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An Integrated Model of Word Processing and Eye-Movement Control During Chinese Reading

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In the Chinese writing system, there are no interword spaces to mark word boundaries. To understand how Chinese readers conquer this challenge, we constructed an integrated model of word processing and eye-movement control during Chinese reading (CRM). The model contains a word-processing module and an eye-movement control module. The word-processing module perceives new information within the perceptual span around a fixation. The model uses the *interactive activation framework* (McClelland & Rumelhart, 1981) to simulate word processing, but some new assumptions were made to address the word segmentation problem in Chinese reading. All the words supported by characters in the perceptual span are activated and they compete for a winner. When one word wins the competition, it is identified and it is simultaneously segmented from text. The eye-movement control module makes the decision regarding when and where to move the eyes using the activation information of word units and character units provided by the word-processing module. The model estimates how many characters can be processed during a fixation, and then makes a saccade to somewhere beyond this point. The model successfully simulated important findings on the relation between word processing and eye-movement control, how Chinese readers choose saccade targets, how Chinese readers segment words with ambiguous boundaries, and how Chinese readers process information with parafoveal vision during Chinese sentence reading. The current model thus provides insights on how Chinese readers address some important challenges, such as word segmentation and saccade-target selection.

Keywords: Chinese reading, eye movements, modeling, word processing, word segmentation

During reading, skilled readers rapidly move their eyes through the text about four to five times per second and can achieve a reading speed of about 250 words per minute (Rayner, Pollatsek, Ashby, & Clifton, 2012). Yet how this is done is not at all clear. In particular, for readers of Chinese, there is one special problem that is not faced by readers of Western alphabetic languages: a row of print consists of a string of characters without any spaces between the words from the first character on a line to the last character on the line. Thus, there are no obvious indicators as to where words begin or end. Yet skilled Chinese readers can read at speeds consistent with that of most skilled readers of alphabetic languages (Liversedge, Drieghe, Li, Yan, Bai, & Hyönä, 2016). This makes it hard to explain how Chinese readers can read text and also leaves open how reading functions across all languages.

There are certain things about the pattern of eye movements that all models of reading have to take seriously. The first is that when readers are making sense of what they are reading, they rapidly move their eyes through the text, but then pausing between movements for brief intervals where the eyes are relatively stable (these intervals are called *fixations*; Ishida & Ikeda, 1989; Wolverton & Zola, 1983). Between these brief looks at the text, there are ballistic eye movements (called *saccades*) through the text about four to five times per second that reposition the eyes from one location to another (Rayner, 1998, 2009a). During these saccades, the reader sees virtually nothing of the page; thus, reading is something like a "slide" show in which information is extracted from a new viewing location (a fixation) at about four to five times per second. The durations of fixations, the positions of these fixations, as well as the order of these fixations of the eyes through the text (usually called a *scan path*) have all been found to be influenced by the underlying cognitive processes that support text

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comprehension (Rayner, 1998, 2009a). This is true not only for the studies of reading in alphabetic languages but also for studies of Chinese reading, as we will soon relate.

To date, however, most models of eye-movement control during reading have focused their efforts on understanding what happens during reading in alphabetic languages. This is unfortunate because it is unclear whether the processes that are posited to support reading in alphabetic languages are sufficient to explain reading in other (nonalphabetic) languages. In the current article, we report a computational model that explains some of the eye-movement behaviors that occur during Chinese reading. We will refer to it as the Chinese reading model (CRM). However, we should warn the reader at this point that this model will not account for every aspect of eye movements connected with reading. To make the research question more focused, we ignored high-level processing such as syntactic processing and semantic processing. Therefore, this study will focus on how words are processed within the perceptual span and how this is related to eye-movement control in Chinese reading. As you will see, that in itself is quite an amount for a model to deal with.

In the following sections, we will first briefly introduce some basic facts about Chinese reading. Then we will review some important findings and models of eye-movement control during reading in alphabetic languages as a basis to contrast with eye-movement control in Chinese reading. Following that, we will introduce some important findings in Chinese reading that are relevant to the current model. Some of these findings are important to motivate the assumptions of the model, and some provide benchmark data to test the model. We will then describe the motivation for constructing a model of eye-movement control in Chinese reading, and introduce the important assumptions of the model. Following that, we will provide the structure of the model and how this model is implemented. Then, we will explain how this model simulates some important eye-movement behaviors in Chinese reading. Finally, we will discuss how this model enhances our understanding of the cognitive processes underlying Chinese reading, and reading in general.

Chinese Writing System

The modern Chinese writing system is used by more than 1.6 billion people in the world (including China, Singapore, etc.). In mainland China, readers from different regions are using either Mandarin or regional dialects[1] (such as Cantonese) as a spoken language but are all using the same Chinese writing system. As in many alphabetic writing systems, Chinese readers read from left to right within a line, and read line by line from top to bottom.

The Chinese writing system has many unique properties. First and most obvious, Chinese is written using characters rather than letters. There are more than 5,000 commonly used Chinese characters and each character represents a syllable. Each character is presented within a square box-like area in the text, and there are small spaces between characters. A character can vary in its complexity as measured by the number of strokes. Some character only has one stroke (e.g., "一" meaning *one*), while some other characters may have more than 20 strokes (e.g., "罐" meaning *jar*). Most characters can make up many different words when combined with other characters (Li, Zang, Liversedge, & Pollatsek, 2015; Yu & Reichle, 2017). For example, the character "人" (meaning *people*) can make up 406 two-character words (101 as the first character, and 305 as the second character of a word), 392 three-character words (53 as the first character, 75 as the second character, and 264 as the third character of a word), 549 four-character words (132 as the first character, 161 as the second character, 113 as the third character, and 143 as the fourth character of a word), and 418 words longer than four characters (Lexicon of Common Words in Contemporary Chinese Research Team, 2008).

Second, there are no blank spaces between words to mark word boundaries. Thus, the beginnings and the ends of words are not apparent for Chinese readers. Finally, Chinese words are short, with most being one or two characters in length. Among the 56,008 words that are included in one published source (Lexicon of Common Words in Contemporary Chinese Research Team, 2008), 6% are one-character words, 72% are two-character words, 12% are three-character words, 10% are four-character words, and less than 0.3% are longer than four characters. When word tokens are taken into account, 70.1% of words are one-character words, 27.1% are two-character words, 1.9% are three-character words, 0.8% are four-character words, and 0.1% are words longer than four characters.

These differences (and others, e.g., prevalent phonological ambiguity) are theoretically interesting, and recently many studies have been conducted to understand the mechanisms of Chinese reading. In fact, investigating some unique properties of Chinese reading could help to answer questions that are simply impossible in other languages. For example, how Chinese readers determine word boundaries is a question that does not exist in English reading. Indeed, some researchers believe that "research investigating Chinese reading has itself started to define and shape some of the key questions concerning human written language comprehension that remain unanswered in the field" (Liversedge, Hyönä, & Rayner, 2013, p. S2). For these reasons, the topic of reading Chinese has attracted substantial attention of a considerable number of researchers during the last decades (Li, Liu, & Rayner, 2015; Zang, Liversedge, Bai, & Yan, 2011). Based on these studies, several concrete hypotheses have emerged about how Chinese reading may be different from reading of alphabetic languages.

Eye-Movement Control in Alphabetic Reading

We will review some important findings and models of eye-movement control during reading in alphabetic languages as a basis for a contrast to Chinese reading. First, eye-movement control is influenced by the progress of word processing. Regarding when the eyes move, the most important findings are that fixation duration on a word is influenced by the frequency of the word in the language (as measured by the number of occurrences per million in a corpus), the length of the word (as indicated by the number of characters), and the predictability of the word (as measured by how often participants in an off-line task can predict

[1] Most people in mainland China can now speak Mandarin, and some of them are still using regional dialects (such as Cantonese) in their everyday life. While some regional dialects are close to Mandarin, many of the regional dialects are very different from it. For example, most Chinese in northern China do not understand Cantonese at all.

the word given the information in the sentence prior to the word). For future reference, the duration of an individual fixation on a word will be termed *fixation duration*, the duration of the first fixation on a word will be termed *first fixation duration* (FFD), and the sum of the fixation durations before the word is exited to the right or left is *gaze duration*. Fixation durations are shorter for words that are higher frequency (Rayner & Duffy, 1986) and/or higher in predictability (Rayner & Well, 1996). Gaze durations are also longer on long words than on short words (Just & Carpenter, 1980), mainly because long words will be the recipients of more fixations than short words.

Another important question is where the eyes move during reading. Many studies have shown that saccade target selection during reading in alphabetic languages is generally affected by low-level visual features such as word length. Initial eye movements to a word usually fall at a *preferred viewing location* (PVL; Rayner, 1979, 2009b), which is a little to the left of the center of a word. English readers (like those of most alphabetic languages) can choose a PVL to which to send their eyes because there are spaces between words, making the word boundaries apparent.

Many models have been proposed to investigate eye-movement control during reading in the last decades such as E-Z Reader (Reichle, Pollatsek, Fisher, & Rayner, 1998; Reichle, Rayner, & Pollatsek, 2003), SWIFT (Engbert, Nuthmann, Richter, & Kliegl, 2005), Glenmore (Reilly & Radach, 2006), and OB1-Reader (Snell, van Leipsig, Grainger, & Meeter, 2018; for a review, see Reichle et al., 2003). These models implement contrasting theoretical proposals about how covert attention, visual processing, word processing, and oculomotor control jointly determine both when and where to move the eyes during reading. However, as we shall see, they are only loosely relevant to how the eyes work in Chinese reading. Rather than discuss them all now, we are going to discuss one successful model (the E-Z Reader model) in a little detail. Among other things, this will make it clear what will have to be changed in order for an eye-movement control model to be able to work in Chinese reading. In the General Discussion section, we will come back and discuss other models of alphabetic reading and see how they fit with what we know about Chinese reading.

The E-Z Reader model makes as its central assumption that the primary purpose of reading is to process each word on the page serially (from left to right) and to move the eyes accordingly (Reichle et al., 1998). If the currently fixated word on the page (word n) is processed, an eye movement is directed to the next word (word $n + 1$). However, if more than one word can be processed on a fixation, then an eye movement can in this case be directed to word $n + 2$ (or occasionally to word $n + 3$). Furthermore, whatever word is selected, the following fixation is directed to the middle of the word that is being selected. There are other hypotheses that have to do with word frequency and length, and with the word predictability as constrained by sentence context (Reichle et al., 1998). As you might expect, the mean reading time for a word decreases as its frequency increases, as its length decreases, and as its probability within the text increases. There are other hypotheses dealing with what happens when a reader does not identify a word after a given amount of time. Does the reader refixate the word? For example, if the word is long, the reader might decide to refixate it. Then, the reader has to direct another eye movement further along the word. This leads to refixations on words.

Central to all of this in the model are the following two ideas: (a) that the eyes process every fixated word (n) when it arises (and occasionally two words, n and $n + 1$ on some fixations, and very occasionally three words); and (b) that the eyes are usually directed to make a fixation to the next word they have not yet processed, but some of the time, they have to remain on a word if they have not fully processed it. As indicated earlier, this model has been successful in dealing with many problems of eye-movement research in alphabetic languages.

However, it should also be clear that it cannot be a basis for an eye-movement model in Chinese. There are two serious problems with the model as it now stands. The first is that the readers of Chinese somehow can recognize a word as a unit even though they cannot segment character strings into words with the aid of interword spaces (Li, Liu, et al., 2015; Li, Rayner, & Cave, 2009); how this is to be achieved by a reader is clearly a much more difficult question than when there are natural beginning and ending points indicated by spaces. The other question is how readers of Chinese know where to move their eyes given that there are no interword spaces to help guide where their eyes should move (Li, Liu, & Rayner, 2011). Models such as E-Z Reader postulate that a word begins and ends in a given location and therefore that the center of the next word can be the target for sending a saccade. With Chinese this seems like an impossible task, because it is not clear where the word centers are, given that there are no obvious cues for where words begin and end in the text. This article attempts to answer both of these questions.

Eye Movements in Chinese Reading

In the last decades, many studies have been conducted to investigate eye-movement behaviors during Chinese reading, and many aspects of eye-movement control during Chinese reading have become known. Some aspects of eye movements during Chinese reading are similar to those in reading in alphabetic languages. For example, Chinese readers also mainly make forward saccades, but occasionally make regressive saccades to the left of a fixation (Zang et al., 2011).

One difference, however, is that average fixation durations are usually longer in Chinese compared with that in English and presumably most other European languages (Liversedge et al., 2016; Rayner, Li, Juhasz, & Yan, 2005). For example, Liversedge, Drieghe, Li, Yan, Bai, and Hyönä (2016) asked native speakers to read comparable material in Chinese and English (Chinese text was translated from English text). They observed that average fixation durations were longer when native Chinese readers read Chinese (245 ms) than when native English readers read English (207 ms). To go with that fact, because Chinese words are usually shorter in length (at least in terms of number of characters vs. letters), Chinese readers skipped words more often (47%) than English readers (36%), and saccade length (again in terms of characters vs. letters) was numerically shorter in Chinese reading (3.19 characters) compared with that in English reading (8.53 letters).

As in reading in alphabetic languages, word properties also affect reading times on words in Chinese reading. Reading times (including FFD and gaze duration) on a word are shorter when the word is a high-frequency word than a low-frequency word (Wei, Li, & Pollatsek, 2013; Yan, Tian, Bai, & Rayner, 2006), or when a word is more predictable (Rayner et al., 2005). Gaze duration and total time on long words (i.e., those comprised of more characters) are longer than on short words (Li et al., 2011). Li, Liu, and Rayner (2011) also showed that the properties of words such as their frequencies affected the skipping rate of words as well. Characters are also salient visual units in Chinese sentences, and many studies have shown that character properties also affect eye-movement behaviors. For example, characters with fewer strokes usually have shorter fixation durations when they are fixated, and also are skipped more often (Li, Bicknell, Liu, Wei, & Rayner, 2014; Yang & McConkie, 1999). A corpus analysis study reported in Li et al. (2014) systemically investigated how word properties and character properties affect eye movements during Chinese sentence reading. Critically, however, they showed that the word effects survive when excluding the influences of character properties, suggesting that word processing plays an important role in Chinese reading.

Chinese readers can only effectively perceive information within a limited region surrounding the fixated position (usually called the *perceptual span*) when they fixate at a given position (Rayner, 1998, 2009a). Inhoff and Liu (1998) used a *moving window paradigm* developed by McConkie and Rayner (1975) to measure the size and shape of the perceptual span in Chinese reading. In those experiments, participants could only view characters within a "window" surrounding a fixation, and all of the characters outside the window were masked with some symbols that were not symbols of words to be read (such as "*X*"s). The size of the window was manipulated, and the window moved with the eyes as the eyes moved. When the size of the window was small, reading speed was greatly reduced compared with that of natural reading. The perceptual span was determined as the minimum size of the window when reading speed is close to that in natural reading, and the general finding was that the perceptual span in Chinese reading extends from one character to the left of fixation, to three characters to the right of fixation. (In comparison, the perceptual span in English reading extends from three to four letters to the left of fixation [McConkie & Rayner, 1976; Rayner, Well, & Pollatsek, 1980], to 14 to 15 letters to the right of fixation [McConkie & Rayner, 1975; Rayner, Well, Pollatsek, & Bertera, 1982]).

The perceptual span in Chinese reading usually not only covers the fixated words, but also at least one or two of the following words, suggesting that readers can perceive information on the right of the fixated word using parafoveal vision. This conclusion has also been confirmed by a phenomenon called *parafoveal preview benefit*, using a gaze-contingent display change technique called the *boundary paradigm* (see Schotter, Angele, & Rayner, 2012 for a review). In this paradigm, readers see a preview word before the eyes cross an invisible boundary, and when the eyes cross the boundary, the preview word changes to the target word. Reading time on the target word is shorter when the target word is identical to the preview word than when they are different (Balota, Pollatsek, & Rayner, 1985; Rayner, 1975), suggesting that the preview word is processed with parafoveal vision. This effect has also been consistently found in Chinese reading (Gu, Li, & Liversedge, 2015; Liu, Inhoff, Ye, & Wu, 2002; Yan, Richter, Shu, & Kliegl, 2009; Yang, Wang, Xu, & Rayner, 2009; Yen, Radach, Tzeng, Hung, & Tsai, 2009). Moreover, preview benefits have been observed when the preview word and the target word share phonology information (Liu et al., 2002; Pollatsek, Tan, & Rayner, 2000; Tsai, Lee, Tzeng, Hung, & Yen, 2004), or semantic information (Yan et al., 2009; Yen, Tsai, Tzeng, & Hung, 2008). Together with the fact that some words are skipped during Chinese reading, these findings suggest that words can be processed to a certain degree (or even fully) with parafoveal vision.

There is also some evidence that Chinese readers may direct their eyes differently than readers of alphabetic languages. English readers usually direct their saccades to a PVL (a little less than half way through the word). This is possible in languages like English because the readers can perceive word length information using parafoveal vision, allowing them to move their eyes to a preferred position. Without interword spaces, how do Chinese readers "decide" where to move their eyes? Several studies observed flat PVL curves (PVL curves plot the frequency of the initial fixations across the letters of words) during Chinese reading (Tsai & McConkie, 2003; Yang & McConkie, 1999), and later studies consistently observed PVL curves peaking at word beginning (Li et al., 2011; Yan, Kliegl, Shu, Pan, & Zhou, 2010; Zang, Liang, Bai, Yan, & Liversedge, 2013). No study has reported PVL curves peaking at word center in Chinese reading, suggesting that Chinese readers do not by default move their eyes to the center of a word as readers of English do.

To further examine this question, Li et al. (2011) embedded either a two-character word or a four-character word into the middle of the same sentence frame. Thus, if Chinese readers saccade to the word center, the peak of the PVL curve in the four-character condition would shift to the right compared with what they observed for the PVL curve in the two-character condition. However, contrary to this prediction, they found that the PVL curve on the four-character word in the four-character condition and the PVL curve on a four-character region in the two-character condition (including the two-character word and two characters following it) were similar (average landing position was 0.98 and 0.99 characters measured from the left of the target words for the two-character condition and the four-character condition, respectively). The results of this study therefore provided no evidence that Chinese readers saccade to the center of words.

However, Yan, Kliegl, Richter, Nuthmann, and Shu (2010) argued something different. They divided trials into two groups based on whether there was one fixation or more than one fixation on the target word, and they found a PVL curve peaked at the word center for words that received single fixations, but peaked at the word beginning when the word was fixated more than once. Based on this finding, they argued that Chinese readers target their saccades to the word center if they can segment the word in parafoveal vision, but that they target the beginning of the word if they cannot. This argument seems interesting, but Li et al. (2011) argued that Yan, Kliegl, Richter, et al.'s (2010) results do not necessarily support their conclusion. An alternative explanation to Yan, Kliegl, Richter, et al.'s (2010) results is that the eyes might fixate near the center of a word by chance, where readers could process the word in one fixation, consequently making a refixation less likely. To illustrate this point concretely, Li et al. (2011) conducted simulations and showed that a model in which saccadic targeting was never word based (e.g., a constant saccade length model) produced very similar patterns of results as observed by Yan, Kliegl, Richter, et al. (2010). Another study showed that the PVL curves are similar to those found by Yan, Kliegl, Richter, et al. (2010) even if Chinese readers read a string of random Chinese characters that do not combine to form words (Ma, Li, & Pollatsek, 2015). Taken together, there is no evidence that Chinese readers target at any specific position within a word during Chinese reading.

Recently, Li and colleagues proposed instead a *processing-based strategy* to account for saccade target selection during Chinese reading (Li et al., 2011; Wei et al., 2013). According to this strategy, readers first attempt to process as much information as possible at a given fixation, and then move their eyes beyond those characters. Later studies tested some important predictions of this strategy (Li, Liu, et al., 2015; Wei et al., 2013). For example, Wei, Li, and Pollatsek (2013) found that a saccade leaving a high-frequency word was longer than one leaving a low-frequency word. Recently, Liu, Reichle, and Li (2015) showed that restricting parafoveal processing reduced the amount of the word-frequency effect on saccade length. That is, the overall result of these studies suggested that, the more characters Chinese readers had perceived to the right of fixation (beginning with the fixated word), the further they would send their eyes forward. Thus, easier-to-process words would be processed more quickly and have a longer saccade length away from them. However, when parafoveal processing was prevented, the difference between saccade lengths leaving a high-frequency word and a low-frequency word did not reach significance.

In summary, compared with reading of English and other alphabetic languages, the processes that control eye movements during Chinese reading have many unique properties. This article will therefore attempt to exploit the unique properties of the Chinese language and writing system to shed further light on the reading of Chinese and how it might be different from the reading of other (alphabetic) languages.

Word Segmentation During Chinese Reading

Even without explicit cues to demarcate word boundaries, Chinese readers have no difficulty in reading Chinese. Some studies have shown that average fluent Chinese readers usually read 400 characters (or 260 words) in a minute, and the time it takes to read comparable content of text is similar between English and Chinese readers (Liversedge et al., 2016; Sun, Morita, & Stark, 1985). This suggests that Chinese readers must use some mechanism to efficiently segment individual words (i.e., determine word boundaries) during reading.

Even without explicit cues (such as spaces) to denote word boundaries, many studies have shown that words have psychological reality in Chinese reading. First, as in English reading (Reicher, 1969), there is a *word-superiority effect*. After briefly viewing a string of characters, Chinese readers could identify a character at a specific position more accurately when it was embedded in a word than within a string of characters that did not constitute a word (Cheng, 1981; Shen & Li, 2012). These results suggest that characters belonging to a word are processed as a unit. Second, preventing Chinese readers from reading characters belonging to a word together significantly slowed down reading (Bai, Yan, Liversedge, Zang, & Rayner, 2008; Li, Gu, Liu, & Rayner, 2013; Li, Zhao, & Pollatsek, 2012). For example, Bai, Yan, Liversedge, Zang, and Rayner (2008) found that inserting spaces between two characters within a word slowed down reading compared with natural reading, while inserting spaces between words did not affect reading speed. Finally, some studies showed that word boundaries affected both character identification and attention deployment during Chinese reading (Li & Logan, 2008; Li & Ma, 2012; Li & Pollatsek, 2011; Li et al., 2009; Zang, Fu, Bai, Yan, & Liversedge, 2018). For example, in Li, Rayner, and Cave (2009) study, Chinese readers briefly viewed a string of four Chinese characters and were asked to report as many characters as possible. These four characters constituted a word in the four-character word condition, while they constituted two words in the two-character word condition (i.e., the first two characters constituted a word, and the last two characters constituted another word). Readers could report all of the four characters accurately in the four-character word condition, while they could only report the first two characters in the two-character word condition. The results suggest that there is a sequential component of processing during Chinese reading so that all the characters belonging to a word are processed equally fast, while the two characters belonging to the next word may be processed later. These studies suggest that words have a psychological reality in Chinese reading, as they do in reading of alphabetic writing systems.

Most theories of word reading in alphabetic writing systems assume that interword spaces play an important role in word segmentation. This raises an issue, without spaces, how do Chinese readers segment words? Li et al. (2009) proposed a computational model of word segmentation and identification in Chinese reading based on the interactive activation framework (McClelland & Rumelhart, 1981). According to Li et al.'s (2009) model, characters in the perceptual span are processed in parallel, with the processing constrained by foveal eccentricity and visual attention. The activation of the units representing individual characters then feed forward to the level of the units representing words, allowing the words comprised of those characters to become activated. The activation of the corresponding word units sends feedback activation to the character level, thereby influencing processing at this level. The processing of characters corresponding to the activated words is therefore facilitated, allowing them to become increasingly activated more rapidly than other characters. Moreover, the word units compete with each other, so that the most activated word dominates the others. At that point in time, the word has been identified and the string of characters containing the word have been segmented. Thus, according to this model, word segmentation and identification happen simultaneously.

Motivation and Aim of the Current Study

In this section, we will briefly summarize the important findings that have been reviewed in the previous sections to motivate the current study, and then we will state the aim of the current study. As reviewed above, many models have been proposed to simulate the eye-movement behaviors of readers of the alphabetic writing systems. These models have motivated many new studies on reading and thus improved our understanding of the basic processes that support reading (e.g., see Rayner, 1998, 2009a). However, to date, all of these models have focused mainly on explaining the cognitive processes involved in reading of alphabetic writing systems like English and German. Therefore, the extent to which readers of different (e.g., nonalphabetic) writing systems use the same or different processes to read text is not clear at present.

Previous models of eye-movement control of alphabetic language reading (such as E-Z Reader, SWIFT, Glenmore, etc.) are not easily modified to simulate eye-movement behaviors in Chinese reading. Those models usually assume that word processing plays an important role in controlling both when to move the eyes and where to move the eyes. In most of these models, it is usually assumed that interword spaces play an important role in word segmentation, and thus they assume that word boundaries play an important role in eye-movement control. However, in Chinese reading, there are no interword spaces or other markers that mark word boundaries explicitly. Thus, it is very difficult to extend existing models to Chinese reading. Some modeling work has been tried to simulate eye-movement behaviors in Chinese reading. Rayner, Li, and Pollatsek (2007) extended the E-Z Reader model to Chinese reading and based on simulations, concluded that lexical information (e.g., word length and frequency) plays a role in guiding the eye movements of Chinese readers. That model assumes that Chinese readers perceive word boundaries with parafoveal vision during Chinese reading as English readers do when they read English text. The following studies, however, have shown that this is not the case (Li et al., 2011; Liu, Reichle, & Li, 2016). In summary, although this work showed that certain aspects of eye-movement control in Chinese could be explained using E-Z Reader, the simulations are of limited value because the model never explained word segmentation. Apparently, more modeling work needs to be done to answer the question of how Chinese readers decide where to move their eyes, and how this is related to word segmentation.

Previous modeling work on Chinese reading cannot be used to simulate eye-movement behaviors in Chinese reading. Some models were proposed primarily to account for findings of character identification (Perfetti, Liu, & Tan, 2005; Yang, Wang, Shu, & Zevin, 2011). Other models, such as the one proposed by Li et al. (2009), can only process separate words. Li et al.'s (2009) model was designed to explain the word segmentation problem in a whole word report task; it thus only simulated data involving four characters, but not in complete sentences. Moreover, the model only simulated the accuracy results of a whole report task but did not simulate reading times in a natural reading task. As Reichle and Yu (2018) pointed out, these models are limited, explaining only parts of the reading process. Thus, a new model is needed to simulate eye-movement behaviors during sentence reading.

Therefore, in the current article, we report a new model that can process entire sentences in the context of natural reading. This requires new assumptions so that the model can deal with eye-movement data, which involves combining the assumptions related to word segmentation with the assumptions related to eye-movement control.

Benchmark Data for Simulation

The goals of the current model are to investigate how words are processed during Chinese sentence reading and how this process is related to eye-movement control. Thus, we mainly focused on simulating data related to these issues in Chinese reading to evaluate whether the model could predict eye-movement behaviors in Chinese reading. It should be noted that there are many other interesting findings in Chinese reading such as character processing (Perfetti et al., 2005; Perfetti & Tan, 1998) and semantic processing (see Yu & Reichle, 2017 for a review). However, these findings are not closely related to the goals of the current model; thus we did not simulate those findings to avoid making the model unnecessarily complex.

First, we simulated traditional benchmark data for eye-movement control models (word-frequency effect, word-predictability effect, and word-length effect). These findings have been simulated by most eye-movement control models of alphabetic writing systems (Engbert et al., 2005; Reichle et al., 1998), and it has been claimed that all the eye-movement control models should be able to simulate these findings (Engbert et al., 2005).

Second, we simulated findings related to saccade target selection during Chinese reading. More specifically, we simulated findings on how Chinese readers choose saccade targets without the aid of interword spaces. A Chinese reading model has to explain the findings of the influence of foveal processing load on saccade length. Some studies found that the length of saccades leaving a high-frequency word was reliably longer than leaving a low-frequency word (Li et al., 2011; Liu et al., 2015; Wei et al., 2013). Moreover, it has been reported that saccades leaving long words are also longer than saccades leaving short words in Chinese reading (Li et al., 2011; Wei et al., 2013). The model also has to simulate the finding that parafoveal processing influences saccade target selection such that the influence of the frequency of the target words on saccade length leaving the target words is smaller when Chinese readers cannot view characters to the right of the target words than when they can (Liu et al., 2015).

Third, we simulated some important findings regarding parafoveal processing during Chinese reading, specifically, preview benefit effects. Studies in Chinese reading have found that reading time on a word is longer when the preview word is different than when it is identical to the target word (Yang et al., 2009; Yen et al., 2009), which suggests that readers can process words with parafoveal vision, and thus less time is needed when a word is processed to a certain level with parafoveal vision. Because the question of how readers process information that falls in the perceptual span has been of central importance in the last decades, a successful eye-movement control model during sentence reading should be able to simulate the above findings.

Finally, we simulated findings on how Chinese readers segment words with ambiguous boundaries. In Chinese text, word boundaries are sometimes ambiguous so that there are multiple ways to segment a Chinese character string. Many studies have been conducted to understand how Chinese readers segment these words with ambiguous boundaries (Ma, Li, & Rayner, 2014; Yan & Kliegl, 2016; Yen, Radach, Tzeng, & Tasi, 2012). A model of Chinese reading also needs to account for these findings.

Assumptions of the Model

The major assumptions were proposed based on previous findings on Chinese reading, and they respect important and established assumptions that are commonly used in models of both alphabetic writing systems and Chinese.

Interaction of Word Processing and Eye-Movement Control

Previous studies have shown that word processing plays an important role in eye-movement control during reading of both alphabetic writing systems and the Chinese writing system (Rayner, 1998, 2009a; Zang et al., 2011). In the current model, we have thus integrated word processing and eye-movement control in a single model. There is one key difference, however, between this model and models of alphabetic writing systems. Chinese readers have to make extra effort to segment words during online reading comprehension in addition to identifying the words because words are not separated by spaces in Chinese text (Li et al., 2009; Ma et al., 2014). Therefore, it is necessary to integrate word processing and eye-movement control in a single model that can make it easier to understand the complex interaction between word processing and eye-movement control, especially for understanding how word-processing status and character-processing status affect the decisions about when and where to move the eyes during Chinese reading (Li et al., 2011; Wei et al., 2013).

Word Processing in Sentence Context

The model only processes a limited number of characters at a time. When the eyes move, the model perceives new information that falls within the perceptual span. When a word is identified, all of the characters belonging to it are removed from the processing part of the model (as will be defined in the next section, this part is called the w*ord-processing module*). In this way, the characters of a sentence are processed chunk by chunk until all of the characters belonging to a sentence are processed.

For the limited number of characters that are being processed by the model at a given time, we adopted most of the important assumptions of the *interactive activation model* (IAM; McClelland & Rumelhart, 1981) to simulate word processing. We did so because the basic assumptions of IAM have been proven to be useful to explain many cognitive activities such as visual word processing (McClelland & Rumelhart, 1981), reading aloud (Coltheart, Rastle, Perry, Langdon, & Ziegler, 2001), eye-movement control during reading (Reilly & Radach, 2006; Snell et al., 2018), and speech perception (McClelland & Elman, 1986). These assumptions have also been successfully used in a model that simulates word processing and word segmentation in Chinese reading (Li et al., 2009). Following the practice of many reading models (McClelland & Rumelhart, 1981), the structure of the present model was specified when the model was designed rather than learned as in some neural network models (Seidenberg & McClelland, 1989). By doing so, the model is more transparent in respect of the functional structure of the human cognitive systems.

Chinese reading, however, has some unique properties, so that we need to make a few new assumptions to allow IAM (developed for word recognition in English) to account for word processing during sentence reading in Chinese. The obvious first property is that there are no spaces between words; therefore, Chinese readers do not know where the word boundaries are using low-level visual information. The original IAM could only identify four-letter words. However, to deal with the lack of interword space problem in Chinese sentence reading, the model also needs to segment words during reading.

The input of the model is a string of Chinese characters; for that reason, there might be one word, two words, or even more words in the perceptual span. Furthermore, the lengths of all the unidentified words are also unknown before they are identified. To deal with these problems, the current model assumes that word segmentation and word processing are a unified process. All of the characters in the perceptual span are processed in parallel, and all the possible words (which are position specific) constituted by the activated characters are also activated, and these word units that overlap in space compete in a "winner-take-all" manner to identify a given word. Because the activated words include all of the possible words that could be constituted by the activated characters, the activated words can vary in length and can start from different positions. When a word wins the competition, it is identified and thus where it starts and ends is also known. By doing so, the word is thus segmented from the character string and the competition goes on like this (sequentially, down the string of characters) until all of the words in the sentence have been identified.

Another difference between reading of Chinese and English (and other alphabetic systems) is that there are more than 5,000 characters in Chinese, and characters are usually more complex with different structures. In the original IAM, feature detectors were employed at each letter position. In contrast, we assumed that the bottom-up identification of characters is done by template matching, which has been widely used in the object recognition literature (Brunelli, 2009; Brunelli & Poggio, 1997). To do so, the images of to-be-recognized objects are compared with the stored representative templates of objects in respect of their similarity, and the to-be-recognized objects are identified as those objects that are the closest match. In the current model, the images of the input characters are compared with the templates of characters represented by character units (not letters as in the original IAM model).

Eye-Movement Control

Previous studies have provided strong evidence that the decision of when to move the eyes and where to move the eyes are generally independent (Rayner & McConkie, 1976; Rayner & Pollatsek, 1981). We made the same assumption in the current model.

The model assumes that two eye-movement mechanisms work together to determine when the eyes move. First, the processing status of the currently fixated word influences the time to move the eyes. The more the fixated word is processed, the less time it needs to initiate an eye movement. Thus, the time it takes to fixate at a position is influenced by, but is not equal to, the time it takes to process the fixated word. Second, there is an autonomous component of the eye-movement mechanism; even if nothing is processed during a given fixation, the eyes will also move after a certain amount of time has elapsed.

Regarding where to move the eyes, we adopted a processing-based strategy to simulate saccade target selection (Li et al., 2011; Wei et al., 2013). According to this strategy, Chinese readers estimate how much information they can process at a given fixation, and then move their eyes to the next character beyond this position.

Architecture of the Model

There are basically two modules in the current model: a word-processing module and an eye-movement control module (see Figure 1 for the architecture of the model). The word-processing module processes words in the perceptual span, and the eye-movement control module decides when and where to move the eyes. The two modules have real-time communication, so they are not independent of each other. The word-

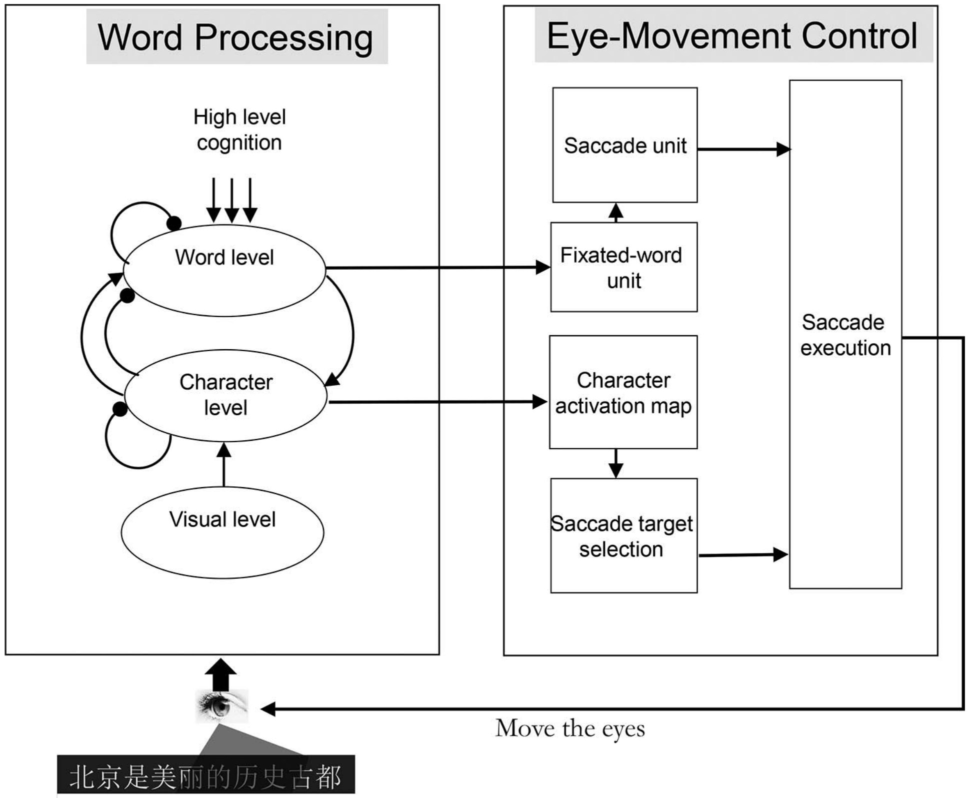

Figure 1. Schematic diagram showing the model's architecture. The arrows between two modules represent communications between modules. In the word-processing module, lines with arrows represent excitatory links, and lines with circles represent inhibitory links.

processing module provides real-time word-processing status and character-processing status information for the eye-movement control module, so that the model can use this information to decide when and where to move the eyes. The eye-movement control module provides an eye-movement signal to the word-processing module, which includes the signal of when and where to move the eyes. Once the word-processing module receives the command to move the eyes, the perceptual span of the word-processing module then moves to a new position specified by the eye-movement control module.

Word-Processing Module

The basic structure of the word-processing module adopts the structure of IAM but with the exceptions mentioned above (e.g., that it incorporates a character rather than a letter level; McClelland & Rumelhart, 1981). There are thus three postulated levels of processing units: a visual level, a character level, and a word level. These three levels of units constitute a network that has links between units at different levels and within individual levels. For each cluster of units, there is a unit corresponding to the assumption of the presence of a corresponding item. For example, at the character level, there is a cluster of units corresponding to all the possible characters at each character position. Each unit has an activation value, which corresponds to the possibility that the unit is present at that specific position. There are feedforward links, as well as feedback links between units at different levels (see Figure 1 for details of these links). Some of the links are *excitatory* links, where the activation of one unit increases the activation of the recipient of the link; other links are *inhibitory*, where the activation of one unit decreases the activation of the recipient of the link. At all three levels, the postulated encoding is position specific. In the word-processing module, there are multiple "slots," with each slot corresponding to one character position in the text. At each slot, there is a visual unit, a set of character units, and a set of word units. The visual unit and character units in a slot only receive bottom-up information from a given character position. Because the encoding at the level of a word requires more detail, it is best that we introduce it later.

The model assumes that the visual input of the model is constrained by the perceptual span. The perceptual span is defined as the number of characters that a reader can effectively perceive at a given fixation during reading. Previous studies have shown that the perceptual span in Chinese reading goes from one character to the left of a fixation to three characters to the right of a fixation (Inhoff & Liu, 1998). Therefore, the word-processing module is assumed to receive new visual information within a perceptual span at each of its five positions, and when the eyes move forward, the perceptual span moves as well. The five characters in the perceptual span could therefore be either one, two, or more than two words, and sometimes include a part of a word.

Even though the visual input at each fixation goes from characters $n - 1$ to $n + 3$ (we use n to refer to the fixated character, $n - 1$ to refer to the character on the left of fixation, $n + 1$ to refer to the character to the right of fixation, etc.), the number of characters that are being processed in the word-processing module is not always fixed. That is, the number of slots in the word-processing module changes dynamically. When the eyes move, new slots corresponding to the new characters in the perceptual span are added into the word-processing module. When a word is identified, all the slots corresponding to the recognized characters are removed from the word-processing module. It should also be noted, however, when the eyes move, if some of the visible positions (from position $n - 1$ to position $n + 3$) have been processed during the previous fixation, they will not be processed again at the new fixation. Therefore, on many fixations, word processing may begin at location n rather than at location $n - 1$ because that location has already been processed during the previous fixation.

Network update. The activations of the units in the network are updated continuously. The units at different levels are updated in a similar way (as described below) and are similar to that used by the original IAM (McClelland & Rumelhart, 1981). At a given time, a unit collects all the inputs from other units that are linked to it, and then it calculates the weighted sum of all the inputs, and the output is then updated using Equation 1. The order of the update is from the lower level to the higher level (i.e., character level and word level, respectively).

To update the activation of a unit, the input of a unit is calculated using Equation 1, where $n_i(t)$ is the input to the network at a given time t, w_{ij} is the weight of a link from another unit j (whose activation is $a_j(t)$), and the value of w_{ij} is positive when the link is excitatory, and negative when the link is inhibitory. The weights of the links are different for different links, which will be described below. The value *free1* is being used to add some extra input for word units and the saccade unit (which will be introduced later), and for all the other units (i.e., character units), *free1* is set equal to 0.

$$n_i(t) = \sum_j w_{ij} a_j(t) + free1 \quad (1)$$

The input of a unit (as described in Equation 1) is "squashed" to a value so that the unit activation falls in the range between 0 and 1 using Equation 2 (Grossberg, 1978).

$$\varepsilon_i(t) = \begin{cases} n_i(t)(1 - a_i(t)) & n_i(t) \geq 0 \\ n_i(t) a_i(t) & n_i(t) < 0 \end{cases} \quad (2)$$

In Equation 2, $a_i(t)$ is the activation of a unit at time t. The activation of a unit ($a_i(t + \Delta t)$) at time $t + \Delta t$ is updated using Equation 3, and $\varepsilon_i(t)$ represents the net activation input into the unit after being scaled as described in Equation 2.

$$a_i(t + \Delta t) = a_i(t) + \varepsilon_i(t) \quad (3)$$

The activation of the unit is kept between 0 and 1 using Equation 4.

$$a_i(t) = \begin{cases} 1 & a_i(t) > 1 \\ a_i(t) & 0 \leq a_i(t) \leq 1 \\ 0 & a_i(t) < 0 \end{cases} \quad (4)$$

Character level. There are a set of character units at each slot, with each unit representing a Chinese character at that position. Each character unit receives feedforward input from the visual unit in the same slot. The input from a visual unit to a character unit (the *jth* unit at slot *i*) is shown in Equation 5.

$$n_{ij}(t) = similarity_{ij}^2 \times exc\_visual\_character \times eccentricity_i \quad (5)$$

In Equation 5, $similarity_{ij}$ represents the similarity between the input image and the template of the character that is represented by that character unit,[2] where *exc_visual_character* is a free parameter that adjusts the weight of the link between the visual unit to character unit *j* at the same position (see Table 1 for a full list of free parameters). The similarity is calculated using the ratio of the number of pixels that have an identical gray level between the input image and the template and the number of all pixels in the image. In the lexicon, there are 5,692 Chinese characters. However, for the purpose of simplicity, only those characters with a similarity score higher than a certain level (0.5) are active.

The input of the character units from the visual level is constrained by visual eccentricity, which is highest at the fovea, and decreases with the distance from the fovea. In the model, we used a *Gaussian* function centered at the fixation position to simulate the influence of acuity of visual perception as a function of distance to fovea; $eccentricity_i$ represents the influence of acuity at the *ith* slot while the eyes fixate on the fix^{th} character, and is determined by Equation 6.

$$eccentricity_i = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(i-fix)^2}{2\sigma^2}} \quad (6)$$

In the equation, σ represents the standard deviation of the distribution. When the slot activation (defined as the activation of the most activated word) at the fixated position is above 0.3, the value of σ is determined by Equation 7, where $frequency_i$ is the frequency of the fixated word, and 4.0251 is the largest log frequency of the words used in the current model. *Eccentricity-_factor* is a free parameter. This simulates the finding that several studies have demonstrated that foveal load can modulate parafoveal processing (Henderson & Ferreira, 1990; Kennison & Clifton, 1995; Kliegl, 2007; Kliegl, Nuthmann, & Engbert, 2006; White, Rayner, & Liversedge, 2005). Thus, a fixation on a high-frequency word allows more parafoveal processing of upcoming word(s). When the slot activation at the fixated position is less than 0.3, σ equals 1.0.

$$\sigma = 1 + \frac{\log(frequency_i)}{4.0251} \times Eccentricity\_factor \quad (7)$$

At a given slot, there are inhibitory links between character units at the same slot, whose weight is *inh_character_character* (see Equation 1 for how weight information gets into the model). This makes character units at the same position compete so that only a single character unit can win the competition at a given slot. There are no links between character units at different slots.

[2] The input of the model is a 16 × 16 pixels grayscale image for each character, and an image of a character is presented at a slot. For simplicity, the model assumes that the input characters and the templates are shown in the same font.

Table 1
Parameters Used in the Model

Parameter	Best-fitting values	Search range
Visual processing		
Eccentricity_factor	4.689	0–5.0
Word Processing		
exc_visual_character	0.099	0.01–1.0
exc_word_character	0.293	0–0.5
inh_character_character	−0.030	fixed
inh_character_word	−0.261	−0.5–0
exc_character_word	0.779	0–1.0
inh_word_word_overlap	−0.319	−0.4–0
threshold_word	0.900	fixed
frequency_gain	0.452	0–0.5
Sentence processing		
predictability_gain	0.180	0.01–0.25
Eye-Movement control		
exc_saccade	0.235	0.001–0.5
exc_saliency_saccade	0.174	0.001–0.5
threshold_eye_target	0.430	0.3–0.8
threshold_eye_move	0.950	fixed

Word level. Because words are not demarcated by interword spaces in Chinese reading, neither word lengths nor word boundaries are known before a word is identified. To address this question, we assume that there is a set of word units at every slot, with each word's initial character being at that specific slot. Thus, word units are also position specific. A word unit may occupy more than one slot if the word unit represents a multiple-character word, and the number of slots it occupies is equal to the number of characters in that word. Many of the word units in the word-processing module are *spatially overlapping* (i.e., two word units are spatially overlapping if they occupy the same slot). The spatially overlapping words compete with each other for a single winner. When the activation of a word unit passes a threshold (i.e., a fixed parameter *threshold_word*, which is equal to 0.9), the word is identified, and it is therefore segmented from the rest of the text. There are 93,992 words in the lexicon (only words with one to four characters were included in the model; this represents 99.2% of Chinese words). Again, only words that contain a character represented in an active character unit at an appropriate position are activated, so that the number of active word units at each slot is much smaller than 93,992 (less than 2,000 word units).

There are feedforward links from a character unit and a word unit if the word unit spatially overlaps with the character unit (no matter whether they are in the same slot or not). These words can start at different positions and can be of different lengths. For example, if a character "人" is present at slot *n*, all of word units including a "人" at slot *n* (e.g., "一鸣惊人," "明白人," "美人," "强人所难," "人," "人民," "人类学," "人云亦云," etc.) are activated, and are connected to the character unit corresponding to "人." The weight of the feedforward link from a character unit to a word unit is a free parameter (i.e., *exc_character_word*) if the word contains that character at an appropriate character position. Otherwise, the weight of the feedforward link is another parameter (i.e., *inh_character_word*). There are lateral links between word units if the two words are spatially overlapping (again, no matter whether they start from the same slot or start from different slots), and the weight of the lateral inhibitory link is a free parameter (i.e., *inh_word_word_overlap*). The inhibitory lateral links make spatially overlapping words compete with each other, and thus only one word can win the competition if they are spatially overlapping. As a result, any character can only be assigned to one identified word. In addition to feedforward links, there are also feedback links from word units to character units. The link from a word unit to a character unit is excitatory (with a weight *exc_word_character*) if a word contains the character represented by the character unit at the appropriate position.

The influence of word frequency. There is an extra input to word units to reflect the influence of word frequency. For word units, the *free1* variable in Equation 1 is set to be *frequency scaling variable* (CFS_i) as described in Equation 8. Where $frequency_i$ is the frequency of the word represented by the word unit *i*, and 4.0251 is the largest log frequency of the words used in the current model, and *frequency_gain* is a free parameter that adjusts the amount of influence of word frequency on word processing.

$$CFS_i = \frac{log(frequency_i)}{4.0251} \times frequency\_gain \tag{8}$$

The influence of predictability. The influence of word predictability is implemented as increasing the activation of the corresponding word unit. The activation of a word unit is increased by a value described in Equation 9, where $predictability_i$ is the predictability of word *i* with the constraint of sentence context, and *predictability_gain* is a free parameter. For simplicity, we assumed that only words that are supported by the bottom-up character level are activated. Thus, those words that are only predicted by sentence context but not supported by bottom-up character level are not activated in the model. Because readers usually use information from all of the words they have read to make a prediction of what the next word should be, this model assumes that the influence of predictability on word $n + 1$ only takes effect when the slot activation at slot *n* (which is equal to the activation of the most activated word unit at a slot) has passed a threshold (0.3 in the simulation).

$$a_i(t + \Delta t) = a_i(t) + predictability_i \times predictability\_gain \tag{9}$$

Eye-Movement Control Module

Control of when to move the eyes. In the current model, when to move the eyes is influenced by the time that it needs to process the fixated word, and the activation of the fixated word is the driving force of eye movements. If the fixated word is processed faster, the eyes stay at that position for a shorter duration. In the model, there is a *fixated-word unit*, which represents the progress of the processing of the fixated word. The activation of the fixated-word unit is equal to the slot activation (again, it is equal to the activation of the most activated word unit at a slot) at the fixated position. The model assumes that the *saccade unit* controls when to move the eyes. The saccade unit, which has an excitatory link from the fixated-word unit, whose weight is another free parameter (i.e., *exc_saliency_saccade*). Once the activation of the saccade unit reaches a threshold (*threshold_eye_move*, which is a fixed parameter that is equal to 0.95), an eye movement is triggered. After a new fixation starts, the activation of the saccade unit returns to 0. For the saccade unit, the *free1* variable in

Equation 1 is set to be a free parameter *exc_saccade.* Because the value of *exc_saccade* is greater than 0, the activation of the saccade unit still increases even if the activation of the fixated-word unit is zero. Adding this parameter to Equation 1 introduces an autonomic component to the eye movement control module: even when the brain does not perceive any information, the eyes move after a certain amount of time (Becker & Jürgens, 1979).

It should be noted that although the activation of the fixated-word unit affects when to move the eyes, the exact time of eye movements is not strictly the time that a word is being identified. It is the activation of the saccade unit that determines when to move the eyes (i.e., the eyes move immediately after the activation of the saccade units passes a threshold), and the activation of the fixated word only influences when to move the eyes through influencing the activation of the saccade unit. Thus, eye movements are not perfectly aligned to the identification of words, and the eyes can move either before or after the fixated word is identified depending on the activation of the saccade unit.

Saccade target selection. In the current model, we adopt the assumptions of the processing-based strategy to determine where to move the eyes (Li et al., 2011; Wei et al., 2013). According to this strategy, readers estimate how many characters they can process at a fixation, and the saccade target is selected to be beyond that position. The model has a character-activation map, which has a unit for each character position in the sentence. The activations of these units are set to 0 at initiation. When a character is identified, its activation is set to 1. When a character is processed by the word-processing module, the character-activation units are updated in real-time synchronously to the activations of the corresponding character units in the word-processing module. The activation of a character-activation unit is set equal to the highest activation level of the character units at the corresponding slot.

To implement this processing-based hypothesis, after an eye movement is triggered, the eye-movement control module will search the character-activation map serially from left to right to find the first unit that has an activation smaller than a certain threshold, which is a free parameter (i.e., *threshold_eye_target*). The corresponding character is selected as the intended landing position of next saccade. The exact landing position within the selected character is determined by the activation of the character-activation map at that position (as shown in Equation 10). In the equation, $CharacterSaliency_i$ represents the activation of the most activated character unit at position *i*, and *threshold_eye_move* is a free parameter as defined before. By doing so, if the character is processed more, the eyes will land further to the right within that character. There is also a Gaussian distribution of noise with a standard deviation (*SD*) of 1.0 for the intended landing position. We introduced this random factor of saccade target selection because some studies have shown that the shape of the distribution of saccade landing is approximately normal (McConkie, Kerr, Reddix, & Zola, 1988). When the eyes are ready to move, the saccade length is shortened by one character if the fixated word has not been recognized. By doing so, the eyes will not move too far away from the fixated word if it has not been recognized yet. This is another way the word-processing module influences eye movements.

$$Position = \frac{characterSaliency_i}{threshold\_eye\_target} \tag{10}$$

Model Implementation and Parameter Search

Model implementation. This model is a computational model, so that all the assumptions of word processing and eye-movement control are implemented by a computer program (see the Appendix for programming details). The input of the model consists of images of a series of characters that constitute a sentence. The model simulates the dynamic procedure of word processing at each fixation, and also simulates the eye-movement procedure until the whole sentence is fully processed. The output of the model is a series of identified words, and the position, starting time, and ending time of each fixation during sentence processing.

Initiation of the model. When the model starts, it randomly chooses either the first or second character of the sentence as a fixation point. Then the word-processing module is initiated as fixating on that character, with the word-processing module being initiated as perceiving information from one character to the left of the fixated character to up to three characters to the right of the fixated character. The activations of all units are initialized to zero at initiation.

Eye-movement measures. To record when to move the eyes, the model needs a timing system. To simplify the model, following the practice of IAM, the model operates in discrete slices rather than continuous time. At each iteration, the activations of all the units in the network are updated once. Thus, we used the duration of an iteration as the unit of the modeling timing system. The starting time of a particular fixation is recorded as the number of iterations that the particular fixation starts on, and the ending time is the number of iterations that the fixation ends on. To compare the durations of fixations in the model with the observed eye-movement data, the number of iterations was transformed to fixation times by multiplying a ratio. This ratio was chosen to make sure that the average fixation duration of the model-predicted data was equal to the mean fixation duration of observed data. The ratio was calculated using the following method. For a given data set, we set a ratio between the average observed fixation duration and the averaged model-predicted fixation duration as measured by the number of iterations. Then we multiplied this ratio by all the model-predicted duration measures (i.e., FFD and gaze duration).

To compare the simulated data with observed eye-movement data, we calculated word-based eye movement measures using the same method as that used in eye-movement research (Rayner, 1998). Because the model does not implement high-level language processing, which was assumed to be the major factor that caused regressions (Rayner, 1998), we only calculated eye-movement measures during first-pass reading. We calculated FFD and gaze duration on the word to capture the "when" aspects of eye movements, and refixation probability (proportion of trials in which a word is fixated more than once during first-pass reading), skipping rate, and saccade length leaving the word (outgoing saccade length) to capture the "where" aspects of eye movements. We also calculated landing positions within a word in some simulations.

Model parameters. There are 14 parameters in the model (see Table 1 for a complete list of the parameters). To keep the number of free parameters as small as possible, three parameters were kept fixed (i.e., *inh_character_character, thresold_word,* and *threshold_eye_move*). Therefore, 11 free parameters can be varied during simulation, with one used for visual processing (Eccentricity_factor), six of these parameters used for word processing (*exc_visual_character, exc-_word_character, inh_character_word, exc_character_word, inh_word_word_overlap,* and *frequency_gain*), one of them related to sentence reading (*predictability_gain*), and three used in eye-movement control (exc*_saccade, exc_saliency_saccade,* and *threshold_eye_target*).

Data set used to find optimal parameters. We used data reported by Wei et al. (2013) to find optimal parameters. In that study, 21 participants read 72 sentences while their eyes were monitored, with 36 of the sentences including a high-frequency two-character word (above 50 occurrences per million) and 36 including a low-frequency two-character word (below five occurrences per million). The predictabilities of these target words were close to zero. As shown in Table 2, that study found a word-frequency effect at the target region. FFDs and gaze durations were significantly longer in the low-frequency condition than in the high-frequency condition. In addition, as shown in Table 2, saccade length was longer when leaving a high-frequency target word than when leaving a low-frequency target word, and fixation probability and refixation probability on the target word were also higher in the low-frequency condition than in the high-frequency condition.

Model fitting method. To estimate how well the model predicts the observed data, we calculated *goodness of fit*. The model processed the same sentences as the human participants read, and then we compared how well the model could predict the eye-movement data of the human participants. We used FFD, gaze duration, fixation probability and refixation probability on the target words, saccade length leaving the target word, and character identification accuracy as the measures to calculate goodness of fit. We used *normalized root-mean square deviation* (*nRMSD*) to measure goodness of fit (Equation 11).

$$nRMSD = \sqrt{\frac{\sum_{i=1}^{n}\left(\frac{y_{ipredicted} - y_{iobserved}}{std_{iobserved}}\right)^2}{n}} \tag{11}$$

In Equation 11, $y_{ipredicted}$ is the model-predicted data, $y_{iobserved}$ is observed data, $std_{iobserved}$ is the standard deviation of the observed data, and n is the number of data points that are being fitted by the model. The smaller the *nRMSD*, the better the model fit. We searched the entire parameter space for the best parameters to generate the smallest *nRMSD*.

Procedure of parameter fitting. Because the parameter space is huge, we used a *parallel genetic algorithm* to find the best-fitting parameters (parameters that could generate the smallest nRMSD; Muhlenbein, Schomisch, & Born, 1991; Whitley, 1994). After we found the best parameters, we ran the model 30 times to simulate 30 participants. We simulated 30 participants because there are two random factors in the model: First, the starting point of eye movements was randomly chosen as the first or second character of a sentence. Second, the distribution of saccade landing positions was a Gaussian distribution centered at the intended landing position. The best parameters found in this procedure were used in all the other simulations. Using the same set of parameters in different simulations is a merit of the current model. It shows that the model's generalizability is good and simulations on different data sets are not based on tweaking the parameter values separately for each data set. See the Appendix for a detailed description of the parameter-fitting method, and see Table 1 for the values of the best parameters.

Simulation Results

We used the model described above to simulate some important findings of eye-tracking studies in Chinese sentence reading. As we said in the Benchmark Data for Simulation section, these findings include how word processing influences eye-movement behaviors, how Chinese readers choose saccade targets, how Chinese readers process information with parafoveal vision, and how Chinese readers segment words with ambiguous boundaries. In all the data sets to be described, Chinese readers read sentences while their eyes were monitored. During simulation, the inputs of the model were all the sentences that were read by Chinese participants in the original experiments. (We will note whenever this is not the case.)

As noted above, we used the same set of parameters as described in Table 1 in all the simulations. That is to say, we did not search for optimal parameters for each individual data set. It should be noted that the equipment, experimenter, participants, and the difficulties of sentences were different across experiments, hence the absolute eye-movement measures were also slightly different across experiments. Therefore, we mainly focused on the differences between conditions instead of the absolute value of the eye-movement measures when evaluating how well the model simulated the findings.

Table 2
Observed and Simulated Word-Frequency Effect (Wei, Li, & Pollatsek, 2013)

	Observed		Simulated	
Measures	High-frequency	Low-frequency	High-frequency	Low-frequency
First fixation duration (ms)	255 (74)	267 (76)	250	272
Gaze duration (ms)	282 (99)	316 (97)	262	300
Outgoing saccade length	2.93 (0.19)	2.77 (0.15)	2.81	2.58
Fixation probability	0.74 (0.19)	0.78 (0.15)	0.73	0.78
Refixation probability	0.12 (0.25)	0.16 (0.24)	0.04	0.10

Note. Numbers in parentheses are standard deviations.

The Influence of Word Processing on Eye-Movement Control

Word-frequency effect. In the current study, we simulated data reported by Wei et al. (2013), which were also used as the data set to find the optimal parameters.[3] As stated earlier, word frequencies can affect many aspects of eye-movement behaviors during sentence reading. The model could accurately identify the characters that were included in the sentences (with an accuracy of 0.99). As shown in Table 2, FFD, gaze duration, fixation probability, outgoing saccade length, and refixation probability had a similar pattern with the observed data. Compared with high-frequency words, low-frequency words were fixated more frequently; and once they were fixated, both FFD and gaze duration were longer, and they were more likely to be refixated. The outgoing saccades leaving low-frequency words were shorter than those leaving high-frequency words, although the model did underpredict the saccade lengths a bit.

The model can predict the word-frequency effects on fixation durations because of the assumption regarding word frequency. As shown in Equation 8, word frequency directly influences the input of the word units. Thus, the activation of the units corresponding to a high-frequency word rises faster than that corresponding to a low-frequency word. The fixated-word unit has excitatory links to the saccade unit, whose activation directly determines when to move the eyes. That is why we observed shorter fixation durations on high-frequency words than on low-frequency words.

The model also successfully predicted the effect of word frequency on saccade length: Saccades leaving high-frequency words are longer than leaving low-frequency words. As shown in Equation 7, the efficiency of parafoveal visual processing is influenced by the frequency of the fixated word. Thus, the characters to the right of fixation are processed more when the fixated word is a high-frequency word than a low-frequency word. Because the model assumes that saccade-target selection is determined by the activation of the characters to the right of fixation, saccades are longer when leaving high-frequency words than low-frequency words.

Word-predictability effect. Rayner, Li, Juhasz, and Yan (2005) found a word predictability effect in Chinese reading that was similar to what has been found in English reading. Sixteen native Chinese readers read 36 Chinese sentences while their eyes were monitored. In one third of the sentences, the target words were highly predictable by sentence context before they reached the target word (i.e., for the high-predictable words, more than 70% of Chinese readers could predict the target words based on sentence context prior to the target word). In another third of the sentences, the target words were unpredictable based on the sentence's context (i.e., for the unpredictable words, less than 10% of Chinese readers could predict the target words based on sentence context prior to the target word). And finally, in the remaining third of the sentences, the target words were only moderately predictable by sentence context (the medium-predictable words). The results showed that the low-predictable words were fixated more often than the medium-predictable words, which were in turn fixated more often than the high-predictable words. Moreover, the fixation durations on low-predictable words were longer than those on medium-predictable words, which were, in turn, longer than those on high-predictable words (see Table 3 for more detail).

We attempted to simulate the sentence processing data of Rayner et al. (2005). However, in the simulation, the model only read 31 out of the 36 sentences from Rayner et al. (2005) because five of the target words were not two-character words. Because word length is an important factor that affects eye-movement behaviors, we removed those five sentences in the simulation to avoid the influence of the variations of word length as a confounding factor that could influence the results (and therefore the observed results reported in Table 3 were data for only the selected items). During the simulation, we used the same parameters as were used to simulate results of word frequency (as described in last section) except *predictability_gain*, which adjusts the influence of word predictability as defined in Equation 9. Because the predictability of each of the target words of Wei et al. (2013) was close to zero, it was impossible to use that set of data to find an optimal value for *predictability_gain*. Thus, we varied the values of *predictability_gain* when we simulated the data from Rayner et al. (2005) in order to find an optimal value for *predictability_gain* that would make the *nRMSD* minimal.

As shown in Table 3, the model could predict the results of Rayner et al. (2005) very well. As can be seen, for both FFDs and gaze durations, there was a decrease between the medium-predictable and high-predictable words (which the model captured), and a difference between the low-predictable and medium-predictable words (which the model also captured). Likewise, the model also captured the increasing probability of fixation on a word with the decreasing probability of its appearing in the text at that point. However, it should be mentioned that the probabilities of fixation on a word were considerably underpredicted in all three cases. (This was also true to a lesser extent in Table 2.)

The current model could simulate the predictability effect because predictability was implemented by increasing the activation value to the corresponding word unit, and the increased activation was higher if the corresponding word is more predictable by sentence context. Thus, the high-predictable words need less time to be identified. As a result, fixation durations are shorter for high-predictable words than low-predictable words. The high-predictable words are more likely to be skipped because the words (and characters) are processed in parallel, and characters belonging to a high-predictable word are processed more in parafoveal vision than low-predictable words.

Word-length effect. In the current study, we simulated results reported by Li et al. (2011). In that study, 32 native Chinese readers naturally read 100 Chinese sentences while their eye movements were monitored. In half of the sentences, the target words were two-character words; in the other half, the target words were four-character words. The predictability of all these words was close to zero and was matched between conditions.

The observed results of this study are shown in Table 4. Compared with short words, long words are less likely to be skipped, and gaze durations on long words are usually longer. Moreover, saccade lengths leaving longer words also tend to be longer than saccades leaving shorter words. We used identical parameters (as shown in Table 1) that were used to predict the word-frequency effects to simulate the results of Li et al. (2011). As shown in Table

[3] Some parameters that are not used to simulate word-frequency data will be described later.

Table 3
Observed and Simulated Word-Predictability Effect (Rayner, Li, Juhasz, & Yan, 2005)

	Observed			Simulated		
Measures	High	Medium	Low	High	Medium	Low
First fixation duration (ms)	261 (53)	266 (41)	286 (56)	250	274	289
Gaze duration (ms)	284 (53)	288 (60)	322 (69)	264	289	314
Outgoing saccade length (characters)[a]	2.49 (0.54)	2.34 (0.50)	2.53 (0.77)	2.73	2.73	2.60
Fixation probability	.75 (.17)	.79 (.15)	.88 (.11)	.67	.69	.74
Refixation probability[a]	0.09 (0.12)	0.07 (0.10)	0.13 (0.12)	.04	.05	.08

Note. Numbers in parentheses are standard deviations.
[a] The numbers were not reported in Rayner et al. (2005), and they were not significantly different between conditions.

4, the model captures most of the important patterns of word-length effects in Chinese reading. There are several patterns that stand out immediately from Table 4. The first is that there was a substantial difference between the FFD and gaze-duration data; notably, there was a small difference between the two- and four-character words in FFDs, while there was a larger difference in gaze durations. The model predicted this very well. Second, the model predicted the fixation probability (first pass) of the words extremely well. Third, the model also predicted outgoing saccade length from two-character words to be shorter than that from four-character words.

Distribution of initial landing positions. The model can also predict one of the most important patterns of the distribution of initial landing positions. As shown in Table 5, the observed results in Li et al. (2011) showed that the probabilities of initial fixation were higher for characters at word beginning, and decreased with the distance from the beginning of the word. Importantly, these results do not suggest that Chinese readers saccade to the word center as do readers of alphabetic languages. As shown in Table 5, the model generated a similar pattern of results. It is also of note that there was little (if any) effect of the length of the target word in the pattern of either the observed or predicted values.

Saccade Target Selection During Chinese Reading

In the above sections, when we introduced the simulations of the word-frequency effects and the word-length effects, we showed that the model could simulate the findings that saccade length is affected by word frequency and length. Moreover, in the section in which we introduced the word-length effect, we have shown that the model can simulate the finding that the PVL curve peaks at the beginning of the word. These are all important findings regarding saccade target selection during Chinese reading. In the next section, we mainly focus on simulating the parafoveal preview effect on saccade target selection.

The model was able to simulate the findings reported by Liu et al. (2015). In that study, Chinese readers read sentences with either a high-frequency target word or a low-frequency target word embedded roughly in their middle. In the valid-preview condition, readers read sentences naturally. In the invalid-preview condition, each character to the right of the target word was masked with a symbol "⋇" before the eyes crossed an invisible boundary to the right of the target word. These "⋇" symbols changed to normal characters after the eyes crossed the boundary. Thus, readers could not view the characters to the right of the target words in the invalid-preview condition. Liu et al. (2015) replicated the findings of Wei et al. (2013) by showing that saccades leaving high-frequency words were longer than those leaving low-frequency words in the valid-preview condition. However, this effect decreased in the invalid-preview condition. These results suggested that preview is important for Chinese readers to decide where to target their next saccade.

As shown in Table 6, the model simulated the important findings of Liu et al. (2015) well: FFDs and gaze durations were longer for low-frequency words than for high-frequency words in both the valid-preview condition and the invalid-preview condition. Interestingly, the saccade length was longer when leaving a high-frequency word than when leaving a low-frequency word in the valid-preview condition. However, the difference of the saccade lengths leaving the target words between the two conditions was much smaller in the invalid-preview condition.

The model could simulate this finding in the valid-preview condition because the difference of saccade length leaving the target word

Table 4
Observed and Model-Predicted Word-Length Effect (Li, Liu, & Rayner, 2011)

	Observed		Simulated	
Measures	Two-character	Four-character	Two-character	Four-character
First fixation duration (ms)	250 (23)	249 (28)	250	249
Gaze duration (ms)	266 (28)	355 (91)	265	342
Outgoing saccade length	2.70 (0.68)	2.90 (0.74)	2.78	3.13
Fixation probability	.66 (0.17)	.93 (0.06)	.74	.96
Refixation probability[a]	.06 (.07)	.39 (.23)	.05	.35

Note. Numbers in parentheses are standard deviations.
[a] Data were not reported in Li et al. (2011).

Table 5
Fixation Probability Distribution on a Four-Character Region of Interest for Words With Different Length (Li et al., 2011)

	Observed				Simulated			
Word length	1	2	3	4	1	2	3	4
Two-character	.36	.33	.21	.10	.38	.37	.19	.05
Four-character	.36	.34	.22	.08	.34	.33	.20	.13

Note. The region of interest includes the four-character target word in the four-character condition, and includes the two characters of the target word and two characters following it in the two-character condition.

was caused by the different amount of information processed with parafoveal vision. In contrast, in the invalid-preview condition, all the characters in parafoveal vision were "⋇," which are unfamiliar symbols that are hard to process parafoveally. Because the "⋇" symbols were difficult to process, the degree to which character units were activated by them (parafoveally) was minimal, and therefore, the modulatory influence of target word frequency on any such activation was very reduced. As a result, the difference in the length of saccades leaving the target words was smaller between the high-frequency condition and the low-frequency condition.

As shown in Table 6, outgoing saccade length was longer in the valid-preview condition than in the invalid-preview condition. The model predicted this effect as well. The model could do so because more characters were processed with parafoveal vision in the valid-preview condition than in the invalid-preview condition for the following two reasons. First, the "⋇" symbols in the invalid-preview condition is not familiar to readers so they are difficult to process. Second, the preview characters made up a word in the valid-preview condition, while the "⋇" symbols did not make up a word in the invalid-preview condition. Therefore, the character units receive excitatory feedback activations from the word units in the valid-preview condition but not in the invalid-preview condition. As a result, the activations of the character units at the preview character position increase faster in the valid-preview condition than in the invalid-preview condition. Because the eye-movement control module relies on the activation of the character units of upcoming characters to decide where to move the eyes, boundary-crossing saccades were longer in the valid-preview condition than in the invalid-preview condition. It should be noted that although the model simulated the pattern of the preview effect on saccade length, it overpredicted the size of the effect. This might have been caused by the fact that we did not make any adjustments to the model parameters between simulations.

It should be noted that Liu et al. (2015) used a different set of stimuli, and in their valid-preview condition they replicated the word-frequency effects observed by Wei et al. (2013). Similarly, we used the same parameters as shown in Table 1, and the model generally replicated the simulation results of the word-frequency effects even when we used another set of experimental stimuli. It suggests that the model is quite robust and can generate the same pattern of results for different sets of materials.

Parafoveal Preview Effects

Many Chinese reading studies have found a preview benefit: Reading times were usually shorter if the word could be viewed with parafoveal vision than otherwise (Gu et al., 2015; Yang et al., 2009). In the current study, we simulated the preview effect observed by Gu, Li, and Liversedge (2015).[4] We chose to simulate this study because the stimuli were easy to access. In Experiment 2 of Gu et al. (2015), Chinese readers read sentences with two-character target words embedded in the middle of the sentences. Before the readers' eyes crossed an invisible boundary located before the target word, two characters were shown at the target word position as the preview. When the eyes crossed the boundary, the previews changed to the target words. The preview could be identical to the target word (valid preview) or different (invalid preview). In the invalid-preview condition, the preview characters were random characters that did not make up a word. The FFDs and gaze durations on the two-character target words were longer in the invalid-preview condition than in the valid-preview condition. These findings were similar to the preview effects as reported by other studies (Yang et al., 2009).

When the model simulates reading in the invalid-preview condition, it behaves normally before the eyes cross the invisible boundary and the word-processing module uses the preview characters as an input at the visual level. When the eyes cross the boundary, the input in the visual level changes to the target word, and the character units and the word units at the corresponding slots and all of the corresponding links are updated accordingly. Meanwhile, the character and word units activated before the eyes crossed the boundary at these slots occupied by the preview characters are still active although the links from the visual level to character level are set as zero because the new input does not support those character units any more. In the valid-preview condition, the model processes sentences normally, as if there is no boundary. As shown in Table 7, the model could simulate the findings well, with FFDs and gaze durations on the target words being longer in the invalid-preview condition than those in the valid-preview condition. It should be noted that the model overpredicted the preview benefit in FFD. This might be caused by the fact that we did not vary the parameters to fit the preview benefit in this simulation.

The model could simulate the preview effect because it assumes that characters in the perceptual span are processed in parallel. Thus, in the valid-preview condition, characters (and words) can be processed to a certain level. Thus, it takes less time to process the words once they are fixated. In contrast, for the invalid-preview condition, the preview characters are different from the characters of the target word; readers thus must process the target words from afresh after their eyes cross the boundary. As a result, it will take a longer time to process the words in the invalid-preview condition compared with the valid-preview condition.

It should be noted that the preview benefit was measured as the reduction in reading times in the valid-preview condition compared with the invalid-preview condition (Rayner, 1978; see Schotter et al., 2012, for a review). However, given that we only have a valid-preview condition and an invalid-preview condition, the difference between the two conditions might involve a valid-

[4] Some of the target words were one-morpheme words and the others were two-morpheme words in the experiment, but eye-movement behaviors were similar for these two kinds of target words. Thus, we did not distinguish between the two kinds of words in the simulation.

Table 6
The Influence of Preview on Word Frequency Effects (Liu, Reichle, & Li, 2015)

Measures	Observed		Simulated	
	High-frequency	Low-frequency	High-frequency	Low-frequency
Valid-preview				
First fixation duration (ms)	255 (40)	278 (51)	252	281
Gaze duration (ms)	276 (57)	320 (85)	266	316
Outgoing saccade length	2.73 (0.62)	2.48 (0.51)	2.92	2.41
Fixation probability[a]	.68 (.17)	.70 (.18)	.70	.73
Refixation probability[a]	.05 (.10)	.08 (.10)	.04	.12
Invalid-preview				
First fixation duration (ms)	287 (45)	307 (45)	281	313
Gaze duration (ms)	323 (74)	384 (102)	336	385
Outgoing saccade length	2.37 (0.57)	2.30 (0.57)	1.98	1.84
Fixation probability[a]	.72 (.13)	.78 (.11)	.75	.77
Refixation probability[a]	.07 (.10)	.14 (.12)	.16	.22

Note. Numbers in parentheses are standard deviations.
[a] Data were not reported in the original article.

preview benefit component and an invalid-preview cost component. In the current study, there is no good way of determining the proportion of the effect that is due to each.

Segmentation of Words With Ambiguous Boundaries

In Chinese text, word boundaries are sometimes ambiguous. That is to say, there are multiple ways to segment a string of characters. There are at least two kinds of words with ambiguous boundaries: incremental words and overlapping ambiguous strings. We will introduce these two kinds of character strings and illustrate how the model deals with them in this section.

The processing of incremental words. In Chinese, some characters belonging to a word can constitute a word by themselves. For some two-character words (which are the most frequently used words in Chinese), either the first character, the second character, or both can constitute a word by themselves. For example, in the word "不断" (meaning *unceasingly*), the first character is a word by itself ("不" meaning *no*), and the second character is another word ("断" meaning *break*).

Previous studies showed that Chinese readers prefer to process incremental words as a longer word even though some of its character(s) may form another word (Shen, Li, & Pollatsek, 2018; Yang, Staub, Li, Wang, & Rayner, 2012). Yang, Staub, Li, Wang, and Rayner (2012) embedded incremental words into sentences, and the incremental words were always plausible in the sentence context. The first character (also a word by itself) was plausible within the sentence context in half of trials, and was implausible in the other half of the trials. They found that whether the first character of a two-character compound word was plausible within its sentence context did not influence the reading time of the two-character word. These results suggested that Chinese readers tend to process two-character words as a whole rather than on a character-by-character basis.

How does the model process the incremental words? When the two characters "不" and "断" are within the perceptual span, both the whole word "不断" and the embedded words "不" and "断" are activated. These words compete for a single winner. Which one wins the competition is mainly determined by the following two factors. First, the competition is influenced by the frequencies of the words. The word with a higher frequency has a better chance of winning the competition. Second, the whole word has some advantage during the competition because it receives feedforward activations from more character units than the embedded words. As a result, the whole word is more likely to win the competition if the frequencies of the embedded words and the whole words are similar.

To illustrate this point, we looked at the model-predicted results of Experiment 2 in Wei et al. (2013), that were discussed in the previous section. In that experiment, Chinese readers processed sentences with high- or low-frequency two-character target words

Table 7
Preview Benefit in Chinese Reading (Gu, Li, & Liversedge, 2015)

Measures	Observed		Simulated	
	Valid preview	Invalid preview	Valid preview	Invalid preview
First fixation duration (ms)	290 (48)	325 (55)	262	353
Gaze duration (ms)	358 (111)	430 (107)	306	421
Outgoing saccade length[a]	2.45 (.69)	2.39 (.62)	2.35	1.93
Fixation probability	.87 (.14)	.92 (.14)	.79	.80
Refixation probability[a]	.22 (.21)	.39 (.21)	.18	.26

Note. Numbers in parentheses are standard deviations.
[a] Data were not reported in the original article.

placed in the sentences. One or both of the characters in 70 out of 72 of the target words were a one-character word by themselves. For these words, the simulation showed that the whole word wins the competition in 99.4% of the trials when the frequency of the target word was high, however, note also that it wins the competition in 99.2% of the trials when the frequency of the whole word was low. In this simulation, the whole word has an absolute advantage in competition and word frequencies play a much smaller role even when the frequencies of the embedded words are higher than those of the compound words in the low-frequency condition.[5] These results are consistent with the conclusion of experimental studies (Shen et al., 2018; Yang et al., 2012) that incremental words are usually processed as a whole in Chinese reading.

The processing of overlapping ambiguous strings. For overlapping ambiguous strings such as "学生活," where the middle character can form a word with the character to its left (e.g., "学生" meaning *student*), and can also form another word with the character to its right (e.g., "生活" meaning *life*). During reading, participants need to determine whether the middle character belongs to the word to the left or to the right.

The findings from some previous studies could shed some light on how Chinese readers process overlapping ambiguous strings (Ma et al., 2014; Yan & Kliegl, 2016; Yen et al., 2012). In Ma et al. (2014), the overlapping ambiguous strings were embedded in Chinese sentences, and Chinese readers were asked to read those sentences while their eyes were monitored. The word frequency of the left-side word in the overlapping ambiguous string was higher than that of the right-side word in half of the trials (i.e., high-low condition), and the frequency of the left-side word was lower than that of the right-side word in the other half of the trials (i.e., low-high condition). The part of the sentence following the ambiguous string served to disambiguate the string. When the sentence context after the overlapping ambiguous string favored the left-side word segmentation, readers made fewer regressions back to the ambiguous region, and second-pass reading times were shorter for the ambiguous region in the high-low condition than that in the low-high condition. In contrast, when the sentence context after the overlapping ambiguous string favors the right-side word segmentation, the results were opposite: Readers made more regressions back to the ambiguous region, and second-pass reading times were longer for the ambiguous region in the high-low condition than that in the low-high condition. These results suggest that the middle character is more likely to be segmented as belonging to the high-frequency word. Based on these results, Ma et al. (2014) suggested that readers used a two-stage strategy to process this kind of character strings during sentence processing. In the first stage, all the words constituted by the characters in the perceptual span are activated, and all the activated words compete for a single winner. When a word wins the competition, the word is identified and at the same time the middle character is assigned to the winning word. In a second stage, readers check whether the initial segmentation is correct or not. If the initial segmentation does not fit the sentence context, readers need to make regressions back to the ambiguous region to correct the error. Recently, Huang and Li (2020b) replicated the findings reported by Ma et al. (2014) with more sentences.

Another important finding related to the segmentation of overlapping ambiguous strings is that Chinese readers have a left-side word preference so that they prefer to assign the middle character in the overlapping ambiguous strings to the word on the left when other factors (such as word frequency) are equal (Huang & Li, 2020a). In Huang and Li (2020a) Chinese readers read sentences containing an overlapping ambiguous string (three-character string ABC), and the frequencies of word AB and word BC were comparable. The prior contexts preceding target words were manipulated to support either the left-side word segmentation (AB-C) or the right-side word segmentation (A-BC). Reading times were shorter, skipping rates were higher, and regression-in probabilities were fewer when the prior sentence context supported the left-side word segmentation (AB-C) construction than when the prior sentence context supported the right-side word segmentation (A-BC) construction. These results suggest that Chinese readers prefer to group the two characters on the left side as a word when word frequencies do not provide any bias. If prior sentence context does not support that kind of segmentation, readers need to spend more time to overcome the preferred segmentation. The left-side word advantage is consistent with similar studies in English reading (Pollatsek, Drieghe, Stockall, & de Almeida, 2010), which showed that English readers prefer to segment the word "unlockable" as "unlock-able" rather than "un-lockable."

The current model could simulate the initial stage of the processing of overlapping ambiguous strings. To do that, the model processed all of the sentences used by Huang and Li (2020b). For the high-low condition, the middle character was assigned to the word on the left in 98.3% of the trials. In contrast, for the low-high condition, the middle character was assigned to the word on the left in 51.7% of the trials, and was assigned to the word on the right in 48.3% of the trials. These simulated results have two important patterns. First, word frequency plays an important role during Chinese word segmentation and the middle character of an overlapping ambiguous string is more likely to be assigned to the high-frequency word when other factors are equal. These results are consistent with Ma et al. (2014). Second, the left-side word has an advantage during the competition so that the left-side word almost always wins the competition when the high-frequency word is on the left. Even when the high-frequency word is on the right, the left-side word still wins the competition in about half of the trials. This result is consistent with the left-side word advantage observed in Huang and Li (2020a).

Consistent with Huang and Li (2020b) and Ma et al. (2014), FFD and gaze duration on the ambiguous region was longer in the low-high condition than in the high-low condition (see Table 8). It should be noted that saccade length and fixation probability were not theoretically interesting in Huang and Li (2020b) and Ma et al. (2014), and so those measures were not reported in the original article. As a matter of fact, these two measures were not significantly different between the high-low condition and low-high condition in both studies (Huang & Li, 2020b; Ma et al., 2014). We reported those measures in Table 8 just for completeness.

The model could simulate the initial stage of processing of the overlapping ambiguous strings because it assumes that words that are

[5] In the low-frequency condition, the frequencies of the embedded words (83 occurrences per million for the word constituted by the first character, and 86 occurrences per million for the word constituted by the second character) were higher than that of the whole word (three occurrences per million).

Table 8
Processing of Overlapping Ambiguous Strings (Huang & Li, 2020b)

Measures	Observed		Simulated	
	High-low	Low-high	High-low	Low-high
First fixation duration (ms)	264 (105)	275 (109)	263	276
Gaze duration (ms)	441 (301)	450 (291)	327	369
Outgoing saccade length[a]	2.69 (1.66)	2.74 (1.46)	2.76	2.63
Fixation probability	.90 (.31)	.92 (.27)	0.90	0.90
Refixation probability[a]	.47 (.50)	.52 (.50)	0.20	0.33

Note. Numbers in parentheses are standard deviations.
[*] Data were not reported in the original article, and they were not significantly different between conditions.

spatially overlapping compete with each other, so that only a single word unit can win the competition among those words units that are spatially overlapping. As a result, a given character can only be assigned to a single word. For example, when the model sees an overlapping ambiguous string "学生活," the word on the left ("学生") competes with the word on the right ("生活"), and only one word can win the competition. Thus, the middle character "生" is either assigned to the word on the left or the word on the right, but not both.

Why do Chinese readers have a left-side word advantage when processing the overlapping ambiguous strings? The word AB has advantages over the word BC because readers' eyes move from left to right and the characters on the left are closer to foveal vision than the characters on the right before the eyes fixate on the overlapping ambiguous string. Therefore, the activations of the character units on the left (e.g., Character A) increase earlier than the activations of the character units on the right (e.g., Character C). As a result, the activation of word AB increases faster than the activation of word BC. Thus, word AB has a better chance of winning the competition during natural reading. As a result, the word AB is more likely to be segmented as a word when other factors are equal.

It should be noted that the current model did not have a semantic-processing component, and thus it cannot simulate findings related to semantic processing. First, as shown in Table 8, the model-predicted gaze durations are generally shorter in duration and the refixation probabilities are lower than those observed in experiments. During reading, the overlapping ambiguous strings might cause some confusion during semantic processing, thus resulting in longer reading times. Because the model does not have a semantic processing component, it predicts shorter gaze durations and fewer refixations compared with the observed data. Second, the model could not detect and correct the errors. When dealing with ambiguity (e.g., deciding which characters are part of which word), a reader might segment a character sequence incorrectly, which only becomes apparent later during reading. In such a case, the reader is likely to regress back to the ambiguous region to correct the initially incorrect interpretation (Ma et al., 2014). As there is no semantic processing component in the model, it does not predict such eye movement behavior (and it is also the reason that regressions are not modeled). This limitation of the model will be addressed in the future.

General Discussion

In the current article, we report an integrated model of word processing and eye-movement control during Chinese reading. We made some new assumptions in addition to the basic assumptions of IAM (McClelland & Rumelhart, 1981) to simulate word processing in Chinese reading. Using these assumptions, the model could segment a string of continuous characters in a sentence into words and identify them during Chinese sentence reading. In addition to these assumptions about how word processing occurs, we made some new assumptions to address decisions on how the eyes move during Chinese reading. The decision is complicated (as you have seen) and the eye-movement control module makes the decision regarding when and where to move the eyes using the activation information of word units and character units. As a result, the model was able to simulate the findings on word processing, saccade target selection, parafoveal processing, and word segmentation that have been observed in Chinese reading.

Word Segmentation

Following Li et al. (2009), we assumed that word segmentation and identification are a unified process with each occurring simultaneously. In the current model, all the characters in the perceptual span are processed in parallel (within the constraint of eccentricity), and all the words that correspond to the activated character units are activated. All the activated word units which are overlapping in space (with different lengths and different starting positions) compete for a single winner. When a word unit wins the competition, it is both segmented from the string of unprocessed characters and it is also simultaneously identified as a word. Because the word units are position specific, the word unit that wins the competition carries the information on where the word starts and where it ends.

Relation Between Word Processing and Eye-Movement Control

The activation of the most activated word unit at the currently fixated slot is the driving force of the eye-movement control module to make decisions regarding when to move the eyes. There is a link from the fixated-word unit, which corresponds to the most active word unit at the fixated position, to the saccade unit. Thus, the activation of the fixated-word unit influences when the eyes move. The activation of the saccade unit will increase faster if the activation of the fixated word is high, which will make the fixation duration shorter. Therefore, the activation of the fixated word influences when to move the eyes, but the eye movements are not aligned to the completion of word identification (as they mostly are in the E-Z Reader model).

As we stated in the Introduction section, there is no evidence that Chinese readers move their eyes to any specific position of a word. This model made the same assumption; therefore, neither the word beginning nor word center is the default target of the next saccade. Instead, in the current model, where to move the eyes is directly determined by the character-activation map and not by a process such as in E-Z Reader. The activation level of the character-activation map at a given position is equal to the activation of the most active character unit at that position. When the time comes for the eye-movement control module to decide where to move the eyes, the model will search the character-activation map from left to right to find a position that is below a certain threshold, and the eyes will saccade to that position. Thus, where to move the eyes is directly determined by the character-activation map. We made this assumption for the following reasons: First, characters are the natural and salient units in Chinese reading. They are separated by small spaces. Thus, it is reasonable to believe that character processing plays an important role when making decisions regarding where to move the eyes. Second, previous studies in Chinese reading did not find evidence showing that the eyes move to any specific position within a word (Li et al., 2011). As can be seen in the Results section, the model could simulate the findings related to saccade target selection well. We should note, however, even though we assumed that characters are the basic units to select the saccade target, word processing also influences saccade target selection through interacting with character processing. That is, word processing and character processing are interactive processes, so that the activation of the word units influences the activation of the corresponding character units through links between them. Thus, word processing also influences where to move the eyes even though the activation of character units is the major factor that determines the location of a saccade target.

Because the character-activation map determines where the eyes move and word processing influences saccade target selection indirectly through influencing character processing, it is possible (but not necessary) that a word will be skipped because the activation of its component characters is above a set threshold, even though the word has not been identified. If this happens, will it cause a regression and reduce the efficiency of reading? We argue that this is not necessarily the case. Because the activation of the characters has reached a set threshold, low-level visual information may have accumulated enough to support word processing. Moreover, even if readers still need to perceive a small amount of visual information to support word processing, they can do so with parafoveal vision even when this word is skipped. Thus, a regression may not be needed when a word is skipped even though that word is not completely identified. At present, this is currently only a prediction of the model, and more experimental work is needed to test this prediction.

Relations With Other Models

Many models have been proposed to account for eye-movement behaviors in reading in the last three decades. The current model is inspired by previous modeling work on both eye-movement control and word processing. We will describe some of the previous models and will describe the relation between the current model and those models (Reichle & Yu, 2018).

IAM. Although IAM is not an eye-movement model, we feel that it is important to mention it at this point. We do so because we believe that the interactive activation principle is an important principle that governs many cognitive processes, and the word-processing module of the current model adopted most of the important assumptions of IAM. However, we made some new assumptions to handle many aspects of the unique properties of Chinese reading. More specifically, we had to deal with the lack of interword space problem in Chinese reading; in IAM, the letters (characters) are separated by spaces before and after the letters (characters) of interest. (We should also point out, that most of the models of alphabetic languages use some sort of approximation of IAM in how readers identify short words.)

Li et al. (2009) reported a model of word segmentation and word identification. The current model adopted some important assumptions of Li et al.'s (2009) model. Both models assumed that word segmentation and word identification are a unified process (unlike the E-Z Reader model). However, there are some differences between the Li et al. (2009) model and the present model. Li et al.'s (2009) model could only process four characters, and it therefore only simulated reporting accuracy for a whole-report task. In contrast, the current model simulates word processing during sentence reading, and thus additional assumptions such as the movement of the perceptual span were added to address problems in sentence reading.

TRACE model. The TRACE model (McClelland & Elman, 1986) was proposed to simulate word processing during speech perception using the most important assumptions of IAM. Like Chinese reading, there are no clear word boundaries in the natural speech signal. Many aspects of the assumptions regarding word segmentation in the current model are inspired by the TRACE model. However, there are some differences. First, during reading, readers can actively move their eyes and attention to perceive information while listeners cannot. Second, readers can simultaneously perceive many characters, while listeners cannot do so. Third, readers can regress to a previously fixated position, while listeners obviously cannot. Thus, some of the assumptions of word segmentation in the current model are distinct from the assumptions of the TRACE model to deal with differences between speech and written text.

Findlay and Walker's framework for eye-movement control. Findlay and Walker (1999) proposed a theoretical framework for eye-movement control that explains how many of the physiological mechanisms of the oculomotor system would work in real time (Findlay & Walker, 1999). This framework posits two separate pathways to control eye movements: one to control *where* the eyes move, and the other to control *when* the eyes move. The saccade targets are selected by the "where" pathway using a saliency map, but with a hierarchy of control systems within the two pathways interacting (via inhibition) to dynamically determine when the saccade will be initiated. The principles of this framework are thus largely consistent with what is known about the neural processes that control eye movements. The framework has also inspired models of eye-movement control in reading (e.g., SWIFT, Glenmore). In the current model, the mechanism of deciding when to move the eyes is also inspired by Findlay and Walker's (1999) framework, namely, that an eye movement is triggered when the activation of the saccade unit passes a certain threshold. It should be noted that we only have a saccade unit in the current model. This makes the current model simpler and easier to implement.

Eye-movement control models in alphabetic languages. As mentioned earlier, the E-Z Reader model is one of the first formal computational models of eye-movement control during reading (Reichle et al., 1998, 2003). This model assumes that words are processed serially. When one word is identified, attention is switched to the next word. This model also assumed that attention and word recognition are related cognitive processes but they are controlled by different mechanisms. The signal to program an eye movement is triggered by a process called the *lexical familiarity check*, and an attention shift is triggered by the completion of word identification. However, in the current model, we assumed that the control of eye movements and word recognition are two different (but related) processes and are controlled by different mechanisms. In the current model, we assumed that attention is mainly focused on the most activated word, but that other characters that do not belong to the currently attended word can also be perceived in parallel until the time occurs when a decision is made to recognize the fixated word. At that point, a decision is started through the eye-movement system to make an eye movement (not like E-Z Reader) although the way it is done is more complicated.

As we mentioned earlier, there were also two other models of reading in alphabetic languages that gained some attention. The SWIFT model differs by assuming that up to four words are processed in parallel. There is a lot of debate on whether as many as four words can be processed in parallel in alphabetic languages (Inhoff, Eiter, & Radach, 2005; Inhoff, Radach, & Eiter, 2006; Pollatsek, Reichle, & Rayner, 2006; Reichle, Liversedge, Pollatsek, & Rayner, 2009). However, we think that this is not the place to go into the argument given that we are trying to understand how Chinese is read. In the current model, we assumed that all characters within the perceptual span are processed in parallel and all the words constituted by the activated characters compete to be a winner. It should also be noted that there are some differences between the current model and SWIFT regarding how words at different positions are processed. Because there are no spaces between words in Chinese, word boundaries are determined during the process of word processing in the current model.

A third model, Glenmore (Reilly & Radach, 2006), also assumes that multiple words are processed in parallel during English reading. The model also uses the interactive activation assumptions (McClelland & Rumelhart, 1981) to simulate lexical processing. However, for the same reasons as the SWIFT model, it also has problems dealing with Chinese reading because the model cannot easily deal with the problem posed by the lack of interword spaces in Chinese.

Common and Unique Properties of Eye-Movement Control During Chinese Reading

The current model mainly focuses on eye-movement control and word processing in Chinese reading. This raises the question of what aspect of the current model is unique to Chinese reading and what aspects of the model are common to all writing systems. Some assumptions of the model are probably unique to Chinese reading: Because there are no spaces between words in Chinese reading, Chinese readers cannot perceive word boundaries with low-level vision, and thus they cannot use the same kind of mechanism most alphabetical readers use to choose where to land a saccade. Thus, the processing-based strategy may be unique to Chinese reading.

The reason that readers of an alphabetic language do not adopt this kind of strategy may be because a saccade to word center is easier and more efficient. For alphabetic readers, there are spaces between words, so that readers are able to perceive word boundaries using parafoveal vision, and saccades are directed to the center of the next word. However, this does not mean that alphabetic readers do not use a processing-based strategy during saccade-target selection at all; it is possible that alphabetic readers might use a combination of a processing-based strategy and a PVL-based strategy (Liu et al., 2016). Actually, there is some evidence that the difficulty of the fixated word could affect the length of the next saccade when readers read text in an alphabetic system. For example, high-frequency words are usually skipped more often than low-frequency words, and the length of a saccade leaving a high-frequency word is usually longer than leaving a low-frequency word (White & Liversedge, 2006). This suggests that the amount of information a reader can perceive in the parafovea influences saccade target selection, which is similar to that claimed by the processing-based strategy in Chinese reading (Wei et al., 2013).

Although there are some unique assumptions in the current model, many of the assumptions may be common to most reading systems. In the current model, the assumptions of IAM are widely used in English reading, and it can readily be used for Chinese reading. In the current model, we also assumed that word processing plays an important role for eye-movement control; this is also common to both Chinese reading and English reading. Thus, we believe that eye-movement control when people read different writing systems may share many common mechanisms.

The current model proposed a way that Chinese readers segment words without the aid of interword spaces. It may be possible to apply the model's principles to simulate reading of multiple-component compound words that are frequent in many alphabetic languages, such as in Germanic languages (e.g., German, Dutch, Swedish) and in Finnish. In these languages, three- or four-component compound words are not uncommon (e.g., "Datenschutzbeauftragter" in German, meaning *data protection officer*). This is similar to Chinese in that the components are also independent words and that they are concatenated so that the boundaries between the components are not visually marked.[6] The model can also be used in other languages that lack interword spaces such as Thai.

Limitations of the Current Model

Although the model successfully predicts some important aspects of word processing and eye-movement control during Chinese sentence reading, it has some apparent limitations. The first one is that we only considered word processing, but ignored many aspects of high-level cognitive processes. We know that syntactic processing, semantic processing, and pragmatic processing all affect eye movements as well. However, we wanted to start out simply, and that is why we have ignored these factors, by mainly looking at eye movements in first-pass reading. In the current

[6] We thank one anonymous reviewer for pointing this out.

model, our major concern is how Chinese readers conduct word segmentation and control when and where to move their eyes when reading Chinese text that lack interword spaces. Thus, word processing is the most relevant cognitive process.

Another limitation is that we have not considered the newest findings of character-order encoding. In the current model, we assumed that characters are constrained by the slots. However, it has been shown that the encoding of character order may not be so strict. Readers could still identify words even when two characters switched their position (Gu & Li, 2015; Gu et al., 2015). Thus, future work is needed to understand these findings. It should also be noted that it is possible to revise the current model to account for this finding. For example, one may assume that the link from the visual level to the character level may not be strictly constrained within a slot. Instead, a unit in the visual level may have links to the character units in neighboring slots. Because the mechanism of word order encoding is still a question under study (Whitney, Bertrand, & Grainger, 2011), especially in Chinese reading (Gu et al., 2015), we are not implementing a mechanism for character-order encoding in the current version of the model.

The model successfully simulated some findings of preview benefit. However, because the current model did not have either a phonological-processing component or a semantic-processing component, the model did not simulate other related findings such as phonological-preview benefits and semantic-preview benefits, which have also been reported in Chinese reading (Pollatsek et al., 2000; Yan et al., 2009). Even though the current version of the model cannot simulate either the phonological-preview or the semantic-preview benefits, it can be extended to account for those effects in the future. Because the model assumes that characters and words within parafoveal vision can be activated to some certain level, the extended model can possibly make some new assumptions regarding how phonological and semantic information associated with these activated characters and words affects the processing of target words. By doing so, the model could be used to simulate the findings of phonological-preview benefit and semantic-preview benefit. Moreover, as we acknowledged earlier, since the model does not have a semantic-processing component, it cannot simulate regressive eye-movement behavior in situations such as when processing overlapping ambiguous strings. For this reason, when the model makes errors during the initial stage of processing, it does not detect and correct the errors as human readers do (Ma et al., 2014).

In the model, both character units and word units are duplicated across positions (there are different sets of character units and word units for different slots). We made this assumption because we followed the assumptions of IAM, and for the reason of convenience. The IAM model had similar redundancy (at the letter level only) and the TRACE model had a similar structure at both the phoneme and word levels. However, we acknowledge that this might be unrealistic because words at different positions should use the same lexicon for processing (Reichle et al., 2009). Even though this hypothesis may be unrealistic, employing this hypothesis is useful for exploratory purposes, as a heuristic, before we have a complete understanding of the structure of cognition. As a matter of fact, models using this kind of framework (such as IAM and TRACE) have gained great success and have been very useful for understanding the mechanisms of printed word and speech processing. Even so, we acknowledge that more theoretical work needs to be done to address this issue in the future.

Although the model could simulate the mean values of different measures in different data sets, it cannot simulate the variances of those observations. In the model, there are two random factors: (a) the initial fixation position within a sentence was chosen as either the first character or the second character, and (b) the landing position was randomly distributed around the intended position. These random factors were not enough to account for the variations in natural reading. In natural reading, readers differ from each other by reading ability, reading strategy, and reading motivation. In the future, these factors need to be considered to simulate the variances in the observed data.

Concluding Remarks

In the current model, we implemented a computational model that simulated a strong and direct relation between word processing and eye-movement control during Chinese reading. The model has also addressed some important questions in Chinese reading such as how Chinese readers segment words and how Chinese readers choose saccade targets in Chinese reading. The model has successfully simulated several important eye-movement results during Chinese reading.

References

Bai, X., Yan, G., Liversedge, S. P., Zang, C., & Rayner, K. (2008). Reading spaced and unspaced Chinese text: Evidence from eye movements. *Journal of Experimental Psychology: Human Perception and Performance, 34,* 1277–1287. http://dx.doi.org/10.1037/0096-1523.34.5.1277

Balota, D. A., Pollatsek, A., & Rayner, K. (1985). The interaction of contextual constraints and parafoveal visual information in reading. *Cognitive Psychology, 17,* 364–390. http://dx.doi.org/10.1016/0010-0285(85)90013-1

Becker, W., & Jürgens, R. (1979). An analysis of the saccadic system by means of double step stimuli. *Vision Research, 19,* 967–983. http://dx.doi.org/10.1016/0042-6989(79)90222-0

Brunelli, R. (2009). *Template matching techniques in computer vision: Theory and practice*. West Sussex, UK: Wiley. http://dx.doi.org/10.1002/9780470744055

Brunelli, R., & Poggio, T. (1997). Template matching: Matched spatial filters and beyond. *Pattern Recognition, 30,* 751–768. http://dx.doi.org/10.1016/S0031-3203(96)00104-5

Cheng, C. M. (1981). Perception of Chinese-characters. *Acta Psychologica Taiwanica, 23,* 137–153.

Coltheart, M., Rastle, K., Perry, C., Langdon, R., & Ziegler, J. (2001). DRC: A dual route cascaded model of visual word recognition and reading aloud. *Psychological Review, 108,* 204–256. http://dx.doi.org/10.1037/0033-295X.108.1.204

Engbert, R., Nuthmann, A., Richter, E. M., & Kliegl, R. (2005). SWIFT: A dynamical model of saccade generation during reading. *Psychological Review, 112,* 777–813. http://dx.doi.org/10.1037/0033-295X.112.4.777

Findlay, J. M., & Walker, R. (1999). A model of saccade generation based on parallel processing and competitive inhibition. *Behavioral and Brain Sciences, 22,* 661–674. http://dx.doi.org/10.1017/S0140525X99002150

Grossberg, S. (1978). A theory of visual coding, memory, and development. In E. L. J. Leeuwenberg & H. F. J. M. Buffart (Eds.), *Formal theories of visual perception* (pp. 7–26). New York, NY: Wiley.

Gu, J., & Li, X. (2015). The effects of character transposition within and across words in Chinese reading. *Attention, Perception & Psychophysics, 77,* 272–281. http://dx.doi.org/10.3758/s13414-014-0749-5

Gu, J., Li, X., & Liversedge, S. P. (2015). Character order processing in Chinese reading. *Journal of Experimental Psychology: Human Perception and Performance, 41,* 127–137. http://dx.doi.org/10.1037/a0038639

Henderson, J. M., & Ferreira, F. (1990). Effects of foveal processing difficulty on the perceptual span in reading: Implications for attention and eye movement control. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 16,* 417–429. http://dx.doi.org/10.1037/0278-7393.16.3.417

Huang, L., & Li, X. (2020a). Early, but not overwhelming: The effect of prior context on segmenting overlapping ambiguous strings when reading Chinese. *Quarterly Journal of Experimental Psychology*. Advance online publication. http://dx.doi.org/10.1177/1747021820926012

Huang, L., & Li, X. (2020b). *The interaction of word frequency and prior sentence context on word segmentation during Chinese reading*. Manuscript in preparation.

Inhoff, A. W., Eiter, B. M., & Radach, R. (2005). Time course of linguistic information extraction from consecutive words during eye fixations in reading. *Journal of Experimental Psychology: Human Perception and Performance, 31,* 979–995. http://dx.doi.org/10.1037/0096-1523.31.5.979

Inhoff, A. W., & Liu, W. (1998). The perceptual span and oculomotor activity during the reading of Chinese sentences. *Journal of Experimental Psychology: Human Perception and Performance, 24,* 20–34. http://dx.doi.org/10.1037/0096-1523.24.1.20

Inhoff, A. W., Radach, R., & Eiter, B. (2006). Temporal overlap in the linguistic processing of successive words in reading: Reply to Pollatsek, Reichle, and Rayner (2006a). *Journal of Experimental Psychology: Human Perception and Performance, 32,* 1490–1495. http://dx.doi.org/10.1037/0096-1523.32.6.1490

Ishida, T., & Ikeda, M. (1989). Temporal properties of information extraction in reading studied by a text-mask replacement technique. *Journal of the Optical Society of America A, Optics, Image Science, and Vision, 6,* 1624–1632. http://dx.doi.org/10.1364/JOSAA.6.001624

Just, M. A., & Carpenter, P. A. (1980). A theory of reading: From eye fixations to comprehension. *Psychological Review, 87,* 329–354. http://dx.doi.org/10.1037/0033-295X.87.4.329

Kennison, S. M., & Clifton, C., Jr. (1995). Determinants of parafoveal preview benefit in high and low working memory capacity readers: Implications for eye movement control. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 21,* 68–81. http://dx.doi.org/10.1037/0278-7393.21.1.68

Kliegl, R. (2007). Towards a perceptual-span theory of distributed processing in reading: A reply to Rayner, Pollatsek, Drieghe, Slattery, & Reichle (2007). *Journal of Experimental Psychology: General, 138,* 530–537. http://dx.doi.org/10.1037/0096-3445.136.3.530

Kliegl, R., Nuthmann, A., & Engbert, R. (2006). Tracking the mind during reading: The influence of past, present, and future words on fixation durations. *Journal of Experimental Psychology: General, 135,* 12–35. http://dx.doi.org/10.1037/0096-3445.135.1.12

Lexicon of Common Words in Contemporary Chinese Research Team. (2008). *Lexicon of common words in contemporary Chinese*. Beijing, China: Commercial Press.

Li, X., Bicknell, K., Liu, P., Wei, W., & Rayner, K. (2014). Reading is fundamentally similar across disparate writing systems: A systematic characterization of how words and characters influence eye movements in Chinese reading. *Journal of Experimental Psychology: General, 143,* 895–913. http://dx.doi.org/10.1037/a0033580

Li, X., Gu, J., Liu, P., & Rayner, K. (2013). The advantage of word-based processing in Chinese reading: Evidence from eye movements. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 39,* 879–889. http://dx.doi.org/10.1037/a0030337

Li, X., Liu, P., & Rayner, K. (2011). Eye movement guidance in Chinese reading: Is there a preferred viewing location? *Vision Research, 51,* 1146–1156. http://dx.doi.org/10.1016/j.visres.2011.03.004

Li, X., Liu, P., & Rayner, K. (2015). Saccade target selection in Chinese reading. *Psychonomic Bulletin & Review, 22,* 524–530. http://dx.doi.org/10.3758/s13423-014-0693-3

Li, X., & Logan, G. D. (2008). Object-based attention in Chinese readers of Chinese words: Beyond Gestalt principles. *Psychonomic Bulletin & Review, 15,* 945–949. http://dx.doi.org/10.3758/PBR.15.5.945

Li, X., & Ma, G. (2012). Word boundaries affect visual attention in Chinese reading. *Plos One, 7,* e48905. http://dx.doi.org/10.1371/journal.pone.0048905

Li, X., & Pollatsek, A. (2011). Word knowledge influences character perception. *Psychonomic Bulletin & Review, 18,* 833–839. http://dx.doi.org/10.3758/s13423-011-0115-8

Li, X., Rayner, K., & Cave, K. R. (2009). On the segmentation of Chinese words during reading. *Cognitive Psychology, 58,* 525–552. http://dx.doi.org/10.1016/j.cogpsych.2009.02.003

Li, X., Zang, C., Liversedge, S. P., & Pollatsek, A. (2015). The role of words in Chinese reading. In A. Pollatsek & T. Rebecca (Eds.), *The Oxford handbook of reading* (pp. 232–244). New York, NY: Oxford University Press.

Li, X., Zhao, W., & Pollatsek, A. (2012). Dividing lines at the word boundary position helps reading in Chinese. *Psychonomic Bulletin & Review, 19,* 929–934. http://dx.doi.org/10.3758/s13423-012-0270-6

Liu, W., Inhoff, A. W., Ye, Y., & Wu, C. (2002). Use of parafoveally visible characters during the reading of Chinese sentences. *Journal of Experimental Psychology: Human Perception and Performance, 28,* 1213–1227. http://dx.doi.org/10.1037/0096-1523.28.5.1213

Liu, Y., Reichle, E. D., & Li, X. (2015). Parafoveal processing affects outgoing saccade length during the reading of Chinese. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 41,* 1229–1236. http://dx.doi.org/10.1037/xlm0000057

Liu, Y., Reichle, E. D., & Li, X. (2016). The effect of word frequency and parafoveal preview on saccade length during the reading of Chinese. *Journal of Experimental Psychology: Human Perception and Performance, 42,* 1008–1025. http://dx.doi.org/10.1037/xhp0000190

Liversedge, S. P., Drieghe, D., Li, X., Yan, G., Bai, X., & Hyönä, J. (2016). Universality in eye movements and reading: A trilingual investigation. *Cognition, 147,* 1–20. http://dx.doi.org/10.1016/j.cognition.2015.10.013

Liversedge, S. P., Hyönä, J., & Rayner, K. (2013). Eye movements during Chinese reading. *Journal of Research in Reading, 36,* S1–S3. http://dx.doi.org/10.1111/jrir.12001

Ma, G., Li, X., & Pollatsek, A. (2015). There is no relationship between the preferred viewing location and word segmentation in Chinese reading. *Visual Cognition, 23,* 399–414. http://dx.doi.org/10.1080/13506285.2014.1002554

Ma, G., Li, X., & Rayner, K. (2014). Word segmentation of overlapping ambiguous strings during Chinese reading. *Journal of Experimental Psychology: Human Perception and Performance, 40,* 1046–1059. http://dx.doi.org/10.1037/a0035389

McClelland, J. L., & Elman, J. L. (1986). The TRACE model of speech perception. *Cognitive Psychology, 18,* 1–86. http://dx.doi.org/10.1016/0010-0285(86)90015-0

McClelland, J. L., & Rumelhart, D. E. (1981). An interactive activation model of context effects in letter perception. 1. An account of basic findings. *Psychological Review, 88,* 375–407. http://dx.doi.org/10.1037/0033-295X.88.5.375

McConkie, G. W., Kerr, P. W., Reddix, M. D., & Zola, D. (1988). Eye movement control during reading: I. The location of initial eye fixations on words. *Vision Research, 28,* 1107–1118. http://dx.doi.org/10.1016/0042-6989(88)90137-X

McConkie, G. W., & Rayner, K. (1975). The span of the effective stimulus during a fixation in reading. *Perception & Psychophysics, 17,* 578–586. http://dx.doi.org/10.3758/BF03203972

McConkie, G. W., & Rayner, K. (1976). Asymmetry of the perceptual span in reading. *Bulletin of the Psychonomic Society, 8,* 365–368. http://dx.doi.org/10.3758/BF03335168

Muhlenbein, H., Schomisch, M., & Born, J. (1991). The parallel genetic algorithm as function optimizer. *Parallel Computing, 17,* 619–632. http://dx.doi.org/10.1016/S0167-8191(05)80052-3

Perfetti, C. A., Liu, Y., & Tan, L. H. (2005). The lexical constituency model: Some implications of research on Chinese for general theories of reading. *Psychological Review, 112,* 43–59. http://dx.doi.org/10.1037/0033-295X.112.1.43

Perfetti, C. A., & Tan, L. H. (1998). The time course of graphic, phonological, and semantic activation in Chinese character identification. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 24,* 101–118. http://dx.doi.org/10.1037/0278-7393.24.1.101

Pollatsek, A., Drieghe, D., Stockall, L., & de Almeida, R. G. (2010). The interpretation of ambiguous trimorphemic words in sentence context. *Psychonomic Bulletin & Review, 17,* 88–94. http://dx.doi.org/10.3758/PBR.17.1.88

Pollatsek, A., Reichle, E. D., & Rayner, K. (2006). Serial processing is consistent with the time course of linguistic information extraction from consecutive words during eye fixations in reading: A response to Inhoff, Eiter, and Radach (2005). *Journal of Experimental Psychology: Human Perception and Performance, 32,* 1485–1489. http://dx.doi.org/10.1037/0096-1523.32.6.1485

Pollatsek, A., Tan, L. H., & Rayner, K. (2000). The role of phonological codes in integrating information across saccadic eye movements in Chinese character identification. *Journal of Experimental Psychology: Human Perception and Performance, 26,* 607–633. http://dx.doi.org/10.1037/0096-1523.26.2.607

Rayner, K. (1975). The perceptual span and peripheral cues in reading. *Cognitive Psychology, 7,* 65–81. http://dx.doi.org/10.1016/0010-0285(75)90005-5

Rayner, K. (1978). Foveal and parafoveal cues in reading. In J. Requin (Ed.), *Attention and performance VII* (pp. 149–162). Hillsdale, NJ: Erlbaum.

Rayner, K. (1979). Eye guidance in reading: Fixation locations within words. *Perception, 8,* 21–30. http://dx.doi.org/10.1068/p080021

Rayner, K. (1998). Eye movements in reading and information processing: 20 years of research. *Psychological Bulletin, 124,* 372–422. http://dx.doi.org/10.1037/0033-2909.124.3.372

Rayner, K. (2009a). Eye movements and attention in reading, scene perception, and visual search. *Quarterly Journal of Experimental Psychology: Human Experimental Psychology, 62,* 1457–1506. http://dx.doi.org/10.1080/17470210902816461

Rayner, K. (2009b). Rayner's 1979 paper. *Perception, 38,* 895–906. http://dx.doi.org/10.1068/pmkray

Rayner, K., & Duffy, S. A. (1986). Lexical complexity and fixation times in reading: Effects of word frequency, verb complexity, and lexical ambiguity. *Memory & Cognition, 14,* 191–201. http://dx.doi.org/10.3758/BF03197692

Rayner, K., Li, X., Juhasz, B. J., & Yan, G. (2005). The effect of word predictability on the eye movements of Chinese readers. *Psychonomic Bulletin & Review, 12,* 1089–1093. http://dx.doi.org/10.3758/BF03206448

Rayner, K., Li, X., & Pollatsek, A. (2007). Extending the e-z reader model of eye movement control to Chinese readers. *Cognitive Science, 31,* 1021–1033. http://dx.doi.org/10.1080/03640210701703824

Rayner, K., & McConkie, G. W. (1976). What guides a reader's eye movements? *Vision Research, 16,* 829–837. http://dx.doi.org/10.1016/0042-6989(76)90143-7

Rayner, K., & Pollatsek, A. (1981). Eye movement control during reading: Evidence for direct control. *Quarterly Journal of Experimental Psychology Section A: Human Experimental Psychology, 33,* 351–373. http://dx.doi.org/10.1080/14640748108400798

Rayner, K., Pollatsek, A., Ashby, J., & Clifton, J. C. (2012). *Psychology of reading*. London, UK: Psychology Press. http://dx.doi.org/10.4324/9780203155158

Rayner, K., & Well, A. D. (1996). Effects of contextual constraint on eye movements in reading: A further examination. *Psychonomic Bulletin & Review, 3,* 504–509. http://dx.doi.org/10.3758/BF03214555

Rayner, K., Well, A. D., & Pollatsek, A. (1980). Asymmetry of the effective visual field in reading. *Perception & Psychophysics, 27,* 537–544. http://dx.doi.org/10.3758/BF03198682

Rayner, K., Well, A. D., Pollatsek, A., & Bertera, J. H. (1982). The availability of useful information to the right of fixation in reading. *Perception & Psychophysics, 31,* 537–550. http://dx.doi.org/10.3758/BF03204186

Reicher, G. M. (1969). Perceptual recognition as a function of meaningfulness of stimulus material. *Journal of Experimental Psychology, 81,* 275–280. http://dx.doi.org/10.1037/h0027768

Reichle, E. D., Liversedge, S. P., Pollatsek, A., & Rayner, K. (2009). Encoding multiple words simultaneously in reading is implausible. *Trends in Cognitive Sciences, 13,* 115–119. http://dx.doi.org/10.1016/j.tics.2008.12.002

Reichle, E. D., Pollatsek, A., Fisher, D. L., & Rayner, K. (1998). Toward a model of eye movement control in reading. *Psychological Review, 105,* 125–157. http://dx.doi.org/10.1037/0033-295X.105.1.125

Reichle, E. D., Rayner, K., & Pollatsek, A. (2003). The E-Z reader model of eye-movement control in reading: Comparisons to other models. *Behavioral and Brain Sciences, 26,* 445–476. http://dx.doi.org/10.1017/S0140525X03000104

Reichle, E. D., & Yu, L. (2018). Models of Chinese reading: Review and analysis. *Cognitive Science, 42,* 1154–1165. http://dx.doi.org/10.1111/cogs.12564

Reilly, R. G., & Radach, R. (2006). Some empirical tests of an interactive activation model of eye movement control in reading. *Cognitive Systems Research, 7,* 34–55. http://dx.doi.org/10.1016/j.cogsys.2005.07.006

Schotter, E. R., Angele, B., & Rayner, K. (2012). Parafoveal processing in reading. *Attention, Perception & Psychophysics, 74,* 5–35. http://dx.doi.org/10.3758/s13414-011-0219-2

Seidenberg, M. S., & McClelland, J. L. (1989). A distributed, developmental model of word recognition and naming. *Psychological Review, 96,* 523–568. http://dx.doi.org/10.1037/0033-295X.96.4.523

Shen, W., & Li, X. (2012). The uniqueness of word superiority effect in Chinese reading. *Chinese Science Bulletin, 57,* 3414–3420. http://dx.doi.org/10.1360/972012-666

Shen, W., Li, X., & Pollatsek, A. (2018). The processing of Chinese compound words with ambiguous morphemes in sentence context. *Quarterly Journal of Experimental Psychology: Human Experimental Psychology, 71,* 131–139. http://dx.doi.org/10.1080/17470218.2016.1270975

Snell, J., van Leipsig, S., Grainger, J., & Meeter, M. (2018). OB1-reader: A model of word recognition and eye movements in text reading. *Psychological Review, 125,* 969–984. http://dx.doi.org/10.1037/rev0000119

Sun, F., Morita, M., & Stark, L. W. (1985). Comparative patterns of reading eye movement in Chinese and English. *Perception & Psychophysics, 37,* 502–506. http://dx.doi.org/10.3758/BF03204913

Tsai, J. L., Lee, C. Y., Tzeng, O. J. L., Hung, D. L., & Yen, N. S. (2004). Use of phonological codes for Chinese characters: Evidence from processing of parafoveal preview when reading sentences. *Brain and Language, 91,* 235–244. http://dx.doi.org/10.1016/j.bandl.2004.02.005

Tsai, J. L., & McConkie, G. W. (2003). Where do Chinese readers send their eyes. In R. Radach, J. Hyona, & H. Deubel (Eds.), *The mind's eye: Cognitive and applied aspects of eye movement research* (pp. 159–176). Oxford, UK: Elsevier. http://dx.doi.org/10.1016/B978-044451020-4/50010-4

Wei, W., Li, X., & Pollatsek, A. (2013). Word properties of a fixated region affect outgoing saccade length in Chinese reading. *Vision Research, 80,* 1–6. http://dx.doi.org/10.1016/j.visres.2012.11.015

White, S. J., & Liversedge, S. P. (2006). Foveal processing difficulty does not modulate non-foveal orthographic influences on fixation positions. *Vision Research, 46,* 426–437. http://dx.doi.org/10.1016/j.visres.2005.07.006

White, S. J., Rayner, K., & Liversedge, S. P. (2005). Eye movements and the modulation of parafoveal processing by foveal processing difficulty: A reexamination. *Psychonomic Bulletin & Review, 12,* 891–896. http://dx.doi.org/10.3758/BF03196782

Whitley, D. (1994). A genetic algorithm tutorial. *Statistics and Computing, 4,* 65–85. http://dx.doi.org/10.1007/BF00175354

Whitney, C., Bertrand, D., & Grainger, J. (2011). On coding the position of letters in words: A test of two models. *Experimental Psychology, 59,* 109–114. http://dx.doi.org/10.1027/1618-3169/a000132

Wolverton, G. S., & Zola, D. (1983). The temporal characteristics of visual information extraction during reading. In K. Rayner (Ed.), *Eye movements in reading: Perceptual and language processes* (pp. 41–52). New York, NY: Academic Press. http://dx.doi.org/10.1016/B978-0-12-583680-7.50008-4

Yan, G., Tian, H., Bai, X., & Rayner, K. (2006). The effect of word and character frequency on the eye movements of Chinese readers. *British Journal of Psychology, 97(Pt. 2), 25,* 9–268. http://dx.doi.org/10.1348/000712605X70066

Yan, M., & Kliegl, R. (2016). CarPrice versus CarpRice: Word boundary ambiguity influences saccade target selection during the reading of Chinese sentences. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 42,* 1832–1838. http://dx.doi.org/10.1037/xlm0000276

Yan, M., Kliegl, R., Richter, E. M., Nuthmann, A., & Shu, H. (2010). Flexible saccade-target selection in Chinese reading. *Quarterly Journal of Experimental Psychology: Human Experimental Psychology, 63,* 705–725. http://dx.doi.org/10.1080/17470210903114858

Yan, M., Kliegl, R., Shu, H., Pan, J., & Zhou, X. (2010). Parafoveal load of word N+1 modulates preprocessing effectiveness of word N+2 in Chinese reading. *Journal of Experimental Psychology: Human Perception and Performance, 36,* 1669–1676. http://dx.doi.org/10.1037/a0019329

Yan, M., Richter, E. M., Shu, H., & Kliegl, R. (2009). Readers of Chinese extract semantic information from parafoveal words. *Psychonomic Bulletin & Review, 16,* 561–566. http://dx.doi.org/10.3758/PBR.16.3.561

Yang, H. M., & McConkie, G. W. (1999). Reading Chinese: Some basic eye-movement characteristics. In H. C. Chen (Ed.), *Reading Chinese script: A cognitive analysis* (pp. 207–222). Mahwah, NJ: Erlbaum Associates, Inc.

Yang, J., Staub, A., Li, N., Wang, S., & Rayner, K. (2012). Plausibility effects when reading one- and two-character words in Chinese: Evidence from eye movements. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 38,* 1801–1809. http://dx.doi.org/10.1037/a0028478

Yang, J., Wang, S., Xu, Y., & Rayner, K. (2009). Do Chinese readers obtain preview benefit from word n + 2? Evidence from eye movements. *Journal of Experimental Psychology: Human Perception and Performance, 35,* 1192–1204. http://dx.doi.org/10.1037/a0013554

Yang, J., Wang, X., Shu, H., & Zevin, J. D. (2011). Brain networks associated with sublexical properties of Chinese characters. *Brain and Language, 119,* 68–79. http://dx.doi.org/10.1016/j.bandl.2011.03.004

Yen, M. H., Radach, R., Tzeng, O. J. L., Hung, D. L., & Tsai, J. L. (2009). Early parafoveal processing in reading Chinese sentences. *Acta Psychologica, 131,* 24–33. http://dx.doi.org/10.1016/j.actpsy.2009.02.005

Yen, M. H., Radach, R., Tzeng, O. J. L., & Tasi, J. L. (2012). Usage of statistical cues for word boundary in reading Chinese sentences. *Reading and Writing, 25,* 1007–1029. http://dx.doi.org/10.1007/s11145-011-9321-z

Yen, M. H., Tsai, J. L., Tzeng, O. J. L., & Hung, D. L. (2008). Eye movements and parafoveal word processing in reading Chinese. *Memory & Cognition, 36,* 1033–1045. http://dx.doi.org/10.3758/MC.36.5.1033

Yu, L., & Reichle, E. D. (2017). Chinese versus English: Insights on cognition during reading. *Trends in Cognitive Sciences, 21,* 721–724. http://dx.doi.org/10.1016/j.tics.2017.06.004

Zang, C., Fu, Y., Bai, X., Yan, G., & Liversedge, S. P. (2018). Investigating word length effects in Chinese reading. *Journal of Experimental Psychology: Human Perception and Performance, 44,* 1831–1841. http://dx.doi.org/10.1037/xhp0000589

Zang, C., Liang, F., Bai, X., Yan, G., & Liversedge, S. P. (2013). Interword spacing and landing position effects during Chinese reading in children and adults. *Journal of Experimental Psychology: Human Perception and Performance, 39,* 720–734. http://dx.doi.org/10.1037/a0030097

Zang, C. L., Liversedge, S. P., Bai, X., & Yan, G. L. (2011). Eye movements during Chinese reading. In S. P. Liversedge, I. D. Gilchrist, & S. Everling (Eds.), *The Oxford handbook of eye movements* (pp. 961–978). New York, NY: Oxford University Press.

Appendix

Modeling Program

The modeling program was written in *ISO C++*. The basic structure of the word-processing module was built on the basis of IAM, and the code of the basic components of the network (e.g., the structure of units, links between units, and unit updating, etc.) was adopted from the IAM model. Of course, the structure of the network was modified to address the word-segmentation problem in Chinese reading. We also wrote new codes to implement eye-movement control. Because the computational load is high when searching for parameters, we used a large-scaled cluster computer, running Linux, to run the model program.

We used a *parallel genetic algorithm* to find the best parameter that minimizes the nRMSD as described in Equation 11. We used the code of *GAlib-MPI* (https://github.com/B0RJA/GAlib-mpi), which is a parallel computing version of *GAlib* (http://lancet.mit.edu/ga/), to implement this. We used a simple genetic algorithm in GAlib, and the population size was 96, the maximum number of generations of search was 100, the probability of mutation was 0.03, and the probability of crossover was 0.65.

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