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Extending the modeling of eye movements in reading with orthographic processing

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Abstract

Modeling techniques have proven to be very useful in providing insight in how humans make eye movements in reading (Rayner, 2009b) and how words are recognized (Barber & Kutas, 2007; Norris, 2013). Several models are quite successful in accounting for the experimental data in eye movement in reading, such as SWIFT (Engbert, Nuthmann, Richter, & Kliegl, 2005) and E-Z reader (Reichle, Rayner, & Pollatsek, 2003). However these models lack in the processing of letters and word identities and have simplified assumptions on word recognition. On the other hand, word recognition models do incorporate letter and word processing with orthographic, phonological and semantic components. However these models are focused on word recognition and not on the integration in natural reading (Norris, 2013). Therefore a novel model of eye movement in reading is described, which incorporates orthographic processing using an open-bigram implementation (Grainger & Van Heuven, 2003; Grainger, 2008). Open-bigrams are an intermediate encoding between letters and words and provide a method for representing the relative positions of letters. Moreover the incorporation of orthographic units provides a mechanism for word recognition and makes a first step in integrating models of eye movements and word recognition in reading. The aim of the current project is to extend and test the current implementation and determine to what extent it can account for the experimental findings of eye movement in reading.

Introduction

Reading is a fundamental skill for functioning in today's society. It represents a complex process that is learned from a young age and is routinely performed throughout our daily life. There are various processes that enable humans to read, such as visual processing, attention, word recognition and oculomotor control (Grainger & Holcomb, 2009; Rayner, 1998). An important limitation in reading is the small range of high-acuity vision. The eyes can only focus on a small number of words at a time and the reader needs to make eye movements over the words in a text. In between the eye movements the eyes remain relatively fixed, during which perceptual information is extracted. Eye movements in reading are influenced by a combination of factors, such as textual properties, lexical processing, attention and comprehension (see Rayner, 1998, 2009, for review). Furthermore, eye movements are very useful in providing insight in the on-line processing during reading, such as language comprehension (Rayner, Sereno, Morris, Schmauder, & Clifton, 1989). Moreover, beginning and dyslectic readers have a different eye movement behavior than normal readers, which might reflect the difficulties they have during reading (Rayner, 1998). Therefore, eye movements provide a good substrate to study the perceptual and cognitive processes during reading, such as the interaction between word recognition and eye movements.

A valuable tool in exploring these factors are modeling techniques, which in addition to traditional experimental research can provide insight in the interaction of the various reading related processes. Moreover, modeling techniques can be used to simulate disorders by disabling certain parts of a functional model. There are two prominent models that focus on eye movements in reading, SWIFT (Engbert et al., 2005) and E-Z reader (Reichle et al., 2003). Both models have psychologically plausible properties and are able to explain a large amount of the experimental results. However, they do not actually process letters and words and therefore have simplified assumptions on word recognition. On the other hand, models of word recognition do incorporate letter and word processing, but are limited to single word recognition and do not incorporate natural reading and eye movements (Norris, 2013). Therefore, both types of models lack a comprehensive insight in the interaction between eye movements and the processing of letters and words. Moreover, they lack a mechanism for the interaction between the processing of different words in a text. Thus, the different processes of reading are modeled in isolation and provide a limited insight in reading. Therefore, it is important to combine both modeling approaches and create a more comprehensive model of reading that actually processes the letters and words. Here, we will present a model that makes a first step in integrating word recognition models with models of eye movement during reading by incorporating orthographic processing. First, we will review the relevant models of eye movement during reading with a detailed focus on the distribution of attention, followed by models of word recognition that are the basis for the integration of orthographic processing.

Eye movements during reading

Both SWIFT and E-Z reader are cognitive models, which means that they incorporate lexical processing in guiding the eye movements (Engbert et al., 2005; Rayner, 2009a; Reichle et al., 2003). The lexical processing that is incorporated represents the frequency and predictability of words. Both models are symbolic rule-based models with mathematical components. The two models have multiple overlapping principles, such as separate processing pathways for when (fixation duration) and where (target selection) the eyes move (Findlay & Walker, 1999), two-stage saccade programming (Becker & Jürgens, 1979) and the tight coupling of fixation duration with lexical processing (Engbert et al., 2005; Reichle et al., 2003). In SWIFT eye movements are generated by using an autonomous random timer that can be delayed by the difficulty of lexical processing of the current word, whereas in E-Z reader a preliminary stage of word identification causes saccade generation. However, there are also several important differences between the models. For instance, they differ in their assumption on the involvement of lexical processing in target selection. In E-Z reader the target selection is influenced by low-level visual features (Reichle et al., 2003), whereas in SWIFT the target selection is influenced by the relative lexical activation of the currently processed words (Engbert et al., 2005). The most notable difference between the two models is that they have a different assumption for the distribution of attention. SWIFT belongs to the class of processing gradient models (PG) in which attention is continuously distributed over the fixated region of text (Engbert et al., 2005). However, E-Z reader has serial attention shifts (SAS) during a fixation, such that only one word can be attended at a time (Morrison, 1984; Reichle et al., 2003).

An important consequence of the distinction in the distribution of attention is that in PG models there is lexical processing of multiple words in parallel, whereas for SAS models lexical processing is confined to one word at a time. Therefore, only PG models can explain lexical parafoveal on foveal (POF) effects, where the lexical processing of the parafoveal word influences the fixation duration of the foveal word (Angele, Slattery, Yang, Kliegl, & Rayner, 2008; Schotter, Angele, & Rayner, 2012). To determine the lexical POF effects the frequency and predictability of the parafoveal words should influence the fixation duration of the foveal word. Multiple studies examined the lexical POF effect using a boundary task, but did not find any significant effects (Angele et al., 2008; Rayner, Juhasz, & Brown, 2007). On the other hand, multivariate analysis of fixation durations were able to show POF effects, but only when the foveal word was short (Kennedy & Pynte, 2005; Kliegl, Nuthmann, & Engbert, 2006; Kliegl, Risse, & Laubrock, 2007; Radach & Kennedy, 2013). One explanation for these conflicting results are the differences in word length and the limitations of the perceptual span (Angele et al., 2008). It might be possible that only for short foveal words there is room for lexical processing of parafoveal words in the perceptual span (Kliegl et al., 2006). Moreover, Wotschack & Kliegl (2011) showed that the lexical POF effect increased when the reading behavior was modulated to a slower reading strategy with increased refixations and decreased word skipping. Thus, even though there are mixed results, the presence of the lexical POF effect at certain situations argue against a strict serial attention and implicates the parallel attention implementation as a more viable assumption. The current model is therefore based on the parallel attention assumption.

Important to note is that both attention assumptions (SAS and PG) allow parallel lower-visual processing, such as the processing of spaces, shapes and letters. However, both SWIFT and E-Z reader do not have letter and word processing and therefore do not implement any form of orthographic processing. Only word length, frequency and predictability represent a word, and the identities of letters and units that make up a word are not included. Therefore, these models do not have an explicit mechanism for incorporating effects that are caused by orthographic processing, such as the orthographic POF effect (Angele, Tran, & Rayner, 2012). However, there are several studies that showed that the letter identity of parafoveal words can have an orthographic POF effect on the fixation duration and word recognition of the foveal word (Angele et al., 2012; Dare & Shillcock, 2012; Grainger, Mathôt, & Vitu, 2014; Schotter et al., 2012; Starr & Inhoff, 2004). For instance, the fixation duration of the foveal word was strongly reduced when the parafoveal word was a repetition, compared to a random word, unrelated word or the actual next word (Dare & Shillcock, 2012). In addition, parafoveal bigrams also showed to facilitate word recognition when the bigrams are in the foveal word compared with different bigrams (Grainger et al., 2014). Moreover, using the boundary technique Dare and Shillcock, (2012) and Angele et al. (2012) showed that this effect was indeed of orthographic nature and not purely visual or influenced by semantic processing.

Word recognition

Before we provide an overview of the current model of word recognition, we will first provide a short background of relevant word recognition models and outline the research that supports the choice of the current model. There are several important basic steps that need to be performed for successful word recognition. First, the input needs to be encoded to represent the identity and order of the letters. Second, these encodings must me matched with the abstract long-term memory representations that form the mental lexicon. Third, the best matching candidate must be selected from the large number of words in the lexicon (Davis, 2010). Furthermore, the word recognition models need to be able to explain the findings from the lexical decision task, such as the word-superiority effect, frequency effect and orthographic neighborhood effect (Barber & Kutas, 2007; Norris, 2013). However, particularly the word-superiority effect and letter position coding play an important role in the development of the current models. The word-superiority effect refers to the phenomenon that real words and their individual letters are recognized more accurately compared to nonwords and their individual letters (Grainger, 2008; Reicher, 1969) and letter positon coding is how the positions of the letters within a word are encoded. Moreover, the importance of the Letter position coding in word recognition is illustrated by the ability of humans to distinguish between anagrams (Davis & Bowers, 2006).

McClelland and Rumelhart (1981,1982) laid the foundation for the current word recognition models with the Interactive Activation model (IAM) and provided a framework that was able to explain the word-superiority effect. The IAM is a hand-wired connectionist model where the letter features, letters and words are represented as nodes in a network with excitatory and inhibitory connections (McClelland & Rumelhart, 1981; Norris, 2013; Rumelhart & McClelland, 1982). A clear limitation of this model is the slot-based coding of letter positions (Grainger & Van Heuven, 2003; Grainger, 2008). In slot-based coding the identity and position of letters are encoded together and a letter is therefore tagged to a specific location. Priming studies with substitution priming, relative position priming and transposed letter priming showed that a more approximate and flexible position coding might be a better solution (Grainger, 2008). For instance, in transposed letter priming the nonword anagrams (*caniso)* have improved priming compared to orthographic controls (*caviro)* (Perea & Lupker, 2004). The nonword anagrams are created by transposing two non-adjacent letters in real words (*casino).* Moreover, relative position priming experiments showed that there is improved priming when the relative order is preserved compared to the matching of absolute positions (Grainger, 2008).

There are multiple solutions that incorporate flexible letter position coding (Davis & Bowers, 2006; Grainger, 2008). These solutions can be categorized into three classes: noisy slot-based coding, spatial coding and context-sensitive coding. In noisy slot-based coding the letters have a Gaussian distribution over multiple slots, such that the representation of a letter can extend to adjacent positions (Gomez, Ratcliff, & Perea, 2008). In spatial coding the relative position is dynamically encoded by the relative pattern of activity across the letter nodes (Davis & Bowers, 2006; Davis, 2010). In context-sensitive coding the relative position of letters is encoded by combining adjacent or non-adjacent letters. An important version of context-sensitive coding is open-bigram coding, which is a method for representing the relative position of letters using ordered letter pairs (Fig. 1) (Grainger & Whitney, 2004; Whitney et al., 2001). Within the open-bigram framework there are two prominent models, but with a difference in the processing order. The SERIOL model assumes that the letters are processed in a serial fashion (Whitney, 2001), whereas the Grainger and Van Heuven (2003) model assumes a parallel processing of the letters. However, studies that manipulated the order of target words before reading showed that for words with unfamiliar letter combinations there was no effect of reversing the letter order on the reading measures (Inhoff, Pollatsek, Posner, & Rayner, 1989). Therefore, these results indicate that there is no internal scan of letters within a word and provide support for the parallel letter processing from the open-bigram model.

There is a large amount of research devoted at distinguishing between these types of flexible position coding theories, providing both evidence for and against the different types of implementations (Davis & Bowers, 2006; Davis, 2010; Di Bono & Zorzi, 2013; Gomez et al., 2008; Grainger & Whitney, 2004; Grainger, 2008; Kinoshita & Norris, 2013; Whitney, 2008). However, each position-coding scheme is able to account for most of the priming evidence that the slot-based coding could not account for (Grainger, 2008). Testing the implementations with a variety of orthographic manipulations and priming tasks with brain-imaging techniques might shed some further light on this topic. However, the incorporation of orthographic processing in the current model is based on the open-bigram framework. The current model implements orthographic processing by incorporating a modified version of the parallel open-bigram scheme from Grainger and Van Heuven (2003). The open-bigram scheme is able to explain transposition priming effects, relative position priming effects (Grainger & Van Heuven, 2003; Perea & Lupker, 2003) and the 'jumbled word effect' (Grainger & Whitney, 2004), thereby supporting the notion that letter identity and letter position is encoded simultaneously (Perea & Lupker, 2003). The 'jumbled word effect' means that words in which the inner letters are re-arranged can still be recognized easily (Grainger & Whitney, 2004).

The open-bigram model has several properties that are supported by neuroimaging research. Cohen and Dehaene (2004) showed that the lateral fusiform gyrus is specialized towards processing words compared to other visual stimuli and they posited the lateral fusiform gyrus as the visual word form area (VWFA). Moreover, additional fMRI experiments with word priming indicated that the neurons in the VWFA are tuned to representations of letter combinations with a hierarchy of local combination detectors sensitive for increasingly larger word segments (Dehaene et al., 2004; Dehaene, Cohen, Sigman, & Vinckier, 2005). In addition, Dehaene et al. (2005) defined a model of orthographic processing in word recognition on the basis of this hierarchy of local combination detectors (receptive fields). These receptive fields indicate that the detectors could be tuned to letters and bigrams (and more) and might act as open-bigrams (Dehaene et al., 2005; Vinckier, Qiao, Pallier, Dehaene, & Cohen, 2011). Furthermore, additional studies showed that the VWFA was sensitive to familiar letter combinations, which supports the existence of a level that processes orthographic letter combinations, such as bigrams (Binder, Medler, Westbury, Liebenthal, & Buchanan, 2006). Therefore, these results support the presence of bigram representations in the brain and do not rule out the existence of open-bigrams.

The current section describes the general structure of the adapted open-bigram model (Grainger & Van Heuven, 2003). The open-bigram model is a structured connectionist model (Fig. 1), without any learning mechanisms. It contains three levels of representation, the alphabetic array, letter representations (monograms and open-bigrams) and the whole-word orthographic representations (Grainger & Van Heuven, 2003). In the current implementation there are bottom-up feed-forward connections between the three levels and lateral inhibition between the word representations. The alphabetic array represents the input to the model and contains the position and identity of each letter of the selected words. The activity of the letters are based on the limitations of perceptual processing of the visual input, and will be discussed in detail in the model specification of the visual input. Next, the activated letters are fed on towards the pre-existing representations of relative position maps (open-bigrams) and monogram representations. Both these representations are location-invariant and only encode identity. Moreover, the letters in the input will activate their respective monogram representations and the letter combinations from the input will activate their respective open-bigrams in the relative position map. However, the open-bigrams are only formed within the limits of a word and only over a specified range of three letters. Thus, the open-bigrams are an intermediate encoding between the letters and word units and provide information about the in-string position and the combined letter activities. Moreover, during reading the input can contain multiple words and therefore both the monogram and open-bigram representations process multiple words in parallel. In addition, both the monograms and open-bigrams have direct excitatory connections with the word units that contain the open-bigrams and monograms and aspecific inhibitory connections with all the word units in de model. A consequence from this implementation is that the model does not assign a unique code to a word and all the word units that contain any of the monograms or open-bigrams can become activated. For instance, as shown in the example of figure 1, the input "silence" activates the monograms and open-bigrams that in turn activates multiple word units. However, important to note is that there are differences in the degree of activity of the different word units and that the activity values are influenced by lateral inhibition of competing word units.

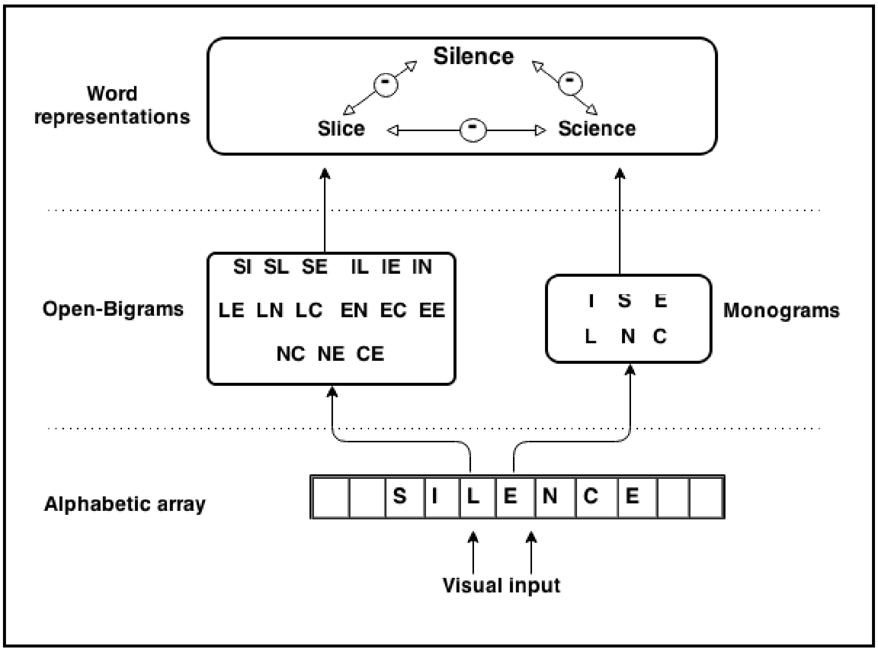


Figure 1. Open-bigram model for orthographic processing**.** The input (Alphabetic array) directly activates the monogram and open-bigram representations (relative position map) which in turn activates the word units. Between the word units there is lateral inhibition based on the degree of overlap and activity. (Adapted from Grainger & Van Heuven, 2003)

The current model is based on several simplifications regarding recurrent connections and higher-level linguistic structures, such as phonological and morphological structures. It is unclear what the precise effect of higher-level linguistic representations is on early orthographic processing, whether the VWFA works in a feedforward fashion mainly representing pre-lexical orthographic processing or works with more recurrent connections with higher-level linguistic information (Carreiras, Armstrong, Perea, & Frost, 2014). In addition, the influence of these higher-level structures on eye movements in reading is less strong and less direct than lower level visual information such as spaces, word length and orthographic information (Rayner, 1998, 2009a). Moreover, an overview of the timing at which various stimulus parameters have an effect, using event-related potentials (ERP), indicated that the influence of phonological and morphological processing is at a later stage of word recognition than the lower level visual information and lexical parameters (Barber & Kutas, 2007). Therefore, for simplicity the current model assumes that there is only feedforward processing and doesn't include the higher-level linguistic structures. Furthermore, the open-bigram model has a hardwired connectionist implementation, which might limit the flexibility and learning capabilities of the model. However, these limitations in learning and fitting enable a more direct examination of the assumptions that underlie structural models. In addition, structural models such as these can provide the appropriate constraints for the connectionist learning models (Norris, 2013) that might have problems with overfitting due to the considerable flexibility in learning.

Method

Model specification

The current section gives a short overview of the complete model of eye movements in reading, providing the neurophysiological basis for the different choices and how the adapted open-bigram model is incorporated. The purpose of the model is to explain and simulate when and where the eyes move through a text, which determines the different types of saccades and the distribution of fixation durations. Specifically, the model should create three types of saccades, regressions (N-1), refixations (N), forward (N+1) and word skips (N+2). The inputs that are used by the model are the letters as they appear in the text, including the word length. Moreover, word frequency information and information on how predictable a word is given its context, are implicitly stored within the model through their effects on the word recognition threshold. Previous approaches of eye modeling in reading were only based on word length, frequency and predictability (Engbert et al., 2005; Reichle et al., 2003). As with the previous approaches the goal is to explain the different types of behavior with general rules for saccade programming (Engbert et al., 2005; Reichle et al., 2003), but including an explicit method of word recognition. In addition, both minimal modeling and biological plausibility were important factors in the creation of the model. The mathematical specification of the model can be found in the appendix. The following section will first describe the key components (Table 1) and the empirical support, after which the details of the model are discussed. The basic process is that a fixation is followed with a saccade and that during a fixation the words and the letters are being processed (Fig. 3). The model is updated in cycles of 25 ms.

Table 1. Model principles

1. Strength of visual input modulated by acuity, attention and crowding.
2. Letter and word processing based on the open-bigram model (Grainger & Van Heuven, 2003)
3. Word recognition:
    a. Threshold based on word length, frequency and predictability
    b. Length matching between the visual input and recognized word units.
4. Saccade timing set by a random clock, but speeded up by word recognition
5. Saccade distance by salience-based target selection and systematic and random saccade errors.

Strength of visual input modulated by acuity, attention and crowding. It is well known that the acuity of human vision is limited and that it decreases with the distance from the center of fixation. Moreover, Rayner (1986) showed with the moving window technique that in skilled readers the perceptual span is limited to 14-15 spaces to the right of the fixation. In addition, a study with parafoveal magnification to compensate for decrease in acuity showed that the perceptual span is also influenced by attention (Miellet, Donnell, & Sereno, 2009). Furthermore, Rayner (1986) showed that by limiting reading with a short window size that skilled readers have a larger reduction in reading rate than beginning readers, supporting the effects of attentional focus on the perceptual span. Therefore, we assumed that the degree of visual processing and the size of the perceptual span is determined by both acuity and attention. Furthermore, the assumption of crowding is based on the presence of lateral inhibition between neighboring letters. For instance, studies that examined the effect of spacing in reading showed that small increases in interletter spacing resulted in faster word recognition (Perea & Gomez, 2012; Slattery & Rayner, 2013).

Letter and word processing based on the open-bigram model. The open-bigram model as described in the word recognition section (Fig. 1) determines the processing of the visual input into the activated word units. The assumptions and justifications of the word recognition model are discussed in detail in the word recognition section. The model has several important assumptions, such as the parallel processing of the words and letters in the visual input, word-to-word inhibition and feedforward connections between the layers. The presence of the orthographic POF effect (Dare & Shillcock, 2012) is a clear indicator of the parallel processing of multiple words. In addition, adjusting the letter order had little effect on the word identification (Grainger & Whitney, 2004; Inhoff et al., 1989), supporting the parallel processing of letters. Moreover, the exclusion of higher level linguistic structures was motivated by the relatively late and weak influence of these structures on eye movements in reading (Barber & Kutas, 2007). It was assumed that the monogram and open-bigram layers were sufficient in modeling word recognition and explaining eye movements in reading.

Word recognition. Previous research clearly showed that word length, frequency and predictability influence eye movement measures during reading (Kliegl, Grabner, Rolfs, & Engbert, 2004; Rayner, 1998; Staub, White, Drieghe, Hollway, & Rayner, 2010; White, Rayner, & Liversedge, 2005). Notably the fixation durations and probabilities increased with word length, whereas they decreased with frequency and predictability (Kliegl et al., 2004; Staub et al., 2010). Considering that these measures indicate the degree of processing of these words (Rayner et al., 1989), they suggest that the length, frequency and predictability of words influence the word identification. Therefore, we assumed that the word recognition threshold increased with word length and decreased with frequency and predictability, roughly based on their respective influence on the fixation durations (Kliegl et al., 2004). Another important assumption is that in order for a word in the visual input to be recognized it must have similar length as the word units that are recognized by the open-bigram model. The underlying idea is that humans are able to match the length of the word unit representations in the brain with the whole-word shape in the visual input.

Saccade timing set by a random clock, but speeded up by word recognition. Saccades are initiated by an autonomous random variable, which creates the variability that is important for reproducing the distributions of fixation durations. However, this stochastic process can be speeded up by word recognition. This speed-up is based on research showing that shorter words and words with a higher frequency or predictability have a decreased fixation duration (Kliegl et al., 2004), indicating a facilitation of word recognition. As mentioned in the previous sections, word recognition is based on several processes, such as the letter and word processing in the open-bigram model and the word recognition threshold. Therefore, the variables that influence these processes, such as the word length and lexical parameters, can also influence the fixation durations (Kliegl et al., 2004). This notion is supported by studies showing that certain parts of lexical processing happen early on word fixation 100-200 ms (Carreiras et al., 2014; Hauk, Davis, Ford, Pulvermüller, & Marslen-Wilson, 2006; Sereno, Rayner, & Posner, 1998). In addition, there is widespread evidence for direct cognitive control of fixation durations in reading in which the lexical and linguistic processing directly influences the timing of a saccade (Rayner & Reingold, 2015; Schotter et al., 2012; Staub et al., 2010).

Furthermore, after the saccade initiation, there is a short delay before the actual saccade is performed, during which the attentional focus is shifted. Therefore, the attentional focus can change without eye movements, but attentional shifts are always followed by eye movements (Findlay & Walker, 1999). Moreover, when a saccade is programmed it cannot be stopped. Both these assumptions are supported by research showing that saccades are preceded by an attentional shift and visual attention is selectively coupled with saccade programming (Deubel & Schneider, 1996; Hoffman & Subramaniam, 1995; Morrison, 1984).

Saccade distance by salience-based target selection and systematic and random saccade errors. The target selection is based on the salience of the right parafoveal words. The salience is based on the acuity, attention and crowding of the visual input. Therefore, the assumption is that mainly low level features determine the forward movements. The motivation comes from research with visual search in scenes and saliency map models that showed that bottom-up mechanisms and salience influence where the eye fixate (Parkhurst, Law, & Niebur, 2002; Underwood, Foulsham, van Loon, Humphreys, & Bloyce, 2006). Moreover, studies with visual search in scenes also showed that the salience based selection can be overruled by cognitive influences. For instance, when subject were told to search for a low salience target the effect of the high salience distractor was negligible (Underwood et al., 2006). These results support the assumption that when the previous or current word is not recognized the salience is overruled and the unrecognized word is selected as the next target. Moreover, (McConkie, Kerr, Reddix, & Zola, 1988) determined that saccades are directed towards the center of a word and that saccades have random errors and systematic errors, which are influenced by the saccade distance.

Implementation

Visual input

For each fixation the visual input was chosen to be the fixated word (fovea) and two words on each side representing the parafovea (N-2, N-1, N, N+1 & N+2). This selection was based on studies that showed the limitations of the perceptual span (Rayner, 1986) and that very little visual information extracted from the lines below (Pollatsek, Raney, Lagasse, & Rayner, 1993). The strength of visual input is determined by acuity, attention and crowding (Fig. 2). The acuity of each letter in visual input is determined by its eccentricity, therefore the acuity of the letters decreases the further a letter is from the center of fixation. Moreover, crowding indicates that letters that are surrounded by spaces have reduced lateral inhibition and therefore increased activity. Furthermore, the attention is parallel distributed over the letters in the visual input, with a Gaussian shape that is centered on the attentional focus. The attentional focus is a point that can be the same as the center of fixation, but can also be another letter in the visual input (Fig. 2). The attentional width determines the spread of the distribution of attention. However, the attention is asymmetrically distributed, such that the attentional width to the right of the center of fixation is larger than the attentional width to the left (Rayner, 1986, 1998). Moreover, the attentional width is narrowed after regressions and widened after forward saccades.

Letter and word processing

The strength of the visual input as described in the previous section determines the activity of the letters in the alphabetic array. In addition, all the letters in the visual input are processed in parallel. Moreover, all the activated bigrams units and monograms units, which are represented in the letter processing layer, influence the word unit activity of the lexicon. As noted in the description of the model (Fig. 1), the monogram units and bigram units have inhibitory connections with all word units and excitatory connections with the word units that contain them. Moreover, all the word units within the lexicon inhibit each other, with the strength of inhibition as a function of the degree of overlap between the word units and the activity of the inhibiting word unit. Furthermore, the activity of all word units decays with a constant rate, set by the decay parameter. A word unit is considered recognized when the activity of the word unit is sufficient and exceeds the word recognition threshold. This threshold is not fixed and is based on the word length, frequency and predictability of each word unit. However, a length check is assumed, such that only the words in the visual input are only flagged recognized when they have a similar length as the recognized word units. Moreover, all the word units that are recognized during a fixation with a similar length as a word in the visual input become allocated to this word. Therefore, multiple recognized word units can get allocated to a word in the visual input. However, the first word unit that gets recognized and allocated during the fixation gets exclusively allocated to the foveal word and cannot be allocated to another word in the visual input during subsequent fixations in the visual input. However, there are no exclusive allocations during a regression or a refixation. A clear implication from the open-bigram implementation is that multiple word units can be recognized during reading, including word units that are combinations from letters from different words in the visual input.

Saccade generation

During a fixation random sampling from a Gaussian distribution determines when a saccade is generated. However, word recognition can increase the probability that a saccade will be generated and can thereby speed up word recognition (Fig. 3). When a saccade is initiated, the attentional focus is moved first and is followed by the actual saccade after four cycles (Fig. 2).

Saccade distance

The saccade distance is determined by the intended saccade distance and the saccade error. The intended saccade distance is based on the target selection and determines to which location the attentional focus will shift. The intended saccade distance is always the middle of the selected target. Target selection is based on salience and the recognition status of the words in the visual input. The salience is the activity of the visual input, based on acuity, attention and crowding, and the most salient word the right of the center of fixation will be the intended target (Fig. 3). However, when the previous word or the current word is not recognized the salience is overruled and the unrecognized word is selected as target. In addition, before the salience is calculated the attention is shifted forward relative to the predictability of the next word, increasing the salience of right parafoveal words. Moreover, the two types of target selection cause different types of saccades. Unrecognized words can cause regressions and refixations, whereas the salience can cause refixations and inter-word forward movements. Thus, the saccade distance is influenced by both lower-visual information (i.e. salience) for forward movements and incomplete lexical processing for regressions and refixations (Rayner, 1998). For the actual saccade distance the intended saccade distance is combined with the saccade error. The saccade error is based on a systematic error and random error (McConkie et al., 1988), with the systematic error as a function of the intended saccade distance.

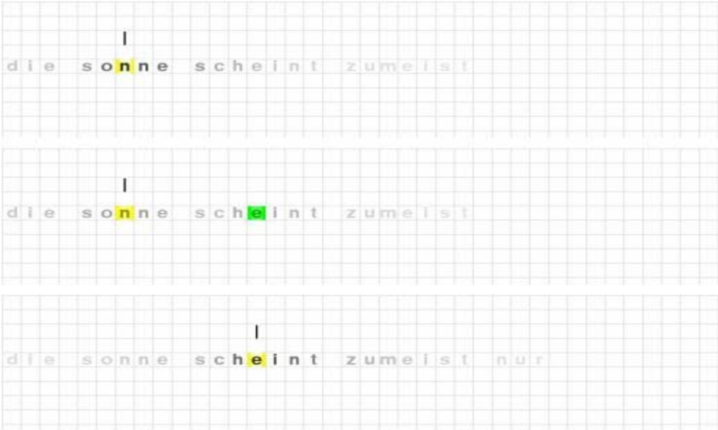


Figure 2. Example of attentional shift preceding a saccade. The yellow marker indicates the center of fixation and the green marker indicates the attention when shifted. The sharpness of the letters is the equal to the degree of processing modulated by acuity and attention.

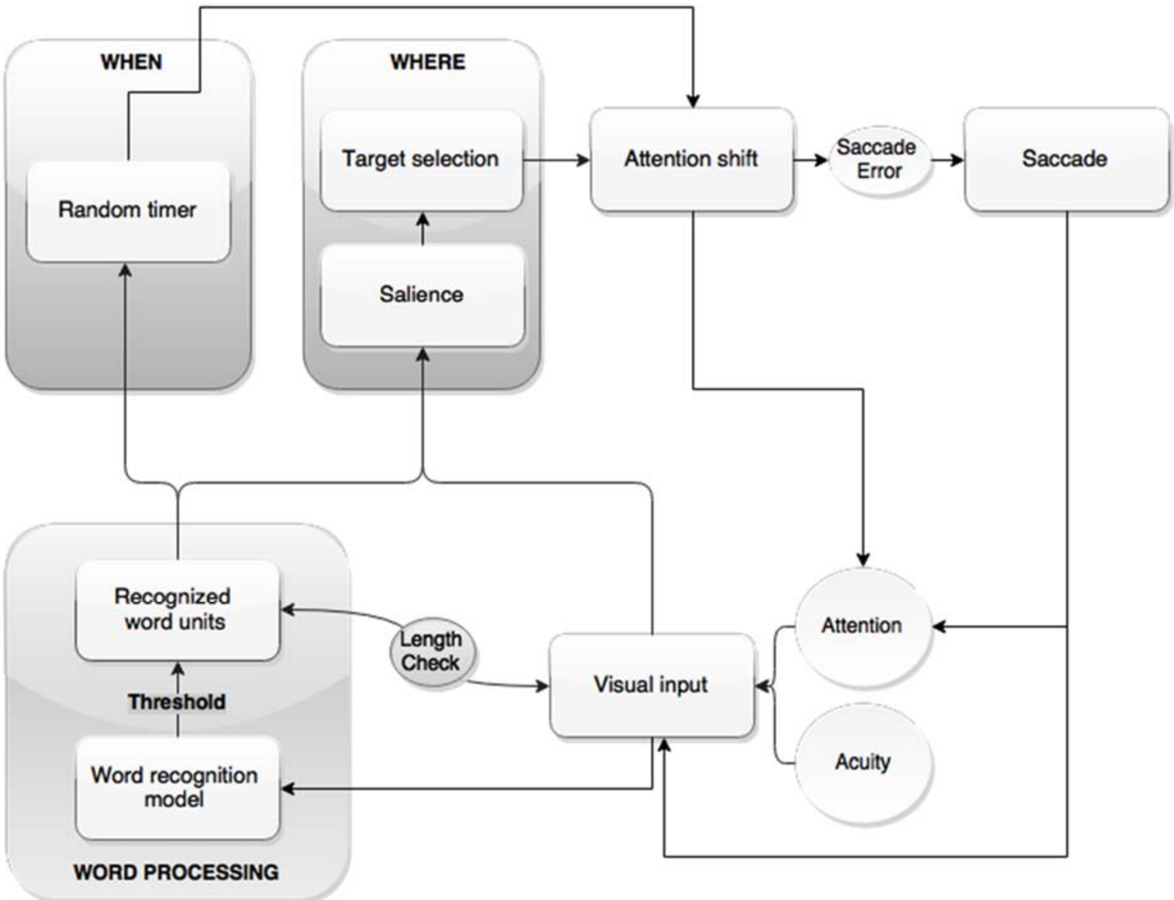


Figure 3. Schematic overview of the model. The visual input contains the selected words from the text, which are modulated by acuity, attention and crowding. The word recognition model determines the activity values of the word units and the word recognition threshold determines if the word units are recognized. A word length check is performed to map the recognized word units with the words in the visual input. The random timer determines when the attention is shifted and a subsequent saccade is generated, but can be speeded up by word recognition. The salience determines the target selection, but can be overwritten by unrecognized words

in the visual input. The target selection determines to where the attention shifts, which in turn affects the influence of attention on the visual input. Moreover, the saccade distance is determined by the target selection and saccade error. When the saccade is a regression or forward movement the attentional width is modulated. The saccade influences the location of the subsequent fixation and therefore determines which words are selected for the visual input.

Results

Model parameters

The simulation results were compared and fitted with a sample from a large cross-sectional eye tracking study during the reading of German texts (Kliegl, Nuthmann, & Engbert, 2006; Kliegl & Laubrock (200?); Laubrock & Kliegl, 2010). The texts that were used are three variants of the Potsdam Sentence corpus (PSC, PSC2 & PPC). The results contain eye tracking data from four healthy young German adults. The model simulation used the same input variables as the German study, the corpora, word frequencies and word predictability. The frequency of the words were taken from the SUBTLEX-DE from Brysbaert et al. (2011) and are log word frequencies from German subtitles from film and TV. The predictability of words were collected using the incremental-cloze task representing the relative frequency of correct guesses (Kliegl et al., 2004). In addition, the lexicon comprised of all the word in the Potsdam Sentence Corpora and the 200 most frequent words from the SUBTLEX-DE.

During the heuristic fitting process only the reading of the PSC2 was simulated and compared with the results from eye tracking data of the three corpora combined. However, the simulated results are a combination of four simulations over all the three corpora. Furthermore, the same eye movement measures were calculated for both the simulated results and German experimental results to enable the model evaluation:

- The fixation durations are traditional eye movement in reading measures (Rayner, 1998); single fixations, first fixation, second fixations, gaze duration and total viewing time.
- The fixation probabilities encompass the probability of a specific saccade type during reading. The word skipping probability and refixation probability are calculated for the first pass reading, whereas the regression probability is the probability that a word is regressed at least once.
- The effects of word-based measures on the fixation durations and fixation probabilities, such as the effects of word length, frequency and predictability.
- The saccade distance is the distance between two subsequent fixations and the initial landing position is the distance of the landing position of the center of fixation relative to the middle of the word.
- Lag and successor effects of the frequency and predictability of the parafoveal words on the foveal fixation duration.

To provide further insight in the process of word recognition and reading, the words in the visual input are matched on identity with their allocated recognized word units. This measure will provides insight in the proportion of correctly recognized words and what types of words have problems with recognition. Furthermore, there are several additional effects that are tested with the model to determine if they reproduce previous research. The neighborhood effects (Acha & Perea, 2008; Perea & Pollatsek, 1998) are determined by incorporating the neighborhood size. The neighborhood size is calculated by comparing the words in the text with the words in the lexicon and calculating the number of words that have one substitution with each other.

To determine the orthographic POF effect an orthographic priming experiment from (Dare & Shillcock, 2012) was replicated. The experiment is based on the boundary paradigm and was implemented in the model using the German PSC. The experiment contained three conditions, the baseline, repeat and control condition (Example 1). In the baseline condition the original sentence was displayed continuously, with no changes. In the control and repeat conditions, the N+1 word was the control word or the repeated word respectively, until the eyes cross the boundary ("|"), then the N+1 word is changed to the post boundary (baseline) condition. The boundary was the space position after the target word. The experiment was created from the three Potsdam sentence corpora. First, the condition sentences were selected that contain two four or two five letter words in sequence with a similar frequency. Second, control words were selected that have a similar frequency and no overlapping letters with the target word. Moreover, the predictable target words were excluded to reduce word skipping. Between each condition there were two random filler sentences selected from the PSC, to prevent the interaction between the conditions sentences. Moreover the text was created such that it contains the six permutations of condition order. There were ten condition sentences with words of length four and five condition sentences of words with length five. The current simulated results contain the average of five sequential simulations of the orthographic priming task.

Example 1:

Die menschheit hat <u>schon</u>| viele katastrophen erlebt	(Baseline)
Die menschheit hat <u>schon</u>| schon katastrophen erlebt	(Repeated)
Die menschheit hat <u>schon</u>| vater katastrophen erlebt	(Control)
Die menschheit hat schon| <u>viele</u> katastrophen erlebt	(Postboundary)

Model predictions

The model should be able to produce the basic distributions of fixation durations and saccade type probabilities. Moreover, the interaction between the input variables with the eye movement measures provides a more elaborate testing of the model results. Various studies showed reliable and independent word length, frequency and predictability effects on both the fixation duration and saccade type probabilities (Kliegl et al., 2004, 2006; Rayner, Sereno, & Raney, 1996; Rayner, 1998; White et al., 2005). Important is that the current model is able to reproduce the effects of these word-based measures on fixation durations and saccade type probabilities. In addition, predictability was found to independently influence word skipping probability (Balota, Pollatsek, & Rayner, 1985; Rayner, Slattery, Drieghe, & Liversedge, 2011). Moreover, the saccade error should be able to create enough variability for the saccade distance and initial landing distributions. Furthermore, the initial landing distribution should be slightly skewed towards the left of the center of the words (McConkie et al., 1988). Moreover, as described in the introduction, the presence of a lexical POF effect would support the assumption of a parallel and distributed attention (Radach & Kennedy, 2013). In addition, the lexical POF effect should mainly be present for short foveal words.

Studies testing with the neighborhood size showed that words with high frequency neighbors had a slower word identification (Acha & Perea, 2008; Perea & Pollatsek, 1998). Because the model incorporates word-to-word inhibition between the words in the lexicon, the model might be able to simulate the effect of high frequency neighbors. In the orthographic POF effect the identity of the parafoveal words (N-1, N+1) should influence the duration of the first pass fixations (REF). More specifically, parafoveal words with a large amount of overlap with the foveal word should reduce the single fixation durations and gaze durations and vice versa.

Simulation results

General effects

The saccade type distributions closely resembled the German experimental results (Fig. 4). However, the simulation had a slightly higher refixation probability and a slightly lower single fixation probability than the German experimental results. Both English and German experimental results were included to provide an insight in the differences. The German saccade type distributions had increased single fixation probability and a decreased probability of refixations, word skips and regressions compared with the English saccade type distributions. Therefore, the eye movement in German reading seems to be biased towards single fixations relative to reading in English. The distributions of the fixation duration measures indicates that the model was able to reproduce the basic shape and variability of fixation durations (Fig. 5). Especially the total viewing time and gaze duration of the simulated results were in good agreement with the experimental results. However, the center of the distributions of the regressions and the first and second fixations were somewhat higher for the simulated results, which indicates that these type of fixations were slower in the simulation. An explanation for the differences might be that the model did not contain the corrective fixations that are in the empirical results. These corrective fixations have a very short fixation duration (< 100ms) and were clearly present in the second fixations and regression of the experimental results.

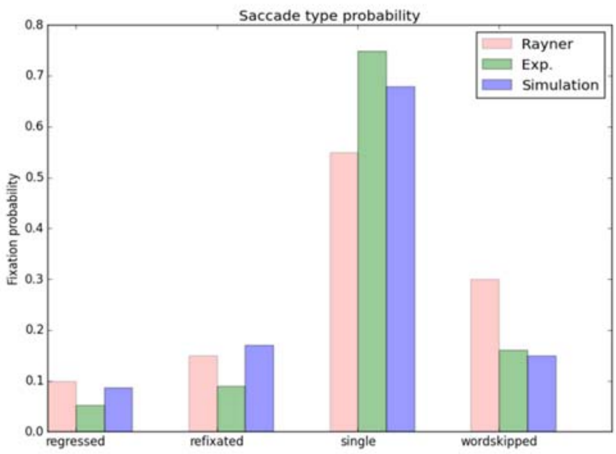


Figure 4. Saccade type fixation probabilities for both English (Rayner, 1998) and German experimental results, compared with the model simulations.

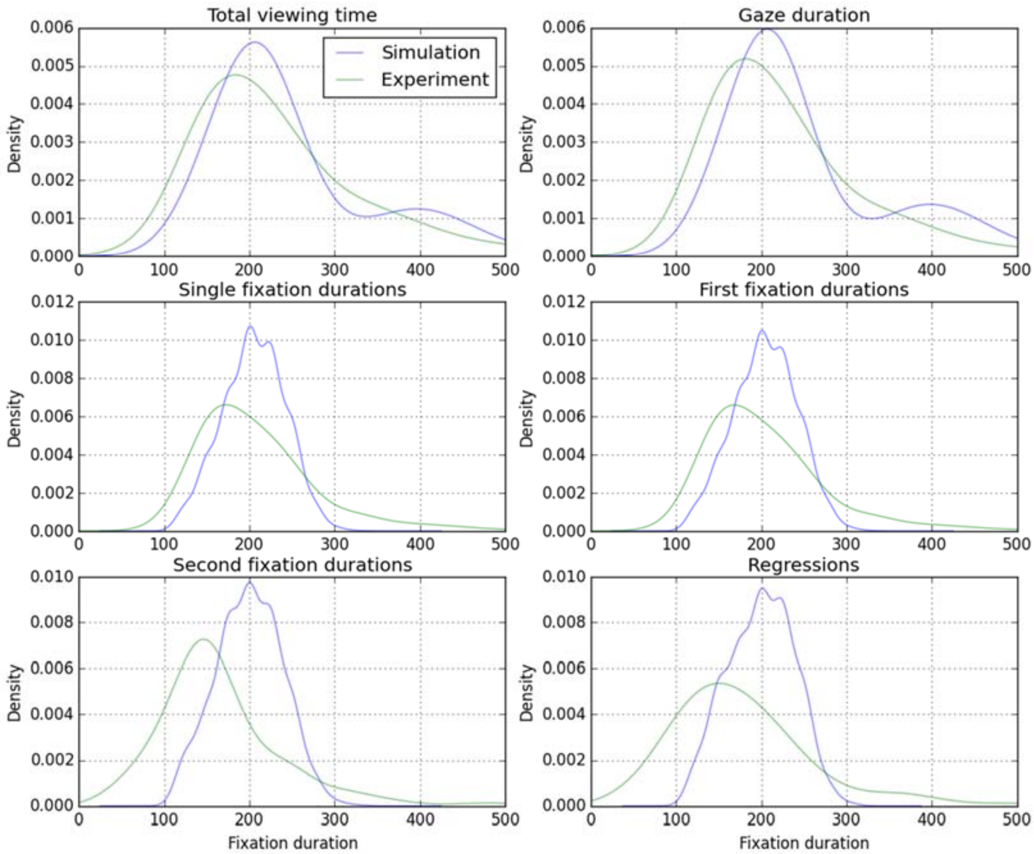


Figure 5. Probability density function of the fixation duration measures for the experimental and simulated results, with a band width of 0.31.

Word-Based effects

The effects of the word-based measures on the fixation duration and saccade type probabilities are illustrated in the figures 6 and 7. These measures were averaged for classes of word length, frequency and predictability. Both the simulated results and the experimental data showed a word length and frequency effect for the gaze duration and total viewing time, such that the fixation duration decreased with word length and increased with log frequency (Fig. 6). Moreover, both word length and frequency had little effect on the single fixation duration. Furthermore, the effects of word length on both skipping and refixation probability were similar for the experimental data and simulated results (Fig. 7). Short words had the highest skipping probability and long words had the highest refixation probability. Moreover, the high skipping probability decreased with word length, whereas the refixation probability increased with word length. In addition, the simulated results also captured the opposite effects of log frequency on the fixation probabilities, such that there was a higher skipping probability for high frequent words and a higher refixation probability for low frequent words. Moreover, the effects of predictability on the saccade type probabilities were very small, but the simulated results did seem to capture the increase of word skipping probability for increasing predictability.

A notable difference between the simulated and experimental results were the increased refixation probabilities in the simulated results (Fig. 7). These additional refixations are also represented in the increased gaze duration and total viewing times of long words (Fig. 6). Moreover, when looking at the cause of the refixations in the model, it turned out that refixations were mainly caused by unrecognized words in the visual input (76 %) and less by the salience mechanism (24 %).

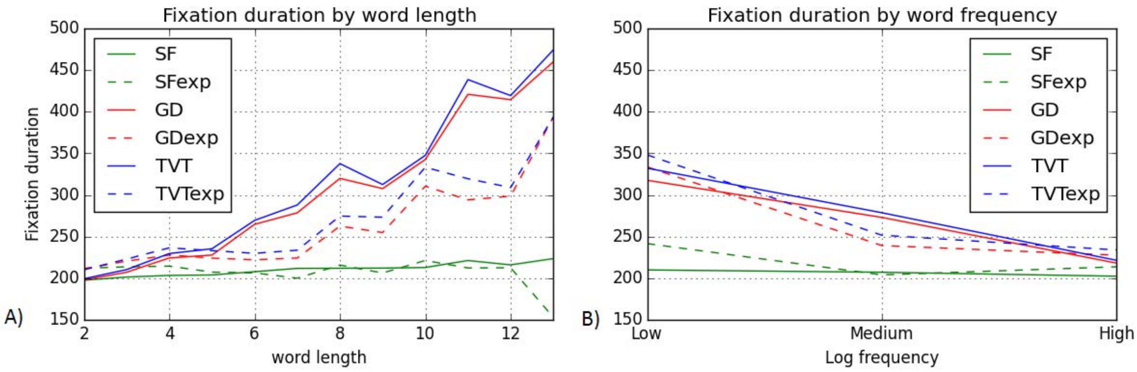


Figure 6. The effects of word-based measures on fixation durations measures for the experimental and simulated results. The simulated results are indicated with solid lines and the experimental results are indicated with dotted lines. Mean duration of single fixations (SF), gaze duration (GD) and total viewing time (TVT) for word length (A) and log frequency class (B).

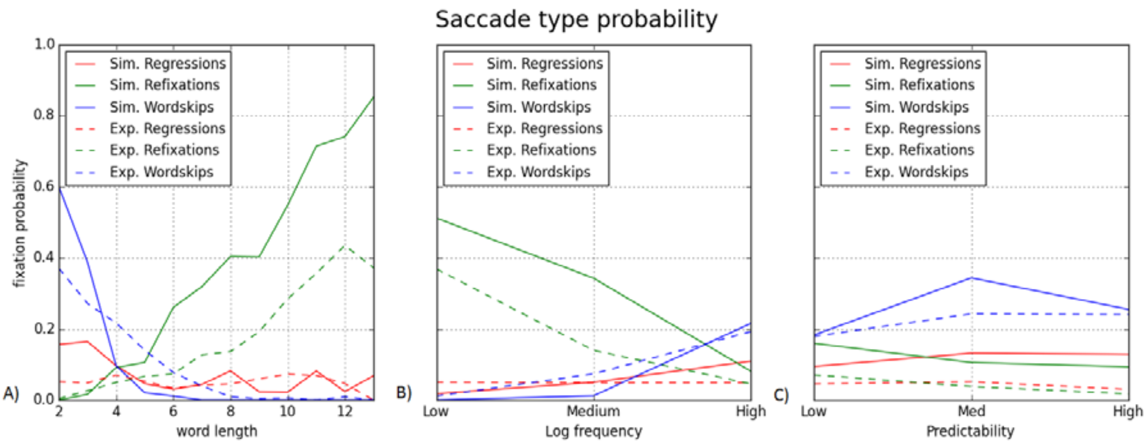
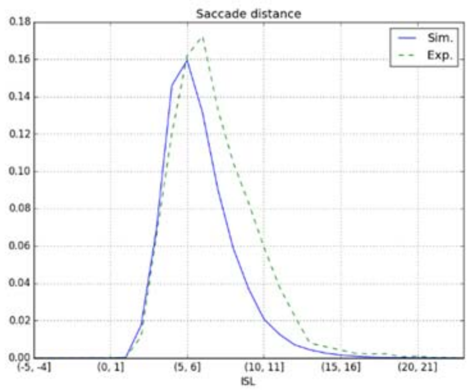


Figure 7. The effects of word-based measures on fixation probabilities for experimental and simulated results. Regression, refixation and word skipping probability for word length (A), log frequency class (B) and predictability (C).

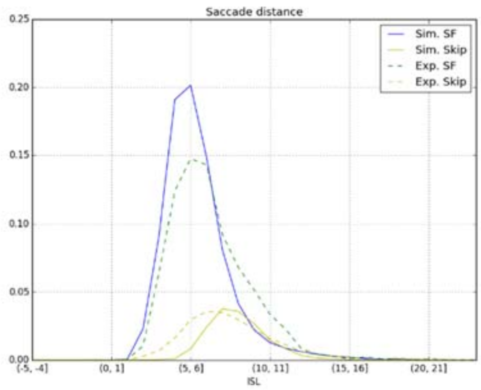
Saccade measures

The distribution of the saccade distances showed a similar center, shape and variability (Fig. 8) for both the simulated and experimental results. Moreover, figure 8b illustrates the difference in saccade distance for normal inter-word forward movements and word skips. The spread of the experimental distances was slightly larger compared to the simulated results. In addition, for the simulated results there was a more pronounced difference between centers of the word skips and normal forward movements. Furthermore, the distribution of the relative landing positions seems to capture the basic properties of the landing position distributions (fig. 9), such that it resembles a

Gaussian distribution with a slight bias towards the left of the center of a word (McConkie et al., 1988; Rayner, 1998). In addition, both the simulated and experimental results had larger deviations in initial landing positions towards the beginning of words than towards the end of words.



A)



B)

Figure 8. The Probability density function of incoming saccade lengths (ISL). The results in A) show the saccade distances for all the forward inter-word movements (no refixations) and B) shows the saccade distances separately for single word forward movements and word skips.

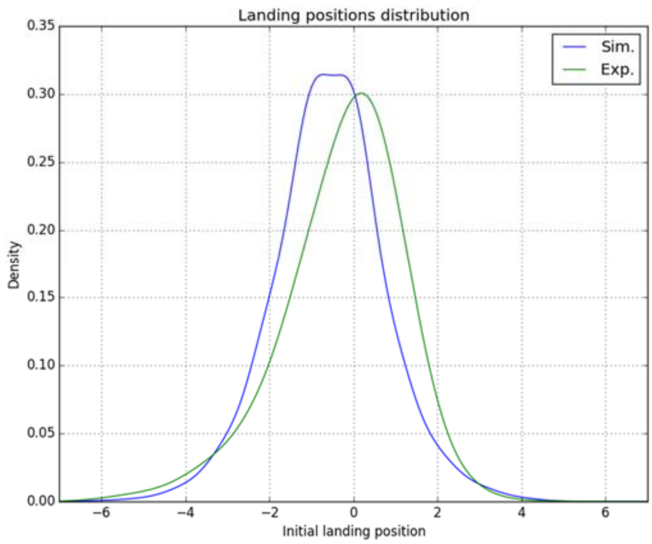


Figure 9. The Probability density function of initial landing positions relative to the middle of the word, for the first-pass eye movements.

Lag and successor effects

For the lag and successor effects the single fixations and gaze durations were plotted against the frequency and predictability of the previous and following words. The lag and successor effects showed whether the lexical processing of the previous and succeeding word influence the fixation duration. Moreover, because the lexical POF effects were mainly found for short words (Kliegl et al., 2006), the results (Fig. 10) only contain the lexical POF effect on the single fixation duration for short foveal words (word length < 6). The results from the lexical POF on the gaze durations were calculated for all foveal word lengths. However, the current results did not provide a good insight in these effects, most likely because the lexical POF effects are generally relatively small and mainly multivariate analyses were able to capture these effects (Kennedy & Pynte, 2005; Kliegl et al., 2006). Furthermore, even the strongest effect, the decrease in fixation duration of the foveal word by the frequency of the previous word (Engbert et al., 2005; Kliegl et al., 2006) was not sufficiently captured by the model (Fig. 10). Therefore, the current simulations do not provide a clear support for the parallel attention mechanism, in which the lexical parameters of parafoveal words can directly influence the fixation duration of the foveal word.

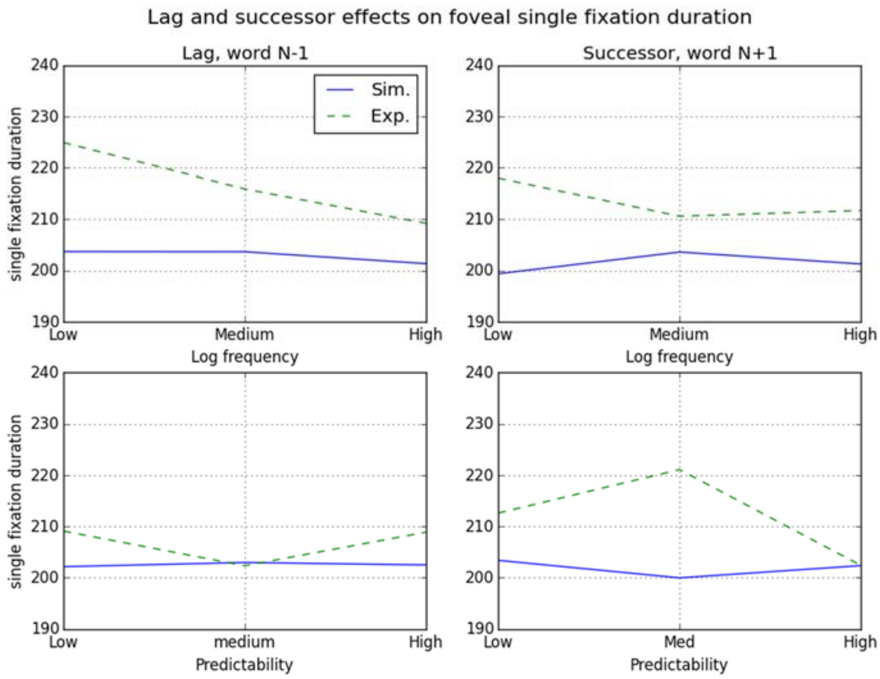


Figure 10. Lag and successor effects of frequency and predictability on single fixation duration for short words (<7), the dotted lines are the experimental results and the solid lines the simulated results.

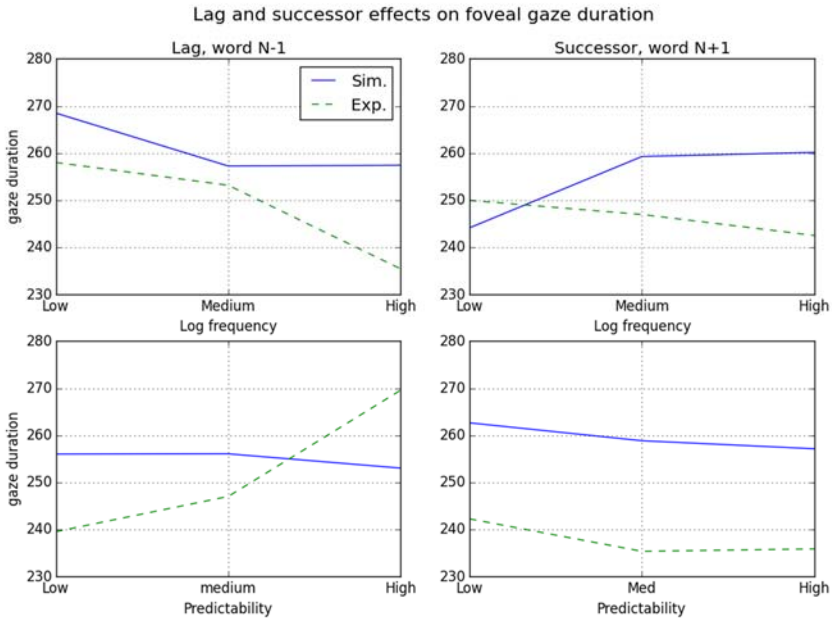


Figure 11. Lag and successor effects of frequency and predictability on gaze duration for all word lengths, the dotted lines are the experimental results and the solid lines the simulated results.

Additional effects

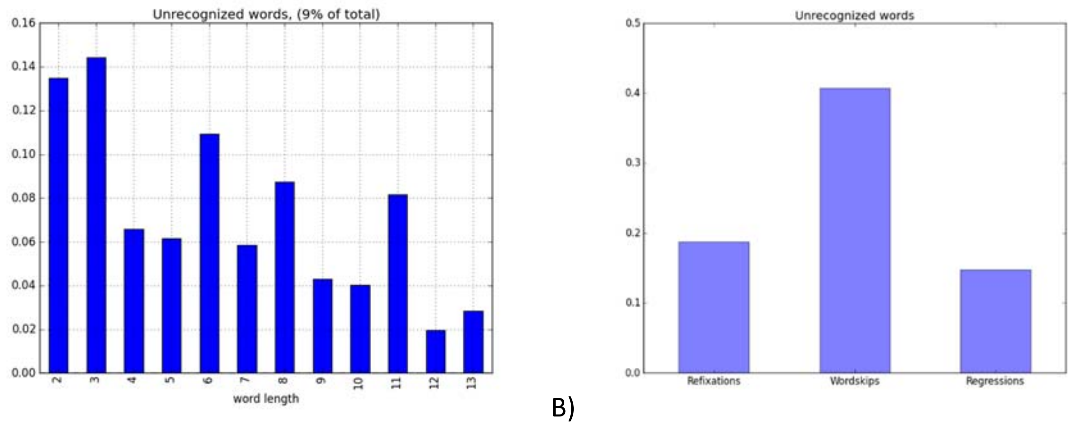
In total 91% of the words were recognized with their correct word unit and 9% of the words were not recognized with the correct word unit. Moreover, the proportion of unrecognized words is higher for shorter words than longer words (Fig. 12 A), with the highest proportion of 0.14 for words of length three. Furthermore, the proportion of unrecognized words is the highest for words that are skipped (Fig. 12 B). Considering that the skipping probability is higher for short words (Fig. 7 A), the increased proportion of unrecognized short words is likely to be due to the increased skipping probability of short words. Furthermore, even after a word is regressed or refixated there are still words that are not correctly recognized (Fig. 12 B). However these correct recognition measures included all the allocated word units to a word in the visual input. The first allocated word plays an important role because it causes the word in the visual input to be flagged as recognized and can therefore directly influence the fixation duration. The correct first recognition was somewhat lower, such that for 73.2% of the fixations the first allocated word unit was the correct word. In addition, in 79.7% of the fixations there was an exclusive allocation of a word unit to the foveal word, from which 81.5% was the correct word.

To determine the neighborhood size effect, the gaze duration was plotted against the number of high frequency neighbors (Fig. 13). The results showed that the average gaze duration increased for a higher number of high frequency neighbors, which suggests that the words with many high frequency neighbors have a larger degree of inhibition on word identification. Moreover, the effect of high frequency neighbors on gaze duration was even stronger for high frequency words (Fig. 13 B). Therefore, these results replicated the inhibiting effects of high frequency neighbors on fixation duration and support the hypothesis that there are effects of lexical competition when reading a text (Acha & Perea, 2008; Perea & Pollatsek, 1998). However, important to note is that the lexicon comprised of all the words from the Potsdam sentence corpora and the 200 most frequent words from the SUBTLEX-DE (Brysbaert et al., 2011). Therefore, the incorporation of the most frequent words might have skewed the effects of the neighborhood frequency effect.

To determine the presence of the orthographic POF effect in the current model a boundary task experiment with different priming conditions was replicated (Dare & Shillcock, 2012). The results showed that the repeated condition had a faster average fixation duration for both the single fixation and gaze durations (Table 2; Fig. 14). In addition the results were more pronounced in the gaze durations and reproduced the parafoveal-on-foveal effect that was captured by Dare & Shillcock (2012) in experiment 2. More specifically, the control condition had the slowest gaze duration, the repeated condition had the fastest gaze duration and the baseline was in between these conditions. However, for the parafoveal preview effect, the fixation duration of the parafoveal word (N+1), the results only partly match the results from Dare & Shillcock (2012). The simulated results (Table 1) show that the baseline condition was the fastest and the control condition the slowest. In the experiment from Dare & Shillcock (2012) the baseline was also the fastest, however the repeat condition was the slowest. Therefore, the current model is able to capture the orthographic POF effects and partly able to capture the preview effects of the orthographic priming paradigm.

In table 3 and 4 additional measures are shown for the conditions of the POF effect (Table 3) and of the Preview effect (Table 4). The correct recognition (1e) property in these tables is the average probability that the first word unit that was allocated to the word in the visual input was the correct word. The refixation probability is the average probability that a word was refixated. For both the POF and Preview effect (Tables 3 & 4) the refixation probability matched the differences in fixation duration, such that the higher the refixation probability, the higher the fixation duration. Moreover, the results from POF effect (Table 3) showed that there was a high correct recognition probability (>0.8) for all conditions. In contrast, the correct recognition probability was lower for the preview effect (Table 4). The lower correct recognition probability in the preview effect indicates a higher probability that the wrong word was allocated to the parafoveal word on subsequent fixations. Moreover, the lower correct recognition probability could explain why the preview effect was not completely reproduced and provides insight in the limitations of the word recognition and matching mechanisms of the model.

There are several effects that were not captured by the model. For instance, the inverted optimal viewing position (IOVP) effect (Vitu, McConkie, Kerr, & O'Regan, 2001), in which the single fixation duration is decreased the further the initial landing position is from the center. In the simulated results the single fixation duration was almost the same for every initial landing position. It might be possible that the inverted optimal viewing position effect is caused by fast corrective refixations due to the saccade errors (Nuthmann, Engbert, & Kliegl, 2005). Therefore, the lack of corrective refixations in the current model might explain the absence of the IOVP effect. Furthermore, the word skipping effects of the single fixations prior to a word skip were not captured by the model. The results from Kliegl & Engbert (2005) showed that the fixation durations prior to word skips were shorter before short high frequency words and longer before long low frequency words, compared with controls (no word skip). Both these effects were not reproduced by the model, there were almost no differences between the fixation durations before word skipping compared with controls. For instance, the difference between the fixation duration before skipped words and controls was 2.4 ms for short high frequency words and 0.3 ms for medium-length low frequency words.



A) B)

Figure 12. Proportion of unrecognized words for word length group (A) and saccade type (B).

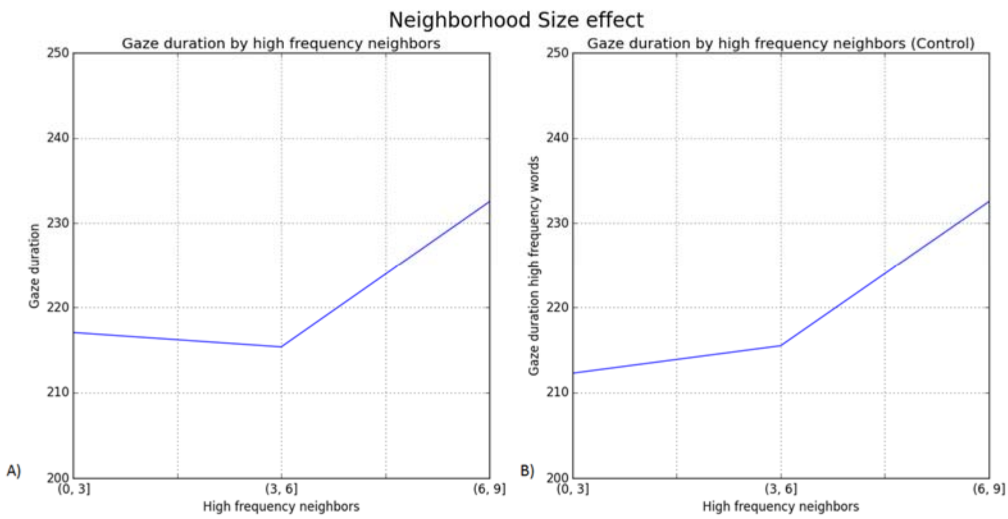


Figure 13. Effect of the number of high frequency neighbors on gaze duration. The gaze duration is plotted for groups with increasing number of neighbors. Plot A) shows the effect of high frequency neighbors on words with all frequencies, and B) shows the effect of high frequency neighbors on only high frequency words.

Table 2. Mean single fixation and gaze durations for orthographic POF simulation.

Measurement type	*Baseline*	*Repeated*	*Control*
Single fixation N (POF)	*203.21*	201.97	205.27
Gaze duration N (POF)	217.71	212.80	232.06
Single fixation N+1 (Preview)	199.54	204.62	209.53
Gaze duration N+1 (Preview)	217.23	228.23	265.37

Table 3. Condition measures for POF gaze duration.

Gaze Duration (Preview)	*Correct recognition (1e)*	*Refixation probability*	*Fixation duration*
Baseline	*0.90*	0.12	217.71
Repeated	0.82	0.11	212.80

Control	0.82	0.18	232.06

Table 4. Condition measures for Preview gaze duration.

Gaze Duration (Preview)	*Correct recognition (1e)*	*Refixation probability*	*Fixation duration*
Baseline	*0.75*	0.08	217.23
Repeated	0.50	0.12	228.23
Control	0.59	0.25	265.37

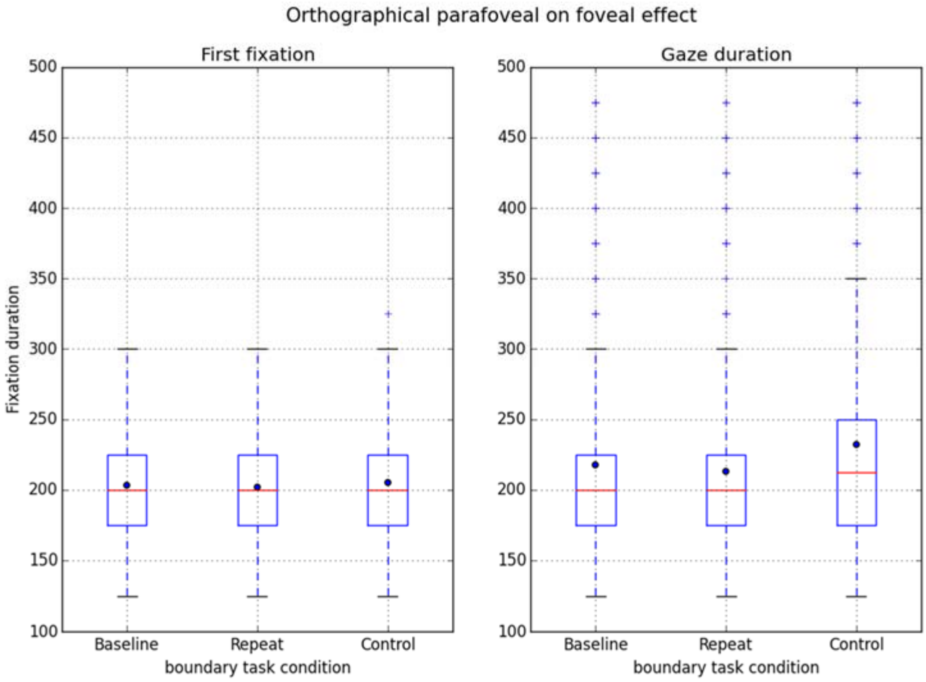


Figure 14. Single fixation and gaze duration for the different orthographic priming conditions using the boundary paradigm, with baseline, repeat and control. The black dots indicate the mean fixation durations.

Discussion

The current paper proposed a new model of eye movements in reading. The current model extends traditional modeling of eye movement in reading with a modified version of the open-bigram model of single word recognition. Moreover, the model provides a test for two novel eye movement in reading functionalities. First, the model provides a test for incorporating orthographic processing in explaining eye movements in reading. Second, the single word recognition model is tested in a realistic reading situation with parallel word processing and eye movements. The simulated results showed that the model is able to reproduce and explain multiple experimentally observed phenomena of eye movement in reading. The model was able to reproduce the distributions of fixation durations, saccade probabilities, saccade distances and initial landing positions and was able to explain the effects of the word-based measures. Therefore, these results show that incorporating letter and word processing can be an important functionality in explaining eye movement in reading.

Moreover, single word recognition models, such as the open-bigram model, can be modulated to perform word processing in a realistic reading situation.

Furthermore, additional results showed that the model was able to reproduce orthographic based effects, such as the inhibiting effect of high frequency neighbors on the fixation duration (Acha & Perea, 2008; Perea & Pollatsek, 1998) and the orthographic POF effect by replicating a priming experiment (Dare & Shillcock, 2012). Therefore, the model was also able to reproduce effects that are based on letter and word processing, that were not explained by the previous approaches of modeling of eye movement in reading (SWIFT and E-Z reader) (Engbert et al., 2005; Reichle et al., 2003). Therefore, the orthographic effects highlight the importance of incorporating explicit letter and word processing in explaining eye movement behavior. Moreover, these results provide support for the functionality of the adapted open-bigram model. Specifically, the orthographic POF effect shows the importance of parallel processing of words in reading and the frequency neighborhood effect shows the importance of the competition between words representations.

An important part of word recognition model is that the recognized word units need to be matched with the words in the visual input. The current model solves this problem by incorporating a similar length based matching and an allocation of recognized words units to the words in the visual input. The high percentage of correctly recognized words (Fig. 12) and correct allocation of the first word units provide a good validation of the functioning of the open-bigram model, including the processing, recognition and allocation of words. However, as noted in the description of the model, a word in the visual input can have multiple recognized word units allocated to it. Therefore, the current word recognition mechanism is not complete, such that there must be a mechanism that determines which of the allocated word units is the correctly recognized word. Furthermore, the exclusive allocation of a word unit to the foveal word is implemented to prevent a premature recognition of the parafoveal word (N+1) when they have the same length. However, the exclusive allocation mechanism can also create problems, for instance in approximately 1% of the cases a parafoveal word (N+1) is exclusively allocated to the foveal word position, thereby preventing the next parafoveal word to be recognized correctly. A possible solution to these problems might be a later stage semantic matching that can select the most likely candidate from the allocated words.

As discussed in the results, there were several effects that the model could not reproduce. Such as the lexical POF effect, the IOVP effect and word skipping effects. As discussed in the results section, the IOVP effect could be reproduced by incorporating fast corrective refixations for mislocated fixations (Nuthmann et al., 2005). In addition, the lexical POF effect plays an important role in the debate of the distribution of attention. However, the current implementation, with a parallel distributed attention, is not able to reproduce lexical POF effects. Several studies suggest a mechanism that could explain these effects. For instance, Henderson & Ferreira (1990) showed that processing difficulty of the foveal word can influence the processing of the parafoveal information. Moreover, a study in Chinese reading showed that the parafoveal difficulty can also influence the processing of the foveal word (Yan, Kliegl, Shu, Pan, & Zhou, 2010). Therefore, both studies suggest a direct and dynamical modulation of the perceptual span by the processing difficulty, which could be a mechanism for reproducing both lexical POF effects and word skipping effects. With this mechanism the difficulty of a word can influence the degree of processing of the parafoveal words, enabling an inter-word interaction between the lexical status and the fixation durations.

Furthermore, the parameter optimization for the current model was based on heuristic trial-and-error adjustments, such that were only manual modifications of the parameter settings. Therefore, there was no quantitative fitting used for the optimization of the parameters settings. At a late stage of the development of the model, multiple optimizations were applied to the model implementation, such that the simulations were faster (100x) and making the usage of a data fitting algorithm a more feasible option. Therefore, incorporating a fitting algorithm, such as a genetic algorithm or grid search, will most likely create an even better fit with the experimental data. Moreover, the model contains several random mechanisms that create variability between different runs, such as the autonomous timer and the saccade error. Therefore, it is important to include extensive quantitative testing to remove any residual effects of variability.

In addition to these improvements it is important to determine the generalizability of the model by testing the model on other German texts and other languages. A possible advantage of the current reading model is that it has explicit word processing based on a psychologically plausible word recognition model. However, because the current word recognition model is structured (hardwired), it might have problems in inter-language generalizability. For instance, the model might perform well on other Germanic languages, but maybe not on languages with larger differences and a different origin, such as Roman languages. Therefore, it is interesting to see to what degree the model parameters need to be adjusted in order to reproduce similar results in other languages. Furthermore, the model performance on other languages provides a good test of the universality of the open-bigram model.

There are various methods to get further insight in the model performance. For instance, testing with different perceptual span parameters to simulate the differences between beginning and skilled readers (Rayner, 1986; Reichle et al., 2013), or determining if the model can be “lesioned” to simulate reading related disabilities such as dyslexia. The current model can be seen as a first step in creating a more universal structured model of reading. Further steps can be taken to extend the modeling of word recognition in reading, with for instance phonological and semantic processing and incorporating of recurrent connections. Furthermore, structured-based modeling may provide the appropriate constraints for the learning based (connectionist) models and will guide the universal modeling of reading as proposed by (Frost, 2012).

Acknowledgements

I would like to thank my supervisor Dr. M. Meeter for his support and feedback during this project.

Appendix

Visual processing

1. The acuity of each letter in the visual input is based on its eccentricity. The effect of eccentricity is based on the relation between the cortical magnification factor and population receptive field size in human visual cortex (Harvey & Dumoulin, 2011). The norm factor is used to make visual acuity at 0 degrees equal to 1.
    a. Letters per degree = .3
    b. Norm factor = 35.555556
    c. δ1 = 0.018
    d. δ2 = 1/64

$$accuity_{letter} = \frac{1}{norm\_factor} * (\delta 1 * eye\_eccentricity * letters\_per\_degree + \delta 2)$$

2. The attention for each letter in the visual input is based on the attentional eccentricity (att_eccentricity) and the attentional width (att_width). The asymmetry parameter creates a different attentional width for the left and right of the center of fixation. The baseline is the minimum attention for a letter in the visual input.
    a. Baseline = 0.25

$$attention_{letter} = \frac{1}{att\_width} * e^{-\frac{att\_eccentricity^2}{2*(att\_width*asymmetry)^2}} + baseline$$

$$asymmetry = \begin{cases} 0.25, & eye\_ecc < 0 \\ 1, & eye\_ecc \geq 0 \end{cases}$$

3. The changes in attentional width are caused by regressions and inter-word forward movements, refixation do no cause a change in attentional width. However the attentional width must remain within the limits of a predefined range of attentional width.
    a. Max attentional width = 5.0
    b. Min attentional width = 3.0

$$Attentional_{width} = Attentional_{width} + width\_change$$

$$widthchange = \begin{cases} -2.0, & regression \\ 0.5, & forward \end{cases}$$

4. The crowding is based on the number of surrounding letters. The initial weight represents the weight for letters that are surrounded by spaces on both sides. The letter weight formula calculates the new letter weight when a surrounding letter is added.
    c. Initial weight = 2

$$weight_{letter} = \frac{initial\ weight}{\sqrt{2}} / \sqrt{2}$$

5. The activity value of a letter in the visual input is based on the product of acuity, attention and crowding

$$visual_{input_{letter}} = attention_{letter} * accuity_{letter} \ * weight_{letter}$$

6. The salience of the words to the right of the fixation are calculated using the acuity, attention and weight of each letter. Important to note is that the attentional focus is changed to the salience attention position before the calculation of the salience of the words in the visual input. The salience of the foveal word is only calculated for the remaining letters, to the right of the center of fixation. The wordpred is the predictability of the next word.
   d. Salience shift = 1.29

$$Salience \ = \sum_{letter=1}^{n} sum(attention_{letter} * accuity_{letter} * weight_{letter})$$

$$salience\_attention_{position} \ = \ salience_{shift} + \ (salience_{shift} \ * \ wordpred)$$

Letter and word processing

1. The activity of letters in the visual inputs are summed in their respective monograms and bigrams representations.

2. The bigrams are only formed within words for a specified bigram range. The word excitation is calculated for all the word in the lexicon that contain the bigrams or monograms that are in the visual input.
   a. bigram_to_word_excitation = 0.004
   b. Bigram_range = 3

$$total\_word\_input {+=} \ bigram\_to\_word\_excitation * bigram\_monogram\_activity$$

3. The word inhibition is calculated for all the words in the lexicon, based on all the bigrams and monograms in the visual input.
   a. bigram_to_word_inhibition = -0.0001

$$total\_word\_input {+=} \ bigram\_to\_word\_inhibition \ * bigram\_monogram\_activity$$

4. The word overlap is calculated between all the words in the lexicon. The overlap is set to zero when the overlap is lower than the minimum overlap.
   a. Minimum_overlap = 2

$$word\_overlap = number\_of\_shared\_bigrams + number\_of\_shared\_monograms$$

5. The total word input is based on the word to word inhibition, degree of overlap and the activity of the inhibiting word.
   a. Word inhibition = -0.002

$$total_{wordinput} {+=} \frac{100}{size(lexicon)} * word2word_{inhibition} * overlap(current_{word}, inhibiting_{word}) * inhibiting_{wordactivity}$$

6. The word activity is scaled such that it remains within the word activity limits. The current word activity is the activity of the word from the previous cycle.
    a. Max activity = 1.0
    b. Min activity = 0.0
    c. Decay = -0.053

$$word_{activity} = currentword_{activity} + \left(\max_{\text{activity}} - currentword_{activity}\right) * total_{wordinput} + (currentword_{activity} - \min_{\text{activity}}) * decay$$

Word recognition

1. The word recognition threshold is based on the non-linear exponent of word length and the inverse of frequency and predictability. The predictability values are only included for the exact context positions from which the predictability was determined.
    a. Freq_strength = 5.5
    b. Pred_strength = 9.0
    c. growth_rate = -0.44
    d. start_val = 0.22
    e. end_val = 0.134

$$Word\ recognition\ threshold = \frac{\text{Freq\_strength} * log(maxwordfreq) - log(crtwordfreq)}{\text{Freq\_strength} * log(maxwordfreq)} * \frac{\text{Pred\_strength} * maxwordpred - crtwordpred}{\text{Pred\_strength} * maxwordpred} * \text{end\_val} - \text{start\_val} * \exp(\text{growth\_rate} * wordlength)$$

2. The length matching formula determines whether two words have a similar length and is relative to the length of the longest word.
    a. β = 0.25

$$Length_{match} = |len(word1) - len(word2)| < \beta * max(\, len(word1), len(word2)\,)$$

Saccade generation

1. For each cycle the current amount of cycles is checked with the attention shift generator, and the attention is shifted when the amount of cycles >= attention shift. The saccade always follows the attentional shift after 4 cycles (100ms).
    a. σ = 2

$$attention_{shift} = N(\mu, \sigma)\begin{cases} \mu = 3.8, & recognized \\ \mu = 5.0, & not\ recognized \end{cases}$$

Saccade distance

1. The saccade distance is based on the intended distance the systematic range error (SRE) and the random error (RE) (McConkie et al., 1988). The intended distance is always the middle letter of the selected target, with the first letter to the left for words of even length. The SRE is based on the differences between the preferred distance and the absolute intended distance. The random error is taken from a Gaussian distribution with a zero mean and a standard deviation based on the absolute intended distance.
    a. Preferred distance = 6.5
    b. δsre = 0.2 (Saccade range error strength)
    c. β_0 = 0.18 (Initial random error sigma)
    d. β_1 = 0.08 (Random error sigma strength

$$Saccade\ distance = Intended\ distance\ + SRE\ + RE$$

$$SRE\ = (preferred\ distance\ - |Intended\ distance\ |) * \ \delta sre$$

$$RE\ = N(\mu, \sigma) \begin{cases} \mu = 0 \\ \sigma = \beta 0 + (|Indended\ distance| * \beta 1) \end{cases}$$

2. For refixations the saccade distance is multiplied with a refixation scaling parameter
$$\text{Refixation size} = 0.15 * Saccade\ distance$$

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