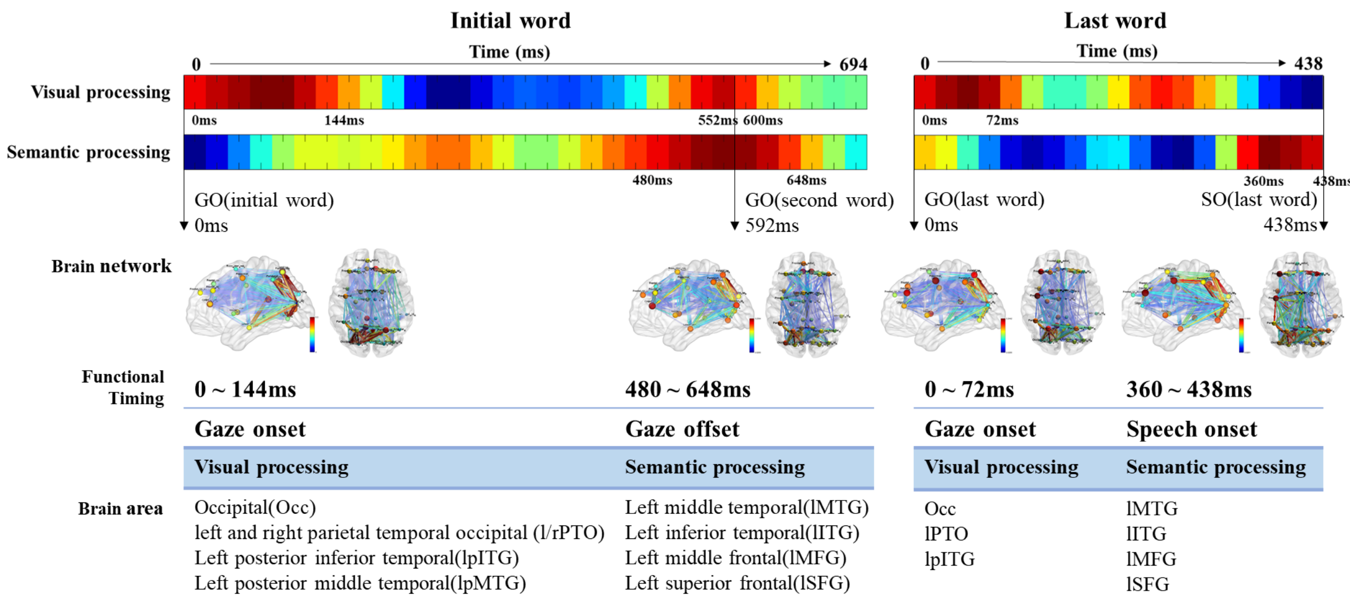

Fig. 3. Correlation coefficients for functional networks. The correlation coefficients is represented by a color scale, with more red colors indicating the higher matching degree of EEG reconstructed spatiotemporal dynamic network and fMRI network template.

In addition, the decreasing trend of the latent time along with the order of words was also reflected in this study based on the eye movement and speech onset boundaries of each word. Specifically, the latent time of the last word was nearly 40% shorter than the initial word. In the later stage of reading, the speech onset got close to or even ahead of the gaze offset. This can be well explained by the semantic association and prediction in coherent sentences. As the word goes on and more content is available, semantic prediction for the following word becomes easier, so that the time spent on the planning of the word get shortened. By analyzing the brain activity of the initial words and the last words, it was found that the initial words cost more time for semantic processing. For the last word, the duration of semantic processing was decreased, while the onset was advanced. All these results indicated that the semantic prediction plays a major role in continuous speech planning.

In fMRI-constraint network analysis, two functional networks pertaining to the experimental task have been carefully examined. The results showed that the activation of the visual processing network is highly consistent with the onset of eye movements. And in the initial words, the SCA result of the semantic processing network indicates that semantic processing occurs during the gaze onset of the second word. This is a good explanation of the anticipatory coarticulation of the look-ahead model from a neuroscience perspective. The Look-ahead model suggested that people will anticipatorily fixate and predict the upcoming word for proceeding with the current word [2], [3]. In our results, the speaker often looks at a word backward before the speech onset of the current word. This can be reflected in the overlaps of the latent time of the first three words.

VI. Conclusion

This study examined the latent time of speech planning with behavioral and neurological techniques, and investigated the functional networks including visual processing and semantic processing involved in speech production during oral reading. The results echo with the look-ahead model and showed a carryover effect where the speaker often looks forward prior to the speech onset of the current word. Our results also showed a gradually decreasing trend of the latent time along with the order of words, which suggested the semantic prediction is a critical influencer to the decrease of latent time in speech planning for continuous speech.

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